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Connectome-Based Predictive Modeling of Creativity Anxiety

Zhiting Ren[a,b,c,1], Richard J. Daker[d,1], Liang Shi[e,1], Jiangzhou Sun[a,b,c], Roger E. Beaty[f], Xinran Wu[a,b,c], Qunlin Chen[a,b,c], Wenjing Yang[a,b,c], Ian M. Lyons[d], Adam E. Green[d,2,**], Jiang Qiu[a,b,c,2,*]

[a] Key Laboratory of Cognition and Personality (SWU), Ministry of Education, Chongqing 400715, China
[b] Faculty of Psychology, Southwest University (SWU), Chongqing, 400715, China
[c] Southwest University Branch, Collaborative Innovation Center of Assessment Toward Basic Education Quality at Beijing Normal University, Chongqing, 400715, China
[d] Department of Psychology, Georgetown University, Washington, DC, 20057, USA
[e] State Key Laboratory of Cognitive Neuroscience and Learning and IDG/McGovern Institute for Brain Research, Beijing Normal University, Beijing 100875, China
[f] Department of Psychology, Pennsylvania State University, State College, PA, 16801, USA

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ABSTRACT

While a recent upsurge in the application of neuroimaging methods to creative cognition has yielded encouraging progress toward understanding the neural underpinnings of creativity, the neural basis of barriers to creativity are as yet unexplored. Here, we report the first investigation into the neural correlates of one such recently identified barrier to creativity: anxiety specific to creative thinking, or creativity anxiety (Daker et al., 2019). We employed a machine-learning technique for exploring relations between functional connectivity and behavior (connectome-based predictive modeling; CPM) to investigate the functional connections underlying creativity anxiety. Using whole-brain resting-state functional connectivity data, we identified a network of connections or "edges" that predicted individual differences in creativity anxiety, largely comprising connections within and between regions of the executive and default networks and the limbic system. We then found that the edges related to creativity anxiety identified in one sample generalize to predict creativity anxiety in an independent sample. We additionally found evidence that the network of edges related to creativity anxiety were largely distinct from those found in previous work to be related to divergent creative ability (Beaty et al., 2018). In addition to being the first work on the neural correlates of creativity anxiety, this research also included the development of a new Chinese-language version of the Creativity Anxiety Scale, and demonstrated that key behavioral findings from the initial work on creativity anxiety are replicable across cultures and languages.

1. Introduction

The ability to think creatively is highly prized across a variety of fields (World Economic, 2016), and an individual's ability to maximize their creative potential only promises to become a more critical determinant of success as creativity emerges as the area of human cognition least replaceable by artificial intelligence (Dartnall, 2013; Jennings, 2010). Research to identify potential barriers to creative achievement is thus a priority. While the timeliness of creativity as a research topic has motivated new and exciting brain-based inquiry into creative cognition (Beaty et al., 2018; Green, 2018; Green et al., 2016; Jung et al., 2013; Weinberger et al., 2017; Wu et al., 2015) the neural bases of factors that may impede creativity have thus far gone unexplored.

Recent research at the behavioral level has identified anxiety that is specific to creative thinking (i.e., creativity anxiety) as a likely barrier to creative achievement. Daker and colleagues (2019) recently developed the Creativity Anxiety Scale (CAS) and, applying this measure, found that creativity anxiety generalized across a wide range of content domains, from areas traditionally viewed as "creative" like music and visual art to areas often seen as less creative, like science and math. It was also found that people reported feeling greater anxiety in hypothetical situations that involved the need to be creative than in similar situations that did not require creativity. This work further showed that individuals who were higher in creativity anxiety exhibited lower levels of real-world creative achievement (measured using the Creative Achievement Questionnaire; CAQ) (Carson et al., 2005) even after con-

* Corresponding author: Jiang Qiu, Faculty of Psychology, Southwest University (SWU), Chongqing, China, 400715, Phone: 86-23- 68367942.
** Adam E. Green, Department of Psychology, Georgetown University, Washington, DC, 20057, USA, Phone: (202) 687-5581.
E-mail addresses: aeg58@Georgetown.edu (A.E. Green), qiuj318@swu.edu.cn (J. Qiu).
[1] Denotes dual lead authorship.
[2] Denotes dual senior authorship.

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trolling for general trait anxiety, suggesting that creativity anxiety may be an important barrier to creative achievement.

No research to our knowledge has yet been conducted to explore the neural basis of creativity anxiety, but promising advances have been made in our understanding of the neural correlates of creative ability. The technique of connectome-based predictive modeling (CPM) has recently been applied to reveal data-driven associations between functional connections in the brain and meaningful psychological traits and clinical outcomes, including creativity (Beaty et al., 2018; Shen et al., 2017). As resting-state data is relatively straightforward to collect and share across acquisition sites and language and cultural barriers, a behavioral index based on whole-brain regions measured at rest is well-suited for both research and clinical contexts. CPM seeks to identify functional connections throughout the brain for which individual differences in connectivity strength predict a given behavioral measure and uses the strength of those connections to predict behavior in novel individuals. An appealing aspect of CPM is that, once a set of connections is identified as predictive of a behavioral variable in one sample, functional connectivity within that same network can be assessed within other independent samples to test whether that set of connections successfully generalizes to predict the same behavioral variable – or other behavioral variables – in the independent samples. Using CPM, Beaty and colleagues (2018) recently identified a large scale network associated with creative thinking ability, which they termed the "creative connectome." After using CPM to identify a set of edges that predicted divergent thinking in the Alternative Uses of Objects task, these researchers found that the same set of edges – largely made up of connections between nodes in the default, executive, and salience networks – generalized to predict creative ability in multiple other samples.

As a data-driven technique, CPM is an especially useful tool for hypothesis-free characterization of connectomic brain-behavior correlations. Just as CPM was used to identify a "creative connectome," it can be used to identify a "creativity anxiety connectome." A key initial question that can be asked is whether the connections that make up the "creativity anxiety connectome" are largely similar those that make up the "creative connectome" identified by Beaty et al. (2018) or whether the two sets of connections are primarily distinct. Testing the degree to which the "creativity anxiety connectome" and the previously identified "creative connectome" are overlapping can indirectly inform the extent to which individual differences in creativity anxiety should be thought of as distinct from differences in creative ability. If the same set of functional connections give rise to both creative ability and creativity anxiety, this suggests that these two constructs may be inherently entwined, and may suggest that our measure of creativity anxiety is merely a proxy for creative ability. If the set of functional connections underlying creativity anxiety is largely distinct from those underlying creative ability, however, this would provide neural evidence that they should be considered separate constructs.

Extant evidence indicates that the neural correlates of anxieties related to specific domains of cognition can differ from the neural correlates of ability in those domains. Task-related neuroimaging work on anxiety specific to math (i.e., math anxiety), for instance, has largely implicated areas associated with affective processing, including the amygdala (Young et al., 2012) and the insula (Lyons and Beilock, 2012), and emotion regulation, including inferior frontal junction, bilateral inferior parietal lobe, rather than areas traditionally associated with mathematical or numerical processing, such as bilateral intraparietal sulcus (Dehaene et al., 2003). While this prior work was focused on task-based fMRI rather than on resting state fMRI, these neuroimaging findings on math anxiety – another anxiety linked to a specific type of cognition – suggest that the neural correlates of anxiety toward a specific type of cognition may be largely distinct from the neural correlates of ability for that type of cognition. Thus, previous work suggests the possibility that a CPM-identified network of functional connections related to creativity anxiety may be largely distinct from the functional connections found to be related to creative ability by Beaty et al., (2018).

In the current study, we aimed to apply connectome-based predictive modeling to identify a data-driven "creativity anxiety connectome" – a whole-brain network that predicts individual differences in creativity-specific anxiety. We further aimed to test whether network edges associated with creativity anxiety in one sample could predict the creativity anxiety of individuals in another sample. Finally, we sought to assess whether the extent to which functional connections identified to be related to creativity anxiety would be distinct from the set of functional connections identified by Beaty and colleagues (2018) to be related to divergent creative ability. While CPM is a data-driven technique and is therefore not well-suited for testing of specific ROI-based hypotheses, inspection of the neuroanatomy of the networks it identifies can be useful for hypothesis generation for future studies. As such, we also inspected the neuroanatomy of the connections that make up the "creativity anxiety connectome" to provide a framework for hypothesis testing in future research. Moreover, while the primary theoretical goal of this work was to conduct a first investigation into the neural basis of creativity anxiety, the present work also afforded the opportunity to develop a Chinese language version of the Creativity Anxiety Scale and to test the replicability of key behavioral findings from recent work identifying the new construct of creativity anxiety.

