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Connector Hubs in Semantic Network Contribute to Creative Thinking

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Semantic memory offers a rich repository of raw materials (e.g., various concepts and connections between concepts) for creative thinking, represented as a semantic network. Similar to other networks, the semantic network exhibits a modular structure characterized by modules with dense internal connections and sparse connections between them. This organizational principle facilitates the routine storage and retrieval of information but may impede creativity. The present study investigated the effect of hub concepts with varying connection patterns on creative thinking from the perspective of a modular structured semantic network. By analyzing a large-scale semantic network, connector hubs (C-hubs) and provincial hubs (P-hubs) were identified based on their intra- and intermodule connections. These hubs were used as cue words in the alternative uses task, a widely used measure of creative thinking. Across four experiments, behavioral and neural evidence indicated that C-hubs facilitate the generation of more novel and remote ideas compared to P-hubs. However, this effect is predominantly observed in the early stage of the creative thinking process, involving changes in brain activation and functional connectivity in core regions of the default mode network and the frontoparietal network, including the dorsolateral prefrontal cortex, angular gyrus, and precuneus. Neural findings suggest that the superior performance of C-hubs relies on stronger interactions between automatic spreading activation, controlled semantic retrieval, and attentional regulation of salient information. These results provide insight into how concepts with varying semantic connection patterns facilitate and constrain different stages of the creative thinking process through the modular structure of semantic network.

Public Significance Statement

This study employed a novel network-based experimental approach to investigate the effect of the modular structure of semantic network on creative thinking. Connector hubs and provincial hubs, identified based on their intra- and intermodule connection patterns, were used as cue words in the alternative uses task, which prompts participants to generate novel ideas. The results demonstrated that connector hubs facilitate the generation of more novel and remote ideas compared to provincial hubs. However, this effect is predominantly observed in the early stage of the creative thinking process and is associated with unique brain activation and functional connectivity. These findings highlight the crucial role of the modular structure of semantic network in modulating creative ideation.

Keywords: creative thinking, semantic network, connector hub, semantic distance, default mode network

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continued

Creativity and innovation do not appear out of thin air, but rather by relying on our memory and knowledge (Benedek et al., 2023; Kenett, 2024). Semantic memory, which stores knowledge and experiences, provides rich "raw materials" (e.g., concepts and connections between concepts) for creative cognitive processing (Abraham & Bubic, 2015; Kumar, 2021). Its structural organization has an important impact on creative thinking (Kenett, 2024; Mednick, 1962; Zhuang et al., 2021). The associative theory of creativity emphasizes that creative thinking involves connecting and combining weakly related, remote concepts in semantic memory to generate novel and useful ideas (Beaty & Kenett, 2023; Mednick, 1962). Empirical evidence consistently shows that the greater the semantic distance between concepts, the more creative their combination tends to be (Beaty & Johnson, 2021; Green, 2016; Heinen & Johnson, 2018; Kenett, 2019; Li et al., 2023; Liu et al., 2021). Recent studies using computational network science and natural language processing methodologies have constructed individual and group-level semantic networks, consistently revealing that higher creativity is associated with a flexible semantic network structure (Benedek et al., 2017; He et al., 2021; Kenett & Faust, 2019; Kenett et al., 2014; Ovando-Tellez, Kenett, et al., 2022). However, little is known about the mechanistic explanations of the role of semantic network in creativity.

Similar to other networks (e.g., social networks, brain networks), semantic network also exhibits a modular structure that can be divided into different modules (also known as clusters and categorizations) using community detection. That is, concepts within modules are densely connected, while concepts between modules are sparsely connected (Bousfield, 1953; Chai et al., 2020; Ferrer I Cancho & Solé, 2001; Siew et al., 2019). Research has increasingly identified the role of modular semantic network structures in memory-related processes processes in both typical (Marko & Riečanský, 2021; Michalko et al., 2023) and clinical (Kenett et al., 2016; Lebkuecher et al., 2024; Matsumoto et al., 2023) populations, suggesting that this organizational principle facilitates the routine storage and retrieval of information (Agustín-Llach & Rubio, 2024; Bornstein & Arterberry, 2010). However, recent findings have revealed that generating creative ideas is associated with less modularity in semantic network (He et al., 2021; Kenett & Faust, 2019; Ovando-Tellez, Kenett, et al., 2022), implying that an overly modular semantic network may potentially hinder creativity. Additionally, it has been proposed that stronger links between modules in the semantic network of highly creative individuals may enhance the flexibility of memory retrieval, a critical aspect of creativity (Kenett et al., 2018; Sarica et al., 2021).

Insights into the role of a modularly structured semantic network in creative thinking can be derived from classical theoretical models. The most common task used to assess creative thinking is the alternative uses task (AUT), which assesses the ability to generate multiple novel solutions for an object (i.e., cue word; Acar & Runco, 2019; Runco & Acar, 2012). In accordance with the spreading activation model of Collins and Loftus (1975), the cue word spontaneously activates the local semantic space within a specific module (Benedek et al., 2023; Hass, 2017). This process is critical since creative ideation requires forming connections between remote concepts (Benedek et al., 2023; Kenett, 2019; Mednick, 1962; Volle, 2018). The existence of modules in a semantic network implies that the creative retrieval process needs to "leave" the module where the cue word is located and break free from the constraints induced by the activation of the local semantic space (Beaty et al., 2023). Thus, for responses generated in the AUT, it could be speculated that responses "outside" the module where the cue word is located are more creative.

Moreover, the division of network modules enables the quantification of the connection characteristics of nodes inside and outside the module. Accordingly, two types of hubs with different connection patterns of intra- and intermodules can be defined. Connector hubs (C-hubs) display a diverse connectivity profile across different modules, which acts as a pivotal role in the information transmission between modules. Provincial hubs (P-hubs) connect to other nodes within their own module, which is important for intra-module communication (Bertolero et al., 2018; Guimerà & Amaral, 2005; Guimerà et al., 2007; Rubinov & Sporns, 2010; van den Heuvel & Sporns, 2013). C-hubs tend to be connected to concepts outside the module, which may reflect the ability to spontaneously induce more remote semantic associations, providing more potential materials or elements for creative idea generation than P-hubs. Thus, it could be hypothesized that C-hubs contribute to generating more novel and remote ideas than P-hubs.

The present study aimed to investigate the role of the modular structure of semantic network in creative thinking by using the two types of hub concepts as the AUT objects (i.e., cue words). Experiment 1 aimed to examine the difference in originality scores between responses inside and outside the module where the cue word is located, thus establishing a link between the modular structure of semantic network and creativity. Then, according to the distinct connection patterns inside and outside semantic modules, Experiment 2 selected C-hubs and P-hubs from a large-scale Chinese lexical database as AUT objects and examined the differences in creativity scores induced by the two types of hub concepts. By manipulating the AUT trial duration (15 s for Experiment 2 and 60 s for Experiment 3), it was possible to further investigate the modulation of hub concepts on the creative thinking process. Finally, Experiment 4 utilized functional magnetic resonance imaging (fMRI) to investigate the neural correlates underlying the influence of hub concepts on creative thinking and to explore mechanistic explanations for the effect of the modular structure of semantic network on creativity.

Transparency and Openness

The determination of sample size, data exclusions, all manipulations, and measures in all experiments were reported. Analysis code,

role in conceptualization and an equal role in formal analysis, investigation, methodology, and writing–review and editing. Jiang Qiu played a supporting role in conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, supervision, writing–original draft, and writing–review and editing.

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materials, behavioral data, and fMRI *t*-maps are available on the Open Science Framework at https://osf.io/t6kxz/ (He, 2024). These experiments were approved by the Institutional Review Board of the Faculty of Psychology at Southwest University, and written informed consent was obtained from each participant. There was no overlap in participants across experiments.

Experiment 1: Creative Thinking and Cross-Module Semantic Associations

Method

To explore whether AUT responses generated outside the module where the cue word is located are more creative than those within the module, Experiment 1 reanalyzed data from our previous study including 192 participants (M_{age} = 19.32 years, age range = 18–22 years, gender reported: 162 females and 30 males) who generated a total of 1,682 alternate uses (i.e., responses) for the object "can" (He et al., 2021). Specifically, participants were asked to list as many interesting, novel, and unusual uses for a can as possible within 3 min. All responses were assessed by four trained raters according to the norming scoring guides (J. Sun et al., 2019; Zhu et al., 2017), including three different dimensions: fluency (the number of meaningful and relevant ideas, which is associated with the ability to generate and consider other possibilities), flexibility (the number of different categories of ideas, which reflects the ability to shift between conceptual fields), and originality (the degree of originality of the ideas, which is associated with thinking "outside the box"). The scoring process involves each rater first assessing the validity of each response. If deemed valid, the rater assigns an originality score ranging from 1 to 5 points to the response. Finally, a flexibility score is also assigned for all valid responses. It is noteworthy that Experiment 1 focuses solely on the originality scores, and the interrater reliability of the originality score was assessed with the intraclass correlation coefficient, ICC (C, k) = 0.94. Responses receiving invalid ratings by more than two raters are excluded from subsequent analyses. The average score given by raters serves as the originality score for each valid response.

Necessary text preprocessing was implemented before calculating the semantic distance, such as correcting typos and deleting degree adverbs. In addition, as some responses do not exist in the corpus, synonym substitutions were included to ensure that word embedding of all responses can be extracted. For example, replacing the response "can be used to collect rainwater" with "collect water." One trained postgraduate who was blind to the goal of this research completed necessary text preprocessing (especially for synonym substitutions), which involved nearly five percent of the responses, and finally obtained 329 different responses.

