Research Article

Title: Altered brain morphological architecture of procrastination trait: basing on structural covariance network model

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Abstract

Background: Procrastination is a prevalent problematic behavior that leads to adverse consequences in many aspects of daily life. Numerous studies have tentatively explored the neurobiological substrate of procrastination, but it remains unclear how these procrastination-related brain regions potentially interact.

Method: To address this issue, 254 participants were recruited and collected their brain structural images. Based on previous studies, we predefined dorsolateral prefrontal cortex(dlPFC), anterior cingulum cortex (ACC), orbital frontal cortex (OFC), parahippocampal gyrus (PHC), ventromedial prefrontal cortex(vmPFC), and insula as regions-of-interest (ROIs) by using Human Brainnetome Atlas(BNA); Voxel-based morphometry (VBM) was used to measure the gray matter volume (GMV) of ROIs; Step-wise linear regression analysis was used to define node; Connectome-based graph-theoretical analysis was conducted to probe topological properties of procrastination gray matter structural covariance network(SCN) and finally compare different degrees of procrastinators' discrepancy on topological properties.

Results: Step-wise liner regression analysis showed that the 5ROIs (dlOFC, ACC, OFC, PHC and Insula), can fit the procrastination scores better than do of sole one or other combination modes. Further graph-theoretical demonstrated three modules for procrastination gray matter SCN, including self-control (dlPFC and ACC), future task reward (PHC and OFC), and task aversiveness (insula). Meanwhile showed the dlPFC and PHC have significant high nodal betweenness centrality (Be-dlPFC = 16, $p < .001$; Be-PHC = 16, $p < .001$, Bootstrap test, sim = 2,000, similarly hereinafter) and the dlPFC-PHC has significant high edge betweenness centrality (Between-dlpfc-phc = 11, $p < .001$) in the procrastination gray matter SCN. In addition, compared with the low procrastination group (lpro), the modularization coefficient, betweenness centrality of nodes and edges were significantly decreased in the high procrastination

group (hpro)（Be-dlPFC: hPro=0, lPro = 10, $p < .01$; Between-dlpfc-phc: hPRO = 3, lpro = 11, $p<.05$).

Conclusion: This study firstly established procrastination gray matter SCN, the results showed the decreased both nodal topological metrics of dlPFC and edge topological metrics of dlPFC-PHC in hpro, which might be biomarkers of procrastination.

Keywords: Procrastination; VBM; graph theory; Structural Covariance Network

1 Introduction

Procrastination refers to the behavior predisposition for voluntarily delay of the intended courses of action (P. Steel, 2007). Procrastination is a common phenomenon (P. Steel, 2007), in cross-cultural researches, 15%–20% of adults suffer from problematic and pathological procrastination (Harriott, Jesse, Ferrari, Joseph, & R., 1996)and more than 75% of college students have reported experiences for critical procrastination (Rozental, 2014). As a personality-like trait, procrastination can steadily influence an individual's behavior and lead to terrible consequences, such as low subjective well-being, lack of fitness, weak mental health (F. M. Sirois, 2011; Piers Steel & Ferrari, 2013), and precarious economic situation(Jr & Zauberman, 2006; Rabin, 1999). To reveal the neural mechanism and provide a scientific basis for the treatment and prevention of procrastination, what the neural substrates are to explain procrastination caught many eyes in recent decades.

Thus far, the concerns for the neurobiological substrate of procrastination have been explored from a few tentative studies. Zhang and colleagues (2016) used regional homogeneity(ReHo) and amplitude of low-frequency fluctuation (ALFF) revealed that procrastination was positively correlated with the regional activity of vmPFC and PHC but negatively correlated with the regional activity of anterior prefrontal cortex

(aPFC) (W. Zhang, Wang, & Feng, 2016). Further, the procrastination was found to be negatively correlated with the GMV of clusters in left dlPFC but positively correlated with the GMV of clusters in the parahippocampal gyrus (PHG) and the OFC(Chen, Liu, Zhang, & Feng, 2019; P. Liu & Feng, 2018) . Likewise, several resting-state functional magnetic resonance imaging (fMRI) studies further revealed that decreased resting-state functional connectivity(RSFC) of vmPFC–dlPFC, dACC-caudate, left dlPFC-lOFC, and left dlPFC-right dMFC connectivities in high procrastination (Xu, Sirois, Zhang, Yu, & Feng, 2021; Yan, Ling, Yuan, & Tian, 2016).

