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Automated Creativity Prediction Using Natural Language Processing and Resting-State Functional Connectivity: An fNIRS Study

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ABSTRACT

Evidence from fMRI research indicates that individual creative thinking ability – defined as performance on divergent thinking tasks, subjectively assessed by human raters – can be predicted based on the strength of functional connectivity (FC) between the brain's default mode network (DMN) and frontoparietal control network (FPCN). Here, we sought to replicate and extend these findings in two ways: 1) using a natural language processing method to objectively quantify creative performance (instead of subjective human ratings), and 2) employing functional near-infrared spectroscopy (fNIRS), a neuroimaging method that allows measuring brain activity in more naturalistic settings (compared to fMRI). By applying elastic-net regression to resting-state functional connectivity data, we constructed two separate prediction models to predict participants' creative performance based on static FC and dynamic FC respectively. Results from the static network analysis indicated that fNIRS-functional connectivity between the DMN and FPCN can reliably predict creative ability (assessed objectively via natural language processing; R^2 = .38). Moreover, we show that dynamic DMN-FPCN functional connectivity predicts creative ability nearly twice as strong as static connectivity (R^2 = .67). Our work demonstrates that objective measures of creativity can be predicted from resting-state functional connectivity and that the procedure can be efficiently implemented within highly naturalistic settings with fNIRS.

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Introduction

Creativity is often operationalized as the ability to generate both novel and appropriate ideas (Abraham, 2018; Diedrich, Benedek, Jauk, & Neubauer, 2015; Runco & Jaeger, 2012). Cognitive theories of creativity emphasize the interplay of bottom-up/generative processes (e.g., making novel conceptual combinations in semantic memory) and top-down/evaluative processes (e.g., determining whether associations are appropriate, and elaborating on them; Barr, Pennycook, Stolz, & Fugelsang, 2014; Beaty, Silvia, Nusbaum, Jauk, & Benedek, 2014; Chrysikou, 2019; Ellamil, Dobson, Beeman, & Christoff, 2012; Ivancovsky, Shamay-Tsoory, Lee, Morio, & Kurman, 2019; Nijstad, De Dreu, Rietzschel, & Baas, 2010). At the neural level, generative and evaluative processes are thought to correspond to the brain's default mode network (DMN) and frontoparietal control network (FPCN), respectively, with several studies finding that individual creative ability – is assessed via performance on divergent thinking tasks, based on human creativity ratings – can be predicted from the strength of functional connectivity (FC) between DMN and FPCN (e.g., Beaty, Benedek, Kaufman, & Silvia, 2015; Beaty et al., 2018; Shi et al., 2018).

In the present research, we aimed to extend this work by leveraging computational models of semantic distance, which offer an automated and objective approach to creativity assessment. We tested whether these objective creativity metrics could be predicted using machine learning models trained on functional near-infrared spectroscopy (fNIRS) data – specifically between the DMN and FPCN – extending past fMRI work using a neuroimaging method that is conducive to studying creativity in naturalistic contexts.

Brain networks and creative thinking

Creativity research is increasingly focused on linking cognitive processes to the activity of large-scale brain networks, including the DMN and FPCN (Beaty, Seli, & Schacter, 2019; Benedek & Fink, 2019). The DMN spans various posterior and midline parietal regions and is typically associated with spontaneous, memory-based

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processes, such as mind-wandering and free association (Fox, Spreng, Ellamil, Andrews-Hanna, & Christoff, 2015). Associative abilities – which rely on connecting concepts in semantic memory (Kenett et al., 2018; Mednick, 1962) – have been found to partially mediate the relationship between resting DMN activity and performance on divergent thinking tasks (Liu et al., 2021; Marron, Berant, Axelrod, & Faust, 2020; Ovando-Tellez et al., 2021). The DMN has been linked to semantic and episodic memory retrieval (Buckner et al., 2008; Raichle, 2015), which has been shown to underpin creative thinking (Beaty et al., 2020; Madore, Thakral, Beaty, Addis, & Schacter, 2019). Moreover, increased gray matter density within regions associated with the DMN has been linked to higher creative abilities (Kuhn et al., 2014). In contrast, the FPCN encompasses lateral prefrontal and anterior inferior parietal brain areas and is associated with primary executive abilities such as goal maintenance, inhibition, and attentional control (Niendam et al., 2012). Executive control is in turn thought to guide and constrain spontaneous associative processes, such as inhibiting unoriginal ideas (e.g., Beaty & Silvia, 2012; Benedek, Jauk, Sommer, Arendasy, & Neubauer, 2014).

Functional connectivity of the DMN and FPCN is hypothesized to support creative thinking through goal-directed memory search and the flexible integration of knowledge (Beaty, Benedek, Silvia, & Schacter, 2016). DMN-FPCN connectivity has been repeatedly demonstrated by previous neuroimaging efforts showing increased cooperation between the DMN and FPCN during creative cognition (Beaty et al., 2015) and artistic performance (Ellamil et al., 2012; Pinho, de Manzano, Fransson, Eriksson, & Ullen, 2014).

Investigations of FC underlying creativity have benefited from the advancement of connectomic analyses. These methods, such as connectome-based predictive modeling (CPM), allow for the prediction of human behavior, cognitive abilities, and individual differences, from measures of whole-brain FC (Shen et al., 2017). CPM has recently been employed to identify functional connectivity underlying individual differences in divergent thinking (Beaty, Kenett, et al., 2018; Beaty, Chen, et al., 2018). In this work, a neural model was built by 1) training the model on creative performance scores (creativity ratings) and functional magnetic resonance imaging (fMRI) data acquired during divergent thinking, 2) internally testing the model via a leave-one-out procedure (to predict the creative performance of individuals in the sample), and 3) externally validated the model on new participants from independent datasets (to predict creativity outside of the sample used to construct the model). Highly creative individuals were distinguished by stronger functional connectivity between the DMN, FPCN, and the salience network (involved in switching between DMN and FPCN; Uddin, 2015). In contrast, less creative individuals showed stronger connections between DMN, cerebellar, and sensory hubs. Other studies have since successfully employed CPM to analyze different facets of creativity, strengthening the notion that FC can predict individual creative ability (Frith et al., 2021; Ren et al., 2021).

Static and dynamic brain network interactions

Functional connectivity between DMN and FPCN during creative task performance is hypothesized to reflect the cooperation of spontaneous/generative and strategic/evaluative processes, respectively. However, it is unclear whether the generation and evaluation phases of creative cognition are sequential or whether people dynamically switch between the two. At the neural level, this switching may manifest in the rapid shifting between the FPCN and DMN (i.e., dynamic connectivity), rather than a largely stable FC state (i.e., static connectivity). In one recent study on dynamic FC and divergent thinking, Li et al. (2017) identified four alternating connectivity "states" – recurring patterns of correlation between brain networks – two of which strongly overlapped with a series of DMN hubs. Crucially, highly creative individuals showed a higher frequency of switching between these two states during rest. Furthermore, Sun et al. (2019) found that variability in resting-state FC between the DMN and several attention networks (partly overlapping with FPCN) positively correlated with verbal creativity, and Feng et al. (2019) demonstrated how the integration of the FPCN and DMN relates to verbal creative performance.

In another fMRI investigation of dynamic FC, temporal variability of network inter-connectivity was observed during creative activity (Beaty et al., 2015). At the beginning of a divergent thinking task, the authors reported increased coupling of the salience network and DMN, followed by a predominant coupling of the DMN and FPCN in the later stages. They interpreted the findings as indicative of early idea generation (DMN-salience connectivity) and later idea evaluation (DMN-FPCN connectivity). In a related study, participants with high trait levels of Openness (a personality trait strongly linked to creativity) demonstrated longer periods of resting-state functional coupling between the DMN, FPCN, salience, and dorsal attention networks (Beaty et al., 2018). Combining dynamic and static connectivity findings points toward the likelihood that creativity rests upon a cooperative interplay of various brain networks,

and respective subnetworks, engaged in both parallel and an alternating fashion, depending on specific cognitive demands.