The semantic similarity was calculated between responses and the cue word using word2vec (Mikolov et al., 2013) with the Chinese corpus of *Baidu Baike* and *Wikipedia* (Liu et al., 2021). Semantic similarity was measured as the cosine angle between feature vectors of each word pair, and semantic distance was calculated as 1 minus the semantic similarity. A detailed description of semantic similarity calculation can be found in our previous work (Liu et al., 2021). Then a 330 × 330 semantic similarity network (329 different responses plus the cue word "can") was constructed, and negative edges were removed to make the network clearer and more interpretable. Subsequently, Newman community detection was performed to partition the matrix into optimal, nonoverlapping modules using the Brain Connectivity Toolbox (Newman, 2006; Rubinov & Sporns, 2010). This methodology involves identifying responses located within the same module as the cue word and those outside the module, followed by conducting an independent-samples *t* test to assess the difference in originality scores between these two types of responses.

Results

First, Pearson correlation revealed a significant positive correlation between semantic distance based on natural language processing and human originality ratings, $r(327) = 0.325$, $p < .001$. The results of community detection are visualized in Figure 1a, revealing that the number of responses is located within the same module as the cue word accounts for 27% (n = 88) of the total responses. Importantly, the originality score of responses outside the module where the cue word is located is significantly higher than responses within the module, $t(327) = 4.56$, $p < .001$, $d = 0.57$, 95% CI [0.32, 0.82] (Figure 1b). These results suggest that higher original ideas not only relate to remote semantic associations but also involve cross-module connections between concepts in semantic network.

Experiment 2: Effect of Hub Concepts on Creative Thinking

Based on the above results, it could be speculated that a concept with more intermodule connections may be more conducive to generating novel ideas. To test this hypothesis, Experiment 2 used a recently released database (i.e., Chinese Lexical Database; C. C. Sun et al., 2018) to identify hub concepts with distinct connectivity profiles inside and outside the module.

Method

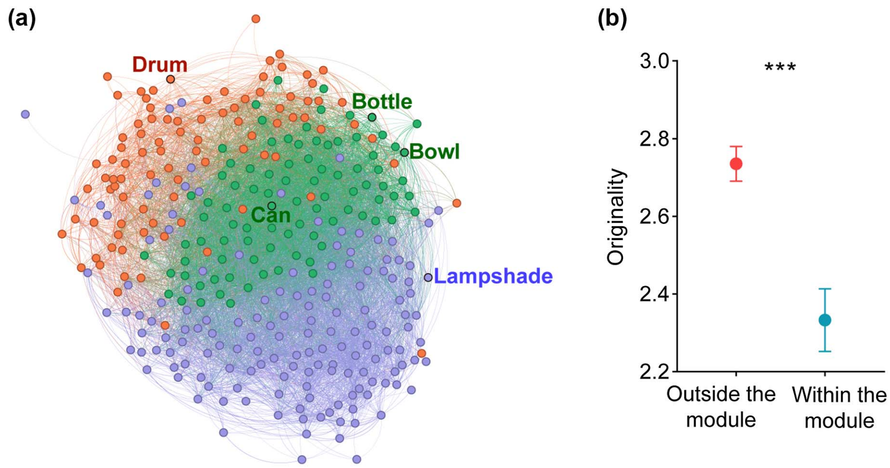
Participants

G*Power was used to estimate the necessary sample size with a moderate effect size (Cohen's d) of 0.50, a power of 0.80, and an α of .05 (one-tailed; Faul et al., 2007) and gave a minimum sample of 27 participants. Given the exploratory nature of this experiment and the desire to enhance statistical power and reliability, as well as the possibility of invalid samples, the sample size was increased based on available time and resources, ultimately recruiting 43 right-handed participants (M_{age} = 20.40 years, age range = 18–23 years, gender reported: 20 females and 23 males). Participants signed informed consent and received payment for their participation.

Materials

The Chinese Lexical Database (C. C. Sun et al., 2018) was used to select C-hubs and P-hubs. This corpus provides rich lexical information for 3,913 one-character words, 34,233 two-character words, 7,143 three-character words, and 3,355 four-character words. Since one-character Chinese words and four-character Chinese words are usually not suitable for the AUT, only two-character and three-character Chinese words were selected. A very small number of words (0.77%) from the Chinese Lexical Database was not included in the corpus that was used to obtain word embedding. Consequently, a 41,056 × 41,056 semantic similarity matrix was constructed, and

Figure 1
Results of Experiment 1



Note. (a) The visualization of the three identified semantic network modules for all responses generated by the cue word "can." For example, two responses ("bottle" and "bowl") are located within the same module as the cue word, while two other responses ("drum" and "lampshade") are situated in different modules. (b) The originality score of the responses outside the module containing the cue word was significantly higher than those of the responses within the module. Error bar represents mean ± SEM. SEM = standard error of the mean. See the online article for the color version of this figure.
*** $p < .001$.

negative edges were removed. Newman community detection was performed to partition the matrix into optimal, nonoverlapping modules using the Brain Connectivity Toolbox (Newman, 2006; Rubinov & Sporns, 2010).

Within-module degree and participation coefficient for each node (i.e., word) were calculated and further transformed into *z*-scores. Within-module degree measures how well-connected a node is to other nodes in the same module. The participation coefficient measures the proportion of connections a node has within its own module versus other modules in the network. Nodes that are important for both intra- and intermodular connectivity are considered as C-hubs with high within-module degree and high participation coefficient, while nodes that are important for only intra-modular connectivity are considered as P-hubs with high within-module degree but low participation coefficient (Rubinov & Sporns, 2010). The illustration of the connection pattern for C-hubs and P-hubs is shown in Figure 2a. Degree centrality was not used to define C-hubs and P-hubs considering that degree centrality is a problematic measure of node importance in correlation networks (Power et al., 2013). According to previous division criteria (Bertolero et al., 2018; Guimerà & Amaral, 2005; Guimerà et al., 2007; Rubinov & Sporns, 2010; van den Heuvel & Sporns, 2013) and considering that there are few words in the corpus that are suitable for the AUT, a slightly loose threshold was adopted to identify hubs: words with within-module degree greater than 0.5 and participation coefficient less than 0.5 are divided into P-hubs, while words with within-module degree greater than 0.5 and participation coefficient greater than 0.5 are divided into C-hubs.

According to the applicability of words in the AUT, 20 C-hubs and 20 P-hubs were selected, as shown in Supplemental Materials. C-hubs have higher participation coefficient than P-hubs, $t(38) = 6.04$, $p < .001$, and there was no significant difference in within-module degree, $t(38) = -0.08$, $p > .05$. To ensure that these words are not significantly different in other important attributes, degree centrality was calculated for each word and other 30 participants were recruited to rate the familiarity, concreteness, and imaginability for each word by 1–7 points. The selected two types of hub concepts are matched on these key attributes (all $ps > .05$).

Procedure

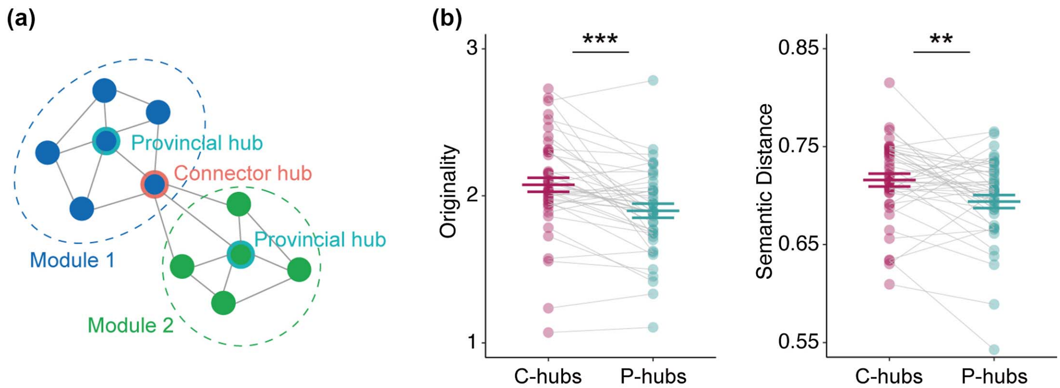
Participants completed the AUT in a quiet computer lab. Each trial began with a central fixation cross for 2 s, then a cue word (i.e., C-hubs or P-hubs) was displayed on the screen. Participants were asked to think of an interesting, novel, and unusual use for the cue word within 15 s. Participants pressed "1" when they generated an answer, then quickly entered the answer into the textbox, and pressed "Enter" to enter the next trial. Forty hub concepts were presented in a fully randomized order.

Statistical Analysis

Three trained raters blind to the purpose of the experiment rated each answer for originality on a 5-point scale, ranging from *very obvious/ordinary use* (1) to *very novel/unusual use* (5), and ICC (C, k) was 0.70. Responses receiving invalid ratings by more than two raters are excluded from subsequent analyses. The average originality score across raters was used for statistical analysis. The semantic distance between cue word and answer was also calculated using word2vec as described in Experiment 1.

Considering the nested data structure, that is, each participant completed multiple concept items, the linear mixed-effects model

Figure 2
Effects of Hub Concepts on Creative Thinking in Experiment 2



Note. (a) The illustration of the connection patterns within and between modules for C-hubs and P-hubs. C-hubs are important in bridging different modules, while P-hubs primarily connect nodes of their own module. (b) The differences of originality and semantic distance between C-hubs and P-hubs. Error bar represents mean ± SEM. C-hubs = connector hubs; P-hubs = provincial hubs; SEM = standard error of the mean. See the online article for the color version of this figure.
** $p < .01$. *** $p < .001$.

was applied to estimate the fixed effect of hub concepts, which was implemented the "lmer" function from the lme4 package in R Version 4.3.1.

Results

The linear mixed-effects model showed that participants generated more original and remote answers for C-hubs compared to P-hubs, originality: $t(1271) = 5.14$, $p < .001$, $d = 0.28$, 95% CI [0.17, 0.40]; semantic distance: $t(1275) = 3.25$, $p = .001$, $d = 0.18$, 95% CI [0.07, 0.29]; Table 1 and Figure 2b.