2. Methods

2.1. Participants

Because CPM is particularly informative when the predictive value of findings from a discovery dataset can be tested on a separate dataset, two samples of participants were recruited for the present study. Both samples were recruited from Southwest University in Chongqing, China, and both completed the survey measures described below and underwent resting-state fMRI. All were right handed and healthy, with no history of mental illness. All participants gave written informed consent to participate. All participants received payment for participation. The study was approved by the Southwest University Brain Imaging Center Institutional Review Board.

Dataset 1 was used as the discovery dataset and was comprised of 281 participants. Twenty-five participants were excluded from analysis because they did not complete the Creativity Anxiety Scale (CAS; see Materials immediately below), and an additional 19 were excluded due to excessive head motion during resting-state fMRI (> 2 mm translation in any axis and >2° angular rotation in any axis) resulting in a final sample of 237 participants (59 males; 21.45±1.69 years old; range: 21.4-26 years).

Dataset 2 was used as the external validation dataset and was comprised of 245 participants. Twenty-three participants were excluded from analysis due to excessive head motion during resting state fMRI. Of the 245 participants, only 147 participants (44 males; 20.03±1.72 years old; range: 18-27 years) completed the CAS. And of those 147 participants who completed the CAS, 101 participants (30 males; 19.9±1.57 years old; range: 18-24 years) additionally completed the Creative Achievement Questionnaire (CAQ) and the State-Trait Anxiety Inventory (STAI; each described in Materials below). For Dataset 2 analyses that involved only the CAS, we used the full sample of 147, and for Dataset 2 analyses that involved the CAS in addition to the CAQ and the STAI, we used the subsample of 101 participants.

2.2. Materials

2.2.1. Creativity Anxiety Scale (CAS)

Creativity anxiety was measured in both samples using a Chinese translation of the Creativity Anxiety Scale (Daker et al., 2019). The CAS is a self-report questionnaire that consists of two types of items: Creativity Anxiety (CA) items, which assess anxiety toward situations that require the involvement of creative thinking (ex. "Having to think in an open-ended and creative way"), and Non-Creativity Anxiety Control

(NAC) items, which assess anxiety toward the noncreative demands of situations presented in CA items (ex. “Having to think in a precise and methodical way”. Each CA item is paired with a NAC item devised to match the context presented in the CA item, but remove the need to be creative. The CAS contains 8 CA items and 8 NAC items (see Supplementary material **S1**), and participants are asked to rate how anxious each situation would make them, on a 5-point intensity scale (None at all = 0, A little = 1, A fair amount = 2, Much = 3, Very much = 4). Consistent with the recommendations of Daker et al. (2019), we treated NAC scores as a control measure and regressed out the effects of NAC items on CA items to ensure that the remaining variance in CA was specific to anxiety about thinking creatively (rather than about the noncreative demands of the presented situations). The resulting residualized CA scores (CA_r) were used for subsequent analysis.

2.2.2. Trait Anxiety

Trait anxiety was assessed in both samples using the trait subscale of the State-Trait Anxiety Inventory (TAI, Spielberger et al., 1970). Participants respond to 20 items on a scale from 1 (Almost never) to 4 (Almost always) to indicate how anxious they generally feel (ex. “I worry too much over something that doesn’t really matter”). Possible scores range from 20 to 80, where higher scores indicate greater levels of general anxiety. Trait anxiety was included as a control measure to ensure that any brain-behavior correlations involving creativity anxiety were not confounded by trait anxiety.

2.2.3. Creative Achievement Questionnaire (CAQ)

A measure of real-world creative achievement was obtained using the Creative Achievement Questionnaire (CAQ, Carson et al., 2005), which is made up of 80 total questions, 8 each from the following domains: Visual Arts, Music, Dance, Architecture, Creative Writing, Humor, Invention, Science, Drama, and Culinary Arts. In each domain, participants are first asked if they have any “training or recognized talent” in the domain, and if the answer is yes, they respond to specific prompts that assess progressively higher levels of attainment. In the domain of Music, for example, item 2 is “I play one or more musical instruments proficiently” (binary Yes/No), and item 8 is “My compositions have been critiqued in a national publication” (enter number of times this applies). Note that while an intended used of the CAQ was to allow for the comparison of creative achievements across the lifespan among exceptionally talented individuals (Carson et al., 2005), several studies have used the CAQ among “normal” college-aged populations to measure engagement with and success in the creative domains included in the CAQ. For instance, previous work has found that measures of creative cognition have predicted real-world creative achievement (as measured by the CAQ) among university students, suggesting that (perhaps unsurprisingly) those who are more creative are more likely to have creative achievements (Prabhakaran et al., 2014). Past work has also shown that creativity anxiety negatively predicts individual differences in CAQ scores among adult populations (mean age 34.56; Daker et al., 2019). A total CAQ score was calculated by summing scores across each domain. As in previous work (Prabhakaran et al., 2014; Daker et al., 2019), these scores were log-transformed to more closely approximate a normal distribution (hereafter referred to as “CAQ_log”).

2.3. fMRI Data Acquisition and Analysis

2.3.1. Image acquisition

All participants completed 8 minutes of resting-state fMRI scanning conducted at the Southwest University Brain Imaging Center on a 3T Trio scanner (Siemens Medical Systems, Erlangen, Germany). During scanning, participants were required to close their eyes but remain awake. 242 volumes were acquired using a gradient echo planar imaging sequence: repetition time = 2000 ms; echo time = 30 ms; slices = 32; thickness = 3 mm; resolution matrix = 64 × 64; flip angle = 90°; field of view = 192 × 192 mm^2; slice gap = 1 mm; and voxel size = 3.4 × 3.4 × 4 mm^3.

2.3.2. Image preprocessing

The resting-state fMRI data were analyzed using the Data Processing Assistant for Resting-State fMRI (DPARSF, http: //resting-fmri.sourceforge.net/) (Chao-Gan and Yu-Feng, 2010) on SPM8 (Wellcome Department of Imaging Neuroscience, London, United Kingdom; www.fil.ion.ucl.ac.uk/spm). The first 10 volumes were discarded to allow the signal to reach equilibrium. The remaining 232 volumes were preprocessed by slice-timing, motion-correcting and normalizing to the standard MNI template with a resample voxel size of 3 × 3 × 3 mm. Next, spatial smoothing with 8 mm full-width at half maximum Gaussian kernel, linear detrend, band-pass temporal filtering (0.01-0.1 Hz), and nuisance covariates regression (24 Friston parameters, white matter, cerebrospinal fluid and global signal) were also applied to the 232 volumes.

2.3.3. Functional network construction

Whole-brain functional connectivity was analyzed for each subject using GRETNA (Wang et al., 2015). Consistent with prior studies involving connectome-based predictive modeling (CPM), the 268-ROI atlas (Shen et al., 2013), was applied to calculate FC in the present study. This atlas was transformed from MNI space to individual space, and the intensity-based registration algorithm was used in BioImage Suite for transformation calculation. Compared with atlases defined by automatic anatomic labels, the current atlas comprises nodes with more coherent timecourses, which represents an improvement over anatomical segmentation schemes because anatomical boundaries do not necessarily match functional ones. This atlas covers the whole brain, including cortical, subcortical and brainstem structures (Shen et al., 2013). Time courses from each ROI were extracted to compute Pearson correlation between each pair of ROIs, generating a 268 × 268 correlation matrix for each subject. Each element of the matrix represents the strength of connection between two individual nodes (sometimes referred to as an “edge”). These correlation matrices were transformed to z-scores using Fisher’s transformation for further analysis.

2.3.4. Connectome-based Predictive Modeling

Connectome-based predictive modeling (CPM), a recently developed method introduced by Shen et al. (Finn et al., 2015; Rosenberg et al., 2016; Shen et al., 2017), was used to predict individuals’ CA_r from whole-brain resting-state functional connectivity using a leave-one-out approach within the discovery dataset of 237 participants (Dataset 1). CPM contains three broad steps: feature selection, model building, and model validation (see **Fig. 1**). Below, we briefly explain each of these steps. For a more in-depth explanation of the CPM technique, see Shen et al., (2017).