Furthermore, Chen and colleagues (2020) found that dlPFC, ACC, insula, OFC, and PHC were significantly correlated with procrastination in gray matter volume (GMV), gray matter density (GMD), cortical thickness (Addis, Ling, Vu, Laiser, & Schacter) and other indicators. Thus, they proposed the triple brain subsystems of procrastination based on this finding: self-control network, emotion regulation network, and episodic prospection network. the current study adopts this theory. Self-control is widely considered to be the most important factor affecting procrastination(Dan & Wertenbroch, 2002; Eerde, 2000; P. Steel, 2010) . Researchers usually attribute procrastination to self-control failure(Ridder, Lensveltmulders, Finkenauer, Stok, & Baumeister, 2012; P. Steel, 2007). Previous studies have found that dlPFC is the center of regulating self-control (Hare et al., 2009), and ACC represents the regulation of cognitive resources(Botvinick, 2007), which belongs to the cognitive control network with dlPFC(Alexopoulos et al., 2012). In the study of procrastination, it can be integrated into the self-control network, which may reduce the occurrence of procrastination by increasing the subjective value of future results. At the same time, procrastination is accompanied by a series of negative emotions. As described in the emotion regulation theory proposed by Sirois and Pychyl (2013), the study of emotion regulation function is also important for understanding procrastination. The insula is usually associated with averseness to the task(Sridharan, Levitin, & Menon, 2008; L. Q. Uddin, 2015), while OFC is found to be an important

area for negative emotion regulation and reassessment (Kanai & Rees, 2011), and they are theoretically integrated into an emotion regulation network to procrastination. It is noteworthy that procrastination is the evaluation and decision-making of future events, so the brain regions associated with imagining the future during exploration were found to be very consistent with expectations, and PHC 's GMV was just found to be positively correlated with procrastination in the study. PHC is mainly involved in episodic memory and episodic future thinking(Okuda et al., 2003; Peters & Büchel, 2010, 2011) . The directivity of this image has an important impact on whether it will show procrastination in the following. Thus, how these networks worked to influence procrastination sparked intensive debates explaining the neural underpinning of procrastination.

From studies that have been reviewed above, it could be observed that despite Chen et al. extending the exploration for the neurobiological substrates of procrastination from local GMV to large-scale networks, the interaction patterns of the procrastination brain structural networks remain unclear. Structural covariance network (SCN) analysis refers to a connectome-based technique to reveal covarying interindividual differences (e.g., coordinated variations in grey matter or white matter morphology) in neural anatomy across groups(Alexander-Bloch, Raznahan, Bullmore, & Giedd, 2013; Evans, 2013) has been broadly used to assessing structural brain organization. A key assumption underlying this methodology is that morphological correlations are related to axonal connectivity between brain regions, with shared trophic, genetic, and neurodevelopmental influences(Alexander-Bloch et al., 2013). SCN analysis is different from the analysis of functional connectivity or structural networks obtained with diffusion imaging, yet it has shown moderately strong overlap with both (Gong et al. 2012; Alexander-Bloch et al. 2013a). The preponderance of SCN analysis is that it focuses on the coordinated structure of the brain regions as opposed to focusing on a specific local structure. For example, Francesca Saviola et al. applied gray matter SCN founded that trait and state anxiety exhibited different structural node changes in Default Mode Network (DMN) and Salience Network(S., A., Katherine, & Peter)

(Saviola, Pappaianni, Monti, Grecucci, & Pisapia, 2020), Heinze, K and colleagues through whole-brain structural covariance analyses revealed subtle changes of connectivity of the default-mode, executive control, salience, motor and auditory networks in Ultra-High Risk (UHR) individuals for psychosis(Kareen et al., 2015). In summary, SCN analysis is less computationally intensive and arguably less sensitive to noise compared with functional imaging. So, we used SCN analysis to explore the altered brain morphological architecture of procrastination.

In summary, the current study aims to explore the interaction neuroanatomical patterns of procrastination. Firstly, to do a proof-of-concept analysis, we used the step-wise linear regression model to fit all the alternative brain regions (i.e., dlPFC、ACC、OFC、insula、vmPFC、PHC) for procrastination tendency; Further, the SCN was built upon across-participant GMV to the triple brain subsystems. By using graph-theoretical analysis, the potential local modules would be investigated; Finally, the whole sample would be split into two groups by top 27% and later 27% procrastination severity for exploring the difference of the topological properties of the gray matter SCN between different degree procrastinators.

2 Materials and Methods

2.1. Participants

254 right-hand college students were recruited and paid for their participation. Exclusion criteria were general contraindications against MRI, the consummation of drugs, the excessive consummation of alcohol and nicotine, medication affecting the central nervous system, history of neurologic or psychiatric disorders, and pregnancy. A total of 19 participants were excluded for further analysis by lack of demographic information. Finally, we retained 234 participants for further analysis ($Mean_{age}$:21.26, SD_{age}: 2.08, $Rang_{age}$: 17-26,169 females). At the same time, we divided the top 27% and the later 27% scorers on Pure Procrastination Scale into the high procrastination group (hpro, n=61) and low procrastination group (lpro, n=59), details for the final sample are described in Table 1.