Experiment 3: Hub Concepts Modulate Creative Thinking Process

Experiment 3 further examined the effect of hub concepts on the creative thinking process by extending the duration of the AUT and asked participants to generate multiple alternate uses for each cue word.

Method

Participants

G*Power was used to estimate the necessary sample size with a moderate effect size (Cohen's d) of 0.50, a power of 0.80, and an α of .05 (one-tailed; Faul et al., 2007) and gave a minimum sample of 27 participants. Based on the highly significant results of Experiment 2, Experiment 3 did not recruit more participants and followed the estimation of G*Power, ultimately recruiting 31 right-handed participants ($M_{age} = 20.68$ years, age range = 18–25 years, gender reported: 21 females and 10 males). Participants signed informed consent and received payment for their participation.

Materials

Hub concepts were identical to Experiment 2.

Procedure

The difference between Experiment 2 and Experiment 3 is that the duration of each trial was extended from 15 s to 60 s, and participants were encouraged to think of as many interesting, novel, and unusual uses as they could. Participants pressed "1" when they generated an idea, then quickly entered the idea into the textbox, and pressed "Enter" to think about the next idea. The time for entering answers was not counted in the task time.

Statistical Analysis

Three trained raters blind to the purpose of the experiment rated three measures (i.e., originality, flexibility, fluency) for each trial according to the norming scoring guides (J. Sun et al., 2019; Zhu et al., 2017). More details can be found in Experiment 1. The ICC (C, k) values for originality, flexibility, and fluency were 0.89, 0.81, and 0.99, respectively. Semantic distance was also calculated between cue word and answer using word2vec as described in Experiment 1. The overall originality score and semantic distance for each cue word are the sum of the scores for all responses. Using a linear mixed-effects model, the first aim was to examine the effect of hub concepts on each measurement of AUT and then to investigate the effect of hub concepts on the early and late stages of the creative thinking process. Considering the varying number of responses generated by participants in each trial, the early and late stages were defined as the first two responses and the last two responses, respectively, to obtain an unbiased estimate. Two-way analysis of variance (ANOVA) was applied to assess the interaction effect between hub concepts and thinking stages, which was implemented via the "mixed" function from the "afex" package in R Version 4.3.1. Post hoc tests used Bonferroni correction for multiple comparisons. Moreover, the effect of hub concepts on each response order was also examined. Given that participants generated an average of fewer than four responses (see Table 1), the effect of the hub concept was examined only for the first four responses, and the

Table 1
Behavioral Results

Measure	Hub type	Experiment 2				Experiment 3				Experiment 4			
		M	*SD*	*t*	Cohen's *d* [95% CI]	*M*	*SD*	*t*	Cohen's *d* [95% CI]	*M*	*SD*	*t*	Cohen's *d* [95% CI]
Originality	C-hubs	2.08	0.34	5.14^{***}	0.28 [0.17, 0.40]	6.55	1.95	2.95^{**}	0.17 [0.05, 0.29]	8.23	3.79	6.10^{***}	0.56 [0.37, 0.75]
	P-hubs	1.89	0.30			6.14	1.91			6.63	3.22		
Semantic distance	C-hubs	0.72	0.04	3.25^{**}	0.18 [0.07, 0.29]	2.35	0.76	0.48	0.03 [−0.09, 0.15]	2.88	1.23	5.79^{***}	0.53 [0.34, 0.72]
	P-hubs	0.70	0.04			2.33	0.73			2.37	1.06		
Flexibility	C-hubs					2.55	0.62	2.60^{**}	0.15 [0.03, 0.27]	2.92	0.95	5.10^{***}	0.47 [0.28, 0.66]
	P-hubs					2.45	0.56			2.56	0.86		
Fluency	C-hubs					3.26	1.07	−0.86	−0.05 [−0.17, 0.07]	3.73	1.53	5.25^{***}	0.48 [0.29, 0.67]
	P-hubs					3.32	1.06			3.17	1.35		

Note. CI = confidence interval; C-hubs = connector hubs; P-hubs = provincial hubs.
** $p < .01$. *** $p < .001$.

significance was adjusted using the false-discovery rate (FDR corrected, $p < .05$) to correct for multiple testing.

Results

First, for the overall performance, results showed that participants obtained higher flexibility and overall originality scores in the C-hubs condition compared to the P-hubs condition, originality: $t(1174) = 2.95$, $p = .003$, $d = 0.17$, 95% CI [0.05, 0.29]; flexibility: $t(1174) = 2.60$, $p = .009$, $d = 0.15$, 95% CI [0.03, 0.27]; but not fluency or overall semantic distance, fluency: $t(1174) = -0.86$, $p > .05$, $d = -0.05$, 95% CI [−0.17, 0.07]; semantic distance: $t(1174) = 0.48$, $p > .05$, $d = 0.03$, 95% CI [−0.09, 0.15]; Table 1 and Figure 3a.

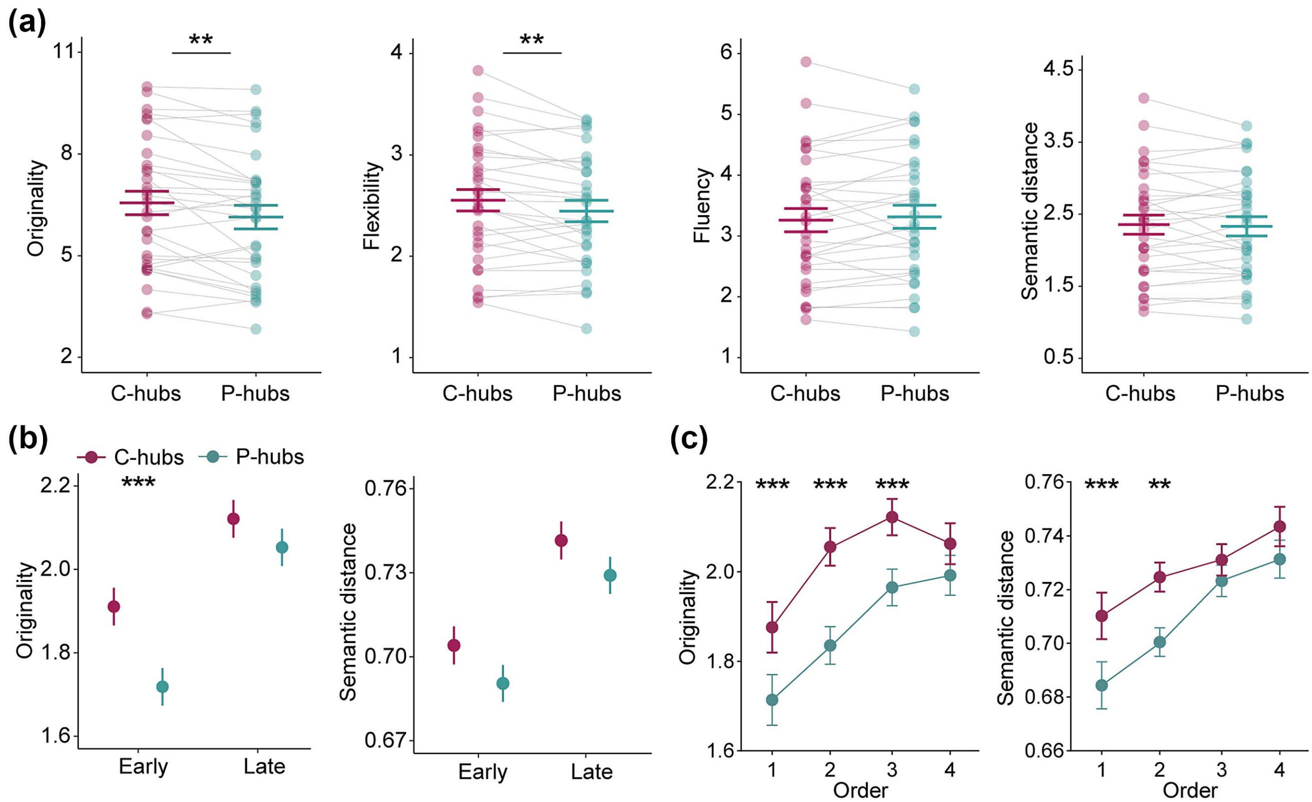
Next, the effects of hub concepts on the early and late stages of the creative thinking process were estimated using two-way ANOVA with a linear mixed-effects model (Figure 3b). For originality, there was a significant main effect of hub concepts, $F(1, 2117) = 30.44$, $p < .001$, and thinking stages, $F(1, 2100) = 135.47$, $p < .001$, with higher originality score for C-hubs compared to P-hubs and higher originality score in the late stage of creative thinking compared to the early stage. Importantly, there was a significant interaction effect between hub concepts and thinking stages, $F(1, 2100) = 7.00$, $p = .008$. Post hoc tests with Bonferroni correction revealed that the difference in originality between C-hubs and P-hubs was greater in the early stage than in the late stage of the creative thinking process. Specifically, responses generated by C-hubs have higher originality score than P-hubs in the early stage of the creative thinking process, $t(2109) = 5.78$, $p < .001$, estimate = 0.19, $SE = 0.03$, while no significant difference was observed in the late stage, $t(2109) = 2.06$, $p > .05$, estimate = 0.07, $SE = 0.03$. For semantic distance, there was a significant main effect of hub concepts, $F(1, 2126) = 6.47$, $p = .011$, and thinking stages, $F(1, 2092) = 55.61$, $p < .001$, with higher semantic distance for C-hubs compared to P-hubs and higher semantic distance in the late stage of creative thinking compared to the early stage. There was no significant interaction effect between hub concepts and thinking stages, $F(1, 2092) = 0.01$, $p > .05$.