The first step of the CPM process is feature selection, the goal of which is to identify edges for which individual differences in connection strength predict CA_r. An optimal threshold is applied to the matrix to retain only edges that are significantly positively and negatively correlated with CA_r scores (**see ‘Optimal threshold exploration’ below**), resulting in the identification of positive and negative edges. Edges that are found to positively predict CA_r – that is, edges for which increased connectivity is associated with increased CA_r – will make up the positive CA network, and edges that are found to negatively predict CA_r will make up the negative CA network. In identifying the sets of edges that make up these networks, we used a leave-one-out approach in which a total of N (in this case, 237) different positive and negative networks are identified, in each case generated by repeating the edge identification process while leaving one participant out of the dataset. The final set of positive and negative edges that make up the positive and negative CA networks are those edges that appear in every iteration of the leave-one-out process. We then calculated each participant’s positive and negative network connectivity strength by summing the strength of

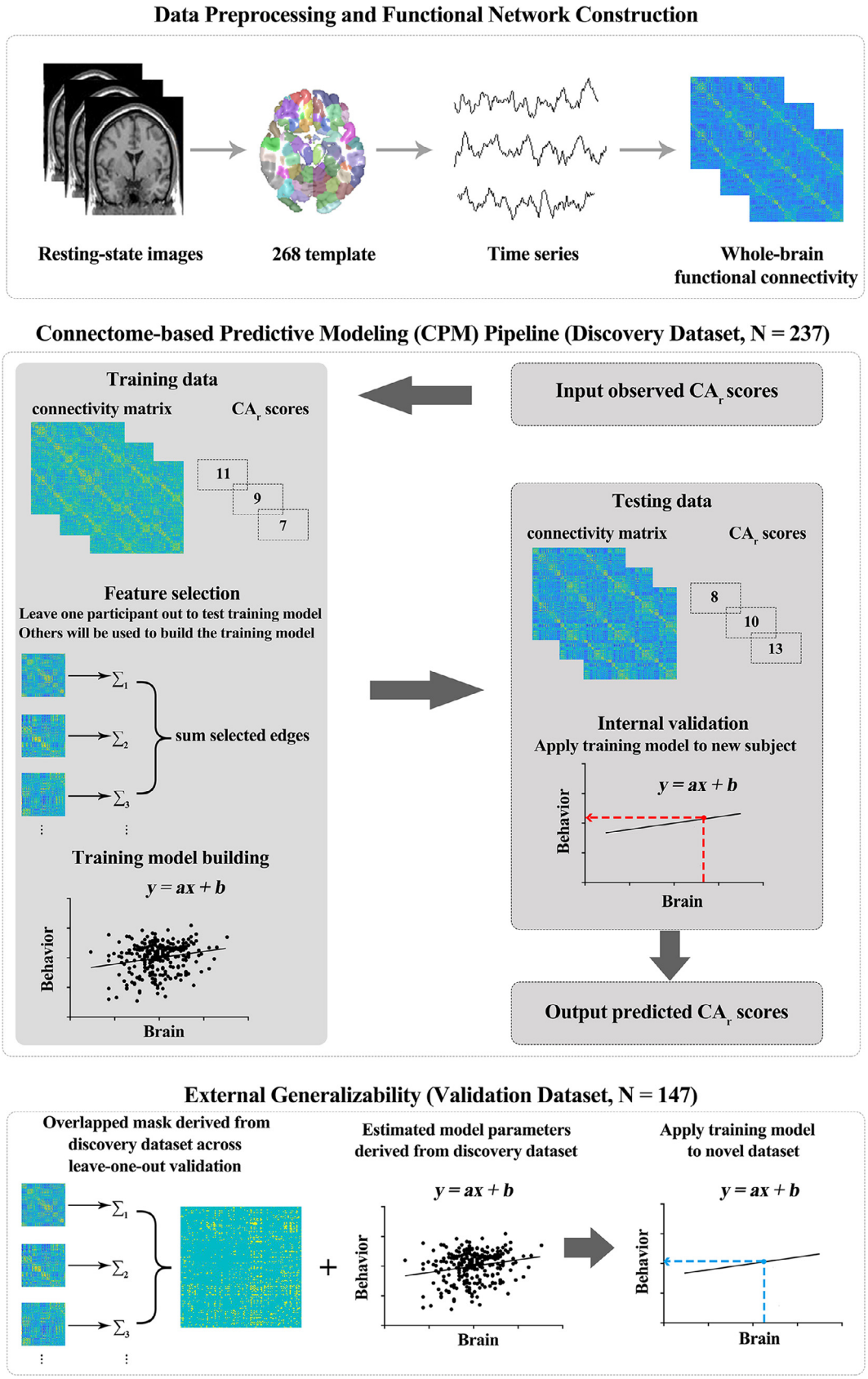

Figure 1. Flowchart for prediction of individual CA_r scores using whole-brain functional connectivity. CA_r, CA score after regressing out the effects of NAC items.

connections within the positive network and the negative network separately. In addition to positive and negative network strengths, we also computed combined network strengths by summing positive and negative network strengths together. Summing the strength of connections within a given network for each participant provides a quantitative summary of the overall strength of functional connectivity each participant has in the relevant connections that have been identified to either positively or negatively predict the outcome measure of interest (in this case, CA_r). At this point in the process, a set of connections that positively and negatively relate to CA_r have been identified, and each participant has been assigned positive, negative, and combined network strengths. These summed network strengths are used in subsequent steps to gauge how effectively the identified networks predict individual differences in CA_r.

The next step in the CPM process is to build linear regressions that model the association between the strength of the positive and negative networks and CA_r. This step also uses a leave-one-out approach. For each iteration of the leave-one-out process, three different linear regression models are built: one in which the summed positive network strengths predict CA_r, one in which the summed negative network strengths predict CA_r, and one in which the combined network strengths predict CAr. After each iteration of these regression models are completed, the resulting models are used to generate predicted CA_r scores for the left-out participant. The left-out participant's summed network strengths are fed into the regression models, and the regression models output predicted CA_r scores. Note that for each participant, three different predicted CA_r scores are generated by this process, one for each of the three regression models: a predicted CA_r score generated by the model using only the summed positive network strengths, a predicted CA_r score generated by the model using only the summed negative network strengths, and a predicted CA_r score generated by the model using the combined summed network strengths. In this step, no significance testing is done; the sole goal is to generate predicted CA_r values using the observed network strengths.

The final step in the CPM process is to determine whether the predicted CA_r values generated by the previous step significantly predict the actual observed CA_r values. The predictive efficacy of the network is reflected in the magnitude and statistical significance of the Pearson correlation between observed CA_r scores and CA_r scores predicted by the CPM model. If observed and predicted CA_r scores are significantly positively related, this suggests that the CPM was successful in its prediction. Note that three different models assessments are made here, one that assess the efficacy of the prediction of the positive CA network, one that assesses the efficacy of the prediction of the negative CA network, and one that assesses the efficacy of the prediction of the combined network. We also performed control analyses to further examine whether the model significantly predicts observed CA_r scores even when controlling for covariates including head motion, age, gender, CAQ_log scores, and TAI scores (see section 2.3.6 'control analyses' below). We next simulated 1,000 permutations to test whether the obtained metrics were significantly better than expected by chance. In each permutation, we randomly shuffled behavioral scores across subjects and reran the above leave-one-out-cross-validation (LOOCV) prediction procedure, which resulted in a distribution of correlation coefficients (r) that would be likely to observe by chance. The number of times the permuted value was greater than the true value was then divided by 1,000, providing an estimated p-value for the actual r-value we observed between observed and predicted CA_r scores.

2.3.5. Optimal threshold exploration

Several studies using CPM have used a threshold of ($p < 0.01$) at the feature selection step, the same as used in the original paper (Jangraw et al., 2018; Rosenberg et al., 2016; Shen et al., 2017). Shen et al. (2017) suggested that the optimal threshold to use at the feature selection step should be explored within an initial dataset under the condition (which the present work satisfies) that a validation dataset is available to test the generalizability of the CPM findings. Optimal threshold exploration involves testing different *p*-value cutoffs for determining whether an edge should be considered as part of a network by varying this cutoff and identifying the one that leads to the highest predictive efficacy of the behavioral measure (in this case creativity anxiety) by the network. We set six thresholds (0.05, 0.01, 0.005, 0.001, 0.0005, and 0.0001) to determine the set of edges and reran the LOOCV procedure at each threshold on the discovery dataset. Here we used the combined network's predictive ability (*r*-value) as the evaluation index.

2.3.6. Control analyses

In order to ensure that the observed relations between resting state functional connectivity and creativity anxiety were as specific as possible, we controlled for several variables at the model evaluation stage on the discovery dataset (when assessing whether predicted CA_r scores generated by CPM significantly correlated with observed CA_r scores). Given that in-scanner motion has been found to be a predominant factor impacting functional connectivity (Horien et al., 2018; Waller et al., 2017; Power et al., 2014; Van Dijk et al., 2012), we controlled for a head motion parameter (mean framewise displacement [FD]) at the model evaluation step. We also controlled for gender and age in our predictions, as these factors have also been shown to relate to functional connectivity (Feng et al., 2018; Hsu et al., 2018).

