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Research Article

Semantic memory structure mediates the role of brain functional connectivity in creative writing

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ABSTRACT

Associative theories of creativity posit that high-creativity individuals possess flexible semantic memory structures that allow broad access to varied information. However, the semantic memory structure characteristics and neural substrates of creative writing are unclear. Here, we explored the semantic network features and the predictive whole-brain functional connectivity associated with creative writing and generated mediation models. Participants completed two creative story continuation tasks. We found that keywords from written texts with superior creative writing performance encompassed more semantic categories and were highly interconnected and transferred efficiently. Connectome predictive modeling (CPM) was conducted with resting-state functional magnetic resonance imaging (fMRI) data to identify whole-brain functional connectivity patterns related to creative writing, dominated by default mode network (DMN). Semantic network features were found to mediate the relationship between brain functional connectivity and creative writing performance. These results highlight how semantic memory structure and the DMN-driven brain functional connectivity patterns support creative writing performance. Our findings extend prior research on the role of semantic memory structure and the DMN in creativity, expand upon previous research on semantic creativity, and provide insight into the cognitive and neural foundations of creative writing.

1. Introduction

Creativity, an aptitude that encompasses the cognitive processes that underlie problem-solving, has been described as key to solving individual, organizational, and social problems (Barbot et al., 2015; Klijn & Tomic, 2010; Said-Metwaly et al., 2017). Semantic memory is considered to be particularly important in creative cognitive process (Gerver et al., 2023; Kenett & Faust, 2019). Building upon suggestions that computational network science analysis can be used to elucidate structural features of semantic memory (Kenett, 2018; Siew et al., 2019), the current study is examining the semantic network (SN) features and resting-state (rs) brain functional connectivity (FC) patterns associated with creative writing performance.

According to Mednick's (1962) associative theory of creative thinking introduced in 1962, individual differences in creativity reflect semantic memory structures such that high-creativity individuals have relatively flat association hierarchy structures that allow facile combining of remote associative elements. Modern computational analysis and network science methods are being employed to examine Mednick's purported relationship between semantic memory and creativity (Kenett, 2018), by reflecting how concepts are represented, organized, clustered and processed in semantic memory (Kenett, 2024; Kumar et al., 2022). By constructing group-level SNs of high-creativity and low-creativity individuals, Kenett et al. (2014) found SNs of the latter were more rigid and spread out compared to high-creativity participants. Group-level SNs cannot fully explain the relationship between individual-level SNs and creativity, because various forms of biases can occur when combining data over individuals (Morais et al., 2013), and

Abbreviations: SN, Semantic network; CC, clustering coefficient; E(G), global efficiency; CW-CPM, creative writing connectome predictive modeling; FC, functional connectivity; rs-FC, resting-state functional connectivity.

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may obscure individual differences related to creativity (Bernard et al., 2019). Emergent methods that enable individual-level SN construction require repetitive data collection from individuals (De Deyne et al., 2016) with various word-generation tasks, which require participants to generate answers/words from cue words, including the remote association task and divergent thinking tasks (Benedek et al., 2017; He et al., 2021; Kenett et al., 2014; Li et al., 2021; Ovando-Tellez et al., 2022). In addition, researchers use the similarity of word pairs to construct individual semantic networks (Kenett et al., 2017). Benedek et al. (2017) developed a semantic judgement rating task to construct individual semantic networks, in which participants judged how closely two words were related to each other. Previous studies have shown that high-creativity individuals exhibit distinct structural properties in their SNs, including high clustering coefficients, low-average shortest path lengths, and relatively low modularity in community structure (Siew et al., 2019). Researchers are still seeking to represent SNs (Benedek et al., 2017) with eloquent methods that provide SN-structure models that can outperform current coarse approximations (Jones et al., 2015; Morais et al., 2013).

To investigate the relationship between semantic memory and creativity in this study, we employed creative writing tasks, where participants listened to a story and were then asked to add on it. We believe that individuals' creative writing performance is connected to how they associate ideas in their semantic memory, as reflected in their writing texts. Taylor and Barbot (2024) found that creative writing performance is directly influenced by associative abilities. They discovered a positive correlation between individuals' verbal fluency and semantic distance in a series of divergent thinking tasks and creative writing performance. However, these metrics were derived from verbal fluency tasks and word association tests rather than directly from the writing texts. Here, we aim to analyze the characteristics of semantic features in the context of creative writing tasks. Creative writing is a process that reflects a breadth of semantic information, developing from oral language production through a cognitive mechanism that re-represents embedded knowledge into a coherent form (Sharpies, 2013). Studies have shown that when stimuli are narrative – semantically complex, coherent, continuous, and lasting more than a few minutes – rather than point-like and random, some higher-order brain areas (e.g., the DMN) respond in significant ways (Lerner et al., 2011). We suggest that the semantic features constructed from the writing text provides a way to capture the connected concepts in semantic memory which are grounded in a contextual theme and require demanding and coherent cognitive effort during the writing process (Shah et al., 2013). Furthermore, we employed two ways of semantic features to validate the hypothesis. The first is the keyword category quantity, which reflects an individual's ability to retrieve concepts from different categories in the semantic memory (Zhang et al., 2023) and is linked to creative flexibility—generating diverse and effective ideas (Ovando-Tellez et al., 2022; Zhang et al., 2023). The second includes quantitative methods for semantic networks based on mathematical graph theory, including clustering coefficient and global efficiency, which capture individuals' abilities to connect remote concepts into novel ideas (Ovando-Tellez et al., 2022) (see Materials and Methods). According to associative theories, semantic memory provides general knowledge to support creative products by combining multiple semantic concepts into novel ideas (Ovando-Tellez et al., 2022; van Genugten et al., 2022). These semantic features enable to assess not only the retrieval but also the organization of semantic memory structure that supports creative idea generation. We hypothesize that text of better creative writing performance will contain rich semantic information that is highly interconnected and transfers efficiently.

In the study, we utilize creative writing performance to assess individual creative abilities because creative writing is a cognitive activity involving creative cognition and reflecting everyday creativity (creative hobbies, problem-solving in leisure or work activities) (D'Souza, 2021; Fürst & Grin, 2018; Hayes, 2000; Kaufman & Kaufman, 2009). For example, Flower and Hayes (1981) argued the cognitive processes of writing as an integration of reflection, text production, and text interpretation, where reflection encompasses planning, problem-solving, and decision-making. A study investigated how Generation (idea production and association) and Selection (idea evaluation and formalization) processes contribute to lead to higher creativity in a writing task (Fürst et al., 2017).

