

Brain networks of happiness: dynamic functional connectivity among the default, cognitive and salience networks relates to subjective well-being

Liang Shi^{1,2}, Jiangzhou Sun^{1,2}, Xinran Wu^{1,2}, Dongtao Wei^{1,2}, Qunlin Chen^{1,2}, Wenjing Yang^{1,2}, Hong Chen^{1,2}, and Jiang Qiu^{1,2,3,*}

¹Key Laboratory of Cognition and Personality (SWU), Ministry of Education, Chongqing 400715, China ²School of Psychology, Southwest University (SWU), Chongqing 400715, China, ³Southwest University Branch, Collaborative Innovation Center of Assessment toward Basic Education Quality, Beijing Normal University, Beijing 100875, China

*Correspondence should be addressed to Professor Jiang Qiu, Faculty of Psychology, Southwest University, No.2 TianSheng Road, Beibei District, Chongqing 400715, China. Tel: 86-23-6836 7942 Fax: 86-23-6836 7942 E-mail: qiu318@swu.edu.cn.

Liang Shi and Jiangzhou Sun contributed equally to this work.

Abstract

Subjective well-being (SWB) reflects the cognitive and emotional evaluations of an individual's life and plays an important role in individual's success in health, work and social relationships. Although previous studies have revealed the spontaneous brain activity underlying SWB, little is known about the relationship between brain network interactions and SWB. The present study investigated the static and dynamic functional connectivity among large-scale brain networks during resting state functional magnetic resonance imaging (fMRI) in relation to SWB in two large independent datasets. The results showed that SWB is negatively correlated with static functional connectivity between the salience network (SN) and the anterior default mode network (DMN). Dynamic functional network connectivity (dFNC) analysis found that SWB is negatively correlated with the fraction of time that participants spent in a brain state characterized by weak cross-network connectivity (between the DMN, SN and frontal-parietal network [FPN]) and strong within-network connectivity (within the DMN and within the FPN). This connectivity profile may account for the good mental adaptability and flexible information communication of people with high levels of SWB. The dFNC results were well replicated with different analysis parameters and further validated in an independent sample. Taken together, these findings reveal that the dynamic interaction between networks involved in self-reflection, emotional regulation and cognitive control underlies SWB.

Key words: subjective well-being; dynamic functional connectivity; default mode network; frontal-parietal network; salience network

Introduction

For many years, positive psychology has received attention from many researchers (Seligman and Csikszentmihalyi, 2000; Lyubomirsky, 2001; Diener, 2013). A central concept of positive

psychology is well-being or happiness. Well-being is composed of hedonic well-being that refers to pleasure attainment and pain avoidance (And and Deci, 2001), and eudaimonic well-being that refers to the realization of one's true potential (Ryff

Received: 23 March 2018; Revised: 3 July 2018; Accepted: 11 July 2018

© The Author(s) (2018). Published by Oxford University Press.

This is an Open Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits non-commercial re-use, distribution, and reproduction in any medium, provided the original work is properly cited. For commercial re-use, please contact journals.permissions@oup.com

and Keyes, 1995) and the experience of purpose or meaning in life (Ryff, 1989). For many people, living a happy life is a lifelong pursuit, and it produces success in health, work and social relationships (Lyubomirsky et al., 2005; Diener and Biswas-Diener, 2011). However, people differ in their experiences of well-being. The construction theory of well-being states that individuals with high and low levels of happiness have systematic differences in multiple cognitive processes, including self-reflection and emotion regulation (Lyubomirsky, 2001). For example, relative to happy people, unhappy people are more sensitive to negative feedback and show self-focused cognition (rumination) (Lyubomirsky et al., 2011), which is associated with symptoms of depression (Nolen-Hoeksema et al., 2008). In contrast, compared to individuals with low levels of well-being, individuals with high levels of well-being are more likely to maintain and enhance positive emotions and thoughts in working memory (Pe et al., 2013) and have stronger abilities of emotional expression and resilience (Gan-Qi and Huang, 2012). In addition, personality traits (e.g. extraversion and self-esteem), life circumstances and culture also influence the levels of well-being (Diener et al., 2003). Consequently, it is interesting and essential to investigate the individual differences in happiness.

It is worth noting that happiness is a broad construct that encompasses positive affect, negative affect and high levels of life satisfaction (Diener et al., 1999; Diener et al., 2015). And it has different meanings in different contexts. For instance, in philosophy, it translates from the Greek concept of eudaimonic and refers to the good life while it refers to a mental or emotional state of well-being in psychology (Taylor, 2016). Evenly, it is conceptualized as a trait rather than a transient emotional state in some studies (Lyubomirsky et al., 2005; Luo et al., 2015a). However, in this study, we are mainly concerned about subjective well-being (SWB) which primarily focuses on the hedonic instead of eudaemonic aspect of well-being and reflects positive emotional function (And and Deci, 2001; Diener et al., 2003).

In recent years, neuroimaging studies have advanced our understanding of the neural sources of the individual differences in SWB (Urry et al., 2004; Van Reekum et al., 2007; Kong et al., 2014, 2015a; Luo et al., 2014; Luo et al., 2015b). The default mode network (DMN) plays an important role in the experience of well-being. Hyperconnectivity within the DMN has been linked to the trait of unhappy people who are more sensitive to negative life events and more prone to rumination (Kringelbach and Berridge, 2009; Lyubomirsky et al., 2011; Stawarczyk et al., 2012). A resting-state functional magnetic resonance imaging (rs-fMRI) study supported this point (Luo et al., 2015a): stronger functional connectivity within regions of the DMN (bilateral medial pre-frontal cortex, bilateral posterior cingulate cortex and left inferior parietal cortex) was associated with lower levels of happiness and higher rumination scores. Structural imaging studies also revealed that DMN is closely related to SWB. A structural magnetic resonance imaging (MRI) study has shown that life satisfaction is associated with regional grey matter volume in the core regions of the DMN, such as the right parahippocampal gyrus, left precuneus and left ventromedial pre-frontal cortex (vmPFC; Kong et al., 2014). In addition, another study also showed that functional connectivity between the vmPFC [within anterior DMN (aDMN)] and the precuneus [within posterior DMN (pDMN)] is positively associated with hedonic and eudaimonic balance index which captures the relative dominance of hedonic and eudaimonic well-being, revealing the role of the DMN in one's inclination towards hedonic or eudaimonic well-being (Luo et al., 2017).