While controlling for head motion, gender, and age are standard in CPM work, there are other possible confounds that are important to control for when predicting creativity anxiety (CA_r). Creativity anxiety is a type of anxiety, so if no other anxiety measures are controlled for, it is possible that relations between resting state functional connectivity and creativity anxiety could be simply be explained by individual differences in anxiety (at the trait level or at the state level) more generally. We took multiple steps to address this. First, as noted above, in addition to items that measure creativity anxiety (CA items), the Creativity Anxiety Scale has built-in control items (Non-creativity Anxiety Control; NAC items) devised to measure and control for anxiety toward similar situations that do not involve creative demands. The CA scores were residualized with respect to NAC scores (see Section 2.2.1), resulting in the CA_r scores that were entered into the CPM analysis pipeline. By regressing out NAC scores, these CA_r scores are quite specific to anxiety toward situations that require creative thinking. We took the additional step of controlling for general trait anxiety (TAI) as well, further ensuring that relations between CA_r and functional connections are not explainable by general anxiety. Being in an fMRI scanner can of course be an anxiety-inducing situation for some, and there are likely to be individual differences in state anxiety, or anxiety experienced in-the-moment (Spielberger et al., 1970), while in the scanner. However, by controlling for these other anxiety measures, possible associations between creativity anxiety and state anxiety while in the scanner would likely be accounted for, as there is no reason to assume that anxiety specific to creative thinking would predict unique variance in state anxiety while in an fMRI scanner that would not be captured by either general trait anxiety or by the built-in NAC items that capture anxiety toward similar situations to those presented in the creativity anxiety items but importantly remove the creative demands. By controlling for these measures, we can be confident that any observed relations between creativity anxiety and resting state functional connectivity are not driven by individual differences in anxiety more generally.

Finally, to ensure that relations between creativity anxiety and resting state functional connectivity were not explained by individual differences in creative achievement, we also controlled for CAQ_log at the model evaluation stage of CPM. The predictive networks used in the current work were therefore constructed by calculating the partial Pearson correlation between the CA_r scores predicted by the CPM framework and the observed CA_r scores after controlling for the effects of head motion, age, gender, TAI scores, and CAQ_log scores.

2.3.7. External generalizability

We next evaluated the external predictive efficacy of the set of CA_r-related edges identified in the discovery sample by testing whether these edges were significantly predictive of CA_r in an independent external validation sample of 147 participants (Dataset 2). Assessing whether results found in one sample hold in another sample is an especially powerful method to assess the generalizability of CPM-based findings (Shen et al., 2017). To do this, we first calculated summed positive CA and negative CA network strengths for each participant in the external validation sample by summing the strengths of the relevant edges identified using the CPM process in the discovery sample. A measure of combined network strength was also computed by summing the positive and negative network strengths together. We then fed those network strengths into regression models to generate predicted CA_r values. As in the case of the discovery dataset, three different sets of predicted CA_r values were generated: one in which the positive CA network strengths are used to predict CA_r values, one in which the negative CA network strengths are used to predict CA_r values, and one in which the combined CA network strengths are used to predict CA_r values. The parameters of the regression models (i.e., the slopes and intercepts) used to generate predicted CA_r values in Dataset 2 were derived from the regression models from the leave-one-out process of generating predicted CA_r values for Dataset 1. In Dataset 1, a total of 237 iterations of each model type was run to generate predicted CA_r values for a different left-out subject in that sample. We took the average of those model parameters to build the regression models that would predict CA_r values for Dataset 2.

To assess the efficacy of these predictions, just as in the discovery dataset, we related the predicted CA_r scores to actual observed CA_r scores (generated by residualizing out the effects of NAC scores on CA scores, consistent with Dataset 1). If the predicted CA_r scores generated using only information from the discovery dataset significantly relate to observed CA_r scores in the external validation dataset, this provides strong evidence for the generalizability of the findings.

2.3.8. Comparing the sets of functional connections related to creativity anxiety to those related to divergent creative ability

Finally, we assessed the extent to which the set of functional connections found to relate to creativity anxiety in the present work overlapped with the set of functional connections found by Beaty et al. (2018) to be related to divergent creative ability. To do this, we obtained the set of functional connections related to divergent creative ability from Beaty et al. (2018) and assessed how many of the precise functional connections the sets of networks had in common. If the sets of networks have relatively few connections in common, this would suggest that the two sets of networks are largely distinct from one another.

3. RESULTS

3.1. Behavioral Results

3.1.1. Factor Analysis Results of the Chinese Translation of the Creativity Anxiety Scale

To ensure appropriate translation of the CAS into Chinese, we conducted an exploratory factor analysis with the translated CAS data from both datasets to determine whether CA items and NAC items loaded strongly on separate factors as predicted. Exploratory factor analysis using maximum likelihood extraction yielded two factors with eigenvalues above 1, suggesting that two factors are appropriate to retain. The rotated solution showed that all CA items loaded on one factor, and all NAC items loaded on the other factor, suggesting that this translated version of the CAS successfully separated CA and NAC scores as separate measures. After examining the rotated factor loadings, two CA items were found to have factor loadings that were substantially lower than factor loadings from the original scale (Daker et al., 2019), and as such two CA items and their paired NAC items were dropped from analysis. For further factor analysis details, see Supplementary Materials **Tables S1 and S2**. The resulting Chinese translation of the CAS consisted of 6 CA items and 6 paired NAC items. Scores for each item type are summed, resulting in a possible range of CA scores from 0-24 and a possible range of NAC scores from 0-24 where higher scores indicate higher levels of anxiety. Reliability of both scores using Cronbach's alpha was high (CA: $\alpha = .91$; NAC: $\alpha = .86$). Together, these results show that anxiety toward situations that involve the need to be creative and anxiety toward similar situations that do not were measured separately, as expected.

3.1.2. Replication of Key Creativity Anxiety Behavioral Findings

Descriptive statistics for CAS scores and all other behavioral measures are reported in Table 1. To test whether anxiety responses were higher for situations that involved the need to be creative than for similar situations that did not involve creative demands (as was found in Daker et al., 2019), we ran paired-samples t tests for each sample. In both Datasets 1 and 2, CA scores were on average significantly greater than NAC scores (Dataset 1: $t(236) = 8.33$, $p < .001$, Cohen's $d = .71$; Dataset 2: $t(100) = 7.09$, $p < .001$, Cohen's $d = .90$). These results show that the finding that adding creative demands to a hypothetical situation increases the extent to which participants anticipate experiencing anxiety in that situation replicates in the present samples.

Daker et al. (2019) also assessed whether there were gender differences in responding on the CAS. They found that CA scores were higher than NAC scores among both men and women, but that this difference was especially pronounced among women. To assess whether these gender differences replicated in the present samples, we ran a 2 (Gender: male, female) x 2 (Item Type: CA, NAC) mixed-factorial ANOVA within each sample. In Dataset 1, we found a significant main effect of Gender [$F(1, 236) = 6.348$, $p = .012$] and a significant main effect of Item Type [$F(1, 236) = 69.210$, $p < .001$], but no significant Gender x Item Type interaction [$F(1, 236) = .374$, $p = .541$]. In Dataset 2, we found a significant main effect of Item Type [$F(1, 146) = 52.748$, $p < .001$], but no significant main effect of Gender [$F(1, 146) = 1.858$, $p = .175$] or Gender x Item Type interaction [$F(1, 146) = 2.54$, $p = .113$]. Together, these results show that the gender differences in CAS responding observed in the American samples from Daker et al., (2019) were not found in the Chinese samples collected in the present research.

We next tested whether CA scores negatively predicted creative achievement (CAQ_log) as Daker et al., (2019) found. In Dataset 1, CA scores did not predict individual differences in CAQ_log scores (when controlling for NAC scores and general trait anxiety scores, $\beta = -.009$, $t(233) = -.139$, $p = .889$). However, in Dataset 2, CA scores negatively predicted individual differences in CAQ_log even controlling for NAC scores and general trait anxiety scores ($\beta = -.240$, $t(93) = -2.32$, $p = .022$).

While some effects from Daker et al., (2019) were either not found or only inconsistently found in the present samples (gender differences in the extent to which CA scores were greater than NAC scores were not observed, and CA predicted creative achievement in one sample but not the other), the behavioral results show that the Chinese translation of the Creativity Anxiety Scale measures anxiety about situations that involve the need to think creatively (CA items) as separate from anxiety toward similar situations that do not involve creative demands (NAC items). Moreover, in both samples, it was found that situations that involve creative demands are on average more anxiety-inducing than similar situations that do not. Both of these findings closely replicate those from the initial creativity anxiety work in Daker et al., (2019), and taken together, suggest that the Chinese translation of the Creativity Anxiety Scale appropriately measures the construct of interest.