Neuroimaging has implicated a multitude of brain regions in creative cognition (Beaty et al., 2016, 2018) and highlighted functional interactions within and between brain networks (Beaty et al., 2016; De Pisapia et al., 2016; Takeuchi et al., 2012). The ability to think creatively often requires people to generate novel and useful ideas by combining semantically remote information (Beaty & Kenett, 2023). This intricate process is facilitated by the interplay of various cognitive functions, including memory, attention, and executive control (Benedek & Fink, 2019). Researchers have focused on the default and executive control networks in studies exploring how self-generated thought and cognitive control contribute to creativity (Abraham, 2014; Beaty et al., 2014, 2016; Lloyd-Cox et al., 2022; Takeuchi et al., 2012). Neural foundations of creative writing reveal common and unique brain activations compared to domain-general creativity. Previous research has highlighted the roles of default and executive control networks in creative writing. Howard-Jones et al. (2005) found that the anterior cingulate cortex (ACC) exhibited increased activity during creative story creation conditions compared to uncreative ones, which may be explained by the heightened working memory load required when seeking associations. Erhard et al. (2014) found high experience in creative writing is associated with a network of prefrontal, specifically the medial prefrontal cortex (mPFC) and dorsolateral prefrontal cortex (dlPFC), and basal ganglia (caudate) activation. Additionally, studies have indicated that creative writing tasks activate memory processing areas. Shah et al. (2013) found that creative writing involves activation in bilateral hippocampi, temporal poles (BA 38) and the cingulate cortex, which are associated with episodic memory retrieval, free-associative and spontaneous cognition and semantic integration (also see Howard-Jones et al., 2005; Lotze et al., 2014). Specialized brain regions are also recruited during creative writing. Shah et al. (2013) found that visual and motor brain areas are activated during brainstorming before creative writing, indicating the visual imagination strategies and motor planning for the following writing execution phase (also see Howard-Jones et al., 2005). These findings suggest specialized brain areas may anticipate in novel idea generation via mental imagery and visual working memory (Chen et al., 2020; Chrysikou & Thompson-Schill, 2010). Others found contradictory results. For instance, a study found less experience in creative writing recruits increasingly bilateral visual areas activation (Erhard et al., 2014). Similarly, Howard-Jones et al. (2005) found the uncreative – creative contrasts include large bilateral activations of the visual cortex, which may be due to focusing attention upon this redescription of the visualized scenario in order to prevent further creativity.

Although we recognize the vital role of these networks, our understanding of the relationship between creative writing performance and network FCs during rest remains relatively limited. This relationship is thought to reflect experience-dependent patterns that underlie behavioral variation (Stevens & Spreng, 2014). A few studies have examined rs-FC patterns related to creative writing performance. Lotze et al. (2014) employed a seed region-based approach and found that rs-FC patterns for experts in creative writing are characterized by reduced left- and interhemipheric FC, reduced left caudate and left temporal pole FC, and increased right-hemispheric FC of the caudate with the intraparietal sulcus. In this study, we explored neural markers of creative writing performance by focusing on whole-brain rs-FC. We employed connectome predictive modeling (CPM) (Shen et al., 2017), a neuroimaging approach that utilizes machine learning to identify creative writing-predictive rs-FC patterns. CPM provides a holistic view of network-behavioral relations by extracting the most relevant FC paths

(Beaty et al., 2018; Ovando-Tellez et al., 2022; Ren et al., 2021; Wang et al., 2024). Based on CPM network strength (Kucyi et al., 2021), we formulated a predictive model for creative writing performance, which was sensitive to variations in creative writing performance, allowing for the identification of network dynamics associated with different levels of creative engagement. We hypothesized that the creative writing performance can be predicted by rs-FC patterns, involving, in particular, the default and executive control networks.

Neuroimaging studies have revealed that semantic memory is supported by the gradual convergence of information throughout large regions of temporal and inferior parietal association cortex (Binder & Desai, 2011). Evidence from semantic cognition studies further links controlled semantic retrieval to rs-FC between default and control networks, while automatic semantic retrieval to rs-FC within the default network (Evans et al., 2020). Additionally, Ovando-Tellez et al. (2022) have found rs-FC patterns predictive of semantic memory structure are associated with real-life creativity. Previous neuroimaging studies strongly indicate the anticipation of semantic memory areas in creative writing (Erhard et al., 2014; Shah et al., 2013). Therefore, in this study, semantic memory structure revealed by writing text may be associated with the rs-FC patterns of creative writing, as both are connected to semantic memory processing. To validate the hypothesis, we employed a series of mediation models.

To this end, we first examined the semantic features of keywords in creative writing products, including concept category quantity and conceptual relationships, and then employed CPM network strength to explore the whole-brain rs-FC patterns predictive of creative writing performance. Finally, we utilized mediation models to scrutinize the contribution of rs-FC and semantic features to creative writing performance.

2. Materials and methods

2.1. Participants

This study, along with our previously published study (Fan et al., 2023), is based on the same data cohort. A cohort of 163 students were recruited (offline) from Southwest University by advertising. All participants provided written informed consent and received corresponding task rewards. All participants met functional magnetic resonance imaging (fMRI) safety criteria and had no history of neurological or psychiatric disorders. The research plan was approved by the Ethics Committee of Southwest University.

Valid story continuations were obtained from 85 participants for story 1 and from 82 participants for story 2, who finished multiple-choice questions about background stories. Valid data for both stories were obtained from 81 participants (61 females; 20.4 ± 2.78 years old). We obtained rs-fMRI data from 57 participants for financial reasons. After removal of 5 participants for excessive head motion (>0.2 mm), rs-fMRI data from 52 participants (41 females; 20.7 ± 1.67 years old) were included in the analyses.

2.2. Experimental procedure and indicators

Participants first listened to recordings of suspenseful story beginnings (story 1: 14′12′'; story 2: 9′25′'), with the stories truncated just before the final reveal of the suspenseful resolution. The source stories were Hitchcock's short stories "Pink Female Thief" (story 1) and "The Police Officer's Sideline" (story 2). Participants were asked to make a creative and unique ending with great imagination and creativity in ten minutes, and then instructed to type their story continuations into a computer (Fig. 1A). Participants underwent rs-fMRI scans after completing the story-continuation task.