All participants gave written informed consent for participation in the study and were informed of their right to discontinue participation at any time. The study was approved by the IRB of Southwest University (China).

2.2. Measures of procrastination

Table 1 Demographic information of two group participants

Characteristic	hPro (N=61)		lPro (N=59)		t or χ^2	
	N	%	N	%	χ^2	p
Fmale	50	81.97%	46	77.97%	0.30	0.58
	Mean	SD	Mean	SD	t	p
Age	21.110	2.114	21.830	1.904	-1.947	0.054
Edcucation	13.114	2.114	13.830	1.904	-1.947	0.054
BMI	20.365	2.219	20.561	2.286	-0.477	0.635
GPS score	43.459	4.047	24.339	3.541	27.503	<0.001
Personality						
Neuroti	37.278	4.768	35.610	4.738	1.922	0.057
Extrave	38.147	5.341	38.678	4.706	-0.576	0.565
Open	37.655	5.121	37.898	4.689	-0.270	0.787
Agreea	36.262	4.912	36.593	4.047	-0.402	0.688
Conscie	38.245	5.652	38.678	4.757	-0.452	0.652

Pure Procrastination Scale (PPS) was adopted to measure the degree of procrastination (Frode & Piers, 2017; P. Steel, 2010), which was based on the General Procrastination Scale (GPS)(Lay, 1986), the Decisional Procrastination Questionnaire (DPQ) (Mann, Burnett, Radford, & Ford, 1997) and the Adult Inventory of Procrastination (AIP) (Mccown, Johnson, & Petzel, 1989). The scale is a self-report measure using 12 Likert-style items, in which the point from 1 (very seldom or not at all like me) to 5 (very often or very true of me). With higher score indicates serious procrastination. Steel reported internal consistency of the PPS at $\alpha = 0.92$(P. Steel, 2010) and had accredited reliability with the current study ($\alpha = 0.89$).

2.3. Structural MRI data acquisition

Structural images were collected with a 3T Siemens Trio MRI scanner (Siemens Medical, Erlangen, Germany). A 16-channel circularly polarized head coil was used, with foam padding to constraint head motion. During scanning, participants were instructed to keep their eyes closed, relax their minds, thought of nothing, and remain motionless as much as possible. High-resolution T1-weighted anatomical images were acquired using a magnetization prepared rapid gradient echo (MPRAGE) sequence, with a total of 128 slices at a thickness of 1.33 mm and in-plane resolution of 0.98 × 0.98 mm2 (TR = 2530 ms; TE = 3.39 ms; flip angle = 7°; FoV = 256 × 256 mm^2).

2.4 Preprocessing and Analysis

2.4.1 Definition of regions-of-interest (ROIs)

We based on previous studies determined the six brain regions(ie., dlPFC seed A8dl_l ;OFC seed A11m_l; ACC seed A32sg_l; PHC seed riHipp_r, vmPFC seed A14m_r, and insula seed vla_l) on BNA (http://atlas.brainnetome.org) as ROIs in the current study (Fan et al., 2016). The details of the ROIs are described in Table 2, spatial position information in Figure 1. We also showed the Euclidean distance between the MNI coordinates of the brain regions, which found by Chen (2020) and Hu et al (2019), and the MNI coordinates of the BNA atlas. The Euclidean distance between the location of the peak voxel for each ROI as obtained in previous studies and the location of centroid for each ROI as obtained when using the BNA atlas. The centroid is defined here as the voxel within the ROI that is nearest, in terms of Euclidean distance, to all other voxels in the ROI(Douw, Nieboer, Stam, Tewarie, & Hillebrand, 2018).

Table 2 Selection of the ROIs

Regions	Chen, in prep	Hu et al., 2019	BNA atlas	Euclidean distance
dlPFC	peak MNI [-43 54 2]	peak MNI [-40 38 24]	peak MNI [-27 43 31]	4.67 (Liu); 7.00 (Hu)
OFC	peak MNI [-4 59 -20]	peak MNI [-20 60 -18]	peak MNI [-6 52 -19]	7.67 (Hu); 3.3 (Chen)
ACC	peak MNI [-6 42 2]	peak MNI [-16 70 -14]	peak MNI [-4 39 -2]	18.33 (Hu); 3.0 (Chen)
PHC	peak MNI [24 -6 -38]	peak MNI [16 -16 -26]	peak MNI [28 -8 -33]	9.00 (Hu); 10.0 (Chen)
vmPFC	peak MNI [4 41 -13]	-	peak MNI [6 47 -7]	4.33 (Chen)
Insula	peak MNI [-30 18 -15]	-	peak MNI [-32 14 -13]	2.67 (Chen)