3.2. CPM Results

3.2.1. Determining the optimal threshold for edge detection

Following the recommendation of Shen et al. (2017), in the discovery dataset, we assessed which p-value threshold for selecting edges led to

Table 1
CA, creativity anxiety. NAC, non-creativity anxiety control; CAQ_log, log transferred CAQ scores.

Measure	N	Mean	SD	Range	CA	NAC	TAI
Dataset 1							
CA	237	12.43	4.49	0-24			
NAC	237	9.29	4.35	0-20	0.13 (p = 0.03)[a]		
TAI	237	41.1	8.68	0-66	0.15 (p = 0.02)[a]	0.12 (p = 0.06)[a]	
CAQ_log	237	0.68	0.42	0-1.97	-0.03 (p = 0.67)[a]	-0.10 (p = 0.11)[a]	-0.05 (p = 0.41)[a]
Dateset 2							
CA	147	11.76	4.42	0-23			
NAC	147	8.50	3.55	0-18	0.19 (p = 0.05)[a]		
TAI	101	40	9.81	23-65	0.21 (p = 0.03)[a]	0.33 (p < 0.001)[a]	
CAQ_log	171	0.86	0.36	0-1.76	-0.20 (p = 0.05)[a]	0.09 (p = 0.35)[a]	-0.04 (p = 0.73)[a]

[a] Correlation analysis. In dataset 1, correlation analysis was conducted in a sample of 237 participants; in dataset 2, correlation analysis was conducted in a sample of 101 participants.

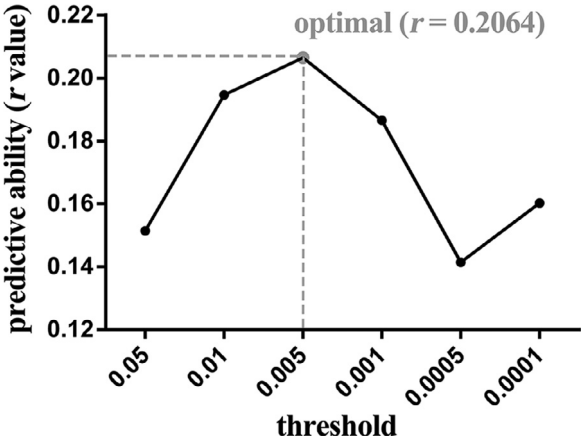

Figure 2. Optimal threshold for predictive model. *r* value = correlation between observed and predicted CA_r scores in combined network. CA_r, CA score after ruling out the effects of NAC items.

the greatest overall brain-behavioral predictive efficacy from six thresholds: 0.05, 0.01, 0.005, 0.001, 0.0005, and 0.0001. Among these six thresholds for determining edge selection, the correlation between the combined network's predicted CA_r scores and observed CA_r scores increased until threshold = 0.005 and then declined (see **Fig. 2**). This indicates the additional connections may provide redundant or unreliable information and do not benefit for the models' predictive power. Consequently, we applied the threshold = 0.005 as the feature selection threshold in the main analysis above. We note that a threshold of 0.005 has recently been used in other recent CPM studies (Feng et al., 2018; Rosenberg et al., 2016).

3.2.2. Predictive efficacy of the model

In the CPM pipeline, the positive and negative network strengths were calculated by summing the edges in the positive or negative tail for each training subject, separately. A set of combined network strengths was also calculated by summing the edges from both the positive and negative networks. After LOOCV, there were 237 positive, negative and combined networks (where one set of networks was created after leaving out each subject). We defined the positive CA network as the set of edges that appeared in the positive network of every iteration of the LOOCV. There were 240 edges in the positive CA network. The negative CA network was defined by the set of edges that appeared in the negative network of every iteration of the LOOCV. There were 197 edges in the negative CA network. The sum of the edges of these two networks represents less than 1.5 percent of the sum of whole-brain's 35778 edges defined by the atlas used in this work (Shen et al., 2013).

The correlation between the observed CA_r scores and predicted CA_r scores represents the predictive efficacy of each network. Results indicated that the positive, negative, and combined CA networks all significantly predicted individual differences in CA_r, as evidenced by positive correlations between the predicted CA_r scores each model generated and actual observed CA_r scores (positive CA network: r = 0.20, p = 0.002, p_{perm} = 0.03; negative CA network: r = 0.21, p = 0.001, p_{perm} = 0.02; combined CA network: r = 0.21, p = 0.001, p_{perm} = 0.01; see **Fig. 3**). p_{perm} values were based on permutation testing (1000 permutations; see Methods for additional detail). After controlling for head motion, age, gender, CAQ_log scores, and TAI scores, all three networks still significantly predicted CA_r scores (positive CA network: $r_{partial}$ = 0.18, p = 0.005; negative CA network: $r_{partial}$ = 0.20, p = 0.0003; combined CA network: $r_{partial}$ = 0.19, p = 0.003). Notably, this shows that the relations between the set of functional connections and CA_r cannot be explained by creative achievement or general trait anxiety.

3.3. Network neuroanatomy in the prediction of CA

We next investigated the neuroanatomy of the identified positive and negative CA networks. Figure 4A shows a circle plot visualization of the edges that make up the positive and negative CA networks. This figure is intended to convey the general neuro-cognitive composition of the positive and negative CA networks based on high-level descriptions of the involved brain regions. Figure 4B shows glass brain plots that display these same connections localized in 3D brain space. These figures show that connections that predicted individual differences in CA_r were not highly localized to specific brain regions but were instead distributed throughout the brain.

Tables 2A and 2B show the nodes that were most well-represented in the positive and negative CA networks, respectively. Each table displays the ten nodes that were involved in the greatest number of connections within each network. Locations of key nodes of the positive CA network included the "default mode network" (DMN; e.g., left superior frontal gyrus (LSFG); BA 10; k = 12; right posterior cingulate gyrus (rPCG); BA 23; k = 7; see **Table 2A**) and in subcortical regions (e.g., right caudate; k = 9; see **Table 2A**). Key nodes of the negative CA network were located in, among other areas, the Fronto-Parietal executive control network [FPN; e.g., right middle frontal gyrus (rMFG); BA 10; k = 8; right superior temporal gyrus (rSTG); k = 5], the salience network (e.g., Supramarginal gyrus; BA 40; k = 9), and the DMN (e.g., left angular gyrus (l); BA 39; k = 5; left precuneus; BA 31; k = 5; see **Table 2B and Fig. 4b**).

3.4. External generalizability

We next assessed whether the networks that predicted CA_r in the discovery dataset of 237 participants (Dataset 1) generalized to a separate dataset of 147 participants (Dataset 2). Models were run on the external