Based on Mozaffari's rubrics (2013), criteria along six subjective

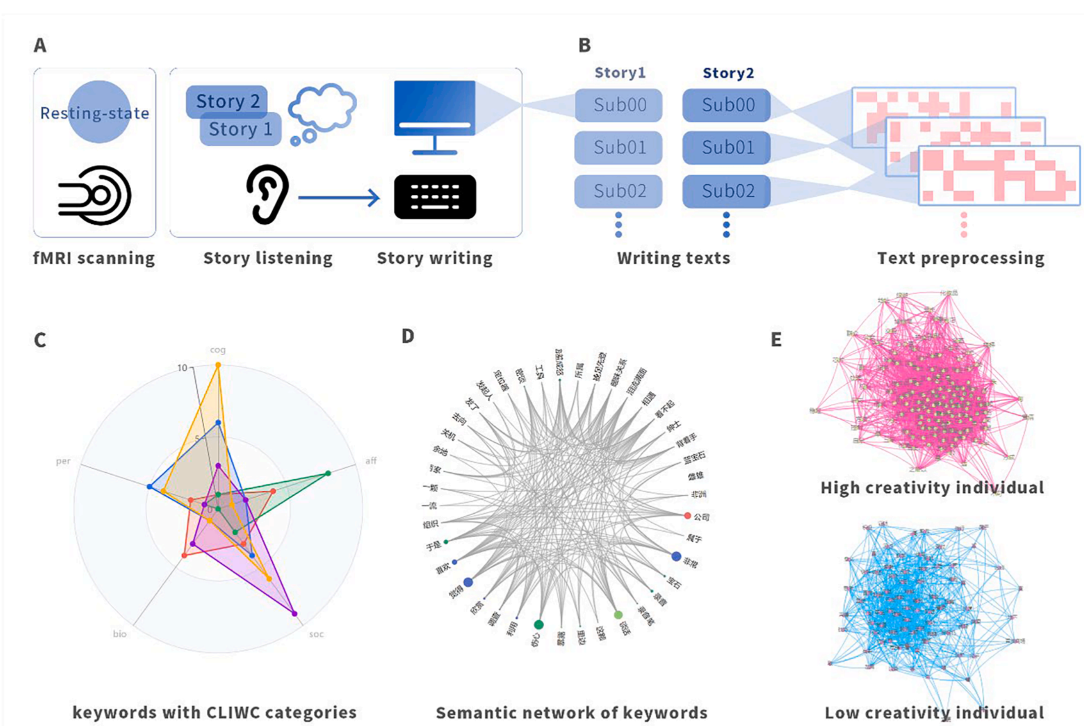

Fig. 1. Experimental procedure and text preprocessing. **A)** Participants were presented with two incomplete suspense stories, given 10 min to contemplate how to continue the story, and then entered text into a computer. Participants' rs-fMRI data were collected. **B)** Story-continuation texts underwent preprocessing and TD-IDF filtering for keywords. **C)** and **D)** Distributions of keyword counts across five CLIWC categories for four participants and an SN graph of keywords for one participant are shown. SN node size represents the square of weighting degree; node color indicates CLIWC category. **E)** SN diagrams (constructed from keywords) of one participant with a high score and one participant with a low score in creative writing performance.

dimensions were generated to evaluate the creativity of creative writing. Confirmatory factor analyses (CFA) from our previous study were used to consolidate the six creative writing rating dimensions—originality, cohesion, rationality, imagery, voice, and characterization (Mozaffari, 2013) —into two factors: originality (novelty) and rationality (appropriateness). In our previous study, we found that originality and rationality exhibited opposing trends in their correlation with the similarity between text continuation and story background (Fan et al., 2023), suggesting the presence of different cognitive components for these two factors. Additionally, we instructed participants to focus solely on generating novel stories, without concern for appropriateness. Therefore, in this study, we chose originality as the measure of the creativity of creative writing. The rating criteria and CFA results are described in detail in our previous study (Fan et al., 2023). The creative writing scores were standardized and averaged across the two stories to minimize the impact of inter-story theme differences.

2.3. Text and preprocessing

Preprocessing was performed on texts written by 79 participants. It included correction of typos, proper noun use, and word segmentation. Each subject's continuation text was reviewed individually for manual correction of spelling and grammar errors. For example, "淤痕" and "砖石" were uniformly modified to "瘀痕"(bruise) and "钻石"(diamond), respectively. English character names were batch-modified to Chinese names: 哈利 (Harry), 麦克 (Mike), 汤姆 (Tom), and 克林顿 (Clinton). Spelling errors in object names and situations where different object names were mixed together were corrected manually. Spelling errors for background place names in submitted texts were corrected (e.g., "Cumberland Shopping Center," "Central Park," "59th Street," and "Sudan Apartment"). Notepad++ was used as a batch correction tool in text correction.

Text segmentation to divide complete texts into combinations of words and delete stop words was conducted in jieba (https://pypi.org/project/jieba/) based on Python 3.7 (https://www.python.org/downloads/release/python-370/). The word counts for story 1 and story 2 were 402.75 ± 148.21 and 370.77 ± 133.88, respectively. After excluding repeated words, the word counts were 209.64 ± 65.52 for story 1 and 196.25 ± 61.87 for story 2 (Fig. 1B).

2.4. Keyword category

The number of keyword categories reflects an individual's ability to retrieve concepts from semantic memory (Zhang et al., 2023). To investigate the retrieval abilities in creative writing, we focused on the relationship between the number of keyword categories and creative writing performance. The CLIWC (2015 version; 79 word categories encompassing 9,719 Chinese words) (Huang et al., 2012) was used to classify keyword categories. The original LIWC was designed to enable evaluative semantic analysis by categorizing words into specific social and psychological categories based on English (Rodriguez & Storer, 2020; Tausczik & Pennebaker, 2010). The CLIWC is highly equivalent to the original LIWC with respect to word detection and has reliable validity (Huang et al., 2012). Two statistical methods were used to determine category quantity. Firstly, all 79 CLIWC category labels were used to quantify categories represented in each text. Secondly, to validate the results within a limited range of categories, five specific category labels were selected: cognitive process, perceptual process, biological process, social process, and affective process. These five labels are associated with story elements, encompassing vocabularies that describe both intrinsic aspects (such as theme, characters, plot, style, setting, perspectives, emotions, and atmosphere) and extrinsic aspects (such as socio-cultural background and psychological dimensions) (Asri, 2015) (Fig. 1C). We applied TF-IDF feature extraction to select the top 20 % of keywords from the segmented words in each text, excluding repeated words, resulting in an average of 26.41 ± 11.06 keywords for story 1 and 22.04 ± 10.36 keywords for story 2. Visit supplementary materials for method of TF-IDF. TF-IDF selects segmented words based on frequency, whereas CLIWC selects words based on word class distribution characteristics. Combining these two methods allows for the screening of important words and discernment of their attributes, thus yielding semantic information. Story 1 writings had a mean of 12.77 ± 5.46 total CLIWC words, which accounted for an average of 51.58 % of the keywords, and 7.81 ± 3.80 uses of the five CLIWC words, accounting for an average of 32.05 % of the keywords. Story 2 writings had a mean of 11.42 ± 5.30 total CLIWC words, accounting for an average of 54.22 % of the keywords, and 7.11 ± 3.78 uses of the five CLIWC words, accounting for an average of 33.93 % of the keywords. To reduce the impact of inter-story theme differences, the quantities of CLIWC categories contained in each subject's keywords in both story-continuation tasks were standardized and added together, effectively yielding a continuous variable.

2.5. Keyword SN structure assessment

To investigate the organization of keywords in creative writing, we constructed individual-level SNs of keywords for each story-continuation product (Fig. 1, D and E). A weighted SN was constructed based on keywords (top 20 % of TF-IDF values from segmented words in a text) and keyword vectors, where nodes represented keywords and edges represented the Pearson correlation between keyword vectors. Edges with correlation coefficients < 0.05 were removed (a filtering method to minimize spurious relations between words) (Kenett, 2018). Whereas previous studies have used cosine similarity to construct matrices (Li et al., 2021; Rahutomo et al., 2012; Sarica & Luo, 2021), we utilized normalized cosine similarities expressed as Pearson correlation coefficients.