Most FC studies of creativity noted above focused on large-scale networks, particularly when attempting to define whole-brain patterns of FC. The question of how specific brain regions within these large networks contribute to creativity remains less well understood. A recent study found increased resting-state FC between the IFG, a hub of the FPCN, and the medial prefrontal cortex (MPFC), a hub of the DMN, during divergent thinking (Takeuchi et al., 2017). Another study examined individuals with organic lesions of the MPFC who presented with concept generation deficits, supporting evidence for the causal role of the DMN in idea generation (Bendetowicz et al., 2018). Studies using transcranial direct current stimulation (tDCS) have shown that the bilateral IFG (e.g., Khalil, Karim, Kondinska, & Godde, 2020; Mayseless & Shamay-Tsoory, 2015) and dorsolateral prefrontal cortex (e.g., Vanderhasselt, De Raedt, & Baeken, 2009; Xiang et al., 2021) support control-related functions relevant for creative thinking. Assessing white matter projections, researchers distinguished the crucial role played by a sub-portion of the right DLPFC in driving patterns of brain activity and ultimately determining divergent thinking ability (Kenett et al., 2018); they also identified activity in the posterior-anterior section of the medial frontal gyrus as correlating with creative performance, possibly evidencing its role in facilitating the switching between the DMN and FPCN.

In a recent study attempting to define the differential engagement of internal and external attention in divergent thinking, Benedek and colleagues reported a higher engagement of the right anterior inferior parietal lobule, a cortical component of the FPCN, in a condition requiring internally directed attention (Benedek et al., 2016). This observation is consistent with the hypothesis that idea generation largely relies on the engagement of internally directed attentional processes (Benedek, Jung, & Vartanian, 2018), evidencing how the FPCN may be responsible for driving self-generated thought and the filtration of irrelevant external stimulation. In a further segmentation of the FPCN, Beaty, Cortes, Zeitlen, Weinberger, and Green (2021) reported how different frontoparietal subnetworks may subserve different cognitive processes in creative thinking. In this vein, it is crucial that neuroscientific research shift toward the definition of smaller-scale interactions within networks such as the DMN and FPCN. This may be investigated by parsing the FC within each network at the edge (i.e., connection) level to expose the specific engagement of sub-structures supporting creativity.

Objectively measuring creativity based on natural language processing

Divergent thinking tasks, arguably the most common paradigm for creativity assessment, have classically relied on human ratings for the evaluation of responses (Said-Metwaly, Noortgate, & Kyndt, 2017). This subjective approach generally involves the human rating of ideas in terms of fluency (quantity) and originality (quality; Jauk, Benedek, & Neubauer, 2014; Reiter-Palmon, Forthmann, & Barbot, 2019; Silvia et al., 2008). Performance on divergent thinking tasks has been crucially linked to creative achievement, a measure of real-life creative accomplishment in the arts and sciences (Kim, 2011). Despite such evidence for the validity of human creativity ratings, questions have been raised regarding their subjectivity, which threatens psychometric properties such as reliability – particularly when raters disagree on what is a more or less creative idea – as well as reproducibility in neuroscience research on creativity. Given these limitations, researchers are increasingly exploring whether creativity assessment can be made more objective and standardized (Beaty & Johnson, 2021; Dumas, Organisciak, & Doherty, 2020; Prabhakaran, Green, & Gray, 2013).

A possible solution to this issue has been put forward in the form of computational models of semantic analysis (i.e., natural language processing, NLP), leveraging principles of distributional semantics to objectively evaluate creative output (Kenett, 2019). The semantic relationships between words in response to a verbal creativity task can be calculated by applying NLP. The links between semantic distance and creativity rest upon the notion that novel ideas are constituted by the retrieval and recombination of distant concepts within semantic memory networks (Kenett et al., 2018; Mednick, 1962).

Semantic distance has been applied to automatically score the alternate uses task (AUT), with past work showing that such models provide an even better representation of semantic originality than human judgments (Forster, Dunbar 2009). A recent investigation of semantic distance applied to the AUT demonstrated its validity in predicting both subjective creativity ratings on the AUT (Beaty & Johnson, 2021; Dumas et al., 2020) and external measures of creativity, including real-world creative achievements (Beaty & Johnson, 2021). Indeed, reported correlations between semantic models and human creativity ratings have been quite large, exceeding .9 (at the latent level) in one recent study (Beaty & Johnson, 2021), pointing to a considerable agreement between human- and machine-derived creativity metrics.

Moreover, by applying NLP methods, the measurement of classic metrics of creativity (i.e., fluency, flexibility, and originality) can be refined by overcoming the reliance on subjective rating measures. For instance, Johnson, Cuthbert, and Tynan (2019) objectively computed idea diversity/flexibility by calculating semantic distance scores – an index of word-pair similarity based on co-occurrence probabilities extracted from large-text corpora. Johnson et al. (2019) proposed that one's creative ideas should be evaluated against group-derived metrics to comprehensively reveal his or her creative thinking process. Distributional semantic modeling of semantic distance uniquely allows one to leverage large repositories of human natural language, permitting this process to be achieved exhaustively and with minimal resources. Nevertheless, studies that selectively leverage semantic distance to investigate creativity will inevitably focus on the respective divergence of creative ideas (i.e., originality), neglecting other metrics like fluency and flexibility. Of note, both fluency and flexibility are also typically determined by subjective human-rater techniques and should thus be considered for inclusion in modern computational scoring techniques.

Notably, the combined use of computational semantic models and neuroimaging methods provides an entirely objective approach to studying creativity, at both the cognitive and the neural levels. This purely quantitative approach presents an opportunity to produce highly replicable findings, compared to studies using human ratings, which can vary based on raters' idiosyncratic perceptions of creativity.

The present study

Increasing neuroimaging evidence points to the central role of the DMN and FPCN in creative thinking, potentially reflecting the cooperation of generative and evaluative cognitive processes (Beaty et al., 2016). Other work has shown that individual variation in DMN-FPCN connectivity can predict a person's creative performance, based on human evaluations of creativity (Beaty et al., 2018; Shi et al., 2018). In the present research, we sought to replicate and extend these findings in two ways: 1) using computational models to objectively quantify creative performance (instead of subjective human ratings) based on NLP, and 2) employing functional near-infrared spectroscopy (fNIRS), a neuroimaging method that allows measuring brain activity in more naturalistic settings (compared to fMRI).

To this end, we applied an elastic-net regression to investigate the contribution of DMN and FPCN (assessed during a resting-state scan) to divergent thinking performance on the AUT (assessed after the scan). In addition to static connectivity, for the first time, we test the predictive power of dynamic connectivity between DMN and FPCN. Here, the variability in the RSFC between specific brain regions was obtained by calculating the functional connectivity variability (FCV) – a widely used metric of dynamic functional connectivity that computes the variability of weights using a sliding window approach (Mooneyham et al., 2017). Taken together, we examine whether findings from the fMRI literature can be extended to more naturalistic contexts using fNIRS and computational approaches to quantifying creativity, providing a model for objectively studying the neural basis of creativity outside the scanner.

Methods

Participants and general procedure

Seventy undergraduate students (59 females and 11 males, mean age = 20.12, SD = 0.60) were recruited for the present study. All were right-handed and with normal or corrected to normal vision. One participant was excluded due to incomplete performance on the creativity tests; five more were excluded for low-quality fNIRS data, assessed with the HOMER2 toolbox (Huppert, Diamond, Franceschini, & Boas, 2009). The final sample was comprised of 64 participants (53 females and 11 males, mean age = 20.05, SD = 0.61).