For response-order effect, responses generated by C-hubs have higher originality score than P-hubs only in the first three responses: first response, $t(1180) = 5.17$, $p < .001$, $d = 0.30$, 95% CI [0.18, 0.41]; second response, $t(1040) = 6.76$, $p < .001$, $d = 0.41$, 95% CI [0.29, 0.54]; third response, $t(816) = 4.12$, $p < .001$, $d = 0.28$, 95% CI [0.15, 0.42]; fourth response, $t(515) = 1.54$, $p > .05$, $d = 0.13$, 95% CI [−0.04, 0.31] (Figure 3c). Similarly, responses generated by C-hubs have greater semantic distance than P-hubs only in the first two responses: first response, $t(1180) = 3.70$, $p < .001$, $d = 0.21$, 95% CI [0.10, 0.33]; second response, $t(1042) = 3.31$, $p = .002$, $d = 0.20$, 95% CI [0.08, 0.32]; third response, $t(822) = 1.04$, $p > .05$, $d = 0.07$, 95% CI [−0.07, 0.21]; fourth response, $t(522) = 1.23$, $p > .05$, $d = 0.11$, 95% CI [−0.07, 0.28] (Figure 3c).

Experiment 4: Hub Concepts Induced Brain Activity During Creative Thinking Process

Finally, Experiment 4 used fMRI to explore the mechanistic interpretation of the effect of hub concepts on creative thinking. C-hubs and P-hubs from Experiment 2 were assigned to the AUT and control task (i.e., object characteristics task [OCT]). The aim

Figure 3
Effects of Hub Concepts on Creative Thinking in Experiment 3



Note. (a) The differences of overall creative performance between C-hubs and P-hubs conditions. (b) The originality score in the early stage of the creative thinking process was modulated by hub concepts. (c) The originality score and semantic distance of the first two responses in the creative thinking process were both modulated by hub concepts. Error bar represents mean ± SEM. C-hubs = connector hubs; P-hubs = provincial hubs; SEM = standard error of the mean. See the online article for the color version of this figure.
** $p < .01$. *** $p < .001$.

was to examine the differences in brain activity induced by two types of hub concepts during the creative thinking process.

Method

Participants

According to the calculation of the median sample size of a single fMRI study in the past 2 decades (approximately 28 participants) by Poldrack et al. (2017), and in line with recent fMRI studies on creative thinking process (e.g., Beaty et al., 2020; Chen et al., 2023), the present experiment recruited 35 right-handed participants. Participants were screened to ensure that they met the safety requirements for magnetic resonance imaging (MRI). One failed to follow task instructions and one withdrew from the experiment. In addition, a widely used criterion of head motion was adopted to exclude participants if the number of volumes with a framewise displacement > 0.5 mm was more than 10% of the total number of volumes in any session to ensure that head motion artifacts were not driving observed effects. Six participants were excluded because of excessive head motion. The final sample size for fMRI data analysis was 27 (M_{age} = 20.48 years, age range = 17–24 years, gender reported: 13 females and 14 males). Participants signed informed consent and received payment for their participation.

fMRI Task

Hub concepts were identical to Experiment 2. Eighteen words from each hub concept type were assigned to the AUT and OCT to constitute three scanning sessions. Each session included six trials for the AUT (three C-hubs and three P-hubs) and six trials for the OCT (three C-hubs and three P-hubs), which were randomly presented. Each trial began with a central fixation cross for 2 s and then the task cue ("AUT" or "OCT") lasting 4 s. For the AUT, participants were required to think of as many interesting, novel, and unusual uses for the cue word as they could within 60 s. For the OCT, participants were required to think of as many typical features of the cue word as possible within 20 s. Participants were asked to report aloud immediately when they thought of a response, but not to speak during thinking. An MRI-compatible microphone was used to record the participants' responses. The interval between trials ranged from 4 to 6 s (mean = 5 s). Before scanning, participants were given task instructions and completed practice trials.

After scanning, Adobe Audition 2020 software was used to process the audio files for noise reduction. Participants listened to their own noise-reduced recordings and wrote answers in order. A research assistant ensured consistency between participants' written content and actual responses by comparing them through listening to audio recordings and determined the vocalization and ending points of each answer according to the sound amplitude, which was then used for subsequent fMRI analysis.

Behavioral Analysis

Behavioral analysis excluded seven participants: five due to audio recording malfunctions and two for noncompliance with experimental instructions or early withdrawal. Thus, 28 participants were included in the behavioral analysis. Statistical analysis was consistent with Experiment 3. The ICC (C, k) values for originality, flexibility, and fluency were 0.94, 0.88, and 0.99, respectively.

Image Acquisition and Preprocessing

The brain imaging data were collected at the Southwest University Brain Imaging Center with a 3T Siemens Prisma Trio MRI scanner and 32-chanel head coil. Functional scans were acquired with a multiband gradient echo-planar imaging sequence: multiband factor = 4, repetition time (TR) = 1,000 ms, echo time (TE) = 30 ms, field of view (FOV) = 195 × 195, flip angle (FA) = 73°, slices = 56, thickness = 2.5 mm, and voxel size = 2.5 × 2.5 × 2.5 mm^3. Participants completed three runs of 610 volumes each. High-resolution T1-weighted structural images were acquired using a magnetization-prepared rapid acquisition gradient echo sequence: TR = 2,530 ms, TE = 2.98 ms, FOV = 224 × 256 mm^2, FA = 7°, slices = 192, thickness = 1.0 mm, and voxel size = 0.5 × 0.5 × 1 mm^3.

Brain imaging data were preprocessed using fMRIPrep 23.2.1 (Esteban et al., 2019), which is based on Nipype 1.8.6 (Gorgolewski et al., 2011). The T1-weighted image was corrected for intensity nonuniformity and then skull-stripped. Brain tissue segmentation of cerebrospinal fluid, white matter, and gray matter was performed on the brain-extracted T1w. Volume-based spatial normalization to the standard space (MNI152NLin2009cAsym) was performed through nonlinear registration. A reference volume and its skull-stripped version were generated and were then coregistered to the T1w reference as a first step in the functional preprocessing. The subsequent preprocessing steps included slice-time correction, head motion correction, and spatial normalization. Finally, the fMRI data were spatially smoothed using an 8-mm full-width at half-maximum Gaussian kernel to improve the signal-to-noise ratio.

Regional Activation fMRI Analysis

The first aim was to investigate differences in brain activity throughout the entire creative thinking task induced by the two types of hub concepts, followed by further examination of how hub concepts modulate brain activity during the early and late stages of the creative thinking process. The first-level contrast involved subtracting the experimental condition (i.e., AUT) from the corresponding control condition (i.e., OCT) for each type of hub concepts, that is, $(AUT_{\text{C-hubs}} > OCT_{\text{C-hubs}}) > (AUT_{\text{P-hubs}} > OCT_{\text{P-hubs}})$. This implies that the number of eligible trials for investigating the effect of hub concepts on the early and late stages of the creative thinking process will be fewer than in the behavioral analysis because behavioral analysis only focuses on AUT trials. To avoid excluding too many trials and participants, the first and last responses of each trial (response number needed to be greater than or equal to 3) were defined as the early and late stages of the creative thinking process, resulting in 23 participants retained for subsequent analysis.

First-level analysis was performed using the general linear model implemented in SPM12. The onset (cue word onset or previous response ending points) and duration (the interval between the previous response ending points and the current response starting points) of the response were included in the design matrix. Framewise displacement and six head motion parameters were also included as nuisance regressors. The design matrix was convolved with the canonical hemodynamic response function, and a high-pass filter of 1/128 Hz was used to remove low-frequency drift from the time series. First-level contrasts were submitted to second-level analysis by using random-effect group model and computing one-sample t test. The significance was set at a voxel-wise threshold of $p < .001$ and a cluster-wise threshold of $p < .05$ (family-wise error corrected). To increase sensitivity of analyses, small volume correction (SVC) was also performed within several regions of interest (ROIs) that are important for creative thinking, including the core regions of frontoparietal network (FPN) such as middle frontal gyrus and inferior parietal lobe, and the core regions of default mode network (DMN) such as precuneus and angular gyrus (Chen et al., 2023; Cogdell-Brooke et al., 2020; J. Sun et al., 2016; Wu et al., 2015). Automated anatomical labeling was used to define these ROIs, and the significance of SVC was set at a voxel-wise threshold of $p < .001$ with a cluster-wise threshold of $p < .05$ (family-wise error corrected).

Functional Connectivity

To explore differences in functional connectivity, generalized psychophysiological interaction (gPPI) analysis was implemented in the CONN Toolbox 22.a (Whitfield-Gabrieli & Nieto-Castanon, 2012). The general linear model for the gPPI analysis contained the following regressors: (a) psychological factors; (b) physiological factors, fMRI signals from the seeds; and (c) psychophysiological interaction factors, interaction terms of the psychological and physiological factors, as well as the nuisance regressors that used in the first-level activation analysis. First, whole-brain seed-to-voxel gPPI analysis was conducted with seed regions defined as a 6-mm radius sphere centered at the peak voxel Montreal Neurological Institute (MNI) coordinates of the significantly activated region. Second, at the large-scale brain network level, the Power functional atlas (Power et al., 2011) was used to define six brain networks (i.e., DMN, FPN, salience network, cingulo-opercular task control network, ventral attention network, and dorsal attention network) that are important for creative thinking (Beaty et al., 2016; Benedek & Fink, 2019; He et al., 2019, 2020; Zhuang et al., 2021), and gPPI analysis estimated functional connectivity between any pair of nodes and then averaged the parameter values within and between networks. The contrast setting and statistical analysis were consistent with the above activation analysis. For large-scale brain network analysis, FDR ($p < .05$) adjustment was used to correct for multiple testing.