In addition, emerging studies have also suggested that the executive control network (e.g. FPN), which is mainly involved in emotion regulation and cognitive control ability is associated with an individual's SWB (Hooker and Knight, 2006a; Gan-Qi and HUANG, 2012; Pe et al., 2013). For example, rs-fMRI studies have found that the amplitude of low-frequency fluctuations in the left dorsolateral pre-frontal cortex (DLPFC) and bilateral orbitofrontal cortex (OFC) is positively correlated with happiness (LUO et al., 2015b). The engagement of DLPFC and OFC is associated with cognitive control and emotional regulation through the inhibition of inappropriate emotions and behaviors (Hooker and Knight, 2006b). Task-based functional MRI studies have also shown that a higher happiness score is associated with stronger activity of the ventral anterior cingulate cortex (ACC) for negative information and sustained activation in the DLPFC and striatum in response to positive events (Van Reekum et al., 2007; Cunningham and Kirkland, 2013; Heller et al., 2013).

Furthermore, the salience network (SN), which plays an important role in switching the executive network and the default network (Goulden et al., 2014), is also involved in well-being. For instance, fractional amplitude of low-frequency fluctuations (fALFF) in the core regions of SN, such as the right ACC and right insula, is positively correlated with social well-being (Kong et al., 2016). The ACC, which is associated with emotion regulation and perception of social pain (Etkin et al., 2011; Cacioppo et al., 2013), may contribute to the regulation of affective response to stressors in life, thereby improving social well-being. The involvement of the insula, which is associated with interoception and understanding others' feelings (Singer et al., 2009; Cox et al., 2011), might help improve emotional awareness, thereby resulting in a high level of social well-being. A structural MRI study also found that eudaimonic well-being is associated with regional grey matter volume of the insula, which is implicated in integrating interoceptive state and managing emotional milieu (Craig and Craig, 2009; Lewis et al., 2013). Additionally, many patients with mental disorders, who exhibit a low level of happiness (Cloninger, 2006), show dysfunction in SN (Menon, 2011). For instance, an increased interaction between the DMN and the SN has been reported in post-traumatic stress disorder (Sripada et al., 2012). In short, these findings suggest that multiple regions associated with emotion (e.g. SN), cognition (e.g. FPN) and self-referential processing (e.g. DMN) may be involved in SWB.

Although the above neuroimaging studies have partly revealed the neural sources of the individual differences in SWB, little work has been done to examine how the interaction of multiple large-scale brain networks (such as the DMN, FPN and SN) during rs-fMRI influences the level of individuals' SWB. In addition, the brain itself is highly dynamic (Calhoun et al., 2014). Recently, an increasing number of studies have used the dynamic functional network connectivity (dFNC) approach (Sakoğlu et al., 2010) to characterize the time-varying properties of functional connectivity (Calhoun et al., 2013, 2014; Leonardi et al., 2013; Keilholz, 2014). Compared with the conventional static functional connectivity approach, the dFNC approach is able to portray the dynamic nature of functional connectivity (FC) on a shorter time scale. A growing number of studies have applied this approach, providing the possibility for the application of dFNC in assessing important psychological variables (Rashid et al., 2016; Shine et al., 2016). Additionally, connectivity state metrics, which were derived from the dFNC approach, also appear to be useful for predicting and characterizing disease (Damaraju et al., 2014; Tagliazucchi and Laufs, 2014). Therefore, we sought to explore both the static and

dynamical brain functional connectivity underlying SWB during rs-fMRI.

In the present study, we aimed to investigate how the static and dynamic functional connectivity among large-scale brain networks during rs-fMRI are associated with the individual differences in SWB. In light of previous studies (Kong et al., 2015a, 2015b 2016; Luo et al., 2014; Luo, 2015b), we hypothesized that SWB would be correlated with the static and dynamic functional connectivity among DMN, FPN and SN. Additionally, we hypothesized that SWB would be related to a certain brain state and its connectivity state metrics derived from the dFNC approach. To test these hypotheses, we first assessed the SWB of healthy individuals in dataset 1 using the index of well-being (Campbell, 1976). Next, group independent component analysis (GICA) was performed to decompose the whole brain into large-scale functional networks. Then, both the static and dynamic functional connectivity were computed for correlation with the SWB score. Reproducibility is a very important problem in scientific research (Blackford, 2017). Concerns regarding the lower statistical power and lack of replication in psychology and neuroscience research field have been raised recently (Ioannidis, 2005; Button et al., 2013; Poldrack et al., 2017). Therefore, it is necessary to validate our results in an independent sample to confirm the reliability and repeatability of our study. We tested and validated the main findings in dataset 1 by using an open access dataset [Southwest University Longitudinal Imaging Multimodal (SLIM) Dataset (International Neuroimaging Data-Sharing Initiative (INDI), http://fcon_1000.projects.nitrc.org/)] (Liu et al., 2017b) that also contains rs-fMRI data and SWB measurement in a format identical to that of the behavioral assessment in dataset 1.

Methods

Participants

Dataset 1. A total of 378 college students, all healthy and right-handed, with no history of neurological or psychiatric disorders, were recruited from Southwest University to participate in the present study. A total of 47 participants were excluded due to excessive head movement (> 2 mm translation in any axis and > 2 angular rotation in any axis). This resulted in a final sample of 331 participants (84 male), aged 18–25 (mean = 20.20 ± 1.34). The study was approved by the Southwest University Brain Imaging Center Institutional Review Board.