Upon arrival, all participants were asked to sign an informed consent form. They initially underwent a 3-min resting-state fNIRS recording with their eyes closed and a 3-min resting-state fNIRS recording with their eyes open. Relatively short scan duration was implemented to avoid possible biases resulting from the fluctuations between wakeful and drowsy/sleep states, which have been shown to arise when scan durations exceed 3 min (Tagliazucchi & Laufs, 2014). Only the data from later sessions were analyzed to avoid capturing the signals' jitter present at the very beginning of the scanning. Participants were instructed to refrain from falling asleep or mentally fixating on specific thoughts during the resting phase. After the resting-state scan, participants completed the object characteristics task (OCT) and the AUT (see *2.4 Behavioral tasks and measurements*).

fNIRS data acquisition and preprocessing

An fNIRS optical topography system (LABNIRS, Shimadzu Corporation, Kyoto, Japan) was used to measure the brain's hemodynamic response during rest. For each participant, three probe sets were placed over their scalp: one over the region of the prefrontal cortex (PFC;

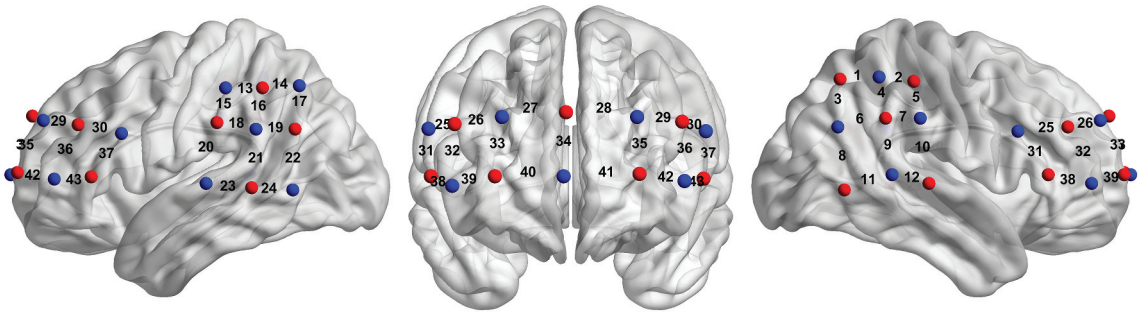

Figure 1. fNIRS probe and channel set in the present study. red indicates the emitters, blue indicates the receivers, and numbers indicate the channels.

2*7 optode probe set, resulting in 19 channels) and two placed bilaterally over the temporoparietal junction (TPJ; 3*3 optode probe set, resulting in 12 channels for each side) – corresponding to cortical hubs of the FPCN and DMN, respectively (see Figure 1). The distance between each adjacent probe was 30 mm, and the sampling rate was set to 10 Hz. The probe positions were obtained using a three-dimensional (3D) magnetic space digitizer (FASTRAK; Polhemus, Colchester, VT, USA). A probabilistic registration (Singh, Okamoto, Dan, Jurcak, & Dan, 2005) was used to determine Montreal Neurological Institute (MNI) coordinates, in accordance with the international 10–20 system.

The data were preprocessed using the HOMER2 toolbox in MATLAB (Huppert et al., 2009). Given that oxyhemoglobin (HbO) has a higher sensitivity to changes in cerebral blood flow compared to deoxygenated hemoglobin (HbR), further analyses were based solely on changes in HbO (e.g., Cui, Bryant, & Reiss, 2012). The raw optical data was converted into changes in optical density. The hmrMotionArtifactByChannel function was run to determine any motion artifacts and the hmrMotionCorrectSpline function served for their correction. Moreover, we applied a bandpass filter with cutoff frequencies set from 0.01 Hz to 0.10 Hz, removing channels with an unacceptable signal quality from any further analysis (Kamran, Mannan, & Jeong, 2016; Mayseless, Hawthorne, & Reiss, 2019). Data from the following channels were ultimately discarded due to unacceptable signal quality determined in HOMER2: CH2, CH5, CH15, CH18, and CH20.

Functional connectivity network construction

After preprocessing the raw data, static and dynamic networks were separately constructed. The static networks were generated by calculating Pearson correlations, with Fisher Z transformations, between each channel pair. This approach yielded a 38 × 38 correlation matrix for each participant.

For the dynamic network construction, we initially calculated sliding window correlations (SWC; Allen et al., 2014) with window lengths of the 60s and step lengths of 1s (Urquhart, Wang, Liu, Fadel, & Alexandrakis, 2020). Pearson correlations were calculated between the channel pairs, separately for each time window, and a Fisher Z transformation was then applied to the data. For each participant, the functional connectivity variability (FCV) was obtained by calculating the standard deviation for the correlation coefficients, defined in terms of variability over time (Fong et al., 2019). The general procedure for the construction of the FC matrix is depicted in Figure 2.

Behavioral tasks and measurements

Following scanning, participants completed two tasks: the AUT and OCT. The AUT was used to assess divergent thinking ability. Participants were asked to think of as many unusual uses as possible for a common item (e.g., "brick"). Three items were used as targets in the AUT: "knife," "chopsticks," and "newspapers." For each item, participants had 1.5 min to verbalize their responses, which were recorded through a microphone.

To objectively score AUT responses, we used a computational semantic analysis developed by Shen and Shao (2019), a topic modeling method based on Jieba (a Chinese text segmentation algorithm; Sun, 2013) and Word2Vec (a common method to calculate semantic distance; Mikolov, Sutskever, Kai, Corrado, & Dean, 2013). As mentioned before, semantic distance has been widely adopted in the study of creativity, especially in automatically evaluating ideas on the AUT (e.g., Beaty & Johnson, 2021; Green, 2016; Heinen & Johnson, 2018). Here, we apply the semantic algorithm of Shen and Shao (2019) to calculate the three classic metrics of divergent thinking: fluency, flexibility, and originality. Similar to previous studies, which applied semantic distance scoring to quantitatively determine aspects of