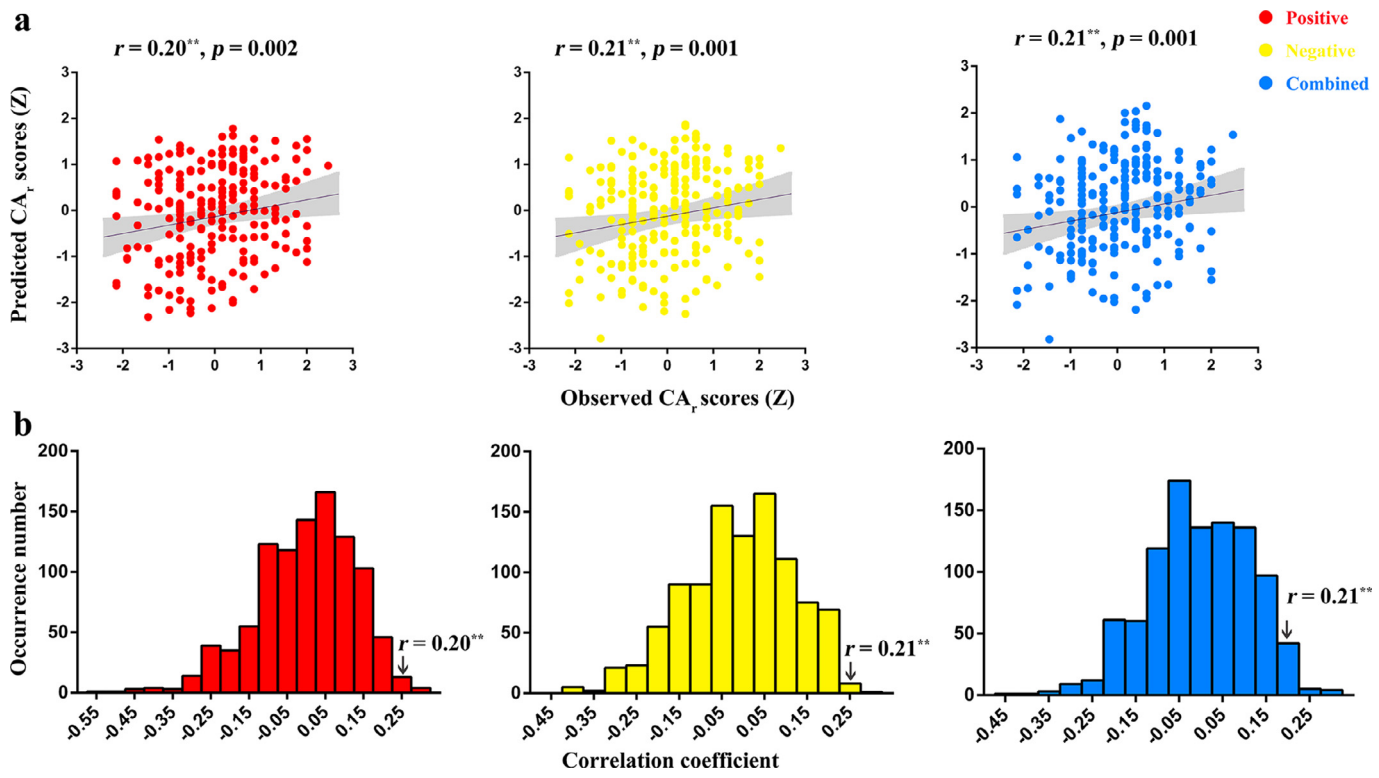

Figure 3. The predictive ability of model. (a) Correlation between observed and predicted CA_r scores in positive, negative, and combined CA networks. Observed and predicted CA_r scores are standardized to z-scores. (b) The distribution of correlation by a permutation test of 1000 times. CA_r, CA score after regressing out the effects of NAC items. CA, creativity anxiety. **p < 0.01.

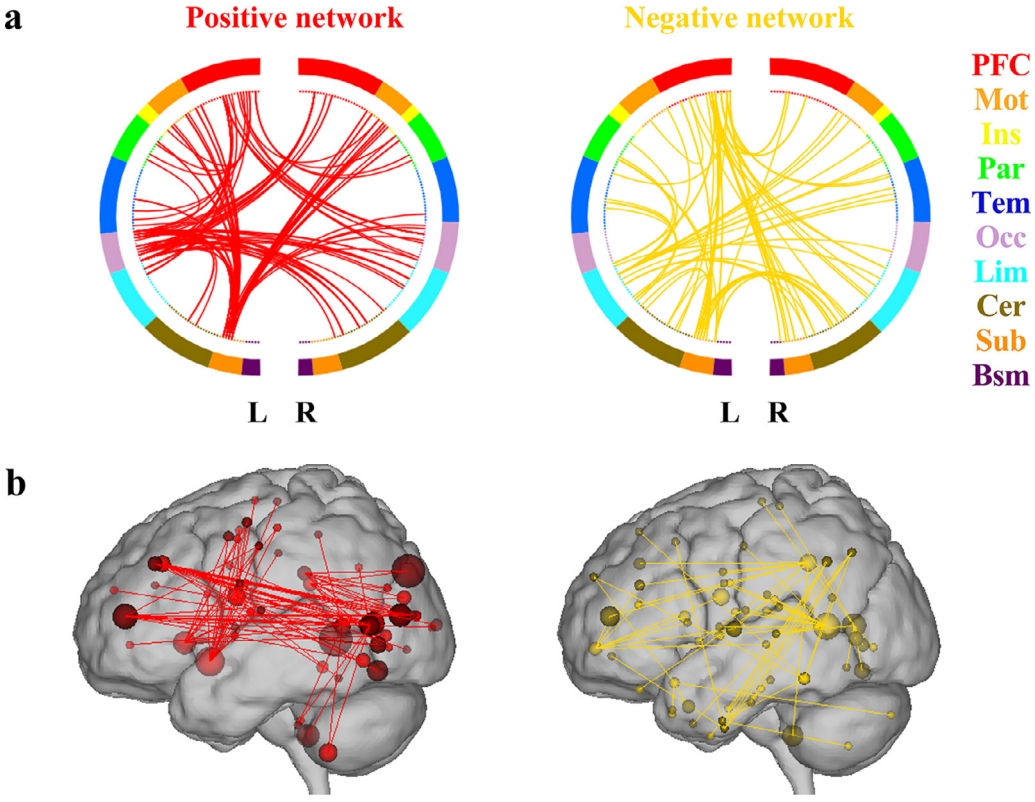

Figure 4. Functional connections predicting individual CA. (a) The functional connections in positive and negative CA networks, plotted as the number of connections within each lobe. (b)The brain network patterns in positive and negative CA networks. CA, creativity anxiety. R = right hemisphere; L = left hemisphere. PFC, prefrontal cortex; Mot, motor; Ins, insula; Par, parietal; Tem, temporal; Occ, occipital; Lim, limbic; Cer, cerebellum; Sub, subcortical; Bsm, brainstem.

Table 2A
Positive CA network neuroanatomy (key nodes). BA, Brodmann area; *K*, degree; L, left hemisphere; R, right hemisphere; n/a, not available. MNI = Montreal Neurological Institute. CA, creativity anxiety. Note that these key nodes were defined as those highest in degree - the number of connections (edges) the node was involved in.

No.	*K*	Node name	Network	L/R	Lobe	BA	MNI coordinates
1	14	Putamen	Subcortical	R	Subcortical	n/a	14, 8.3, -9.5
2	12	Superior frontal gyrus	Default Mode	L	Prefrontal	10	-6, 48.1, 11.7
3	11	Caudate	Subcortical	R	Subcortical	n/a	12.6, 20.2, -0.7
4	10	Calcarine fissure	Visual	L	Occipital	n/a	-22.1, -66.7, 7.4
5	9	Caudate	Subcortical	R	Subcortical	n/a	13.7, -4.2, 20.9
6	8	Superior frontal gyrus	Default Mode	R	Prefrontal	8	23.9, 30.7, 36.4
7	8	Calcarine fissure	Visual	R	Limbic	23	28.4, -53.8, 7.1
8	7	Posterior cingulate gyrus	Default Mode	L	Limbic	23	-5, -36, 32
9	7	Posterior cingulate gyrus	Default Mode	R	Limbic	23	5.1, -38.9, 27
10	7	Superior frontal gyrus	Default Mode	L	Prefrontal	9	-27.3, 34.1, 36.4

Table 2B
Negative CA network neuroanatomy (key nodes). BA, Brodmann area; *K*, degree; L, left hemisphere; R, right hemisphere; n/a, not available. MNI = Montreal Neurological Institute. CA, creativity anxiety. Note that these key nodes were defined as those highest in degree - the number of connections (edges) the node was involved in.

No.	*K*	Node name	Network	L/R	Lobe	BA	MNI coordinates
1	12	Calcarine fissure	Visual	R	Limbic	23	28.4, -53.8, 7.1
2	9	Supramarginal gyrus	Salience	R	Parietal	40	54.2, -45.2, 36.9
3	8	Middle frontal gyrus	Frontal-Parietal	R	Prefrontal	10	30.5, 54.9, -3.5
4	8	Calcarine fissure	Visual	L	Occipital	n/a	-22.1, -66.7, 7.4
5	5	Superior temporal gyrus	Frontal-Parietal	R	Temporal	n/a	60.8, -43.3, -17.6
6	5	Angular gyrus	Default Mode	L	Parietal	39	-42, -65.6, 41.7
7	5	Fusiform gyrus	Visual	L	Temporal	n/a	-30, -5.8, -40.9
8	5	Gyrus rectus	Default Mode	R	Prefrontal	11	9.6, 17.8, -19.5
9	5	Precuneus	Default Mode	L	Limbic	31	-6.5, -53.9, 37.4
10	4	Inferior temporal gyrus	Default Mode	L	Temporal	20	-49.3, -4.7, -37.4