Results

Behavioral Results

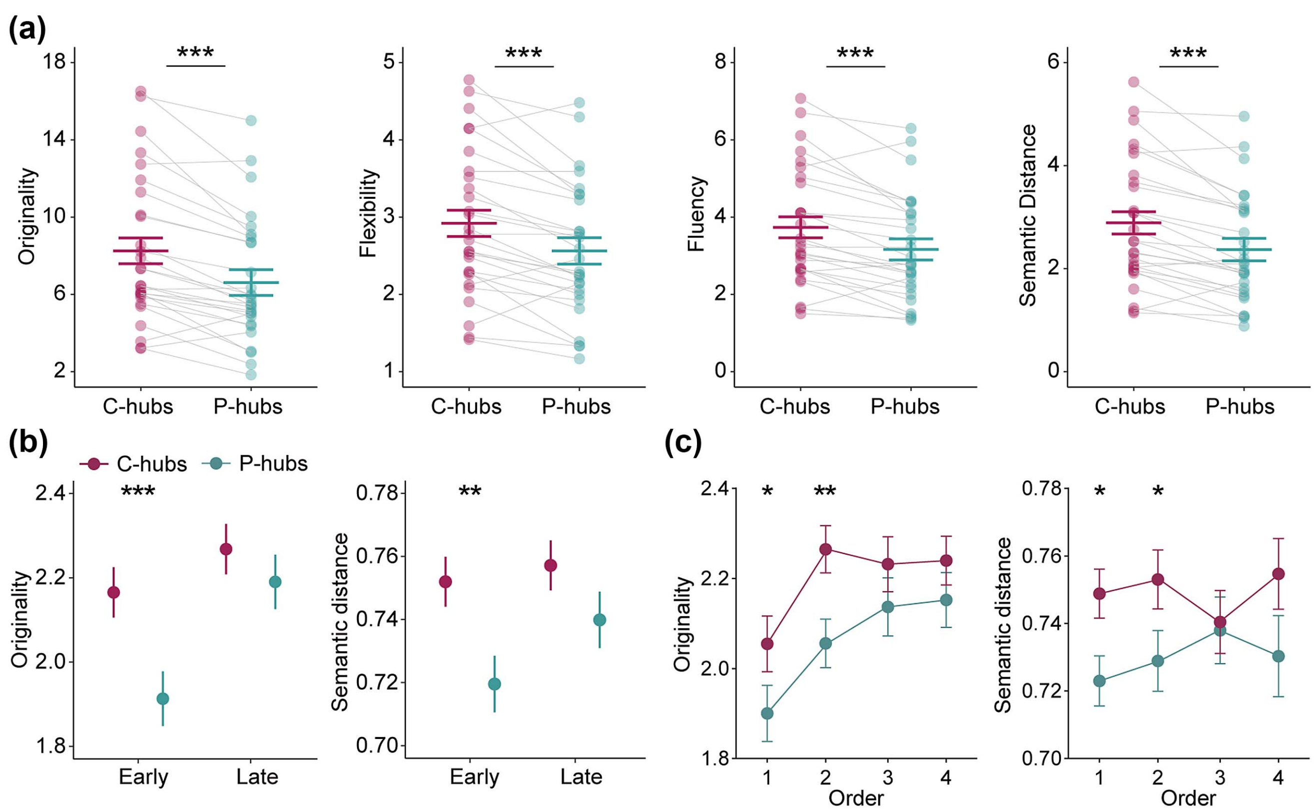
First, results showed that participants exhibited better overall task performance in the C-hubs condition compared to P-hubs condition: overall originality, $t(448) = 6.10$, $p < .001$, $d = 0.56$, 95% CI [0.37, 0.75]; flexibility, $t(448) = 5.10$, $p < .001$, $d = 0.47$, 95% CI [0.28, 0.66]; fluency, $t(448) = 5.25$, $p < .001$, $d = 0.48$, 95% CI [0.29, 0.67]; overall semantic distance, $t(448) = 5.79$, $p < .001$, $d = 0.53$, 95% CI [0.34, 0.72] (Table 1 and Figure 4a).

Next, the effects of hub concepts on the early and late stages of the creative thinking process were estimated using a two-way ANOVA with linear mixed-effects model (Figure 4b). For originality, there was a significant main effect of hub concepts, $F(1, 873) = 16.85$, $p < .001$, and thinking stages, $F(1, 851) = 23.39$, $p < .001$, with higher originality score for C-hubs compared to P-hubs and higher originality score in the late stage of creative thinking compared to the early stage. Importantly, there was a significant interaction between hub concepts and thinking stages, $F(1, 851) = 4.94$, $p = .026$. Post hoc tests with Bonferroni correction revealed that the difference in originality between C-hubs and P-hubs was greater in the early stage than in the late stage of the creative thinking process. Specifically, answers generated by C-hubs have higher originality score than P-hubs in the early stage of the creative thinking process, $t(866) = 4.49$, $p < .001$, estimate = 0.25, SE = 0.06, while no significant difference was observed in the late stage, $t(866) = 1.38$, $p > .05$, estimate = 0.08, SE = 0.06. For semantic distance, there was a significant main effect of hub concepts, $F(1, 875) = 12.54$, $p < .001$, and a marginal significant main effect of thinking stages, $F(1, 856) = 3.35$, $p = .067$, with higher semantic distance for C-hubs compared to P-hubs and higher semantic distance in the late stage of creative thinking compared to the early stage. Although there was no significant interaction effect between hub concepts and thinking stages, $F(1, 856) = 1.18$, $p > .05$, paired-sample t test showed that answers generated by C-hubs have higher semantic distance than P-hubs in the early stage of the creative thinking process, $t(435) = 3.12$, $p = .002$, $d = 0.30$, 95% CI [0.11, 0.50], but not in the late stage, $t(436) = 1.69$, $p > .05$, $d = 0.16$, 95% CI [−0.03, 0.36].

For response-order effect, answers generated by C-hubs have higher originality score than P-hubs only in the first three answers: $t(448) = 2.80$, $p = .011$, $d = 0.26$, 95% CI [0.07, 0.44]; second answer, $t(401) = 3.64$, $p = .001$, $d = 0.35$, 95% CI [0.16, 0.55]; third answer, $t(301) = 1.46$, $p > .05$, $d = 0.16$, 95% CI [−0.06, 0.39];

Figure 4

Effects of Hub Concepts on Creative Thinking in Experiment 4



Note. (a) The differences of overall creative performance between C-hubs and P-hubs conditions. (b) The originality score and semantic distance in the early stage of the creative thinking process were both modulated by hub concepts. (c) The originality score and semantic distance of the first two responses in the creative thinking process were both modulated by hub concepts. Error bar represents mean ± SEM. C-hubs = connector hubs; P-hubs = provincial hubs; SEM = standard error of the mean. See the online article for the color version of this figure.

* $p < .05$. ** $p < .01$. *** $p < .001$.

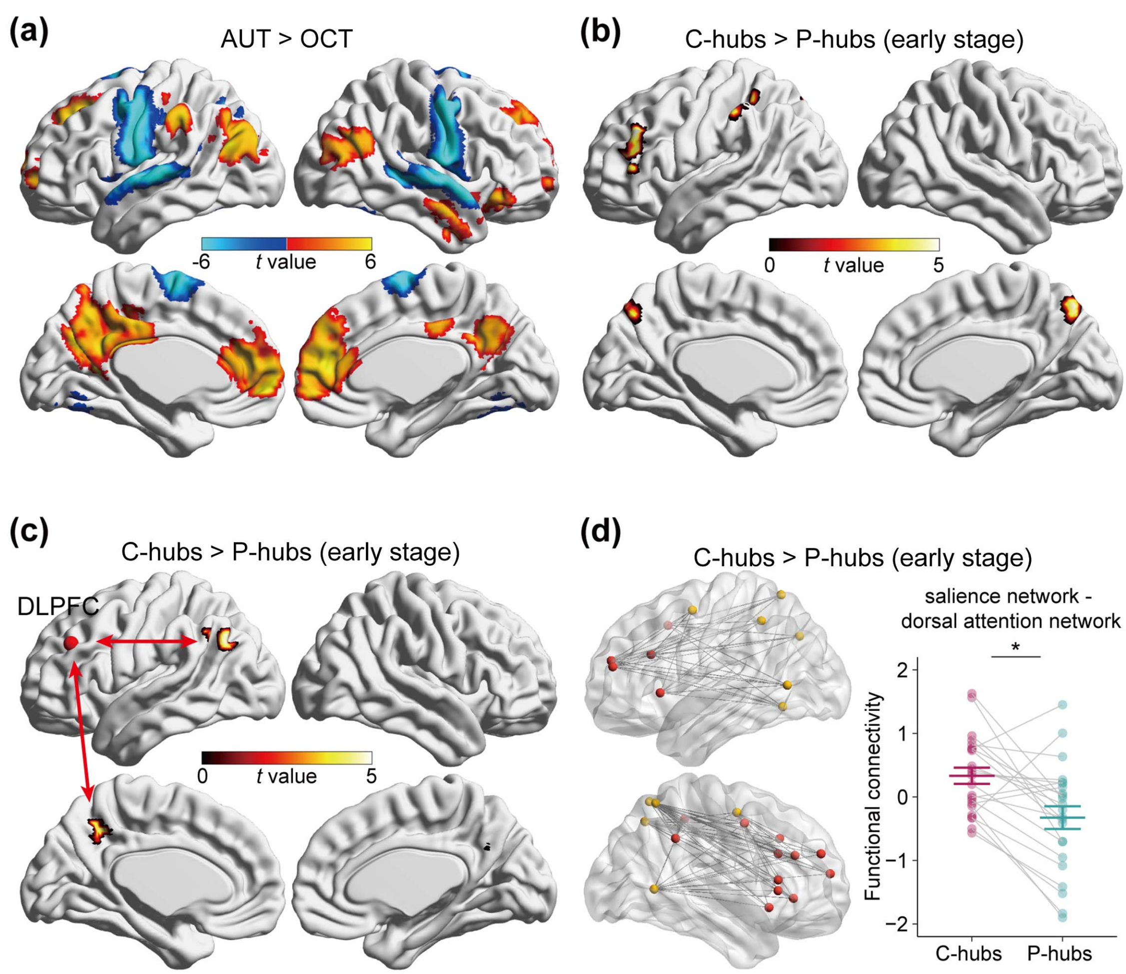
fourth answer, $t(207) = 1.24$, $p > .05$, $d = 0.17$, 95% CI [−0.11, 0.45] (Figure 4c). Similarly, answers generated by C-hubs have greater semantic distance than P-hubs only in the first two order: first answer, $t(450) = 2.57$, $p = .042$, $d = 0.24$, 95% CI [0.05, 0.42]; second answer, $t(402) = 2.31$, $p = .043$, $d = 0.22$, 95% CI [0.03, 0.42]; third answer, $t(304) = 0.20$, $p > .05$, $d = 0.02$, 95% CI [−0.20, 0.25]; fourth answer, $t(209) = 1.55$, $p > .05$, $d = 0.21$, 95% CI [−0.06, 0.49] (Figure 4c).