Dataset 2. A total of 230 subjects were acquired from time point 3 data of the SLIM Dataset (INDI, http://fcon_1000.projects.nitrc.org/) (Liu et al., 2017b). All participants were right-handed, had no history of neurological or psychiatric disorders and provided written informed consent. A total of 18 students were excluded (> 2 mm translation in any axis and > 2 angular rotation in any axis), leaving a final sample of 212 subjects (97 male, aged 19–27, mean = 22.36 ± 1.49).

Behavioral assessment. SWB was assessed using the Index of Well-being (Campbell, 1976), which contains two parts: index of general affect (8 items, e.g. ‘What is the affective state you are experiencing now?’) and life satisfactory questionnaire (1 item: ‘How satisfied are you with your life?’). Participants were required to indicate the extent of their agreement on a 7-point scale, ranging from strongly disagree to strongly agree. The overall SWB index is the weighted sum of the two scores. Higher scores indicate higher levels of SWB. The internal consistency coefficient of the index of general is 0.89, and its test-retest coefficient is 0.43. The validity coefficient between

the index of general affect and life satisfaction questionnaire is 0.55 (Wang et al., 1999). This scale has been widely used in China (Xinhua, 2004; Yue et al., 2006; Geng et al., 2009). In the present study, this scale showed adequate reliability (Cronbach’s alpha = 0.90). The behavioral assessment was the same both in the two datasets.

Image acquisition and pre-processing. The rs-fMRI scan was performed on a 3T Trio scanner (Siemens Medical Systems, Erlangen, Germany) at the Brain Imaging Center, Southwest University. The scanning consisted of 242 contiguous volumes, which were obtained 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 = 220×220 mm²; voxel size = $1 \times 1 \times 1$ mm; slice gap = 1 mm; and voxel size = $3.4 \times 3.4 \times 4$ mm³. Participants were instructed to close their eyes, not think about anything in particular and remain awake. The rs-fMRI images were pre-processed using the Data Processing Assistant for rs-fMRI (DPARSF, <http://resting-fmri.sourceforge.net/>) (Yan and Zang, 2010) based on Statistical Parametric Mapping 8 (SPM8) (Wellcome Department of Imaging Neuroscience, London, United Kingdom; www.fil.ion.ucl.ac.uk/spm). After discarding the first 10 volumes to allow the signal to equilibrate, the rest of the rs-fMRI images were corrected for slice time difference and head motion. Then, the images were spatially normalized to the standard MNI template with a resample voxel size of $3 \times 3 \times 3$ mm and spatial smoothing with an 8 mm full-width at half maximum Gaussian kernel. The scanning parameters and pre-processing procedures were the same for both datasets.

Group independent component analysis. Spatial ICA was performed to decompose all pre-processed data into functional components using the group ICA of fMRI toolbox (GIFT) toolbox (<http://mialab.mrn.org/software/gift/>) (Calhoun et al., 2001). GICA identifies independent components (ICs) through three steps: dimensionality reduction, ICs estimation and back reconstruction. Each of the ICs has an associated time course (TC) and a spatial map (SM). First, a two-step principal components analysis was conducted to reduce the data into 20 components, because lower model order (e.g. 20 ICs) yielded refined components that better correspond to known anatomical and functional segmentations (Smith et al., 2009; Abou-Elseoud et al., 2010). Subsequently, the Infomax algorithm (Bell and Sejnowski, 1995) was utilized in ICs estimation, which was repeated 20 times in ICASSO, to generate a stable set of 20 components. Next, a GICA method was reconstructed for the subject-specific components. After reconstruction, the SMs and TCs of ICs for all participants were obtained. The subject-specific SMs and TCs were then converted to z-scores. Here, all ICs were evaluated based on the group IC maps according to the following criteria (Kim et al., 2009; Zuo et al., 2010; Xu et al., 2013): the functional components exhibited peak cluster location in grey matter and low spatial overlap with white matter structures, vascular, ventricles, motion and susceptibility artifacts. According to the above studies (Kong et al., 2014; Luo et al., 2015a; Kong et al., 2016; Brunetti et al., 2017), five ICs [aDMN, pDMN, SN, left FPN (lFPN) and right FPN (rFPN)] were identified for further analysis. The ICs were selected based on the largest spatial overlap with the network spatial template from previous studies (Smith et al., 2009; Allen et al., 2011) using the spatial sorting function of the GIFT. In addition, prior to computing functional connectivity, the TCs of the five ICs were post-processed to remove remaining

noise sources, including detrending, despiking and low-pass filtering with a high-frequency cutoff of 0.15 Hz (Allen et al., 2014). Moreover, variances associated with the motion for each subject were also regressed from the TCs using realignment parameters (rp*.txt file). The mean framewise displacement (FD) (Power et al., 2012) was also regressed out in the group statistical analysis. Finally, for all functional network connectivity (FNC) analyses, correlations were transformed to z-scores using Fisher's transformation.