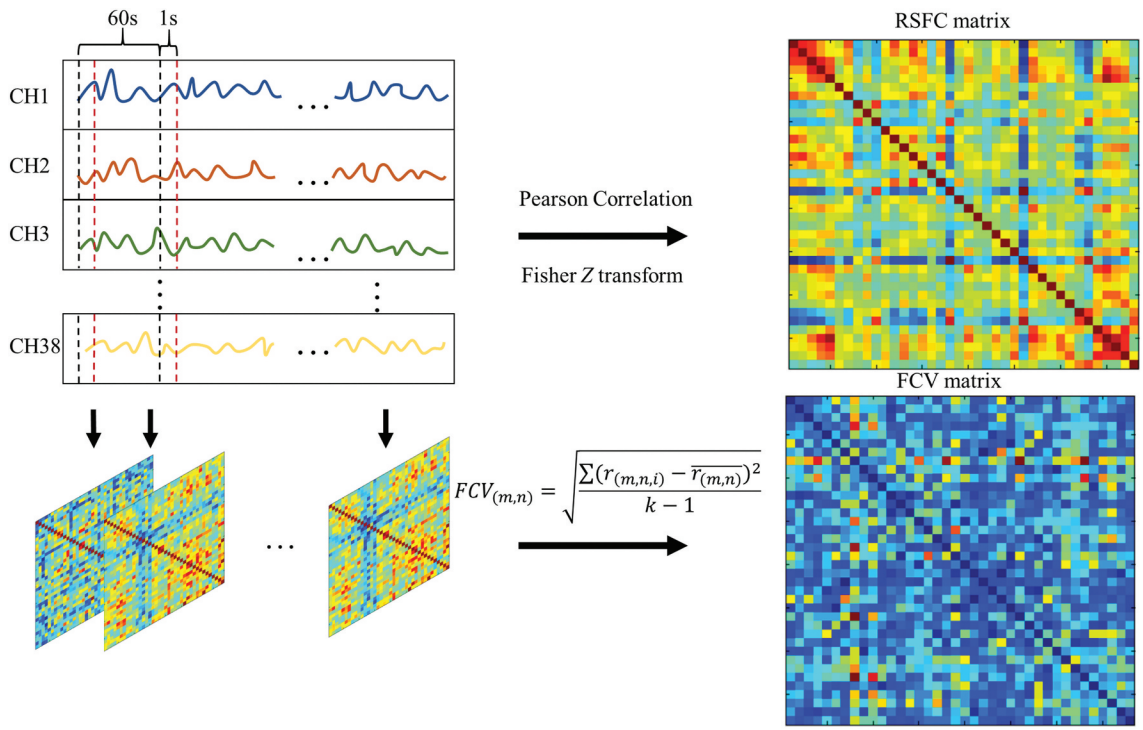

Figure 2. Static and dynamic RSFC network construction. After preprocessing, the static RSFC matrix was constructed by calculating Pearson correlations and applying Fisher *Z* transformations. The FCV matrix was constructed based on the SWC with window lengths of the 60s and step lengths of 1s. *Note*. CH: channel; RSFC: resting-state functional connectivity; SWC: sliding window correlation; FCV: functional connectivity variability.

creative task performance, we used NLP methods (i.e., Jieba and Word2Vec) to optimize the measurement of classic metrics.

This present rating system was devised as follows: (1) Raw verbal data was collected from a voice recorder and segmented to obtain regular phrases, implementing a regularization and filtering of nonsense characters like digits and punctions; (2) Further segmentation of the phrases obtained in step 1 was performed through Jieba, and invalid responses (e.g., "I don't know," "that's all I got") were filtered out; (3) The first few words (the exact number of words were determined by the algorithm) with the highest frequency were deemed as "latent keywords," then primary classification of words was performed based on the latent keywords, which yielded several categories; (4) The words showing the highest frequency within its corresponding category was determined as the "topic word"; (5) Phrases and words were assigned to topics, and those that did not belong to any topic were labeled as low-frequency words; (6) Further classification of low-frequency words was achieved by applying the Word2Vec (Mikolov et al., 2013) algorithm; (7) Fluency, flexibility, and originality scores were then calculated for each participant based on the classification. Fluency was derived by counting all the valid answers of each participant. Flexibility was calculated by summarizing the number of topics encompassed by the AUT responses. Originality was calculated based on the relative frequency of each answer to the present sample, where 2 points were assigned for answers with a total frequency of less than 5%, and 1 point for a frequency of 5–10%. In Shen and Shao (2019)'s original work with this method, the Kendall coefficient between human rating and the results of the rating system ranges from .627 to .860. In the present study, the Pearson correlation between three indicators within every AUT item range from .851 to .990 (see Appendix Table 1). Given the high correlations between the three metrics, we conducted Bartlett's test and Kaiser-Meyer-Olkin (KMO), which illustrated that the data were appropriate for factor analysis (KMO = .669, .745, and .697 for a knife, chopsticks, and newspapers respectively and p values of Bartlett's test were all < .001). Therefore, Principal Component Analysis (PCA) was conducted for each item; each participant's AUT performance was thus quantified by the average of these three PCA scores.

The OCT was administered as a control task (Beaty et al., 2018). During the OCT, participants were asked to verbalize as many characteristics as possible for a common item in 1.5 min. For example, participants received an auditory prompt (e.g., "What characteristics

Table 1. Regression weights of each edge in the prediction model based on static RSFC.

Seed			Target			
Channel	Region	Network	Channel	Region	Network	Weight
3	ANG.R	DMN	13	SMG.L	FPCN	0.1886
4	SMG.R	FPCN	25	IFG.R	FPCN	0.4477
13	SMG.L	FPCN	24	MTG.L	DMN	0.3522
24	MTG.L	DMN	26	DLPFC.R	FPCN	0.1720
24	MTG.L	DMN	33	DLPFC.R	FPCN	0.2263
31	IFG.R	FPCN	40	SFG.R	DMN	0.4132
31	IFG.R	FPCN	41	SFG.L	DMN	0.1798
8	FG.R	DMN	43	IFG.L	FPCN	−0.3977
11	MTG.R	DMN	43	IFG.L	FPCN	−0.6355

Note. L: left; R: right; RSFC: resting-state functional connectivity; DMN: Default Mode network; FPCN: Frontal-Parietal network; ANG: Angular gyrus; SMG: Supramarginal gyrus; MTG: Middle Temporal gyrus; IFG: Inferior Frontal gyrus; DLPFC: Dorsolateral Prefrontal gyrus; SFG: Superior Frontal gyrus; FG: Fusiform gyrus.

does a brick have?") played through a voice recorder. After removing duplicate and irrational answers (e.g., "a key is soft and wet"), performance on each item was quantified by the number of answers reported during the task. In the present study, three items were used in the OCT: "keys," "electric wires," and "plastic bags." Participants' OCT performance was quantified by their average OCT scores.

Predictive modeling

A bivariate correlation was initially conducted to identify which edges (i.e., the correlation coefficient for channel pair) related to creative performance (after dimension reduction). Only those edges that significantly correlated with the AUT performance ($p < .05$, uncorrected) were entered into the prediction model. Then, based on those edges, an elastic-net regression was conducted. Elastic-net regression is a widely used regression method that is adopted when predictors are strongly outnumbered by the observations, and the collinearity of predictors makes a simple ordinary least squares (OLS) regression inappropriate for model construction (due to possible over-fitting problems). There are two parameters in the elastic-net regression, α, and λ. The former parameter is a positive value ranging from 0 to 1, indicating the proportion of L1 and L2 penalizations (i.e., ridge penalization and LASSO penalization, for further discussion, see Zou & Hastie, 2005). When α is 0, the model becomes a ridge regression model; when it is 1, the model becomes a LASSO regression model. Then, λ is also a positive value with a self-paced range, indicating the severity of the penalty. When λ is 0, the model becomes an OLS regression model, and when the λ reaches the maximum, the weights of all predictors are set to 0. In general, L1-norm (i.e., LASSO penalization) was implemented to remove invalid predictors, and L2-norm (i.e., Ridge penalization) was implemented to stabilize the model by keeping the squared sum of the coefficients as low as possible. Importantly, by introducing L1-norm and L2-norm, possible over-fitting problems are avoided, particularly in cases when the OLS regression model has many predictors.

For each α value between 0.001 and 1, in steps of 0.001, we construct 100 predictive models with different λ values until the weights of all predictors are set to 0, yielding a total of 100,000 predictive models. A leave one out cross-validation (LOOCV) was then conducted on each model to identify the model which comprised the lowest mean square error (MSE). The model displaying the minimal MSE was selected as the optimal prediction model. The interpretation rate (R^2) could then be obtained and the MSE of model fit was calculated with 10,000 permutation tests. The p-value reflected the probability that the MSE obtained from randomized data is lower than the MSE in our prediction model (Duan, Van Dam, Ai, & Xu, 2020). Two models can be thus obtained: 1) a static network based on correlation coefficients, and 2) a dynamic network based on the standard deviations of the correlation coefficients (see Figure 3).

Results

Prediction of creativity based on the static network

We began by attempting to predict AUT performance based on static network connectivity between DMN and FPCN. When α was set at 0.049 and λ at 0.4018, the model fit showed the lowest MES (0.8290). As depicted in Figure 4, the predicted AUT performance explained 37.69% of the variance observed in the actual AUT performance. A permutation test of the MSE showed that the elastic-net regression model can significantly predict actual AUT performance (p =.0027). The edges which contributed to the prediction model are depicted in Figure 5, and the weights of each edge in the prediction model are displayed in Table 1. This static connectivity thus yielded a significant prediction of AUT performance from DMN-FPCN connectivity, replicating and extending fMRI findings using fNIRS and automated creativity scoring.