fMRI Results

Sanity checks were first conducted for the AUT > OCT contrast throughout the entire task, and results showed robust brain activation in the core regions of DMN and FPN (Figure 5a), which replicate previous AUT studies (Chen et al., 2023; Cogdell-Brooke et al., 2020; J. Sun et al., 2016; Wu et al., 2015). Although no significant effect of hub concepts in brain activation was observed throughout the entire task, C-hubs induced stronger activations compared to P-hubs only in the early stage of the creative thinking process (Figure 5b), including the left dorsolateral prefrontal cortex (DLPFC) extending into the left inferior frontal cortex, $t(22) = 5.24$, $p_{\text{cluster}} = .021$, voxel size = 236, peak MNI: $x = -44$, $y = 36$, $z = 32$; the left inferior parietal lobe, $t(22) = 5.11$, $p_{\text{cluster}} = .015$, voxel size = 260, peak MNI: $x = -64$, $y = -30$, $z = 50$; and the precuneus, $t(22) = 5.33$, $p_{\text{svc}} = .011$, voxel size = 114, peak MNI: $x = 2$, $y = -72$, $z = 50$.

Next, gPPI analysis further revealed that only in the early stage of the creative thinking process, C-hubs induced stronger functional connectivity compared to P-hubs, including functional connectivity between the left DLPFC and precuneus, $t(22) = 5.27$, $p_{\text{cluster}} < .001$, voxel size = 297, peak MNI: $x = -8$, $y = -52$, $z = 42$; between the left DLPFC and the left angular gyrus, $t(22) = 5.26$, $p_{\text{cluster}} < .001$, voxel size = 288, peak MNI: $x = -56$, $y = -62$, $z = 36$ (Figure 5c);

Figure 5
fMRI Results of Experiment 4



Note. (a) The brain activation of AUT > OCT contrasts throughout the entire task. (b)–(d) Stronger activation and functional connectivity induced by C-hubs compared to P-hubs in the early stage of the creative thinking process. fMRI = functional magnetic resonance imaging; AUT = alternative uses task; OCT = object characteristics task; C-hubs = connector hubs; P-hubs = provincial hubs; DLPFC = dorsolateral prefrontal cortex. See the online article for the color version of this figure.
* $p < .05$.

as well as between the salience and dorsal attention networks, $t(22) = 3.84$, $p = .019$ (Figure 5d). However, no significant effect of hub concepts on brain activation and functional connectivity was observed in the late stage of the creative thinking process.

General Discussion

This study applied a novel network-based manipulation to examine the effect of C-hubs and P-hubs in semantic network on creative thinking. Consistent evidence suggests that creative thinking benefits from rich connections between modules in semantic network (Kenett, 2024), with C-hubs contributes to generating more original and remote answers compared to P-hubs. Importantly, this advantage is primarily evident in the early stage of the creative thinking process. These findings provide novel insight into the role of semantic network structure in creative thinking, expanding the associative theory of creativity (Beaty & Kenett, 2023; Mednick, 1962) and emphasizing that establishing cross-module connections may be key in generating more original and remote ideas.

According to the principle of modular organization of semantic network and the spreading activation model of semantic processing (Bousfield, 1953; Collins & Loftus, 1975; Ferrer I Cancho & Solé, 2001; Kenett & Faust, 2019), results of Experiment 1 showed that the generation of creative ideas relates not only to remote semantic associations but also to cross-module connections between concepts in semantic network. These results replicate and extend previous findings regarding the positive correlation between creativity and semantic distance (Beaty & Johnson, 2021; Green, 2016; Heinen & Johnson, 2018; Kenett, 2019; Li et al., 2023; Liu et al., 2021). Critically, this evidence showed that responses outside the module containing the cue word are more creative than responses within the same module, suggesting that the memory retrieval process during creative thinking may need to break the mindset triggered by the automatic activation of cue word-related semantic space (Beaty et al., 2023).

The intriguing relationship between the semantic network modules and creative thinking inspired further investigation into the effect of hub concepts with different connectivity characteristics inside and outside the semantic network module (i.e., C-hubs and P-hubs) on creative thinking. Consistent evidence revealed that participants generated more original and remote responses for C-hubs compared to P-hubs, with this advantage mainly concentrated in the early stage of the creative thinking process.

These results convey important implications for understanding the creative thinking process (e.g., automatic spreading activation and controlled search process; Beaty & Kenett, 2023; Mednick, 1962). A previous study showed that a rich semantic neighborhood can modulate creative thinking by providing more possible associations and facilitating the automatic spreading of semantic activation (Beaty et al., 2023). The definition of hub concepts further distinguished the connections inside and outside the semantic module. Results highlighted that rich connections between semantic modules help activate more semantic concepts in different domains, which may provide more valuable “raw materials” for creative thinking to promote remote conceptual combinations (Zhang et al., 2023; Zhuang et al., 2021).

However, this effect is only observed in the early stage of the creative thinking process, implying that the involvement of controlled search process in the later stage might mitigate the difference of the two types of hub concepts in automatic spreading activation between modules. Similarly, for a concept with less semantic richness, a recent study highlights that cognitive control compensates for such sparse semantic connectivity by driving search processes in a top-down fashion (Beaty et al., 2023; Volle, 2018), which may facilitate strategic and deliberate conceptual combination (Beaty et al., 2023). Considering that cognitive control plays a more important role in the late stage of the creative thinking process (Cheng et al., 2016), P-hubs may gradually break away from the semantic constraints within the module and establish associations with remote concepts outside the module through the controlled search process. Future work might elucidate the cognitive mechanism by combining additional free association tasks (Ovando-Tellez, Benedek, et al., 2022) and dual-task paradigms (e.g., reduce participants’ cognitive control resources while performing AUT; Camarda et al., 2018).

Interestingly, alternations in brain activity are also pronounced early in the creative thinking process. The core regions of the DMN and FPN (i.e., the DLPFC, precuneus, and angular gyrus) showed greater activation in the C-hubs condition compared to the P-hubs condition. These activation findings suggest that rich cross-module semantic connections involve more spontaneous memory retrieval and task-related semantic control during creative thinking (Beaty et al., 2016; Benedek & Fink, 2019; He et al., 2020; Volle, 2018). The gPPI analysis further revealed stronger functional connectivity between the DLPFC and the precuneus, as well as between the DLPFC and the angular gyrus. The functional connectivity between the core regions of the DMN and FPN has been widely reported in creativity research and is considered a fundamental neural mechanism of creative thinking (Beaty et al., 2016; Benedek & Fink, 2019; Frith et al., 2021; He et al., 2019, 2020; Zhuang et al., 2021). The present findings highlight that the functional coupling between automatic spreading activation and controlled semantic retrieval supports better performance of C-hubs in creative thinking, providing partial evidence for the cognitive mechanism underlying the hub concept effects mentioned above.

At the large-scale brain network level, Experiment 4 additionally revealed stronger functional connectivity between the salience and dorsal attention networks, offering new insights into the potential attention processes involved in generating creative ideas for C-hubs. This may involve the filtering and integration of salient semantic information from outside modules. Together, these findings extend previous individual difference research (Benedek et al., 2017; He et al., 2021; Ovando-Tellez, Kenett, et al., 2022) by exploring the mechanistic interpretation of the role of semantic network structure in creative thinking from the perspective of network modules. Evidence from brain activation and functional connectivity comprehensively reveals that better performance of C-hubs in the early stage of the creative thinking process relies on the interactions between automatic spreading activation, controlled memory retrieval, and attentional regulation of salient information.

There are some limitations that should be mentioned. Different corpora for training word vectors have an impact on the calculation of semantic distance (Forthmann et al., 2019) and the semantic relationship reflected by a large natural corpus may not closely represent knowledge in the human brain (but see Caucheteux et al., 2023). Future studies should consider combining human descriptions and distributed semantic representation to obtain more precise semantic features of concepts. Additionally, hub concepts in this study were defined using a Chinese corpus. Future studies should validate the effect of hub concepts on creative thinking in other languages. Although individual differences in AUT can predict creative activities and achievement in real life, future studies could use other task paradigms to expand the current findings, such as creative writing in Programme for International Student Assessment (Organisation for Economic Co-Operation & Development, 2019). This task can obtain long-text answers, making it possible to acquire abundant semantic information and quantify semantic network structure using novel methods (Fan et al., 2023; Johnson et al., 2023). Finally, in interpreting the results, it should be noted that the effect of hub concepts on creative thinking has not yet been linked to creativity training.

Conclusion

This research highlights that C-hubs in semantic network with more cross-module connections contribute to novel idea generation in the early stage of the creative thinking process, involving stronger activation and functional coupling in several core brain networks related to creativity. These findings deepen the understanding of how novel ideas build on semantic memory from the perspective of semantic network modules.

Constraints on Generality

The present findings are based on a sample of Chinese undergraduate and graduate students, a population that may possess high cognitive abilities and educational levels. Additionally, all experimental materials used in this study were derived from a Chinese corpus. Caution should be exercised when attempting to generalize these findings to broader populations and other language groups.