Static FNC analysis. The static FNC was defined by the Pearson correlation between the whole TCs (across 232 time points) of IC pairs (Jafri et al., 2008). The pairwise correlation was performed between the five ICs for all subjects. The association between FNC and SWB score was estimated as the Pearson correlation. Additionally, to control for possible confounding variables, multiple regression was conducted to investigate the correlation between FNC and behavioral score, regressing out age, gender and mean FD. Multiple comparisons were performed using the false discovery rate (FDR).

dFNC analysis. dFNC was conducted in the GIFT toolbox. A sliding window approach was applied to segment the resting-state time series. Based on previous studies that have shown that cognitive states could be correctly identified on 30–60 s of data (Shirer et al., 2012), a window of 60 s width (30 TR), sliding in steps of 1 TR was applied to divide the TC of each IC into 202 windows. Next, the k-means algorithm was applied to cluster concatenated dFNC matrices across all subjects to assess the frequency and structure of reoccurring FNC connectivity patterns. The number of clusters was set as 4 using the elbow criterion, calculated as the ratio of within-cluster distances to between-cluster distances. We also validated our main results using different sliding window lengths and different numbers of clusters (see 'Validation analysis'). Then, three temporal metrics of connectivity state expression derived from each subject's state vector (Allen et al., 2014) were calculated: (i) fraction of time spent in each state, measured as the proportions of all windows in each state; (ii) mean dwell time in each state, measured as the average number of consecutive windows in the same state; (iii) number of transitions, measured as the number of state transitions. To test the association between the behavioral score and connectivity state expression, we correlated the SWB score with three metrics, separately, regressing out age, gender and mean FD. Because the distribution of the three temporal metrics was non-normality, Spearman's (rank) correlation was used here. Multiple comparisons were performed using the FDR.

Validation analysis. To test the reliability of our work, we examined whether our main results were affected by the different parameters, including the sliding window length and the number of clusters. (i) Window length. To date, there is still no consensus about the optimal window length of the sliding window approach. Some studies have reported that cognitive states can be correctly identified when the window length is set to 30–60 s (Shirer et al., 2012), others showed that the changes in functional connectivity are not sensitive to the window length in the range of 20–40 s (Li et al., 2014) and still others found that a window length of 44 s is a good trade-off between the quality of connectivity estimation and the ability to resolve dynamics (Allen et al., 2014). Therefore, in addition to the window length of 60 s in the main analysis, we also reran the dFNC analysis with another two window lengths (20 s and 44 s). The number of clusters here was set as 4 to compare with the main analysis.

(ii) Number of clusters. Although the number of clusters was 4 in our main analysis, we also set the number of clusters as 5 and 6 in accordance with previous studies (Allen et al., 2014; Abrol et al., 2016; Liu et al., 2017a; Marusak et al., 2017) in order to evaluate the potential influence of the number of clusters. The sliding window length here was set as 60 s to make it comparable to the main analysis. Moreover, we further validated the main results in dataset 1 in an independent sample (dataset 2) to test the repeatability of our work. In dataset 2, the behavioral assessment of SWB, functional magnetic resonance imaging (fMRI) image acquisition and pre-processing and GICA, as well as dFNC analytical procedure, including all setup parameters (window length = 60 s, number of clusters = 4), were consistent with the main analysis in dataset 1 mentioned above. Finally, we examined the similarity of the SWB-related state between the main results and the results from different analysis parameters in dataset 1 using the Pearson correlation. In the same vein, the similarity of the SWB-related state between the main results in dataset 1 and the results in dataset 2 was also calculated. Multiple comparisons were performed using the FDR.

Results

Table 1 shows the mean and s.d. for age, gender and SWB score of all subjects that were included in the final analysis of two datasets.

Static FNC-behaviour correlation analysis

A correlation analysis was conducted to examine the association between the SWB score and the static FNC. The results showed that the SWB score was negatively correlated with functional connectivity between the SN and aDMN ($r = -0.16$, $P < 0.05$, FDR corrected) (Figure 1). After controlling for age, gender and mean FD, the negative correlation between the SWB score and functional connectivity between the SN and aDMN was still significant.

dFNC analysis

As mentioned above, we adopted a k-means approach to clustering the dFNC from all subjects into four connectivity states. Figure 2A shows the cluster centroid and the percentage of occurrences of each matrix (arranged in the order of emergence). The matrix reflects the functional connectivity between five networks. Analysis of the correlation between the SWB score and three temporal metrics derived from each subject's state vector revealed that state 4, which was characterized by weak functional connectivity among all five networks and strong functional connectivity between the aDMN and pDMN, as well as strong functional connectivity between the lFPN and rFPN, was related to the SWB score (Figure 2B). Specifically, the fraction of time spent in state 4 was negatively correlated with the SWB score ($r = -0.16$, $P < 0.05$, FDR corrected). The mean dwell time in state 4 was negatively correlated with SWB score ($r = -0.21$,

Table 1. Descriptive statistics of behavioral measures in two datasets

Mean ± s.d.	Dataset 1	Dataset 2
Age	20.18 ± 1.39	22.36 ± 1.49
Gender (M/F)	84/247	97/115
SWB	42.61 ± 8.71	44.89 ± 10.38