To test model specificity, we fit the model to the OCT control task (i.e., number of object characteristics produced). The model explained 7.84% of the variance observed in the OCT performance. Critically, a Steiger Z-test showed that the OCT prediction accuracy was significantly smaller than the AUT prediction accuracy ($t = 2.8918$, $p = .0027$), indicating that the model predicts creative ability (AUT) more strongly than simple generative abilities (OCT).

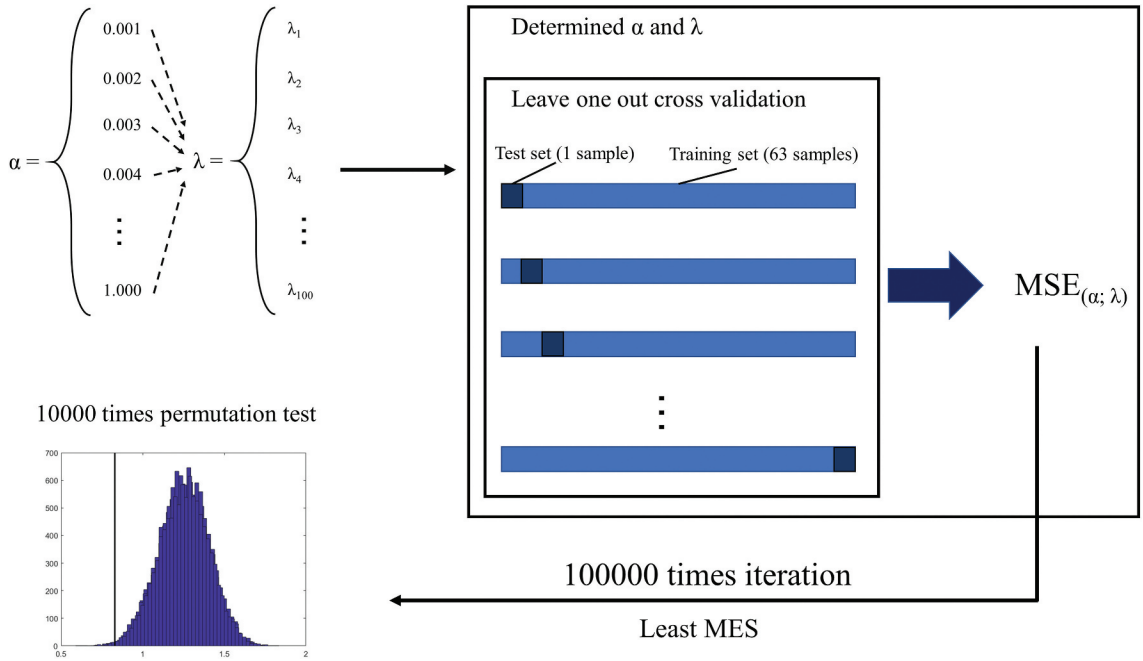

Figure 3. General procedure of predictive modeling. For every determined *α* and *λ*, a LOOCV was performed to estimate the MSE of the elastic-net regression model; 100,000 (1,000*100) MSEs were eventually yielded. The model which showed the least MSE was treated as the optimal model. Moreover, a permutation test was performed based on the predicted creative performance and observed creative performance. *Note*. LOOCV: leave one out cross-validation; MSE: mean square error.

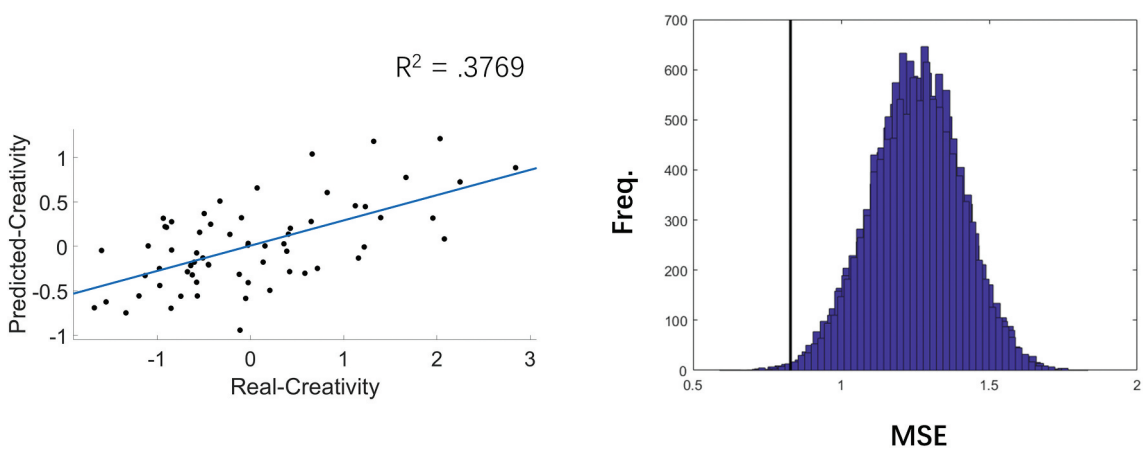

Figure 4. Results of the elastic-net regression based on static RSFC. Left: the relationship between predicted creative performance and actual creative performance; Right: the result of the permutation test, where the black line indicates the MSE in the elastic-net regression. *Note*. RSFC: resting-state functional connectivity; MSE: mean square error.

Prediction of creativity based on the dynamic network

Next, we tested whether creative ability could be predicted based on dynamic connectivity between DMN and FPCN. Setting *α* at 1 and *λ* at 0.0480 resulted in the model fit with the lowest MES (0.8341). The edges which contributed to the prediction model are depicted in Figure 6 and the weights of the edges in the prediction model are shown in Table 2.

Like the static network prediction model, the dynamic network model significantly predicted actual AUT performance ($p = .0003$). Remarkably, the dynamic prediction was almost twice as strong as the static prediction, explaining 66.89% of the variance in creativity scores (Figure 7). Compared to the static model, the dynamic model included more within-network predictive edges, particularly between nodes within the FPCN. In addition, several FPCN-DMN edges were negatively weighted, in contrast to the static network, which

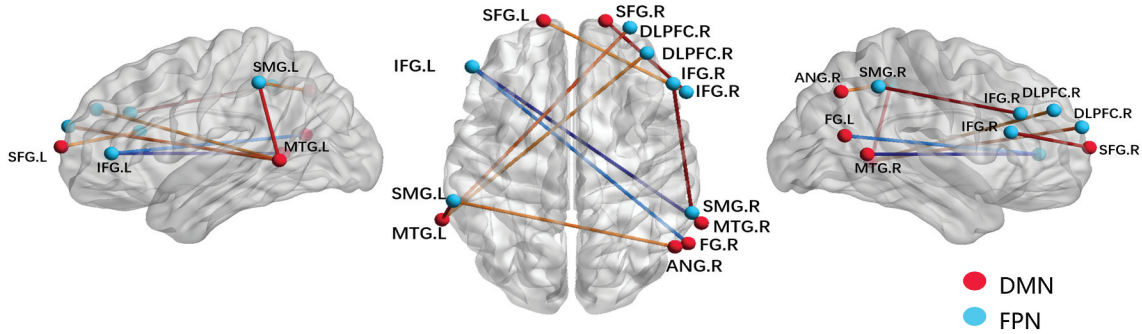

Figure 5. Static RSFCs contribute to the prediction of creativity. For edges, warm colors indicate positive weights and cool colors indicate negative weights. The closer the edge is to primary red or blue, the stronger the association with AUT creativity. *Note*. L: left; R: right; RSFC: resting-state functional connectivity; DMN: Default Mode network; FPCN: Frontal-Parietal network; SMG: Supramarginal gyrus; SFG: Superior Frontal gyrus; STG: Superior Temporal gyrus; IFG: Inferior Frontal gyrus; DLPFC: Dorsolateral Prefrontal gyrus; ANG: Angular gyrus; MTG: Middle Temporal gyrus; FG: Fusiform gyrus.