2.4.2.VBM analysis

Structural images were processed with Statistical Parametric Mapping software (SPM12: http://www.fil.ion.ucl.ac.uk/spm/software/spm12) operated in Matlab R2019b (MathWorks Inc., Natick, MA, USA). Firstly, for better image registration, all T1-weighted anatomic images displayed in SPM12 were manually reoriented to place the anterior commissure at the origin of the three-dimensional Montreal Neurological Institute (MNI) space. Secondly, the reoriented images were segmented in grey matter (GM), white matter (WM), and cerebral spinal fluid in SPM12 (Ashburner and Friston 2005). Thirdly, the DARTEL algorithm was used to generate a group-specific template based on the participants. For each participant, a flow field storing the deformation information for warping the participants' scans onto the template was created. These were used to spatially normalize grey matter images to MNI space using affine spatial normalization as implemented in the normalization algorithm included in the DARTEL toolbox. To preserve the grey matter volumes (GMV) within a voxel, the images were modulated using the Jacobian determinants derived from the spatial normalization by DARTEL. Finally, data were spatially

smoothed with an 8-mm full-width at a half-maximum (FWHM) Gaussian kernel to increase the signal-to-noise ratio.

Statistical analysis of GMV of brain regions was performed using SPM12 software. The global GMV was added as a global measure for proportional global scaling (Peelle, Cusack, & Henson, 2012). The global or ROIs' GMV were calculated by the MATLAB script get_totals provided by Ridgway (http://www.cs.ucl.ac.uk/staff/g.ridgway/vbm/get_totals.m). We applied explicit masking using the population-specific masking toolbox in SPM8 to restrict the search volumes within gray matter and white matter (http://www.cs.ucl.ac.uk/staffff/g.ridgway/masking/). This approach was used instead of absolute or relative threshold masking to decrease the risk of false negatives caused by overly restrictive masking, and potentially interesting voxels were excluded from the statistical analysis (Ridgway et al., 2009). Next, to exclude the promiscuous effect of individual difference in the total GMV, we calculated the relative GMV utilizing dividing the GMV of ROIs by the total GMV, and then it was transformed into Z scores.

2.4.3 Graph theoretical-based brain network analysis

Graph-theoretical analyses were performed to quantify the topological metrics of structural connectivity networks by the Graph Theoretical Network Analysis (GRETNA) Toolbox (https://www.nitrc.org/projects/Gretna) (Wang et al., 2015). At present, the method of using graph theory to analyze complex brain networks has been widely used in the study of brain images. Graph theory can be used to quantify the topological properties of brain networks or connectomes. In Graph-theoretical analyses, the brain is modeled as a graph composed of nodes and edges, where nodes denote ROIs or voxels, edges denote the interactions or connections among nodes. The topology of brain networks usually consists of three aspects: global attributes (for example clustering coefficient, shortest path length et. al), modularity regional nodal attributes(such as degree(k) and betweenness centrality(be))(Filippi et al., 2013; Sporns & Olaf, 2013). Among them, global attributes reflect the ability of the brain

complex network to separate and integrate information, modularity reflects the anatomical or functional connection of brain regions performing specific functions, and local node feature reflects the key brain regions in the brain complex network(C & E, 2015). In the current study, we described the modularity regional nodal attributes of procrastination gray matter SCN.

2.5 Statistical Analysis

2.5.1 Demographic Differences Analysis

Independent-Samples T-Tests and chi-square tests were run to compare the differences between hpro and lpro in the demographic differences. To ensure the reliability of the regression model, we tested collinearity diagnostics between procrastination and covariates with $r > 0.30$ and $P < 0.05$ for the critical co-linearity. Results showed that co-linearity between PPS and eight covariates (gender, $r = -0.029$, $P = 0.752$; BMI, $r = -0.045$, $P = 0.623$; conscientiousness, $r = -0.009$, $P = 0.919$; extraversion, $r = -0.053$, $P = 0.563$; neuroticism, $r = 0.068$, $P = 0.462$; agreeableness, $r = -0.001$, $P = 0.992$; openness, $r = 0.02$, $P = 0.829$), co-linearity between PPS and two covariates (ages, $r = -0.225$, $P = 0.013$; education, $r = -0.225$, $P = 0.013$).

2.5.2 Prediction for Procrastination with Step-wise Linear Regression Model

To do a proof-of-concept analysis and define nodes of procrastination gray matter SCN, after calculating the GMV of the six ROIs by VBM. We further used the GMV as independent variables, the PPS score as the dependent variable. Previous studies have suggested that some aspects of brain asymmetries interacted with gender (Kulynych, Katalin, Jones, & Weinberger, 1994), and age had a significant effect on brain morphology as well (Good et al., 2001). To exclude the effects of demographic variables on individual brain structure and procrastination measurement, we put gender, age, education, BMI, big-five personality traits (ie., Neuroti, Extrave, Open, Agreea, Conscie) as the covariates of no interests (Table 3).