Note: s.d. = standard deviation, M/F = male/female, SWB = subjective well-being

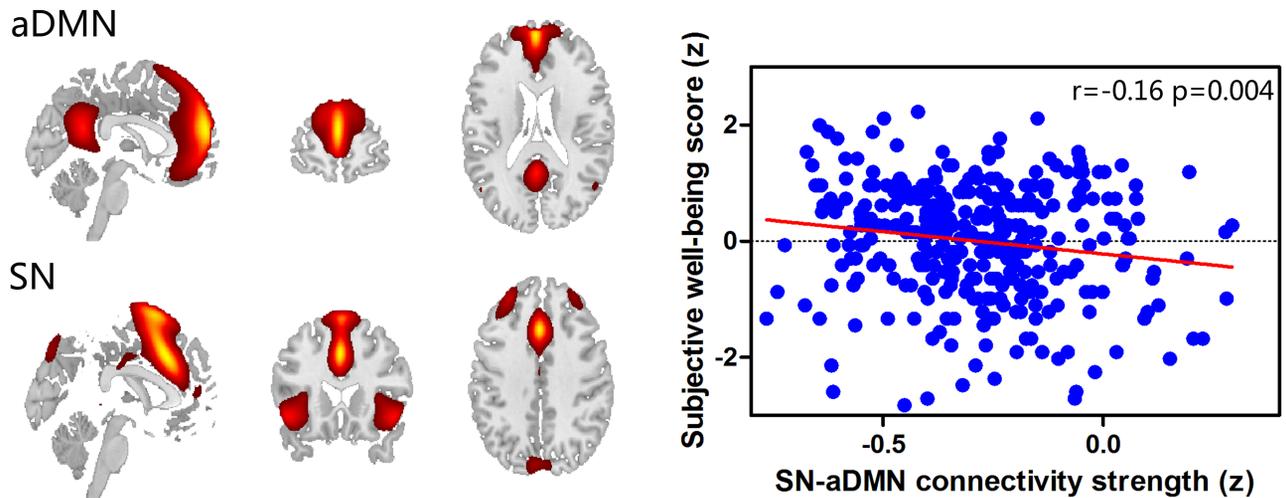


Fig. 1. Left: The SM of the aDMN and SN derived from group spatial independent component analysis of dataset 1. Right: Scatter plot depicting the negative correlation between the SWB score and functional connectivity between SN and aDMN from dataset 1. The significance level for corrections was set at $P < 0.05$. Multiple comparisons were performed using the FDR. SN and aDMN.

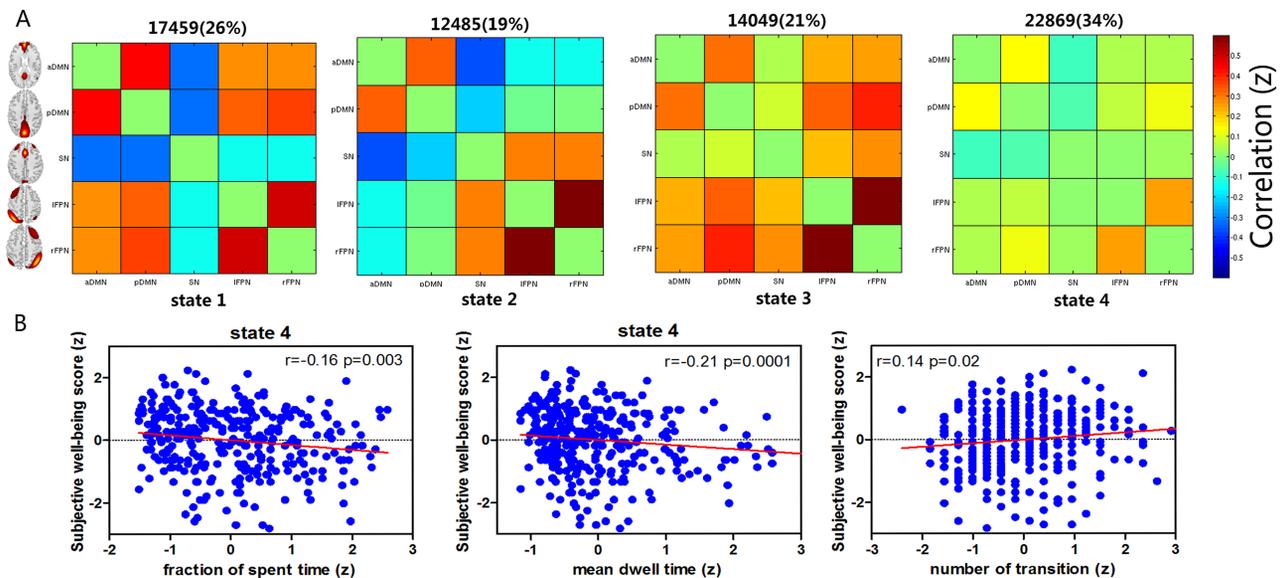


Fig. 2. The four cluster medians of all subjects in dataset 1 are shown in (A) along with the total number, percentage of occurrences and ICA components representing the five networks. The color bar represents the z value of FNC. (B) Scatter plots depicting the correlations between the SWB score and three temporal metrics derived from each subject's state vector in dataset 1. Left: negative correlation between the SWB score and the fraction of time spent in state 4. Middle: negative correlation between the SWB score and the mean dwell time in state 4. Right: positive correlation between the SWB score and the number of transitions. The significance level for correction was set at $P < 0.05$. Multiple comparisons were performed using the FDR. aDMN, pDMN, SN, lFPN and rFPN.

$P < 0.05$, FDR corrected). Additionally, the total number of transitions across states was positively related to the SWB score ($r = 0.14$, $P < 0.05$, FDR corrected). After controlling for age, gender and mean FD, these results were still significant.

Validation analysis

First, similar results were obtained using different sliding window lengths or different numbers of clusters in dataset 1. The specifics are described below. (i) Window length. We found that the SWB score was negatively correlated with the fraction of time spent in state 1 ($r = -0.15$, $P < 0.05$, FDR corrected) when the window length was set as 20 s (Figure 3A). When the window length was set as 44 s, we also found that the SWB score was negatively correlated with the fraction of time spent in state 3 ($r = -0.16$, $P < 0.05$, FDR corrected) and was negatively correlated

with the mean dwell time in state 3 ($r = -0.18$, $P < 0.05$, FDR corrected) (Figure 3B). (ii) Number of clusters. We found that the SWB score was negatively correlated with the fraction of time spent in state 3 ($r = -0.19$, $P < 0.05$, FDR corrected) and was negatively correlated with the mean dwell time in state 3 ($r = -0.18$, $P < 0.05$, FDR corrected) when the number of clusters was set as 5 (Figure 3C). When the number of clusters was set as 6, we also found that SWB score was negatively correlated with the fraction of time spent in state 4 ($r = -0.20$, $P < 0.05$, FDR corrected) and was negatively correlated with the mean dwell time in state 4 ($r = -0.15$, $P < 0.05$, FDR corrected) (Figure 3D). Second, the main findings in dataset 1 were well replicated in dataset 2. Consistent with the static FC result in dataset 1, there was a significant negative correlation between SWB score and the static SN-aDMN connectivity in dataset 2 ($r = -0.15$,