SN structure assessment was quantitated with clustering coefficient and global efficiency measures, which have been correlated to creativity (Benedek et al., 2017; Bernard, Kenett, Tellez, Benedek, & Volle, 2019; Kenett & Faust, 2019; Ovando-Tellez et al., 2022). Clustering coefficient (CC) reflects the extent of connectedness within neighbors. CC for a network refers to the average probability that two neighbors of a node are also neighbors themselves. Global efficiency (E(G)), which is inversely related to the average shortest path length, measures the overall capacity of the network for parallel information transfer between nodes through multiple edges (Bassett & Bullmore, 2006; Saghayi et al., 2020). Together, these two metrics provide insights into both local connectivity and global information transfer efficiency within the network. We calculated the standardized CC and E(G) for the keyword SN in each story and averaged them across two stories respectively.

SN analysis was conducted with the NetworkX package in Python 3.7 (https://github.com/networkx/networkx). The Gensim tool package (Rehurek & Sojka, 2010) was used to obtain 300-dimensional word vectors of keywords, which were derived from the Chinese corpus of Baidu Baike and Wikipedia, a pre-trained corpus built via Python's Jieba Chinese parser that has ∼ 1 billion-word tokens and a vocabulary of 1,539,701 words. The Word2Vec tool was used to train word vector representation (https://code.google.com/archive/p/word2vec/) (Liu et al., 2021).

2.6. Data acquisition and preprocessing

Imaging was conducted with a 3-T Siemens Prisma scanner (Erlangen, Germany) at Southwest University; rs-fMRI images were obtained via gradient-echo echo planar imaging with a 1000-ms repetition time, 20-ms echo time, 73° flip angle, a field of view of 195 × 195 mm^2, a voxel size of 2.5 × 2.5 × 2.5 mm^3, and 56 slices of 2.5-mm thickness. The fMRI data were preprocessed with FMRI Prep, including head motion correction, slice timing correction, spatial normalization, and smoothing. For a more detailed explanation of the fMRI preprocessing, please refer to our previous study (Fan et al., 2023).

2.7. Predictive modeling

The relationship between creative writing performance and network FCs during rest remains relatively limited. Here, we adapted the CPM method to identify whole-brain rs-FC patterns predictive of creative writing performance. The analysis incorporated ten-fold cross-validation; during each fold, we computed the partial correlation between each edge in the FC matrix and within-participant sum score of z-scored creative writing ratings, controlling for gender, age, and mean frame-wise head motion, as these factors have been found to be related to FC (Feng et al., 2024; Shen et al., 2017). Only edges exhibiting correlations with the creative writing scores (cutoff, $p < 0.01$ two-tailed) were retained, resulting in positive and negative edge masks. In the main analyses, we applied a p-value threshold of 0.01 for edge selection. For a detailed exploration of the rationale behind selecting this threshold, including an evaluation of multiple thresholds and their predictive performance, please refer to supplementary materials. To characterize FC patterns predictive of creative writing, we examined the network strength of the participants' creative writing CPM. This method is referred to as CW (creative writing)-CPM from here forward (Kucyi et al., 2021). We calculated a single S (network strength) value as the combined contribution of positive and negative edge sums as follows (Fig. 2A). N refers to the weighted edges of the positive or negative network mask. Previous studies have shown that analyzing positive and negative networks separately may lead to informational redundancy (Rosenberg et al., 2016; Wu et al., 2023), whereas combining them into a single S value provides a more integrated understanding of their contribution to creative performance. For example, see Wang et al., 2024.

$$S = \sum_{n=1}^{N} pos_n - \sum_{n=1}^{N} neg_n$$

In held-out-participants, we performed a Pearson correlation between model-predicted and observed creative writing scores. Final positive and negative masks were obtained by multiplying ten positive masks and negative masks generated from ten-fold cross-validation. FC edges obtained by subtracting the sum of FC with positive- and negative-masks were used to construct a predictive brain network model of creative writing.

To determine whether predicted versus observed dataset correlations differed significantly on a group level, a distribution of null values was generated. All CW-CPM procedures were repeated in a 1000-iteration permutation test to obtain null correlation values. Rho coefficient and p values were reported for the permutation test (Fig. 2B). The CPM analysis code referred to public github scripts (https://github.com/YaleMRRC/CPM).

2.8. CW-CPM internal validation

To validate our CW-CPM, we employed a leave-one-out validation (LOOV) approach, controlling for gender, age, and mean frame-wise head motion (Shen et al., 2017), a highly stringent method wherein the predictive creative writing model was trained on all but one subject and tested on the left-out subject. This procedure was repeated for each subject, and overall model performance was evaluated by computing the mean and standard deviation of the prediction accuracy across all participants. Consistent with our ten-fold validation, LOOV yielded a significant result ($r = 0.3101$, $p < 0.05$), indicating that our CW-CPM method was robust.

2.9. Analysis of functional neuroanatomical patterns contributing to the CW-CPM

We assigned each node to one of the seven canonical Yeo-Krienen intrinsic functional networks (Schaefer et al., 2018) based on the network strength mask generated from the ten-fold cross-validation CW-CPM and investigated whether specific networks contribute more to creative writing than others. We performed a series of CW-CPM procedures iteratively, gradually removing network-pair edges from the network strength mask to reveal whether CW-CPM results changed by comparing the series coefficients generated from the corresponding CW-CPM procedures. We employed the quartile method to identify any abnormal coefficients, which would indicate significant changes, and were able to identify specific network pairs that played a notable role in creative writing.