Table 3 Step-wise linear regression model to predict procrastination

Dependent Variable	predictive variables	R^2	β	t	P
PPS score	Model 1	0.005			
	Age		0.015	0.776	0.438
	Gender		-0.010	-0.111	0.911
	Model 2	0.092			
	Age		0.015	0.776	0.438
	Gender		-0.010	-0.111	0.911
	ACC		0.263	5.389	<0.001
	Model 3	0.143			
	Age		0.015	0.776	0.438
	Gender		-0.010	-0.111	0.911
	ACC		0.263	5.389	<0.001
	dlPFC		-0.183	-3.599	<0.001
	Model 4	0.180			
	Age		0.015	0.776	0.438
	Gender		-0.010	-0.111	0.911
	ACC		0.263	5.389	<0.001
	dlPFC		-0.183	-3.599	<0.001
	insula		0.137	3.492	0.001
	Model 5	0.213			
	Age		0.015	0.776	0.438
	Gender		-0.010	-0.111	0.911
	ACC		0.263	5.389	<0.001
	dlPFC		-0.183	-3.599	<0.001
	insula		0.137	3.492	0.001
	PHC		0.179	3.001	0.003
	Model 6	0.229			
	Age		0.015	0.776	0.438
	Gender		-0.010	-0.111	0.911
	ACC		0.263	5.389	<0.001
	dlPFC		-0.183	-3.599	<0.001
	insula		0.137	3.492	0.001
	PHC		0.126	2.996	0.003
	OFC		0.104	2.167	0.031

2.5.3 Brain-Behavior Association Analysis

To define edges of procrastination gray matter SCN, according to the results of stepwise linear regression analysis, ROIs in the model with the best fitting effect was defined as nodes, edges were determined according to the correlation of nodes. Therefore, we further used correlation analysis to calculate ROIs correlation matrix (Table 4).

3 Results

3.2 Prediction for Procrastination with Step-wise Linear Regression Model

To obtain deep insights into the predictive role of brain gray matter structural on the procrastination, step-wise linear regression analysis was used to fit the model for dependent variable "scores of the procrastination" on independent variables including GMV of dlPFC, GMV of ACC, GMV of vmPFC, GMV of PHC, and GMV of insula, and age and gender as covariates variables. The entered measure of the step-wise process was defined with a probability of $F \leq 0.05$ for each independent variable, however one would be refused into the model in case of the probability of $F \geq 0.10$ for the dependent variable. Subsequently, the step-wise iteration would automatically stop until no one could fit this criterion. Finally, GMV of dlPFC, GMV of ACC, GMV of OFC, GMV of PHC, and GMV of insula were available to enter the multiple regression model for the explanation on the procrastination. The final model (model 6) included above five variables was captured as the optimal model to significantly predict procrastination with account for 23% of total variance independent variable ($R^2_{\ change}$=0.224, $p<0.05$; $\beta_{[GMV\_ACC]}$= 0.263, $p<0.001$; $\beta_{[GMV\_dlPFC]}$= -0.183, $p<0.001$, $\beta_{[GMV\_insula]}$= 0.137, P=0.001, $\beta_{[GMV\_\ PHC]}$= 0.126, p=0.003 and $\beta_{[GMV\_OFC]}$= 0.104, p=0.031). The covariates, age and gender have not significant explanation (β_{age}= 0.022, p=0.306; β_{gender}= -0.051, p=0.602) and vmPFC was not included in the model(p=0.99).

3.3 Brain Behavior Association Analysis

3.3.1 Pearson's Correlations of procrastination

To define edges of gray matter SCN, we further used correlation analysis to explore whether there exist correlations between the five brain regions in model 6 (ie., dlPFC, ACC, OFC, PHC, insula). Correlation analysis results showed significant positive and negative correlations between the GMVs of dlPFC, ACC, OFC, PHC, insula, and PPS score (Table 4). The GMV of dlPFC was significantly positively correlated with ACC ($r=0.169$, $p<0.01$), the GMVs of dlPFC and ACC were significantly negatively correlated with PHC ($r_{dlPFC}=-0.140$, $p<0.05$; $r_{ACC}=-0.144$, $p<0.05$). Furthermore, consistent with previous research(citation), the GMV of dlPFC was significantly negatively correlated with PPS score ($r = -0.169$, $p<0.01$) and the GMVs of ACC, OFC, PHC, insula were significantly positively correlated with PPS scores ($r_{ACC}=0.304$, $p < 0.01$; $r_{OFC}=0.158$, $p<0.05$; $r_{PHC}=0.144$, $p<0.05$; $r_{insula}=0.207$, $p<0.01$).