References

Abraham, A., & Bubic, A. (2015). Semantic memory as the root of imagination. *Frontiers in Psychology*, *6*, Article 325. https://doi.org/10.3389/fpsyg.2015.00325

Acar, S., & Runco, M. A. (2019). Divergent thinking: New methods, recent research, and extended theory. *Psychology of Aesthetics, Creativity, and the Arts*, *13*(2), 153–158. https://doi.org/10.1037/aca0000231

Agustín-Llach, M. P., & Rubio, J. (2024). Navigating the mental lexicon: Network structures, lexical search and lexical retrieval. *Journal of Psycholinguistic Research*, *53*(2), Article 21. https://doi.org/10.1007/s10936-024-10059-8

Beaty, R. E., Benedek, M., Silvia, P. J., & Schacter, D. L. (2016). Creative cognition and brain network dynamics. *Trends in Cognitive Sciences*, *20*(2), 87–95. https://doi.org/10.1016/j.tics.2015.10.004

Beaty, R. E., Chen, Q., Christensen, A. P., Kenett, Y. N., Silvia, P. J., Benedek, M., & Schacter, D. L. (2020). Default network contributions to episodic and semantic processing during divergent creative thinking: A representational similarity analysis. *NeuroImage*, *209*, Article 116499. https://doi.org/10.1016/j.neuroimage.2019.116499

Beaty, R. E., & Johnson, D. R. (2021). Automating creativity assessment with SemDis: An open platform for computing semantic distance. *Behavior Research Methods*, *53*(2), 757–780. https://doi.org/10.3758/s13428-020-01453-w

Beaty, R. E., & Kenett, Y. N. (2023). Associative thinking at the core of creativity. *Trends in Cognitive Sciences*, *27*(7), 671–683. https://doi.org/10.1016/j.tics.2023.04.004

Beaty, R. E., Kenett, Y. N., Hass, R. W., & Schacter, D. L. (2023). Semantic memory and creativity: The costs and benefits of semantic memory structure in generating original ideas. *Thinking & Reasoning*, *29*(2), 305–339. https://doi.org/10.1080/13546783.2022.2076742

Benedek, M., Beaty, R. E., Schacter, D. L., & Kenett, Y. N. (2023). The role of memory in creative ideation. *Nature Reviews Psychology*, *2*(4), 246–257. https://doi.org/10.1038/s44159-023-00158-z

Benedek, M., & Fink, A. (2019). Toward a neurocognitive framework of creative cognition: The role of memory, attention, and cognitive control. *Current Opinion in Behavioral Sciences*, *27*, 116–122. https://doi.org/10.1016/j.cobeha.2018.11.002

Benedek, M., Kenett, Y. N., Umdasch, K., Anaki, D., Faust, M., & Neubauer, A. C. (2017). How semantic memory structure and intelligence contribute to creative thought: A network science approach. *Thinking & Reasoning*, *23*(2), 158–183. https://doi.org/10.1080/13546783.2016.1278034

Bertolero, M. A., Yeo, B. T. T., Bassett, D. S., & D'Esposito, M. (2018). A mechanistic model of connector hubs, modularity and cognition. *Nature Human Behaviour*, *2*(10), 765–777. https://doi.org/10.1038/s41562-018-0420-6

Bornstein, M. H., & Arterberry, M. E. (2010). The development of object categorization in young children: Hierarchical inclusiveness, age, perceptual attribute, and group versus individual analyses. *Developmental Psychology*, *46*(2), 350–365. https://doi.org/10.1037/a0018411

Bousfield, W. A. (1953). The occurrence of clustering in the recall of randomly arranged associates. *The Journal of General Psychology*, *49*(2), 229–240. https://doi.org/10.1080/00221309.1953.9710088

Camarda, A., Borst, G., Agogué, M., Habib, M., Weil, B., Houdé, O., & Cassotti, M. (2018). Do we need inhibitory control to be creative? Evidence from a dual-task paradigm. *Psychology of Aesthetics, Creativity, and the Arts*, *12*(3), 351–358. https://doi.org/10.1037/aca0000140

Caucheteux, C., Gramfort, A., & King, J.-R. (2023). Evidence of a predictive coding hierarchy in the human brain listening to speech. *Nature Human Behaviour*, *7*(3), 430–441. https://doi.org/10.1038/s41562-022-01516-2

Chai, L. R., Zhou, D., & Bassett, D. S. (2020). Evolution of semantic networks in biomedical texts. *Journal of Complex Networks*, *8*(1), Article cnz023. https://doi.org/10.1093/comnet/cnz023

Chen, Q., He, R., Sun, J., Ding, K., Wang, X., He, L., Zhuang, K., Lloyd-Cox, J., & Qiu, J. (2023). Common brain activation and connectivity patterns supporting the generation of creative uses and creative metaphors. *Neuropsychologia*, *181*, Article 108487. https://doi.org/10.1016/j.neuropsychologia.2023.108487

Cheng, L., Hu, W., Jia, X., & Runco, M. A. (2016). The different role of cognitive inhibition in early versus late creative problem finding. *Psychology of Aesthetics, Creativity, and the Arts*, *10*(1), 32–41. https://doi.org/10.1037/aca0000036

Cogdell-Brooke, L. S., Sowden, P. T., Violante, I. R., & Thompson, H. E. (2020). A meta-analysis of functional magnetic resonance imaging studies of divergent thinking using activation likelihood estimation. *Human Brain Mapping*, *41*(17), 5057–5077. https://doi.org/10.1002/hbm.25170

Collins, A. M., & Loftus, E. F. (1975). A spreading-activation theory of semantic processing. *Psychological Review*, *82*(6), 407–428. https://doi.org/10.1037/0033-295X.82.6.407

Esteban, O., Markiewicz, C. J., Blair, R. W., Moodie, C. A., Isik, A. I., Erramuzpe, A., Kent, J. D., Goncalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S. S., Wright, J., Durnez, J., Poldrack, R. A., & Gorgolewski, K. J. (2019). fMRIPrep: A robust preprocessing pipeline for functional MRI. *Nature Methods*, *16*(1), 111–116. https://doi.org/10.1038/s41592-018-0235-4

Fan, L., Zhuang, K., Wang, X., Zhang, J., Liu, C., Gu, J., & Qiu, J. (2023). Exploring the behavioral and neural correlates of semantic distance in creative writing. *Psychophysiology*, *60*(5), Article e14239. https://doi.org/10.1111/psyp.14239

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Ferrer I Cancho, R., & Solé, R. V. (2001). The small world of human language. *Proceedings. Biological Sciences*, *268*(1482), 2261–2265. https://doi.org/10.1098/rspb.2001.1800

Forthmann, B., Oyebade, O., Ojo, A., Günther, F., & Holling, H. (2019). Application of latent semantic analysis to divergent thinking is biased by elaboration. *The Journal of Creative Behavior*, *53*(4), 559–575. https://doi.org/10.1002/jocb.240

Frith, E., Elbich, D. B., Christensen, A. P., Rosenberg, M. D., Chen, Q., Kane, M. J., Silvia, P. J., Seli, P., & Beaty, R. E. (2021). Intelligence and creativity share a common cognitive and neural basis. *Journal of Experimental Psychology: General*, *150*(4), 609–632. https://doi.org/10.1037/xge0000958

Gorgolewski, K., Burns, C. D., Madison, C., Clark, D., Halchenko, Y. O., Waskom, M. L., & Ghosh, S. S. (2011). Nipype: A flexible, lightweight and extensible neuroimaging data processing framework in python. *Frontiers in Neuroinformatics*, *5*, Article 13. https://doi.org/10.3389/fninf.2011.00013

Green, A. E. (2016). Creativity, within reason: Semantic distance and dynamic state creativity in relational thinking and reasoning. *Current Directions in Psychological Science*, *25*(1), 28–35. https://doi.org/10.1177/0963721415618485

Guimerà, R., & Amaral, L. A. N. (2005). Cartography of complex networks: Modules and universal roles. *Journal of Statistical Mechanics*, *2005*(2), Article P02001. https://doi.org/10.1088/1742-5468/2005/02/P02001

Guimerà, R., Sales-Pardo, M., & Amaral, L. A. N. (2007). Classes of complex networks defined by role-to-role connectivity profiles. *Nature Physics*, *3*(1), 63–69. https://doi.org/10.1038/nphys489

Hass, R. W. (2017). Semantic search during divergent thinking. *Cognition*, *166*, 344–357. https://doi.org/10.1016/j.cognition.2017.05.039

He, L. (2024). *Connector hubs in semantic network contribute to creative thinking*. https://doi.org/10.17605/OSF.IO/T6KXZ

He, L., Kenett, Y. N., Zhuang, K., Liu, C., Zeng, R., Yan, T., Huo, T., & Qiu, J. (2021). The relation between semantic memory structure, associative abilities, and verbal and figural creativity. *Thinking & Reasoning*, *27*(2), 268–293. https://doi.org/10.1080/13546783.2020.1819415

He, L., Li, Y., Zhuang, K., Chen, Q., Sun, J., Yang, W., Wei, D., & Qiu, J. (2020). Network connectivity of the creative brain: Current knowledge and future directions. *Kexue Tongbao*, *65*(1), 25–36. https://doi.org/10.1360/TB-2019-0112

He, L., Zhuang, K., Li, Y., Sun, J., Meng, J., Zhu, W., Mao, Y., Chen, Q., Chen, X., & Qiu, J. (2019). Brain flexibility associated with need for cognition contributes to creative achievement. *Psychophysiology*, *56*(12), Article e13464. https://doi.org/10.1111/psyp.13464

Heinen, D. J. P., & Johnson, D. R. (2018). Semantic distance: An automated measure of creativity that is novel and appropriate. *Psychology of Aesthetics, Creativity, and the Arts*, *12*(2), 144–156. https://doi.org/10.1037/aca0000125