2.10. Mediation analysis

We performed mediation analyses to investigate the indirect effect of

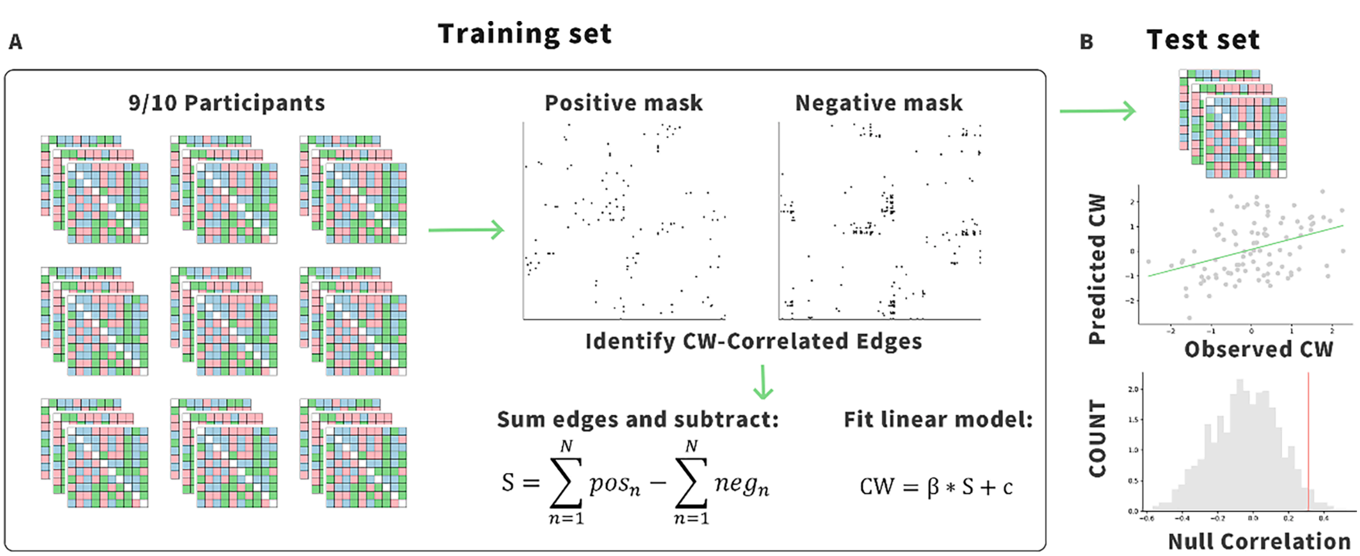

Fig. 2. CW-CPM construction procedure. Participants' FC matrices were divided into tenths; nine tenths served as the training set and one tenth served as the test set. **A)** Training-set FC matrices were related to creative writing z-scores by Pearson partial correlation analysis, and edges with $p < 0.01$ (two-tailed) were retained, resulting in positive and negative masks. Positive and negative FCs were summed separately and subtracted to obtain an S value, which was used to construct a general linear regression model with creative writing z-scores. **B)** Training-set predicted and observed creative writing z-scores were submitted to Pearson correlation analysis. The correlation coefficient r obtained from ten-fold CW-CPM was greater than the distribution of r values obtained from a 1000-permutations test ($p < 0.05$).

semantic features, focusing on its mediating role in the relationship between CW-CPM and creative writing performance. Indirect-effect significance was tested with the bootstrapping method, computing non-standardized indirect effects for each of 1000 bootstrapped samples. The 95 % CI was computed by determining indirect effects at the 2.5th and 97.5th percentiles.

3. Results

3.1. Quantity of keyword categories and creative writing performance

The top 20 % of keywords generated by each participant, assessed based on TF-IDF (term frequency-inverse document frequency) values, were subjected to CLIWC (Chinese version of the Linguistic Inquiry and Word Count) analysis (Table A2). When all CLIWC category labels were included in the analysis, the quantity of keyword categories represented by individual participants' top-20 % keywords correlated with their creative writing scores ($r = 0.498$, $p < 0.001$). When only five CLIWC category labels were included, the quantity of keyword categories of the top-20 % keywords also correlated positively with the participants' creative writing scores ($r = 0.311$, $p < 0.01$) (Fig. 3A). Better creative writing performance was characterized by an enrichment in the types of word categories in the text, including more diverse and extensive word use. This phenomenon was observed in the number of word categories associated with general language features, as well as in the categories related to story elements.

3.2. Keyword SN metrics and creative writing

We then constructed a SN for each story-ending text from each subject based on their top-20 % keywords, and calculated and averaged the CC and E(G) of those SNs. CC and E(G) were used to examine local connectivity and global information transfer efficiency within the network in relation to creative writing performance. CC was positively correlated with creative writing scores ($r = 0.449$, $p < 0.001$), as was E(G) ($r = 0.471$, $p < 0.001$) (Fig. 3B). Better creative writing performance was associated with greater local connectedness and more efficient global information transfer within the semantic memory structure, as revealed by the analysis of written texts.

3.3. Keyword semantic features and creative writing

We next performed the Pearson correlation between top-20 % keywords semantic features and creative writing score by controlling for nodes number in the semantic network. The results are shown in Table 1. The quantity of all CLIWC categories of keywords correlated directly with their creative writing scores ($r = 0.440$, $p < 0.001$). However, the correlation between five CLIWC category quantities of keywords and creative writing scores was non-significant ($r = 0.213$, $p = 0.057$). Participants' CC values correlated directly with their creative writing scores ($r = 0.448$, $p < 0.001$), as did E(G) ($r = 0.513$, $p < 0.001$). These results suggest the stability of behavioral results above. To further validate the relationship between creative writing performance and the semantic features of writing texts, we identified keywords at various TF-IDF thresholds (10 %, 15 %, 20 %, 25 %, 30 %) (Table A3). The highest significance was observed at the 20 % and 25 % thresholds. These thresholds may better capture the diversity and effectively-mapped structure of semantic memory that support creative writing performance.

Table 1
Partial correlation coefficients.

	CLIWC categories (all labels)	CLIWC categories (5 labels)	CC	E(G)
Creative writing score	0.440*** $p < 0.001$	0.213 $p = 0.057$	0.448*** $p < 0.001$	0.513*** $p < 0.001$

Note. controlling for nodes number in the semantic network. All p values corrected for multiple comparisons using false discovery rate correction. CC clustering coefficient, E(G) global efficiency.

3.4. Predictive brain connectivity patterns

First, ten-fold cross-validation CPM iterations revealed 199 edges, including 64 and 135 edges, which correlated positively and negatively, respectively, with creative writing scores ($r = 0.3115$, $p < 0.05$). Edges were distributed widely throughout the brain with high-degree nodes in occipital lobe cortex, visual associative cortex, primary visual cortex, prefrontal cortex, temporal cortex, posterior cingulate cortex, and the somatomotor network (Fig. 4, A, B and D). Then, the network strength value (S) was obtained by subtracting the sum of positive and negative network FC edges. A higher S value indicates a greater contribution of positive edges and the reversed negative edges. For the method of FC feature extraction, please visit supplementary materials.

3.5. Functional neuroanatomical basis of SNs

By comparing CW-CPM coefficients with dropped network-pair edges, we identified coefficients that deviated significantly from the distribution. Coefficients that deviated downward originated from CW-CPMs that dropped edges between visual network (VIS) and default mode network (DMN) (k = -98, $r = 0.2473$) and within the DMN (k = 14,

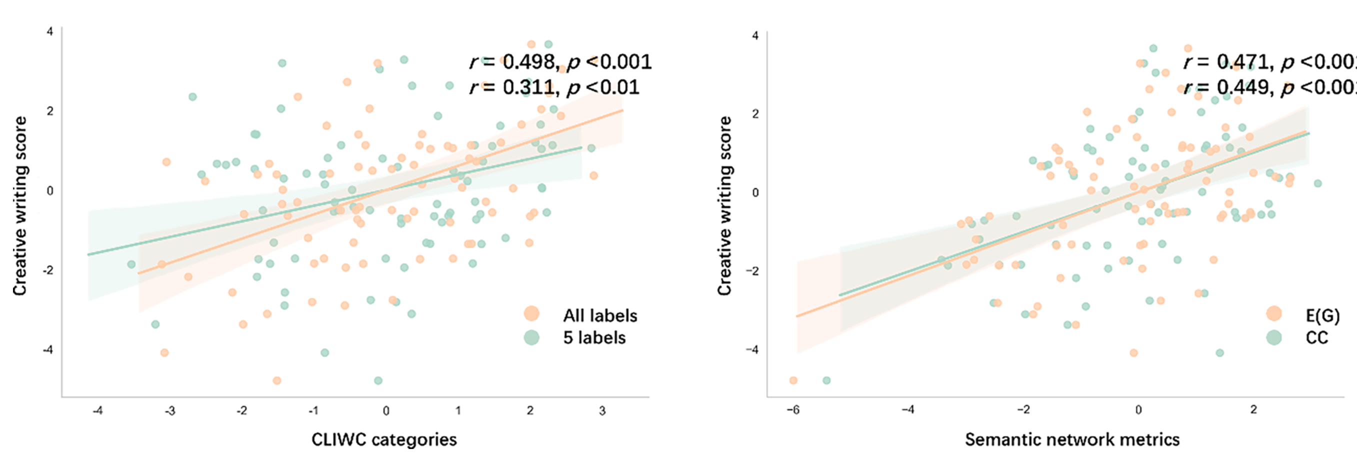

Fig. 3. Semantic features of keywords in creative writing. Plots of Pearson correlations among **A)** CLIWC category quantities, **B)** SN metrics, and creative writing score (uncorrected). Classification methods are color-coded.