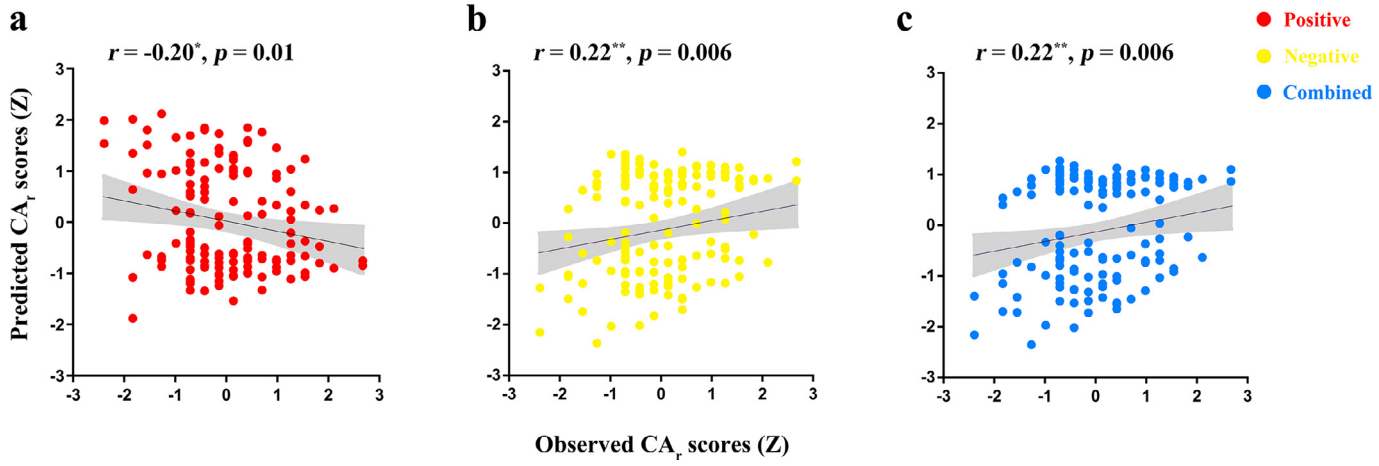

Figure 5. Scatterplots for external validation. (a) Correlation between observed and predicted CA_r scores in positive CA network. (b) Correlation between observed and predicted CA_r scores in negative CA network. (c) Correlation between observed and predicted CA_r scores in combined CA network. Observed and predicted CA_r scores are standardized to z-scores. CA, creativity anxiety. $^{*}p < 0.05$, $^{**}p < 0.01$.

generalizability dataset to assess whether predicted CAr scores generated by models using the set of edges identified in the discovery dataset significantly related to observed CA scores of those in the generalizability dataset. Results revealed a significant prediction of CA_r for the negative network [r (147) = 0.22, p = 0.006, see **Fig. 5a**] and combined network [r (147) = 0.22, p = 0.006, see **Fig. 5b**], but not the positive network [r (147) = -0.20, p = 0.01]. Note that while $p < 0.05$ for the positive network, the direction of the result suggests that the predicted CA_r scores are negatively related to observed CA_r scores in the external generalizability dataset, which is not meaningful. These results suggest that the set of edges identified in the negative network are especially robust in predicting individual differences in creativity anxiety.

3.5. Degree of overlap between the 'creativity anxiety connectome' and the 'creative connectome'

Finally, we set out to assess the extent to which the set of functional connections related to creativity anxiety identified in the present research overlapped with the set of functional connections related to divergent creative ability identified in previous work by Beaty and colleagues (2018). Both the 'creativity anxiety connectome' and the 'cre-

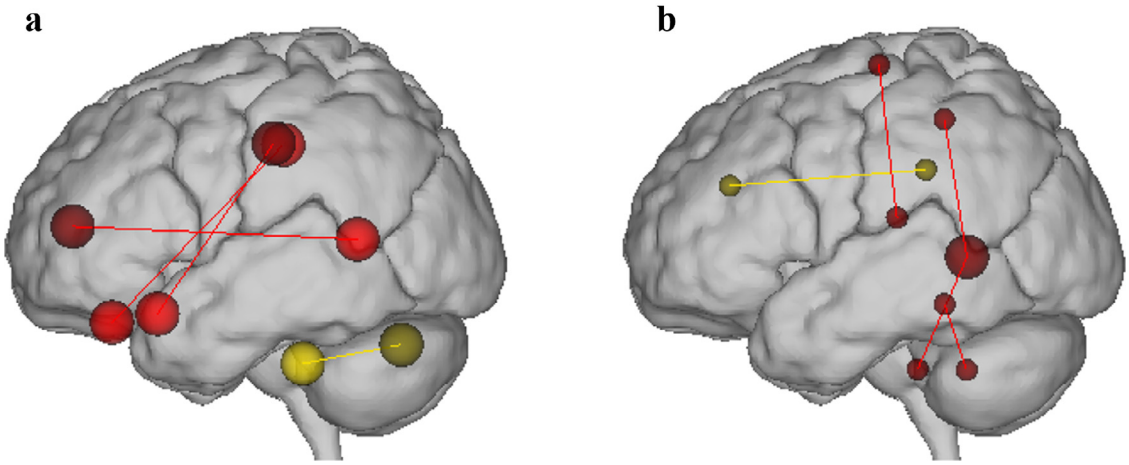

Figure 6. The common edges between the 'creativity anxiety connectome' and the 'creative connectome'. (a) The red edges correspond to the common edges between the positive CA network and the positive creative ability network; the yellow edges correspond to the common edges between the negative CA network and the negative creative ability network. (b) The red edges correspond to the common edges between the positive CA network and the negative creative ability network; the yellow edges correspond to the common edges between the negative CA network and the positive creative ability network.

ative ability' connectome are comprised of two networks each: a positive and negative network. It should be noted that only the negative creativity anxiety network generalized to predict CAr scores in an external sample in the present work, and only the positive creative ability network generalized to predict creative ability in Beaty et al. (2018).

To compare these networks, we obtained the set of functional connections related to divergent creative ability identified by Beaty et al. (2018). While purely descriptive, the results show a very small degree of overlap between the networks. For full details on the exact functional connections that the various networks have in common, see Supplementary Material Table S2. Out of a total of 240 connections in the positive CA network, only 3 (or 1.25%) are shared with the positive creative ability network (see Fig. 6a), and only 4 (or 1.67%) are shared with the negative creative ability network (Fig. 6b). Likewise, out of a total of 197 connections in the negative CA network, only 1 (or 0.51%) is shared with the positive creative ability network (Fig. 6b), and only 4 (or 1.67%) are shared with the negative creative ability network (Fig. 6a). This demonstrates that the set of functional connections that predict creativity anxiety are largely distinct from the set of functional connections that predict divergent creative ability.

4. Discussion

While a considerable amount of progress has been made in identifying neural bases of creativity, no research to date has examined the neural basis of creativity anxiety, a recently identified potential barrier to creative achievement. In the present study, a connectome-based predictive modeling approach identified a "creativity anxiety connectome" – a set of functional connections throughout the brain that predict individual differences in creativity-specific anxiety. Importantly, the associations between creativity anxiety and the sum of edge strengths that made up the "creativity anxiety connectome" were not explainable by individual differences in trait anxiety, creative achievement, and other relevant variables, demonstrating the specificity of the links between creativity anxiety and the summed network scores of the creativity anxiety networks. CPM further indicated that the set of connections in the negative network related to creativity anxiety identified in one sample generalized to predict creativity anxiety in an independent sample, demonstrating the replicability of this effect. Finally, we found that the identified set of functional connections related to creativity anxiety was largely distinct from those identified to be related to divergent creative ability (Beaty et al., 2018), further demonstrating the specificity of the creativity anxiety connectome.

The finding that the "creativity anxiety connectome" was largely distinct from the "creative connectome" identified by Beaty et al., (2018) suggests that the neural basis of creativity anxiety differs from that of creative ability. This finding provides indirect evidence that creativity anxiety should be considered distinct from creative ability, and that self-reported anxiety toward creativity, as measured using the Creativity Anxiety Scale, is not merely a proxy for creative ability. More broadly, this finding was consistent with the idea that anxiety toward a given domain and ability in that domain can have largely distinct neural bases as also indicated by previous task-based fMRI work in the domain of math (Young et al., 2012; Lyons & Beilock, 2012).

It should be noted that, while a strength of CPM lies in its ability to condense complex sets of functional connections into a manageable set of values, CPM results are not intended to support strong claims about specific functional connections (Shen et al., 2017) – in other words, CPM is more concerned with using neural data to make predictions than with hypothesis testing. As such, any interpretation of the neuroanatomy of the networks CPM identifies rests on reverse inference and should be considered speculative pending further research. Examining the neuroanatomy of the networks identified by CPM can provide opportunities to develop hypotheses for future research on creativity anxiety, so this speculation can be useful. It is important to note, however, that the present methods did not afford direct comparisons between highly localized areas that made up the creativity anxiety network and those that have been implicated in other cognitive constructs, so the spatial resolution of the comparisons we can make to previous fMRI work is limited.