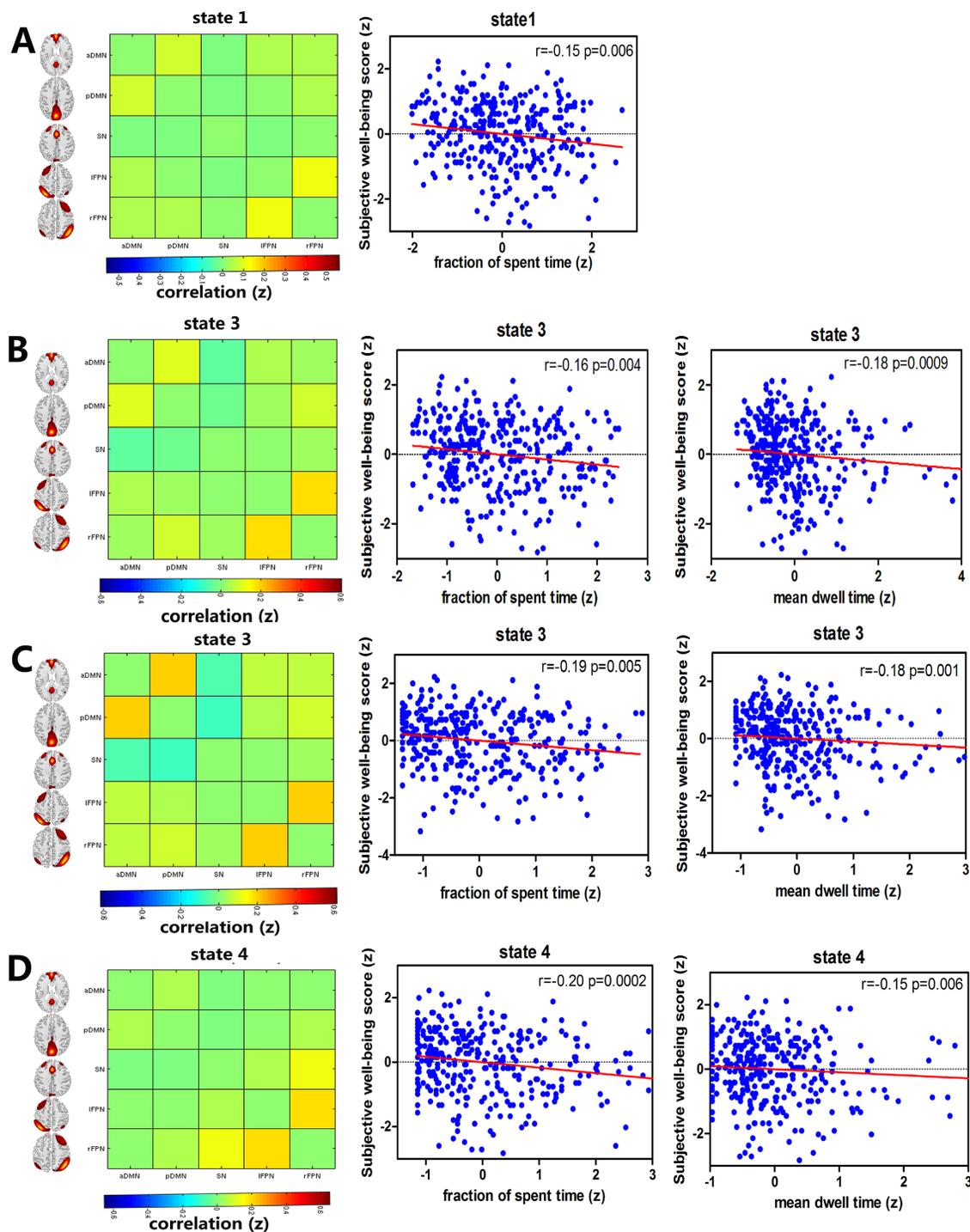


Fig. 3. Association between temporal metrics derived from subjects' state vector and behavior score using different analysis parameters in dataset 1. (A) Heat map depicting the negatively correlated brain state when the window length was set as 20 s (i.e. state 1) with ICA components representing the five networks. Scatter plot depicting the negative association between the SWB score and the fraction of time spent in state 1 when the window length was set as 20 s. (B) Heat map depicting the negatively correlated brain state when the number of clusters was set as 5 (i.e. state 3) with ICA components representing the five networks. Scatter plot depicting the negative association between the SWB score and two temporal metrics (the fraction of time spent in state 3 and the mean dwell time in state 3) when the number of clusters was set as 5. (C) Heat map depicting the negatively correlated brain state when the number of clusters was set as 6 (i.e. state 4) with ICA components representing the five networks. Scatter plot depicting the negative association between the SWB score and two temporal metrics (the fraction of time spent in state 4 and the mean dwell time of state 4) when the number of clusters was set as 6. (D) Heat map depicting the negative correlation between the brain state when the window length was set as 44 s (i.e. state 3) and the ICA components representing the five networks. Scatter plot depicting the negative association between the SWB score and two temporal metrics (the fraction of time spent in state 3 and the mean dwell time in state 3) and positive correlation between the SWB score and the number of transitions when the window length was set as 44 s. The color bar represents the z value of FNC. The significance level for correction was set at $P < 0.05$. Multiple comparisons were performed using the FDR. aDMN, pDMN, SN, IFFN and rFFN.