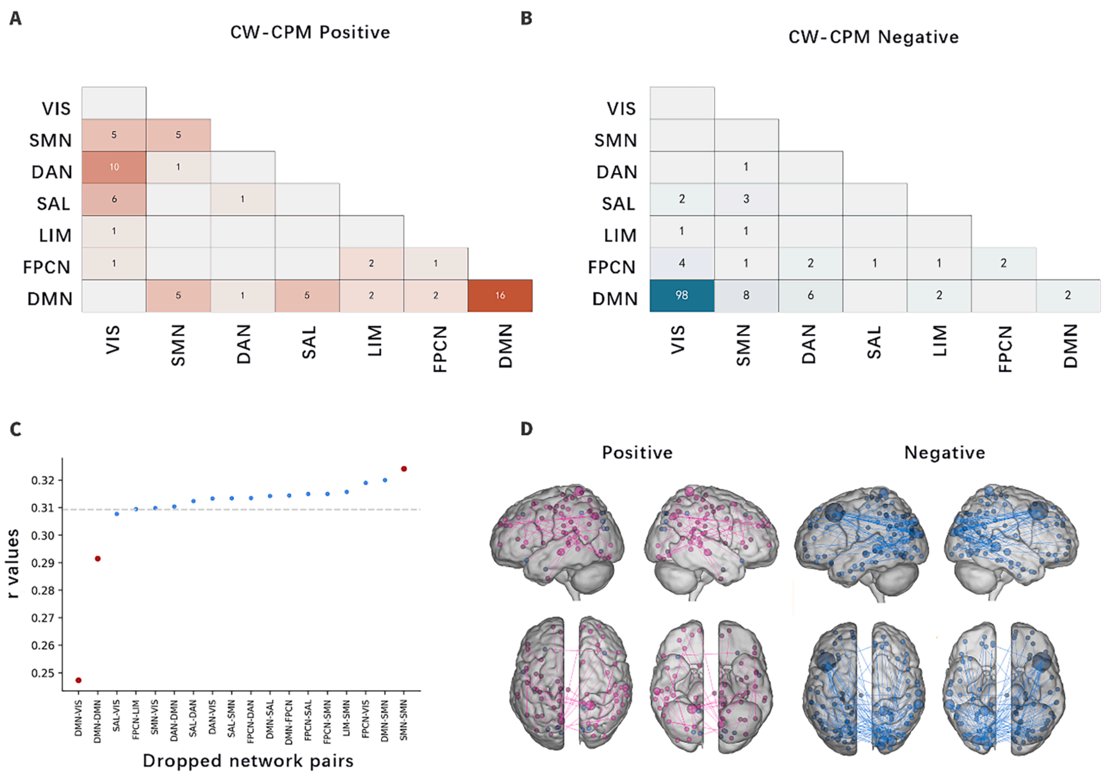

Fig. 4. Functional anatomy of CW-CPM. **A)** and **B)** The number of edges, among those within the CW-CPM positive and negative mask, assigned to each within- or between-network pair based on the Schaefer400 and Yeo-Krienen 7-network atlases. **C)** Distribution of CW-CPM *r* values after sequentially removing network-pair FCs. Blue and red dots represent *r* values within and outside of the 25–75 % range, respectively. The gray horizontal line represents the mean value. **D)** Edges strongly contributing positively (pink) and negatively (blue) to the CW-CPM. A threshold of 10 degrees was applied; nodes with $\geq$ 10 contributing edges are shown. VIS, visual network; SMN, sensorimotor network; DAN, dorsal attention network; SAL, salience network; LIM, limbic network; FCPN, frontoparietal control network; DMN, default mode network.

k = -2, $r = 0.2915$). Coefficients that deviated upward were observed in the dropped sensorimotor network (SMN) connections (k = 5, $r = 0.3241$) (Fig. 4C). Overall negative VIS-DMN edges were strongly predictive of creative writing performance. Positive DMN-DMN edges were also influential despite their rarity. The dropped SMN-SMN CPM edges suggested that connections within the SMN may influence prediction. In summary, although CW-CPM predictions were based on a complex, distributed pattern of interacting networks, key components associated with increased creative writing performance were a) increased DMN-DMN correlation; and b) increased DMN-VIS anticorrelation.

3.6. Mediation analysis

In the previous analyses, we found a relationship between semantic features and creative writing performance and conducted CW-CPM to reveal the rs-FC patterns predictive of creative writing performance. In the final step, we conducted mediation analyses to examine the indirect effect of semantic features, focusing on its mediating role in the relationship between CW-CPM and creative writing performance.

We explored the mediating role of CLIWC categories (both for 5 labels and all labels). The indirect effects were not statistically significant ($\beta = 0.036$, $p = 0.136$; $\beta = 0.049$, $p = 0.136$), with 95 % CI of [-0.004, 0.144] and [-0.014, 0.182], respectively. The direct effects were significant ($\beta = 0.084$, $p < 0.001$; $\beta = 0.080$, $p < 0.001$), and the total effects were significant ($\beta = 0.088$, $p < 0.001$ for both analyses).

We explored the mediating role of SN metrics. Using CC as a mediating variable, the indirect effect was statistically significant ($\beta = 0.056$, $p < 0.05$), with 95 % CI of [0.019, 0.248]. The direct effect was significant ($\beta = 0.082$, $p < 0.001$), and the total effects was significant ($\beta = 0.088$, $p < 0.001$) (Fig. 5A). Using E(G) as a mediating variable, the indirect effect was statistically significant ($\beta = 0.058$, $p < 0.05$), with 95 % CI of [0.029, 0.269]. The direct effect was significant ($\beta = 0.082$, $p < 0.001$), and the total effects was significant ($\beta = 0.088$, $p < 0.001$) (Fig. 5B). All p values corrected for multiple comparisons using false