Johnson, D. R., Kaufman, J. C., Baker, B. S., Patterson, J. D., Barbot, B., Green, A. E., van Hell, J., Kennedy, E., Sullivan, G. F., Taylor, C. L., Ward, T., & Beaty, R. E. (2023). Divergent semantic integration (DSI): Extracting creativity from narratives with distributional semantic modeling. *Behavior Research Methods*, *55*(7), 3726–3759. https://doi.org/10.3758/s13428-022-01986-2

Kenett, Y. N. (2019). What can quantitative measures of semantic distance tell us about creativity? *Current Opinion in Behavioral Sciences*, *27*, 11–16. https://doi.org/10.1016/j.cobeha.2018.08.010

Kenett, Y. N. (2024). The role of knowledge in creative thinking. *Creativity Research Journal*. Advance online publication. https://doi.org/10.1080/10400419.2024.2322858

Kenett, Y. N., Anaki, D., & Faust, M. (2014). Investigating the structure of semantic networks in low and high creative persons. *Frontiers in Human Neuroscience*, *8*, Article 407. https://doi.org/10.3389/fnhum.2014.00407

Kenett, Y. N., & Faust, M. (2019). A semantic network cartography of the creative mind. *Trends in Cognitive Sciences*, *23*(4), 271–274. https://doi.org/10.1016/j.tics.2019.01.007

Kenett, Y. N., Gold, R., & Faust, M. (2016). The hyper-modular associative mind: A computational analysis of associative responses of persons with Asperger syndrome. *Language and Speech*, *59*(3), 297–313. https://doi.org/10.1177/0023830915589397

Kenett, Y. N., Levy, O., Kenett, D. Y., Stanley, H. E., Faust, M., & Havlin, S. (2018). Flexibility of thought in high creative individuals represented by percolation analysis. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(5), 867–872. https://doi.org/10.1073/pnas.1717362115

Kumar, A. A. (2021). Semantic memory: A review of methods, models, and current challenges. *Psychonomic Bulletin & Review*, *28*(1), 40–80. https://doi.org/10.3758/s13423-020-01792-x

Lebkuecher, A. L., Cosgrove, A. L., Strober, L. B., Chiaravalloti, N. D., & Diaz, M. T. (2024). Multiple sclerosis is associated with differences in semantic memory structure. *Neuropsychology*, *38*(1), 42–57. https://doi.org/10.1037/neu0000924

Li, Y., Du, Y., Xie, C., Liu, C., Yang, Y., Li, Y., & Qiu, J. (2023). A meta-analysis of the relationship between semantic distance and creative thinking. *Xinli Kexue Jinzhan*, *31*(4), 519–534. https://doi.org/10.3724/SP.J.1042.2023.00519

Liu, C., Ren, Z., Zhuang, K., He, L., Yan, T., Zeng, R., & Qiu, J. (2021). Semantic association ability mediates the relationship between brain structure and human creativity. *Neuropsychologia*, *151*, Article 107722. https://doi.org/10.1016/j.neuropsychologia.2020.107722

Marko, M., & Riečanský, I. (2021). The structure of semantic representation shapes controlled semantic retrieval. *Memory*, *29*(4), 538–546. https://doi.org/10.1080/09658211.2021.1906905

Matsumoto, Y., Nishida, S., Hayashi, R., Son, S., Murakami, A., Yoshikawa, N., Ito, H., Oishi, N., Masuda, N., Murai, T., Friston, K., Nishimoto, S., & Takahashi, H. (2023). Disorganization of semantic brain networks in schizophrenia revealed by fMRI. *Schizophrenia Bulletin*, *49*(2), 498–506. https://doi.org/10.1093/schbul/sbac157

Mednick, S. A. (1962). The associative basis of the creative process. *Psychological Review*, *69*(3), 220–232. https://doi.org/10.1037/h0048850

Michalko, D., Marko, M., & Riečanský, I. (2023). Response modularity moderates how executive control aids fluent semantic memory retrieval. *Memory*, *31*(6), 871–878. https://doi.org/10.1080/09658211.2023.2191902

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). *Efficient estimation of word representations in vector space*. arXiv preprint. https://doi.org/10.48550/arXiv.1301.3781

Newman, M. E. J. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America*, *103*(23), 8577–8582. https://doi.org/10.1073/pnas.0601602103

Organisation for Economic Co-Operation and Development. (2019). *PISA 2021 creative thinking framework: Third draft*.

Ovando-Tellez, M., Benedek, M., Kenett, Y. N., Hills, T., Bouanane, S., Bernard, M., Belo, J., Bieth, T., & Volle, E. (2022). An investigation of the cognitive and neural correlates of semantic memory search related to creative ability. *Communications Biology*, *5*(1), Article 604. https://doi.org/10.1038/s42003-022-03547-x

Ovando-Tellez, M., Kenett, Y. N., Benedek, M., Bernard, M., Belo, J., Beranger, B., Bieth, T., & Volle, E. (2022). Brain connectivity-based prediction of real-life creativity is mediated by semantic memory structure. *Science Advances*, *8*(5), Article eabl4294. https://doi.org/10.1126/sciadv.abl4294

Poldrack, R. A., Baker, C. I., Durnez, J., Gorgolewski, K. J., Matthews, P. M., Munafò, M. R., Nichols, T. E., Poline, J. B., Vul, E., & Yarkoni, T. (2017). Scanning the horizon: Towards transparent and reproducible neuroimaging research. *Nature Reviews Neuroscience*, *18*(2), 115–126. https://doi.org/10.1038/nrn.2016.167

Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., Vogel, A. C., Laumann, T. O., Miezin, F. M., Schlaggar, B. L., & Petersen, S. E. (2011). Functional network organization of the human brain. *Neuron*, *72*(4), 665–678. https://doi.org/10.1016/j.neuron.2011.09.006

Power, J. D., Schlaggar, B. L., Lessov-Schlaggar, C. N., & Petersen, S. E. (2013). Evidence for hubs in human functional brain networks. *Neuron*, *79*(4), 798–813. https://doi.org/10.1016/j.neuron.2013.07.035

Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. *NeuroImage*, *52*(3), 1059–1069. https://doi.org/10.1016/j.neuroimage.2009.10.003

Runco, M. A., & Acar, S. (2012). Divergent thinking as an indicator of creative potential. *Creativity Research Journal*, *24*(1), 66–75. https://doi.org/10.1080/10400419.2012.652929

Sarica, S., Song, B., Luo, J., & Wood, K. L. (2021). Idea generation with technology semantic network. *Artificial Intelligence for Engineering Design, Analysis and Manufacturing*, *35*(3), 265–283. https://doi.org/10.1017/S0890060421000020

Siew, C. S. Q., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive network science: A review of research on cognition through the lens of network representations, processes, and dynamics. *Complexity*, *2019*(1), Article 2108423. https://doi.org/10.1155/2019/2108423

Sun, C. C., Hendrix, P., Ma, J., & Baayen, R. H. (2018). Chinese lexical database (CLD): A large-scale lexical database for simplified Mandarin Chinese. *Behavior Research Methods*, *50*(6), 2606–2629. https://doi.org/10.3758/s13428-018-1038-3

Sun, J., Chen, Q., Zhang, Q., Li, Y., Li, H., Wei, D., Yang, W., & Qiu, J. (2016). Training your brain to be more creative: Brain functional and structural changes induced by divergent thinking training. *Human Brain Mapping*, *37*(10), 3375–3387. https://doi.org/10.1002/hbm.23246

Sun, J., Liu, Z., Rolls, E. T., Chen, Q., Yao, Y., Yang, W., Wei, D., Zhang, Q., Zhang, J., Feng, J., & Qiu, J. (2019). Verbal creativity correlates with the temporal variability of brain networks during the resting state. *Cerebral Cortex*, *29*(3), 1047–1058. https://doi.org/10.1093/cercor/bhy010

van den Heuvel, M. P., & Sporns, O. (2013). Network hubs in the human brain. *Trends in Cognitive Sciences*, *17*(12), 683–696. https://doi.org/10.1016/j.tics.2013.09.012

Volle, E. (2018). Associative and controlled cognition in divergent thinking: Theoretical, experimental, neuroimaging evidence, and new directions. In R. E. Jung & O. Vartanian (Eds.), *The Cambridge handbook of the neuroscience of creativity* (pp. 333–360). Cambridge University Press. https://doi.org/10.1017/9781316556238.020

Whitfield-Gabrieli, S., & Nieto-Castanon, A. (2012). Conn: A functional connectivity toolbox for correlated and anticorrelated brain networks. *Brain Connectivity*, *2*(3), 125–141. https://doi.org/10.1089/brain.2012.0073

Wu, X., Yang, W., Tong, D., Sun, J., Chen, Q., Wei, D., Zhang, Q., Zhang, M., & Qiu, J. (2015). A meta-analysis of neuroimaging studies on divergent thinking using activation likelihood estimation. *Human Brain Mapping*, *36*(7), 2703–2718. https://doi.org/10.1002/hbm.22801

Zhang, J., Zhuang, K., Sun, J., Liu, C., Fan, L., Wang, X., Gu, J., & Qiu, J. (2023). Retrieval flexibility links to creativity: Evidence from computational linguistic measure. *Cerebral Cortex*, *33*(8), 4964–4976. https://doi.org/10.1093/cercor/bhac392

Zhu, W., Chen, Q., Xia, L., Beaty, R. E., Yang, W., Tian, F., Sun, J., Cao, G., Zhang, Q., Chen, X., & Qiu, J. (2017). Common and distinct brain networks underlying verbal and visual creativity. *Human Brain Mapping*, *38*(4), 2094–2111. https://doi.org/10.1002/hbm.23507

Zhuang, K., Yang, W., He, L., Yan, T., Zeng, R., Liu, C., & Qiu, J. (2021). Understanding the creative cognitive mechanism based on semantic network: Status and prospects. *Journal of Psychological Science*, *44*(5), 1104–1110. https://doi.org/10.16719/j.cnki.1671-6981.20210511

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