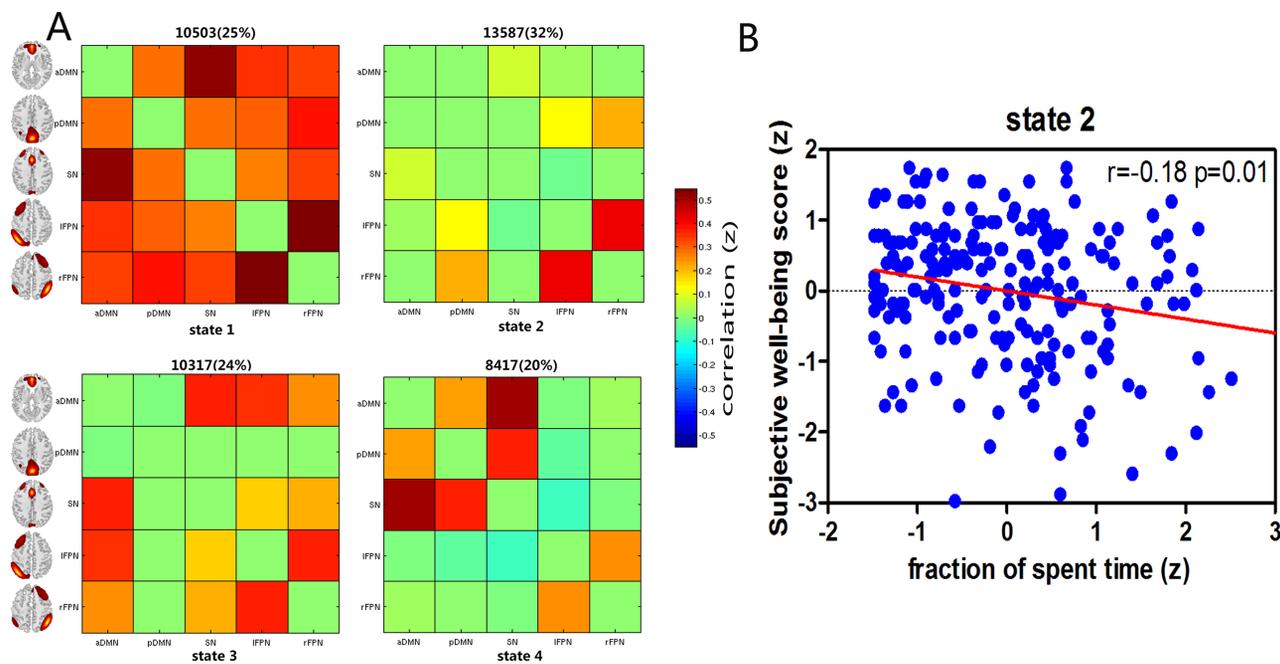


Fig. 4 . The four cluster medians of all subjects in dataset 2 are shown in (A) along with the total number, percentage of occurrences and ICA components representing the five networks. The color bar represents the z value of FNC. (B) Scatter plots depicting the negative association between the SWB score and the fraction of time spent in state 2 of dataset 2. The significance level for correction was set at $P < 0.05$. Multiple comparisons were performed using the FDR. aDMN, pDMN, SN, IFFN and rFFN.

Table 2 . Similarity analysis of patterns all significant SWB-related states

State 4 (W = 60 s; C = 4; dataset 1)	r	p
State 1 (W = 20 s; C = 4; dataset 1)	0.8924	5.1473e-04 ^a
State 3 (W = 44 s; C = 4; dataset 1)	0.9896	5.0234e-08 ^a
State 3 (W = 60 s; C = 5; dataset 1)	0.9230	1.4039e-04 ^a
State 4 (W = 60 s; C = 6; dataset 1)	0.7539	0.0118 ^a
State 2 (W = 60 s; C = 4; dataset 2)	0.7181	0.0193 ^a

Note: W = sliding window length, C = number of clusters. ^aThe correction was significant after FDR correction.

$P = 0.03$). Besides, there was also a negative correlation between the SWB score and the fraction of time spent in state 2 in dataset 2 ($r = -0.18$, $P < 0.05$, FDR corrected, Figure 4). Third, the similarity analysis between patterns of all SWB-related states showed that the connectivity pattern of all SWB-related states, whether in dataset 1 or in dataset 2, is positively correlated with state 4 in the main results (all $r > 0.7$, $P < 0.05$, FDR corrected) (Table 2).

The results in datasets 1 and 2 showed high similarity. The result that the fraction of time spent in a specific state was positively correlated with SWB score is significant and consistently reliable. Moreover, the connectivity patterns of SWB-related states showed high similarity between the two datasets. However, there were also some comparisons in which the two datasets differed. In dataset 1, we found a negative correlation between the SWB score and the mean dwell time in a specific state, as well as a positive correlation between the SWB score and the total number of transitions across states, while these correlations were not significant in dataset 2.

Discussions

The present study used both the ICA and dFNC approaches to investigate the relationship between SWB and large-scale brain

FNC during rs-fMRI (both static and dynamic) in two large independent datasets. Static FNC results showed that the strength of functional connectivity between SN and aDMN was negatively correlated with SWB. dFNC results showed that SWB was negatively correlated with the fraction of time spent in state 4 and the mean dwell time in state 4. The characteristics of state 4 were weak cross-network connectivity (between DMN, SN and FPN) and strong within-network connectivity (within DMN and within FPN). In addition, SWB was positively correlated with the total number of transitions across states. More importantly, the main findings were well replicated with different analysis parameters and further validated in an independent sample. Taken together, our results revealed that dynamic interactions between networks involved in self-focused processing, emotional regulation and cognitive control underlies SWB.