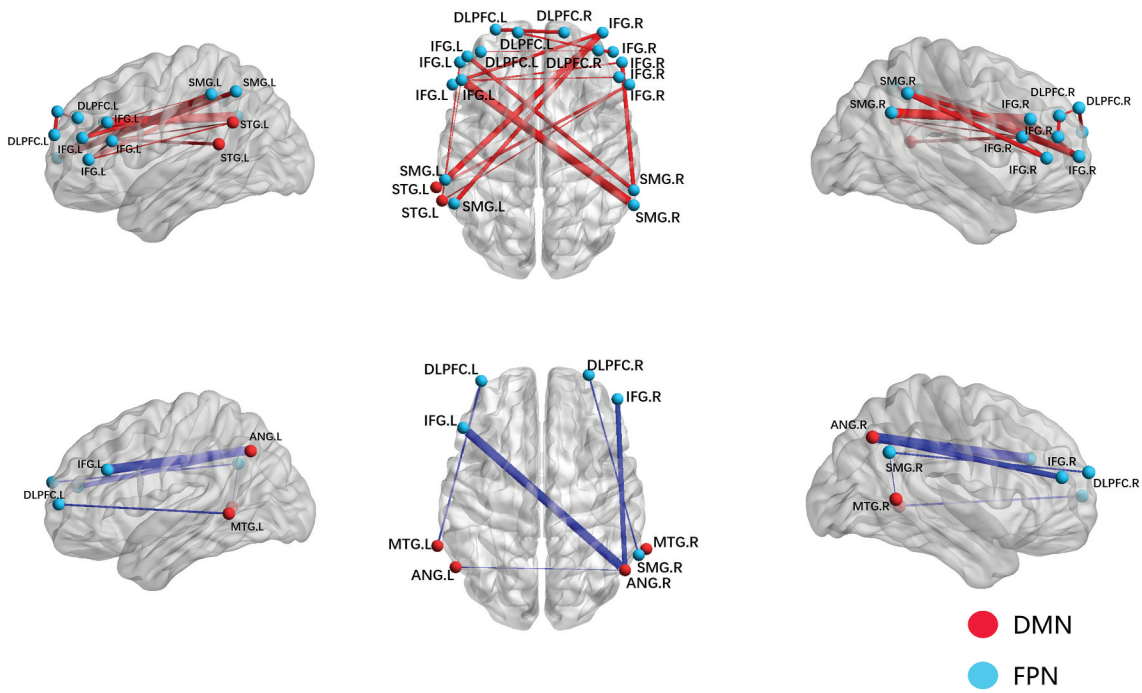

Figure 6. Results of the elastic-net regression based on dynamic RSFC. Left: the relationship between predicted creative performance and actual creative performance; Right: results from the permutation test, where the black line indicates the MSE in the elastic-net regression. Note. RSFC: resting-state functional connectivity; MSE: mean square error.

consisted of mostly positively weighted FPCN-DMN edges. The results indicate that creative ability – assessed via automated and objective metrics – can be robustly predicted from dynamic functional connectivity within and between the DMN and FPCN.

Finally, we fit the dynamic network model to OCT performance. Critically, this model did not yield a significant relationship between the predicted AUT performance and OCT performance (r = .21, p = .0999), pointing to its specificity for predicting creative ability and not simple generative capacity.

Discussion

We investigated whether creative ability could be predicted based on fNIRS functional connectivity between DMN and FPCN. Building on previous fMRI research (Beaty et al., 2018), we extended previous findings by applying fNIRS recorded resting-state brain activity and constructing prediction models based on entirely objective behavioral data (i.e., automated creativity scores, as opposed to subjective human creativity ratings). We constructed two

Table 2. Regression weights of each edge in the dynamic RSFC prediction model.

Seed			Target			
Channel	Region	Network	Channel	Region	Network	Weight
4	SMG.R	FPCN	36	IGF.L	FPCN	0.8826
4	SMG.R	FPCN	38	IFG.R	FPCN	0.8848
6	SMG.R	FPCN	30	IFG.L	FPCN	1.961
13	SMG.L	FPCN	39	IFG.R	FPCN	1.369
14	SMG.L	FPCN	39	IFG.R	FPCN	0.9248
19	STG.L	DMN	31	IFG.R	FPCN	0.2171
21	STG.L	DMN	31	IFG.R	FPCN	0.6406
25	IFG.R	FPCN	30	IFG.L	FPCN	0.1983
26	DLPFC.R	FPCN	28	DLPFC.L	FPCN	0.3603
26	DLPFC.R	FPCN	29	DLPFC.L	FPCN	0.0862
26	DLPFC.R	FPCN	32	IFG.R	FPCN	0.6621
27	DLPFC.R	FPCN	35	DLPFC.R	FPCN	0.7248
30	IFG.L	FPCN	39	IFG.R	FPCN	0.7004
37	IFG.L	FPCN	38	IFG.R	FPCN	0.3341
3	ANG.R	DMN	17	ANG.L	DMN	−0.987
3	ANG.R	DMN	30	IFG.R	FPCN	−1.933
3	ANG.R	DMN	32	IFG.R	FPCN	−1.486
6	SMG.R	FPCN	33	DLPFC.R	FPCN	−1.097
24	MTG.L	DMN	42	DLPFC.L	FPCN	−1.135

L: Left; R: Right; RSFC: resting-state functional connectivity; DMN: Default Mode network; FPCN: Frontal-Parietal network; SMG: Supramarginal gyrus; STG: Superior Temporal gyrus; IFG: Inferior Frontal gyrus; DLPFC: Dorsolateral Prefrontal gyrus; ANG: Angular gyrus; MTG: Middle Temporal gyrus.

separate models, based on either a static or a dynamic network. Both models successfully predicted actual AUT performance measures. The dynamic model, however, showed a substantially stronger prediction, nearly doubling the prediction of the static network model. Notably, a robust prediction of creative ability was achieved with only three minutes of resting-state fNIRS data. Taken together, our results replicate and extend past fMRI efforts in deriving brain-based predictions of creativity, expanding the current literature by validating previously observed effects in a more naturalistic neuroimaging environment and through objectively-derived behavioral data.

Static network prediction of creative ability

In line with previous studies (Beaty et al., 2018; Shi et al., 2018), we found that RSFC between the core hubs of the FPCN and DMN significantly and strongly predicted performance on divergent thinking tasks. In addition to identifying large-scale predictive networks, another goal of the present work was to identify specific regions within FPCN and DMN that contributed to creativity prediction. To this end, we used elastic-net regression to obtain the weights associated with each edge (connection) in the prediction models. This approach revealed the important roles of the right frontal gyrus (i.e., DLPFC and IFG) and the left MTG in predicting performance on the AUT.