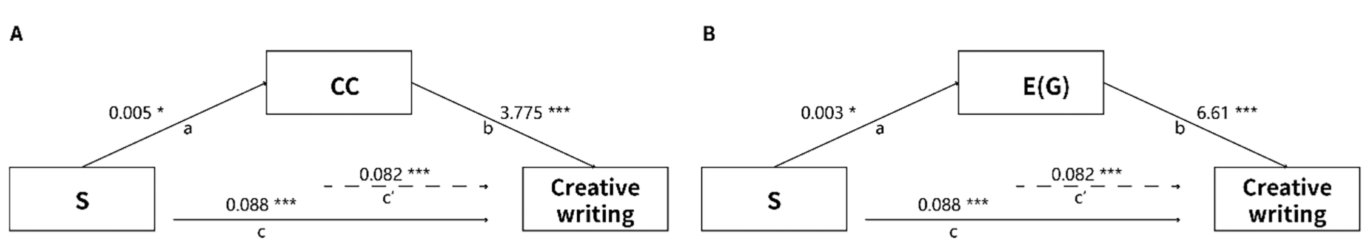

Fig. 5. Mediation analyses. Path diagrams of the mediation models are illustrated with regression coefficient beta weights. The total effect and direct effect are represented by path c and path c', respectively. The indirect effect is the product of paths a and b. **A)** Role of CC in mediating the relationship between S and creative writing scores. **B)** Role of E(G) in mediating the relationship between S and creative writing scores. S network strength, CC clustering coefficient, E(G) global efficiency. $^{*}p < 0.05$, $^{**}p < 0.01$, and $^{***}p < 0.001$. All p values corrected for multiple comparisons using false discovery rate correction.

discovery rate correction.

4. Discussion

The present study uncovers the semantic features of creative writing products, the predictive whole-brain rs-FC patterns associated with creative writing performance, and the mediating role of the rs-FC patterns in the relationship between semantic features and creative writing performance. We found that better creative writing performance was associated with abundant semantic information related to key content, and the information was highly connected and transferred efficiently. CW-CPM uncovered the whole-brain rs-FC patterns predictive of creative writing performance, with DMN-DMN coupling and DMN-VIS decoupling playing a dominant role in the prediction. Lastly, semantic features were positive mediators between CW-CPM and creative writing performance.

4.1. Semantic features of creative writing

We first investigated the semantic features contributing to creative writing. Our use of TF-IDF and CLIWC methods enabled us to screen for important words and uncover their meanings. TF-IDF analysis helped to filter out syntactic (conjunctions, modification of nouns, etc.) and semantic (hyponymy, meronymy, etc.) (De Deyne et al., 2016), We constructed SNs based on our TF-IDF analysis of the top-20 % of keywords in story-continuation texts. Our analyses with two CLIWC classifications (all and five categories) revealed that keywords contained greater numbers of CLIWC categories across both classification methods are associated with creative writing performance.

The present CLIWC results align with previous observations about creativity. According to associative theories, high-creativity individuals exhibit low-restraint associative strength to generate words from diverse perspectives (Mednick, 1962). Ovando-Tellez et al. (2022) related inter-category switches to an individual's ability to combine remote associates and, in keeping with the work of Zhang et al. (2023), they described these behavioral differences in terms of differing organization of semantic memory networks. Our result suggested that individuals may scan broad-use categories in their own semantic memory networks to generate ideas for use in creative writing (Benedek et al., 2012). Category quantity may likewise reflect an associative ability based on the organization of one's semantic memory structures. Associative ability reflects a search process operating on a semantic memory network structure (Beaty & Kenett, 2023). By travelling further in semantic space, individuals activate concepts from a broader range of categories during creative writing.

Next, we constructed individual-level SNs based on the top 20 % of keywords extracted from the story-continuation texts using TF-IDF analysis. We then measured clustering coefficient (CC) and global efficiency (E(G)) to examine the ability to integrate concepts into novel ideas. These network science metrics provide a computational framework for modeling cognitive structures such as semantic memory (Christensen & Kenett, 2021). According to the associative theory of creativity (Beaty & Kenett, 2023; Benedek et al., 2012; Mednick, 1962), highly creative individuals possess a more flexible organization of concepts within their semantic memory, allowing them to retrieve remote associations more easily (Kenett, 2018; Mednick, 1962). In line with this, we found positive correlations between both CC and E(G) with creative writing performance. CC reflects the degree of local connectivity. High CC suggests a tightly clustered network, which may enable the linking of closely related concepts. E(G) measures a network's overall capacity for parallel information transfer across multiple nodes, facilitating broader, more remote concept integration. Our findings are consistent with studies reporting the relationship between semantic associative ability and creative behavior (Ovando-Tellez et al., 2022). Specifically, individuals with a more flexible semantic memory structure benefit from both localized connectedness and global integrative efficiency, which together contribute to enhanced creative output. In a nutshell, we analyzed the relationships between semantic features and creative writing performance, which suggested that a flexible semantic memory structure plays a supportive role in creative writing.

In this study, we employed a corpora-based approach to construct individual SNs from participants' written stories. Textual corpora-based methods offer valuable advantages for representing semantic memory. When generating text, individuals engage in both semantic retrieval (Beaty et al., 2020) and the integration of a broad array of associations to contextualize their ideas (Bellana et al., 2022), reflecting deep cognitive processing. Furthermore, natural settings allow for a direct exploration of creative performance, surpassing controlled test settings (Runco et al., 2017). By using written texts, we gain a richer understanding of individual cognitive structures, highlighting the relevance of this approach despite its complexities.

4.2. Neural basis of creative writing

We identified FC patterns predicting creative writing performance by applying CPM. CW-CPM results were obtained by subtracting the sum of FC with positive and negative masks (i.e., network strength), leading to the discovery of 199 edges that correlate directly (64 edges) and inversely (135 edges) with creative writing performance. We employed a leave-one-out validation (LOOV) approach to internally validate the CW-CPM. By comparing the CW-CPM coefficients with dropped network-pair edges, we identified key components that contribute significantly to CW-CPM. When intra-DMN edges and DMN-VIS edges were dropped, CPM coefficients were lower than 75 % of the coefficient distribution. When intra-SMN edges were removed, CPM coefficients were higher than 75 % of the coefficients.

Our findings indicate distinct roles for different brain network FC in creative writing. Specifically, the decoupling FC between DMN and VIS, coupling FC within DMN appear to facilitate creative writing performance. The DMN has been implicated in a variety of cognitive functions—including semantic processing (Binder & Desai, 2011), encoding and retrieving episodic memories (Huijbers et al., 2013), and thinking creatively about a problem (Kühn et al., 2014; Takeuchi et al., 2011)—and it has been reported to be active during spontaneous thought states, such as mind wandering or daydreaming (Fox et al., 2015; Mason et al., 2007). These previous findings suggest that the DMN allows contemplation of stimuli not present in the environment, enabling complex introspective forms of higher-order thought (Konishi et al., 2015). Furthermore, previous investigations into creative cognition have suggested that occipital cortex deactivation may be indicative of internal attention processes (Benedek et al., 2016). As the deactivation of the visual cortex may be due to not focusing attention upon the visualized scenario in order to promote further creativity (Howard-Jones et al., 2005). Greater decoupling of the DMN from medial visual regions was found to be associated with more frequent mind-wandering (Zhang et al., 2019). Studies have also found that reduced FC to the visual cortex has been associated with increased divergent thinking, with supporting evidence found in both rs-FC (Orwig et al., 2021) and FC based on task-fMRI (Japardi et al., 2018). Taken together, these results suggest reduced synchronization between DMN and VIS allows the brain to focus more on internally generated thoughts (dominated by DMN) rather than external sensory information (processed by VIS), thus enhancing creativity.