Table 4 Pearson's Correlation analysis （N=234）

	dlPFC	ACC	OFC	PHC	insula	PPS
dlPFC	1					
ACC	0.169**	1				
OFC	-0.01	0.055	1			
PHC	-0.140*	-0.144*	0.051	1		
insula	0.057	0.090	0.007	-0.092	1	
PPS	-0.169**	0.304**	0.158*	0.144*	0.207**	1

** p<0.01； *p<0.05

3.5 Modularity characteristics for gray matter SCN

To further reveal the modular topological properties of the gray matter SCN of six brain regions (ie., dlPFC, ACC, OFC, PHC, insula), we used 2000 bootstrap iterations to generate the null distribution of modularity, the result showed that the modularity mode of the covariant network of procrastination gray matter is significant, and these ROIs can be divided into three models (Figure 2b), module 1 includes dlPFC and ACC, module 2includes PHC、OFC and PPS, module 3 includes insula（Bootstrap test, sim = 2,000 p = .0024）. Then, based on the modularity mode, we further compared whether there were differences in the modules between hpro and lpro. The result

showed that the modularization coefficient of hpro was significantly lower than the lpro （hPro = 0.82,lPro = 1.17, p < .05, Bootstrap test, sim = 2,000.

3.4 Network topological metrics for structural connectomes

Degree and betweenness centrality were proven to be the most pivotal nodal measures to quantitatively describe the position of nodes within the network, reflecting the capability of regions on parallel information processes in brain connectomes (Gross, 2008; Sporns & Olaf, 2011)In node-based test, significantly high betweenness of dlPFC and PHC was also found in the procrastination gray matter SCN (Be-dlPFC = 16, p <.001; Be-PHC = 16, p <.001, Bootstrap test, sim = 2,000), no significant results were found on other nodes (Figure 2 c). Further, we explored the changes of nodes betweenness centrality between hpro and lpro.The results showed that , compared with the lpro, the betweenness centrality of dlPFC in the hpro decreased significantly and even disappeared （Be-dlPFC-hPro=0,Be-dlPFC-lPro = 10, p < .01, Bootstrap test, sim = 2,000 ） ,however, no significant difference in the changes of betweenness centrality of PHC between the hpro and lpro (Be-PHC-hPro=9,Be-PHC-lPro = 11, p < .18, Bootstrap test, sim = 2,000).

Finally, we found that the dlPFC-PHC connection has a significant high edge betweenness centrality in the procrastination gray matter SCN (Between-dlpfc-phc = 11, p < .001, Bootstrap test, sim = 2,000) (Figure 2 d). At the same time, we explored the changes of this edge betweenness centrality between the two groups. the result showed that, compared with the lpro, the edge betweenness centrality of dlPFC-PHC connection decreased significantly (hpro = 3, lpro = 11, p < 0.5, Bootstrap test, sim = 2,000).