The bilateral IFG, part of the FPCN, is typically associated with higher-order processes such as inhibition and cognitive control (Swick, Ashley, & Turken, 2008). In a recent meta-analysis of neuroimaging data, Chen, Beaty, and Qiu (2020) found consistently strong engagement of the right IFG across different domains of creativity. The right IFG was indicated to play a specific role in idea generation, likely supporting idea manipulation and allowing task-relevant goals to be maintained. Crucially, Beaty et al. (2018) found that RSFC between the right IFG and the DMN can robustly predict performance on creative tasks. Supporting this finding, we found that RSFC between the right IFG and several

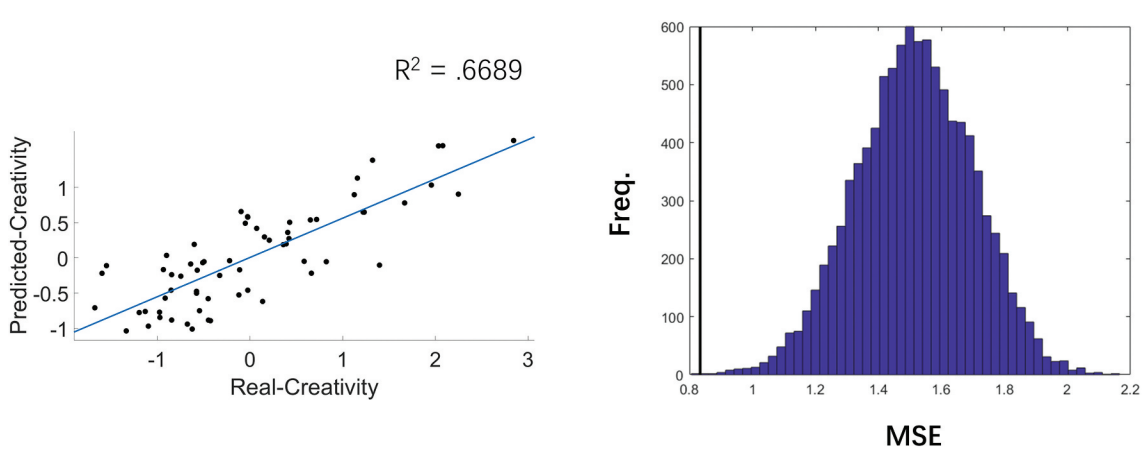

Figure 7. Dynamic RSFC contributions to the prediction of creativity. Upper: Edges that positively weighted in the prediction model. Lower: Edges which negatively weighted in the prediction model. Bolder lines indicate a greater absolute value of weights. *Note*. L: Left; R: Right; RSFC: resting-state functional connectivity; DMN: Default Mode network; FPCN: Frontal-Parietal network; SMG: Supramarginal gyrus; STG: Superior Temporal gyrus; IFG: Inferior Frontal gyrus; DLPFC: Dorsolateral Prefrontal gyrus; ANG: Angular gyrus; MTG: Middle Temporal gyrus.

hubs of the DMN and FPCN – the bilateral SFG and right SMG, respectively – strongly contributed to the prediction of creative performance.

Interestingly, RSFC between left IFG and other DMN hubs was negatively weighted in the prediction model while right IFG showed an opposite pattern. In a recent study applying tDCS over the bilateral IFG, inhibition of the left IFG and excitation of the right IFG resulted in higher flexibility and originality scores on an AUT (Khalil et al., 2020). Moreover, applying causal modeling techniques to fMRI data, the right IFG was found to exert unidirectional control over the MTG and IPL during divergent thinking (Vartanian et al., 2018). Consistent with these studies, the present study emphasized the engagement of the right IFG in AUT performance. On the other hand, previous fMRI studies have reported increased functional connectivity between left IFG and DMN regions associated with divergent thinking performance (Beaty et al., 2014; Takeuchi et al., 2017). Thus, although the current findings are consistent with past fMRI studies implicating left IFG connectivity to DMN, the direction of connectivity (negative vs. positive) varied across imaging modalities (fNIRS vs. fMRI) and statistical methods (prediction vs. correlation).

In a similar vein, we also observed positive contributions of the right DLPFC, but not the left DLPFC, in the prediction model. As suggested by Vanderhasselt et al. (2009), the left DLPFC is largely specialized for the rapid and sequential up-regulation of the attentional set, while the right DLPFC is related more to overall attentional control. Considering the role of the left MTG in supporting memory retrieval (for further discussion, see Xu et al., 2015), RSFC between the right DLPFC and left MTG may indicate a degree of executive control over memory retrieval critical for creative performance.

In contrast with previous reports that verbal creativity can be predicted from inter-hemispheric RSFC (Chen et al., 2019), our static RSFC prediction model is seen to leverage a largely right-lateralized connectivity pattern. One possible explanation for this difference may rest on our use of an NLP method to evaluate creativity, biasing our prediction model to focus on brain connectivity relevant to the elements of creativity captured by our computational method. The prediction model may thus have a higher sensitivity to the neural structures that underpin semantic memory and processing, as these would be of higher predictive value for creative performance determined from distributional semantic models. Notably, although the bilateral IFG and DLPFC have been related to semantic processes during creative thinking (Becker, Sommer, & Kuhn, 2020; Sun et al., 2016), the right hemisphere has been shown to more selectively support the processing of distant semantic relationships (Schmidt, DeBuse, & Seger, 2007). Altogether, the right-lateralization observed in our static RSFC prediction model may be partly attributed to the NLP-based evaluation system favoring recombinations of distant semantic concepts as being more creative.

Dynamic network prediction of creative ability

By adopting FCV measurements as the predictors in an elastic-net regression model, we found that temporal variations in the RSFC of FPCN and DMN can robustly predict AUT performance. Moreover, the FCV-based prediction model showed a stronger prediction than its static counterpart (R^2: .67 vs .38). The correlation between predicted creative performance and OCT performance was non-significant for the dynamic model and moderately significant for the static model. In other words, the prediction model based on dynamic networks showed greater model specification than that based on static networks.

Most of the positively weighted predictors were defined by edges within the FPCN. Moreover, the dynamic network edges were primarily *within* the FPCN, whereas the static network edges showed more predictive edges *between* FPCN and DMN. This seems to suggest that fluctuating engagement of the FPCN – as assessed by FCV – may be a dynamic neural feature of creative ability. Notably, the FPCN has been widely reported to be associated with executive control abilities (Niendam et al., 2012). In a recent study, variations over time in localized cortical activity were investigated via calculations of brain entropy (BEN; Shi et al., 2020). BEN is a measure of the variability in the functional configurations of the activity within a neural system. It was found that levels of BEN for the IFG and DLPFC were positively correlated with divergent thinking ability, suggesting that variability in FPCN connectivity patterns would influence creativity. Variability in FC within the FPCN may represent the dynamic recruitment of different executive abilities (i.e., shifting, inhibition, and updating), each drawing upon a unique connectivity pattern. These dynamically engaged cognitive features may then underpin the cognitive flexibility required to switch attention between goal-directed and self-generated thought, which is considered a core cognitive component of creative thinking (Beaty et al., 2016).

Interestingly, and in contrast to the static network, a majority of the negatively weighted predictors in the dynamic model involved edges between the FPCN and

DMN. Among them, the FCV between the right ANG and bilateral IFG accounted for the greatest weight. This may indicate that instability in the RSFC between the right ANG and bilateral IFG may disrupt divergent thinking performance. Increasing evidence indicates that the ANG is involved in long-term memory retrieval (for a review, see Ramanan, Piguet, & Irish, 2018). In the context of creativity, Fink et al. (2010) observed stronger activations of the right ANG when participants engaged in an OCT than when they engaged in an AUT, while the opposite was true for the left ANG. Pick and Lavidor (2019) extended these findings by demonstrating that divergent thinking could be enhanced with the deactivation of the right ANG. These studies indicate that the right ANG may selectively support information extraction and combination to support creative thought.

We crucially observed a more robust prediction of creativity when leveraging FCV than from static RSFC. This finding indicates that creativity can be better characterized by the dynamic features of RSFC within the FPCN, than when averaging its activity across time. Firstly, this marks the importance of assessing the dynamic patterns of brain activity when attempting to uncover the functional neural underpinnings of creative cognition, as these may prove more informative than static brain network investigations. Secondly, this allows us to make some tentative conclusions with regard to the cognitive processes that are marked by activity in these brain networks.