If we view the role of the visual network in creative writing as generating mental imagery, an inverse relation of visual network activity with creative writing performance may seem contradictory. Indeed, Shah et al. (2013) detected strong bilateral occipital-temporal cortex and bilateral visual cortex activation during creative writing, whereas Howard-Jones et al. (2005) and Erhard et al. (2014) obtained results wherein applied visual mental imagery strategies appeared to inhibit creativity. Further research is needed to clarify and differentiate visual system contributions to creative writing.

However, CW-CPM found that FPCN did not play a dominant role in predicting creative writing performance in this study. Previous research has shown that DMN-FPCN interactions are crucial for creativity, but this depends on the cognitive components engaged (Abraham, 2014; Kenett et al., 2018; Ovando-Tellez et al., 2022). For instance, studies on semantic creativity found that semantic switching involves the DMN, FPCN, and salience networks, highlighting memory-control interactions, while semantic clustering engages control, salience, and attentional networks, reflecting attentional control (Ovando-Tellez et al., 2022). Furthermore, controlled semantic retrieval involves DMN-FPCN connectivity, while automatic semantic processes rely more on internal DMN connectivity (Evans et al., 2020). The story-continuation task in this study, which is open-ended, may have led to a focus on DMN-driven spontaneous thinking, as open-ended tasks tend to rely more on DMN than FPCN (Chrysikou & Thompson-Schill, 2010). Moreover, the creative writing score was based on novelty. A recent study demonstrated that novelty and appropriateness of creativity rely on different neural mechanisms. Novelty was associated with the DMN, reflecting associative processes, while appropriateness was linked to the limbic network. However, the FPCN showed less weighted in both novelty and appropriateness predictions (Wang et al., 2024). The FPCN is involved in complex control and integration of cognitive and memory processes (Evans et al., 2020; Wang et al., 2024). The open-ended nature of the task and its emphasis on novelty might explain the lack of FPCN-related FC in our findings.

Our analysis revealed that all SMN-SMN FC edges were positively correlated, and removing these edges led to an increase in predictive accuracy (reflected in a higher r value). This suggests that SMN-SMN coupling may not play a central role in predicting creative writing performance. Instead, SMN-SMN coupling might introduce noise or unnecessary variance, as it is associated with bodily perception and movement (Mantel et al., 2018), which could interfere with the cognitive processes essential for creativity. Previous studies on FC in fMRI data show that sensorimotor regions exhibit correlated low-frequency fluctuations during rest, driven by spontaneous neuronal activity rather than high-frequency physiological noise (Rissman et al., 2004). However, creative writing involves higher-order cognitive processes, such as memory retrieval, flexible mental shifting, and concept association (Flower & Hayes, 1981). Removing SMN-SMN FC could enhance predictive accuracy by allowing more cognitively relevant networks, such as those involved in memory and semantic processing, to dominate the model. This shift may result in stronger and more precise predictions of creative writing performance. For instance, Shah et al. (2013) found that SMN activation during creative writing was reduced when a writing movement baseline control condition was incorporated.

In this study, we found that the rs-FC patterns represented by CW-CPM significantly predicted creative writing performance, mediated through semantic network properties such as CC and E(G). This supports our hypothesis that the semantic memory structure revealed through writing texts is associated with rs-FC patterns underlying creative writing, reflecting broader neural mechanisms tied to semantic memory processing. These results align with previous studies, which have demonstrated that rs-FC patterns related to semantic memory structure predict creative ability (Ovando-Tellez et al., 2022). Moreover, neuroimaging evidence suggests that different types of semantic retrieval are supported by distinct rs-FC patterns relating to DMN (Evans et al., 2020). Our findings build on the literature by showing that specific rs-FC patterns dominated by DMN can predict performance in real-world creative tasks like writing via semantic memory structure.

Our study has several limitations. Firstly, we used only suspenseful stories because they are engaging and thereby tend to promote creativity. With respect to ecological validity, it is not known whether similar findings would be obtained with other genres (Doumit et al., 2013). Secondly, the TF-IDF feature extraction/threshold selection method used may not identify all keywords accurately. Our threshold for selecting relevant words was determined by evaluating the correlation coefficients between creative writing performance and semantic features across a range of TF-IDF thresholds. Future work should advance the feature extraction approach. For example, Zhang et al. (2020) proposed a feature extraction approach based on TF-IDF and game-theoretic shadowed sets. Thirdly, we recruited lower number of participants for running a CPM analysis, and our use of rs-fMRI to examine creative writing ability should be validated in larger-scale studies in the future. Then, our participant sample consisted mainly of college students, which may not fully represent the semantic memory structure and neural basis of writing experts. Next, while Word2Vec word embeddings provides interpretable semantic dimensions for cross-participant comparisons (Liu et al., 2021; Wang et al., 2024; Zhang et al., 2023), it overlooks context-dependent variations in continuous narratives. Future studies could benefit from contextualized embeddings (e.g., BERT, GPT) to better capture dynamic semantic shifts (Johnson et al., 2022; Song et al., 2024). Lastly, we conducted mediation analyses using cross-sectional data, which is limited to reveal the causal mechanisms (Li et al., 2023). Future studies should adopt a longitudinal approach to study the relationship between changes in semantic memory structure and creativity (Kenett, 2024).

In conclusion, the present study advances our understanding of creative writing by providing data describing predictive features of individuals' written texts and brain FCs and by establishing mediation models. Our findings shed light on the cognitive and neural underpinnings of creative writing. Moreover, this study demonstrates the potential of integrating advanced network-based methods in explorations of the interplay between cognitive and neural networks.

Artificial Intelligence: During the preparation of this work the authors used ChatGPT in order to polish the sentences. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Ethics: This research received approval from the Ethics Committee of Southwest University.

Computational Reproducibility: The authors are applying for a Computational Reproducibility Badge which will be awarded pending checks by the STAR Team.

Author contributions.

Jing Gu: Data curation; methodology; formal analysis; visualization; writing – original draft; writing – review & editing. **Xueyang Wang:** Investigation; data curation; conceptualization; supervision; methodology; writing – review & editing. **Cheng Liu:** conceptualization; data curation; software; supervision; methodology. **Kaixiang Zhuang:** Writing – review & editing. **Li Fan:** Investigation; data curation; software; validation. **Jingyi Zhang:** Investigation; data curation. **Jiangzhou Sun:** Supervision; writing-review & editing. **Jiang Qiu:** Funding acquisition; project administration; resources.

Funding.

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Uncited references.

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CRediT authorship contribution statement

Jing Gu: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Xueyang Wang:** Writing – review & editing, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Cheng Liu:** Supervision, Software, Methodology, Data curation, Conceptualization. **Kaixiang Zhuang:** Writing – review & editing. **Li Fan:** Validation, Software, Investigation. **Jingyi Zhang:** Investigation, Data curation. **Jiangzhou Sun:** Writing – review & editing, Supervision. **Jiang Qiu:** Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bandl.2025.105551.

Data availability

Data will be made available on request.

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