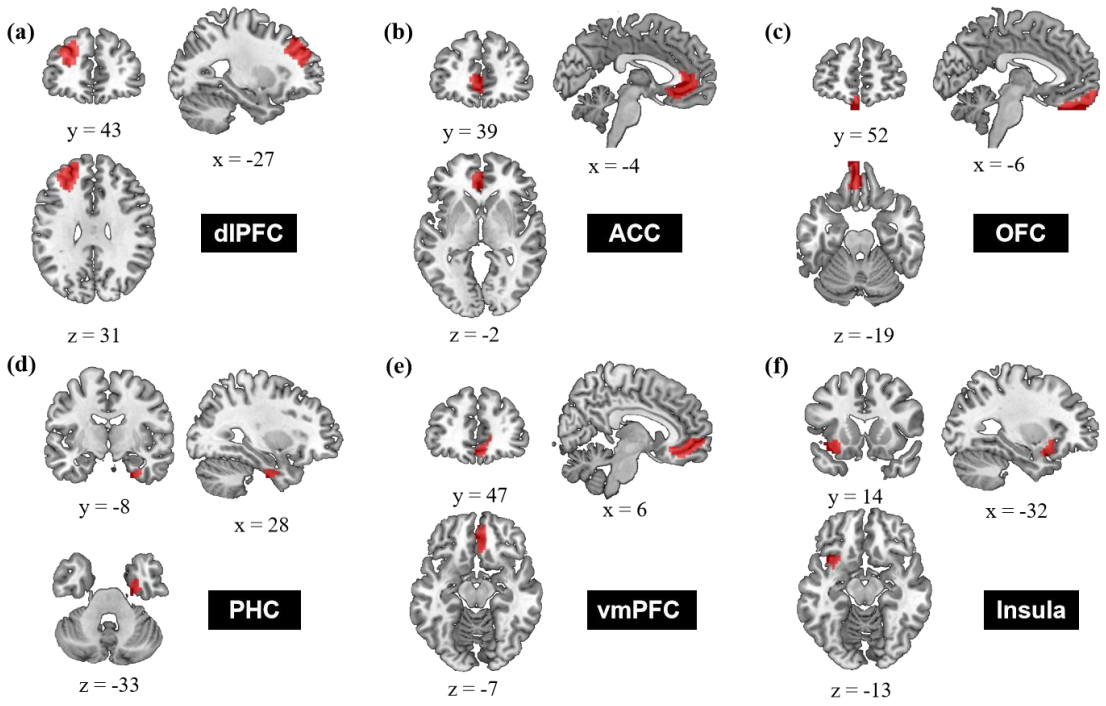

Figure 1. Spatial position information of ROIs. dlPFC (seed A8dl_l) = dorsolateral prefrontal cortex, ACC (seed A32sg_l) = Anterior cingulum cortex, OFC (seed A11m_l) = orbital frontal cortex, PHC (seed riHipp_r) = parahippocampal gyrus, vmPFC (seed A14m_r) = ventromedial prefrontal cortex(vmPFC), Insula (seed vla_l). All ROIs has unilateral characteristics consisitent with previous studies.

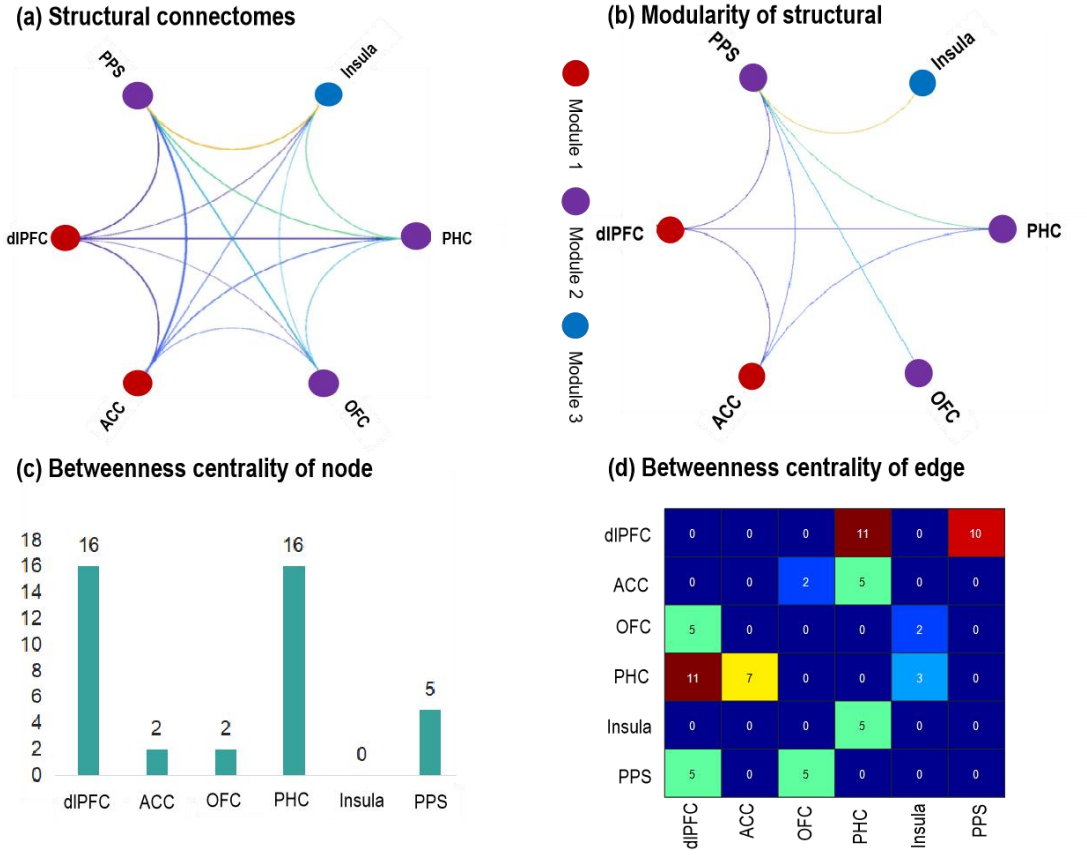

Figure 2. Brief Framework of the processes for the network-based metrics. (a) Shows the Structural connectomes of ROIs (ie., dlPFC, ACC, OFC, PHC, Insula, PPS). (b) Shows the modularity of structural connectomes of ROIs. (c) shows the betweenness centrality of node (d) shows the betweenness centrality of edge

4 Discussion

In the current study, we investigated the topological properties of gray matter SCN of procrastination. The results of step-wise linear regression analysis showed that the model including dlPFC, ACC, OFC, PHC, and insula has a better prediction effect and verify the accuracy of ROIs selection. Further, the modular partitions of procrastination showed that the gray matter SCN consists of three modules (module 1: dlPFC and ACC; module 2: PHC and OFC; module 3: insula). In the node-based analysis, we found the dlPFC and the PHC have significantly high node betweenness centrality. In the edge-based analysis, we found the connection of dlPFC-PHC has a significantly high edge betweenness centrality. The modularization coefficient and node betweenness centrality of dlPFC in the hpro decreased significantly and no significant difference in PHC compared with the lpro. Similarly, compared with the

lpro, edge betweenness centrality of the dlPFC-PHC of the procrastination gray matter SCN in the hpro decreased significantly. These findings, therefore, substantiate the existence of potential interaction between the triple brain subsystems of procrastination and further a new advance in unearthing the neural mechanisms of procrastination.