The negative CA network identified in the present study, which generalized across samples and also predicted individual differences in creative achievement, was comprised of connections within and between areas throughout the brain, including the following networks: executive, default mode, salience, visual, and limbic networks. In the negative CA network, the stronger connections predict lower CAr. That connections between regions within executive and default mode networks were part of the CPM-identified network that predicted higher levels of creativity anxiety is broadly consistent with work by Beaty and colleagues (2018) showing that greater connectivity between areas in these networks predicted greater levels of divergent creative ability. It is important to note, however, that the exact edges identified in the creativity anxiety connectome are largely distinct from the set of edges associated with creative ability. Interrogation of the negative CA network additionally revealed that connections within and between prefrontal control areas and limbic and subcortical areas were also part of the set of

connections that, when summed, predicted individual differences in creativity anxiety. These nodes were centered in brain regions that are often implicated in affective processing (Hariri et al., 2000; Herman et al., 2005; Ochsner and Gross, 2005; Wager et al., 2008). Speculatively, these tighter connections of prefrontal areas that have been shown to be involved in emotion regulation to limbic and subcortical areas implicated in emotional responses themselves may suggest that individuals with greater emotion regulation abilities are less likely to develop creativity anxiety (Ochsner and Gross, 2005; Wager et al., 2008). Overall, the neuroanatomy of the negative CA network seems to implicate both areas that are classically involved in creative cognition and areas that are involved in affective responding and regulation, suggesting that both domain-specific and domain-general factors are likely to underlie differences in the neural profiles of those with high and low creativity anxiety. Additionally, we found that areas within the visual network also made up part of the negative CA network. While speculative, it is possible this reflects individual differences in the tendency to focus attention externally (i.e., on visual information) versus internally (i.e., on one's thoughts), consistent with prior interpretations of creativity-related activity within occipital areas (Boccia et al., 2015). This same interpretation – internal attention – is often made to explain the involvement of the default mode network activity during creative cognition as well (Andrews-Hanna, 2012; Beaty et al., 2016; Adnan et al., 2019; Beaty et al., 2015; Yeh, Hsu, & Rega, 2019). Given that both visual and default mode network areas were implicated as related to creativity anxiety, future work could address whether individual differences in creativity anxiety are associated with differences in the tendency to focus attention internally or externally.

Although the positive network – which was comprised of nodes including the default mode network and subcortical regions – showed significant predictive performance in the discovery dataset, the external generalizability analyses revealed that this network failed to predict CA_r scores in the expected direction in an independent external validation sample. In fact, we observed a negative association between predicted CA_r scores and observed CA_r scores in the external validation sample. Finding that only one of the identified networks successfully generalizes to predict the behavioral variable of interest in an external sample is not uncommon in work using connectome-based predictive modeling (see, for example, Beaty et al., 2018; Feng et al., 2019; and Wang et al., 2020), nor is finding a negative association between predicted and observed variable of interest (see, for example, Feng et al., 2018). The consensus from these prior studies has been that these null results or results in the unexpected direction are not particularly meaningful (aside from providing evidence against the generalizability of the original finding) and may arise as a result of overfitting the data in the original dataset, a common pitfall of machine learning-based techniques (Dietterich, 1995; Belkin, Hsu, & Mitra, 2018). It should be noted, however, that finding that one network does not generalize does not suggest that the network that does generalize is any less meaningful. In Beaty et al., (2018), for instance, the positive network was found to generalize to predict divergent creative ability in a separate sample, but the negative network was not. That same positive network was then applied to two additional external samples and in each case showed robust prediction of divergent creative ability. Together, this work provides additional support for assessing external validation in addition to leave-one-out cross validation as an important step to determine the generalizability of CPM findings (Shen et al., 2017).

Future work using the connectome-based predictive modeling technique could be done to assess whether, for instance, the same pattern of functional connections we observed here using resting state data could predict creativity anxiety more strongly if measured in a situation in which participants are anticipating an upcoming creative task, for instance. Creating a situation where participants either have to be creative or anticipate being creative may lead to more robust correlations between observed creativity anxiety scores and those predicted by the connectome-based predictive modeling approach. Indeed, previous work has found that predictive models built from task fMRI data often outperform models built from resting-state fMRI data, likely due to the unconstrained nature of collecting resting state fMRI data (Greene et al., 2018). Moreover, while in this and past work (Daker et al., 2019) creativity anxiety negatively predicted individual differences in real-world creative achievement, no work has yet assessed whether creativity anxiety predicts task-based creative performance. Future behavioral work can be done to establish whether such a relationship exists, and if so, CPM-based work could be completed to assess the extent to which the functional connections we observed in this research are specific to creativity anxiety or whether they could be explained by creative ability. Note, however, that in this work we did control for creative achievement when establishing the set of functional connections that relate to creativity anxiety. Moreover, our analysis shows that the exact set of connections found in our 'creativity anxiety connectome' shows very little direct overlap with the set of connections found in the 'creative connectome' found in Beaty et al., (2018). Together, this suggests that the connections observed here appear to be fairly specific to creativity anxiety, but work in the future could be done to rule out other possible confounds. One of the key benefits of the CPM approach is the ability to easily apply profiles of connectivity identified in one context to test predictions in new contexts and datasets, facilitating clear tests of replicability and generalizability across studies. We have made the set of connections related to creativity anxiety that we identified in the present research available for other researchers (see Supplementary material **Dataset S1 and S2**). We additionally note that while CPM is a very useful data-driven technique, by design it does not directly assess the relative importance of specific connections within the networks that it identifies or the theoretical implications thereof. It is our hope that the present work will inform future hypothesis-driven research that employs other methods to better understand the neural correlates of creativity anxiety.

In addition to exploring for the first time the neural correlates of creativity anxiety, the present work also represents the development of a Chinese language version of the Creativity Anxiety Scale. Results of exploratory factor analysis showed that the Chinese translation of the Creativity Anxiety Scale produces separable responses to items meant to measure anxiety toward situations that require creativity (CA items) and control items meant to measure anxiety toward similar, but non-creative situations (NAC items). Moreover, in both of the samples involved in the present research, anxiety ratings were higher for hypothetical situations that involved creativity than those that did not. Taken together, these results show that the Chinese translation of the CAS measures the construct of creativity anxiety well, opening the door for research on creativity anxiety in Chinese-speaking samples (the largest native-speaking population on Earth). Interestingly, while gender differences in the extent to which CA scores were higher than NAC scores were observed in American samples in Daker et al., (2019), no such differences were found in the present Chinese samples. Additionally, only one of the two Chinese samples collected for the present research showed that creativity anxiety predicted individual differences in creative achievement. Future cross-cultural work can be done to better understand how and why creativity anxiety may operate differently in American and Chinese cultural contexts.

5. Conclusion

After developing a Chinese language version of the Creativity Anxiety Scale and replicating key behavioral findings on creativity anxiety, we conducted the first investigation into the neural correlates of creativity anxiety by performing connectome-based predictive modeling of resting state fMRI data to predict individual differences in creativity anxiety. A network of whole-brain functional connections that predicted individual differences in creativity anxiety – comprised largely of areas within executive, salience, and default mode networks and in limbic and subcortical regions – was identified. The profile of functional connec-

tions related to creativity anxiety in one sample was found to predict individual differences in creativity in an independent sample, demonstrating the replicability of these findings. Moreover, the functional connections relating to creativity anxiety were found to be largely distinct from those that previous research identified as relating to divergent creative ability (Beaty et al., 2018), demonstrating the specificity of our results and providing initial neural indication that creativity anxiety is a distinct construct from creative ability.

Declaration of Competing Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgements

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Statement of author contributions

Zhiting Ren, Richard J. Daker and Liang Shi made the same contribution. Zhiting Ren, Richard J. Daker and Liang Shi analyzed the data and wrote the paper. Adam E. Green and Jiang Qiu proposed the idea of the study and drafted the outline of the manuscript. Xinran Wu and Jiangzhou Sun proposed the original idea of data analysis. Zhiting Ren and Richard J. Daker completed revisions to the manuscript, with guidance from Adam E. Green, Roger E. Beaty and Ian M. Lyons. Roger E. Beaty, Qunlin Chen, Wenjing Yang and Ian M. Lyons offered technical assistance in analyzing data, suggested additional analyses and helped with their interpretation. All co-authors contributed to data acquisition. We also extend our gratitude to all participants.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.neuroimage.2020.117469.

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