Creativity requires both spontaneous/generative and strategic/evaluative processes (Beaty et al., 2014; Ivancovsky et al., 2019; Nijstad et al., 2010), and the integration of these two processes can be revealed by the coupling of FPCN and DMN (Beaty et al., 2015; Kleinmintz, Ivancovsky, & Shamay-Tsoory, 2019). However, whether these two cognitive processes occur sequentially, in parallel, or are repeatedly alternated during creative thinking is unclear. Our findings indicate that creativity is positively associated with the dynamic recruitment, during rest, of networks associated with executive and generative processes respectively. In turn, this would suggest that dynamic patterns in the engagement of relevant cognitive processes may similarly predict other creative outcomes. Specifically, creativity seems to depend during rest on the ordered dynamic recruitment of executive processes, indexed by the FPCN, and an inconsistent involvement of long-term memory retrieval, indexed by the DMN. Summing up, these results indicate that switching between different thinking processes is crucial for creative thinking (Li et al., 2017), and more importantly, that the nature of creative thinking can be better represented by its dynamic feature. Further evidence is nevertheless required to extend the present findings to task-based functional brain activity.

Prediction of creativity from natural language processing

Previous attempts at predicting creative thinking abilities have operationalized creativity in terms of subjective human judgments (Beaty et al., 2018). However, human creativity ratings have notable limitations, such as when raters disagree on what is a more or less creative idea, which has psychometric implications for reliably measuring creativity, as well as the replicability of neuroscience findings. In the present work, we show that automated creativity scoring based on distributional semantic properties can be predicted based on brain activity.

We computed fluency, flexibility, and originality for each participant's performance on AUT based on semantic algorithms, allowing us to fit our model to an objective measure of creativity. Objective scores based on semantic distance have been consistently shown to correlate with other measures of creativity (Beaty & Johnson, 2021; Dumas & Dunbar, 2014; Dumas et al., 2020; Heinen & Johnson, 2018). By formulating the first predictive model of creativity from objective measures, we provide evidence that an entirely computational pipeline can be applied to creative thinking prediction. The refinement of this approach will permit a more optimal integration of creativity assessment with machine learning technologies in the future.

Using fNIRS to naturalistically study the neuroscience of creativity

Besides the theoretical contributions of the present study, an important practical implication is the novel application of fNIRS to construct creativity prediction models from RSFC. Replicating prior fMRI findings using fNIRS opens the door to predicting creativity from neural data collected in more naturalistic contexts, in contrast to the highly constrained MRI environment that may conceal more valid resting-state dynamics (e.g., due to restricted mobility). Prior work has found differences in resting brain activity due to postural differences. For example, Unwalla, Cadieux, and Shore (2021) reported performance differences in a perception task between a "lying down" group and a "sitting up" group. It is likely that most alterations to the experimental design, such as changes in the setting or the participants' posture, will affect the neural, cognitive, and behavioral correlates of a creativity task. Given the constraints on the ecological validity that arise from using fMRI, it is important to consider alternative neuroimaging techniques such as fNIRS.

Our results indicate that adopting fNIRS to capture the RSFC between the DMN and FPCN, allows for the efficient prediction of divergent thinking performance. Crucially, the data was gathered via a procedure that better represents real-life resting-state conditions than fMRI procedures, whilst maintaining the rigor consistent with lab environments. Altogether, we believe that it is important for future efforts in creativity neuroscience research to strive for ecological validity, such as by incorporating neuroimaging technologies that allow for more mobility (e.g., fNIRS).

Limitations and future directions

In addition to the novel contributions of the present work, a few limitations should be noted. Due to the relatively small sample size, all the data collected in the present study was entered into the training set (Duan et al., 2020), potentially decreasing the generalizability of our results (e.g., over-fitting). However, given the elastic-net penalization applied in the present study, the potential for over-fitting can be avoided (e.g., Liu, Zhang, & Wu, 2014; Xin, Hu, & Liu, 2017; Zhou, Tao, & Wu, 2011). Nevertheless, future studies are required to replicate our findings with a larger sample size to allow for the use of separate training and test sets. Moreover, we put a strict restriction on participants' age to avoid possible bias for different age groups have different verbal creative abilities (Leon, Altmann, Abrams, Gonzalez Rothi, & Heilman, 2019) and RSFC changes across ages (Fjell et al., 2015; Xiao et al., 2018), which unavoidably decreased the generalizability of our results. Meanwhile, given the imbalanced sex ratio (84% female), our prediction model was mainly built on females' RSFC, which may also decrease the generalizability of our results. Therefore, future studies involving participants with a wider age distribution and balanced sex ratio are required to replicate our findings. Additionally, it should be noted that the study was carried out in a laboratory setting. While this allowed us to minimize confounding influences on the data collected, assumptions of strong ecological validity should be drawn with caution. Future efforts are therefore encouraged to extend these findings to increasingly naturalistic conditions.

Additionally, to depict a clear neural model of creativity, behavioral implications (e.g., cognitive mechanisms) of the observed RSFC were limited to inference. A previous study (Marron et al., 2020) reported the mediating role of specific associative thinking abilities in driving the relationship between RSFC and creativity. Behavioral implications of the RSFC and FCV observed in the present study should be further investigated in future studies. Finally, we adopted relatively short scan durations, particularly when compared to those suggested by previous studies (Birn et al., 2013; Zuo et al., 2013). This was implemented to avoid possible biases caused by the fluctuations between wakeful and sleep states, which are known to occur with scan durations exceeding 3 min (Tagliazucchi & Laufs, 2014). Nevertheless, it is remarkable that individual creative ability can be reliably predicted from such short scan durations – achieving even higher prediction levels than prior whole-brain fMRI studies (e.g., Beaty et al., 2018) – using convenient and relatively inexpensive fNIRS technology.

Conclusions

The present research offers the first evidence that fNIRS can be used to construct a predictive neural model of creativity, operationalized in terms of natural language processing, from pre-task RSFC. In doing so, it advances our current knowledge both from a theoretical and a practical standpoint. We extend fMRI findings from Beaty et al. (2018) based on human creativity ratings by demonstrating that creativity can be similarly predicted in terms of natural language processing and fNIRS signals. Using a static network prediction model, we observed a right-lateralization of the FPCN, potentially relating to specific executive abilities relevant to creative thinking. Using a dynamic network prediction model, we analyzed patterns of FCV, allowing us to expose the critical role of dynamic states of brain connectivity, which predicted creativity scores more strongly than the static model. We believe the next steps in this line of research lie in the proper elucidation of the mechanistic relationships that may contribute to RSFC prediction of creativity. Our work provides a framework for predicting creativity based on neural activities recorded in a more naturalistic setting, motivating future work to study the impact of creativity interventions on brain dynamics.

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Disclosure statement

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Appendix

Table A1. The correlation between AUT performance.

	k_flu	k_flex	k_org	c_flu	c_flex	c_org	n_flu	n_flex	n_org
k_flu	–								
k_flex	0.982a**	–							
k_org	0.952***	0.982***	–						
c_flu	0.435***	0.439***	0.474***	–					
c_flex	0.412***	0.413***	0.451***	0.980***	–				
c_org	0.421***	0.423***	0.458***	0.970***	0.990***	–			
n_flu	0.483***	0.491***	0.458***	0.446***	0.451***	0.465***	–		
n_flex	0.427***	0.433***	0.404***	0.401***	0.405***	0.426***	0.931***	–	
n_org	0.420***	0.434***	0.415***	0.345**	0.345**	0.361**	0.851***	0.932***	–

Note. k: knife; c: chopsticks; n: newspapers; flu: fluency; flex: flexibility; org: originality.
a$p < .05$, ** $p < .01$, *** $p < .001$