Model 1 demonstrated the self-control network of procrastination including dlPFC and ACC. Numerous studies have shown that the dlPFC is the hub of self-control, the function of dlFPC was selectively responsible for the top-down cognitive control for downstream signals(Figner et al., 2010; Hare et al., 2009; MacDonald & A., 2000) . Meanwhile, in node-based analysis, we found the dlPFC has significantly high nodes betweenness centrality. This is consistent with previous research on self-control as a core competencies predictor of procrastination(Laura A. Rabin & Nutter-Upham, 2011). Importantly, structural abnormalities of the dlPFC also have been interpreted as a lack of self-control thereby predicting more serious procrastination(Hu, Liu, Guo, & Feng, 2018; Peiwei Liu & Feng, 2017) . In addition, adequate evidence has illustrated the role of ACC as conflict monitoring and reinforcement learning of the error signals during making a decision(Hare et al., 2009; MacDonald & A., 2000) . Encouragingly, dlPFC and ACC have integrated a network called cognitive control network (Alexopoulos et al., 2012; Bae et al., 2006). Naturally, it was reasonable to perceive model 1(dlPFC and ACC) as a self-control network.

Model 2 demonstrated the future task reward network of procrastination including PHC and OFC, more specifically, the interaction of episodic prospection and reward processing to influence procrastination. Meanwhile, in node-based analysis, we also found the PHC has significantly high nodes betweenness centrality in procrastination gray matter SCN. The PHC is part of a network mediating human's ability of episodic future thinking, which allows people to pre-experience future rewards through mental stimulation (S. Zhang, Liu, & Feng, 2019). Rebetez, Barsics, et al. (2016) have reported that high procrastinators indeed showed worse performance in episodic

future thinking. In addition, several fMRI research showed that OFC activity increases accompany increasing expected reward and decrease after depreciation of the predicted outcome(Breiter, 2009; Ja., O'Doherty, & Rj., 2003). Encouragingly, PHC was anatomically connected to the OFC (Witter, Wouterlood, Naber, & Haeften, 2010). These findings derived from previous literature hinted at this standpoint that model 2(PHC and OFC) could be perceived as a system called "future task reward" network, which was specialized to inspire motivation to act confronted task.

Model 3 demonstrated the role of insula on procrastination. The insula was specialized to emotional processes for the averseness in task engagements(Chen et al., 2019). As the key subcortical region for the salience network, the insula acted a key role in social emotion and averseness on the task-induced signals(Uddin & Lucina, 2014). Furthermore, a functional brain imaging study substantiates this case straightforward that the insula responds selectively to the facial expressions of disgust and the disgust-inducing pictures(Wicker et al., 2003; Wright, He, Shapira, Goodman, & Liu, 2004). On balance, we concluded that model 3 (insula) could be defined as a system called "task averseness", which inspires the motivation to avoid a task(S. Zhang, Liu, et al., 2019).

More specially, the recent theory proposes that procrastination has intrinsic temporal nature as a form of temporal self-regulation failure (Gustavson, Miyake, Hewitt, & Friedman, 2014) and mirroring a primacy of present self over the needs of the future self (F. Sirois & Pychyl, 2013). Those viewpoints are further supported and enriched by the temporal decision model(TDM)(S. Zhang, Liu, et al., 2019). The TDM for procrastination illustrates the conflict between the pursuit of future task reward and aversiveness to negative emotions evoked by doing a task, and self-control plays a moderating role in the balance between them(S. Zhang, Becker, Chen, & Feng, 2019; S. Zhang, Liu, et al., 2019). Furthermore, individuals with high self-control can enact goal-congruent behaviors by regulating their negative emotions or modulating their concerns for long-term benefits(Mcguire & Kable, 2013; Tornquist & Miles, 2019).

Inevitable, this study has some inherent limitations that should warrant caution. Firstly, structural covariation network constructed is an undirected structural network, future work will include directed action network or dynamic functional connectivity analysis on the neural basis of procrastination such as Magnetoencephalography (MEG). MEG is an invaluable functional brain imaging technique, permits spatiotemporal tracking of cortical pathways with sub-millisecond temporal resolution and provides direct, real-time monitoring of neuronal activity which is necessary for gaining insight into dynamic cortical networks.

In conclusion, the current study provides evidence for network-based cortical volume reductions in procrastination and suggests that the dlPFC and the dlPFC-PHC connection can predict procrastination well. These results also provide novel evidence about the triple brain subsystems of procrastination.

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