The results of static FNC analysis showed that SWB is negatively correlated with functional connectivity between SN and aDMN and may provide neurological evidence for the cognitive basis of SWB. SWB is composed of two components: an affective component, which refers to affect balance and happy or unhappy emotional states, and a cognitive component, which refers to cognitive control and evaluation of life (Diener et al., 1985; Pavot and Diener, 1993; Diener et al., 2003). Regarding affective components, happy people are associated with positive emotional expression and resilience (Gan-Qi and Huang, 2012; Pe et al., 2013). Unhappy people are sensitive to negative emotional events and dwell excessively on self-conscious thoughts (Kringelbach and Berridge, 2009; Lyubomirsky et al., 2011). The SN is active when people perceive salience and emotional stimuli (social pain or pleasure) (Cox et al., 2011; Cacioppo et al., 2013). For instance, social rejection would lead to increased activity in the regions within the SN, such as the dorsal ACC and insula (Eisenberger et al., 2003). A task-fMRI study has also shown that a higher happiness score is associated with increased activity of the ventral ACC for negative information (Van Reekum et al., 2007). The intrinsic activity of the DMN is associated with the

inclination to rumination (Nolen-Hoeksema et al., 2008), which is associated with the depressive disorder (Sheline et al., 2010). For instance, there was a positive correlation between rumination score and functional connectivity within the DMN (Luo et al., 2015a). In terms of the cognitive component, a recent study found that psychological resilience, an ability allowing individuals to positively adapt and respond to stress and adversity (Luthar et al., 2000), was negatively correlated with cross-network connectivity between the DMN and the SN (Brunetti et al., 2017). The resilience score is positively correlated with levels of life satisfaction (Hu et al., 2015). Functional connectivity between the SN and the aDMN plays an important role in SWB. Patients with mental disorders who exhibit a low level of happiness (Cloninger, 2006) show disrupted equilibrium between the DMN and the SN (Sripada et al., 2012). For instance, an increased interaction between the DMN and the SN has been reported in post-traumatic stress disorder (Yin et al., 2011) and increased connectivity between the insula and the DMN was associated with higher self-report anxiety (Dennis et al., 2011). These may suggest that enhanced DMN-SN connectivity, which is involved in sustained hypervigilance and hyperarousal, is harmful to well-being. In brief, our finding of a negative correlation may account for the fact that people with low levels of SWB are sensitive to negative emotional events, while people with high levels of SWB are associated with good mental adaptability and resilience.

Our study also extends the result of static FNC to a more subtle time scale by adopting the dFNC approach. The dFNC results showed that SWB was negatively correlated with the fraction of time spent in state 4 and the mean dwell time in state 4. That is to say, people who spent more time in state 4 and are inclined to dwell on state 4 would exhibit a lower level of SWB. State 4 is characterized by weak functional connectivity between networks (DMN, FPN and SN) and strong functional connectivity within the DMN (connectivity between the aDMN and pDMN), as well as strong functional connectivity within the FPN (connectivity between the lFPN and rFPN). Overall, weak functional connectivity between networks and strong functional connectivity within networks refer to functional segregation and integration (Rubinov and Sporns, 2010), which is associated with flexible information transfer (Achard and Bullmore, 2007). Weaker functional connectivity between networks indicates less-efficient information transfer between networks (Tian et al., 2018). Previous studies suggested that functional segregation and integration involve the maturity of the brain, and disruption of the development of segregation and integration may be associated with mental disorders (Fair et al., 2007; Stevens et al., 2009; Dosenbach et al., 2010), such as autism spectrum disorder (ASD) and depression, that exhibit low levels of happiness (Wells et al., 1989; Goodman et al., 2000; Cloninger, 2006). For instance, a meta-analysis found that depressed patients exhibit hypoconnectivity between brain networks involved in cognitive control and salience or emotional processing (Kaiser et al., 2015). Similarly, global weak functional connectivity among networks involved in social perception and communication was also found in youth with ASD (Rudie et al., 2011; Yerys et al., 2017). Therefore, these studies indicated that higher levels of SWB may be related to more-efficient information transfer between networks. The SWB result was positively correlated with the total number of transitions across states, which also supports this point. Rapid transitions between different states may be indicative of cognitive flexibility (Scott, 1962), which refers to the mental ability to switch one's thinking to accommodate various changes (Leber et al., 2008). Cognitive flexibility was positively correlated

with the level of mindfulness, which was linked to improvements in well-being (Moore and Malinowski, 2009). In short, these findings suggest that high levels of SWB are associated with flexible interactions between multiple brain networks involved in cognitive control and emotional processing.

In addition, strong within-network connectivity (within the DMN and within the FPN) in state 4 might be associated with the self-reflection and cognitive control processes that underlie SWB (Andrews-Hanna et al., 2013; Heller et al., 2013). The activity of the DMN is associated with unconstrained self-referential cognition (Buckner et al., 2008; Raichle et al., 2001). A previous study has shown that increased functional connectivity within the DMN is associated with lower levels of happiness and is positively correlated with the inclination to ruminate (Luo et al., 2015a). It reveals that unhappy people may be lost in negative emotion and spend more time on negative life events (Nolen-Hoeksema et al., 2008). Then, the FPN, which is associated with working memory, task-set switching, inhibition and flexibility (Vincent et al., 2008; Niendam et al., 2012), also plays a great role in the experience of SWB (Abdel-Khalek, 2010; Kong et al., 2015a, 2016). For example, a voxel-based morphometry study found that regional grey matter volume in multiple pre-frontal regions, such as the superior frontal gyrus (SFG) and mid-cingulate cortex, was negatively associated with quality of life (Takeuchi et al., 2014). In the same vein, an rs-fMRI study has also shown, based on fALFF in the SFG and OFC, that increased activity in these regions was associated with disruption of inhibitory ability in patients with cognitive-affective brain disorder (Zhou et al., 2014), negatively correlated with cognitive well-being (Kong et al., 2015a). In summary, our findings provide a neural basis for the self-reflection processing and cognitive evaluation process that underlies SWB.

Finally, the main results in dataset 1 were well replicated when using various analytical parameters, including the sliding window length and the number of clusters, and were further validated in an independent sample (dataset 2) to confirm the reliability and repeatability of our work. The results within dataset 1 and within dataset 2 all showed high similarity. In addition, it seems that the results of dataset 2 were not completely consistent with the main results of dataset 1. There are two potential reasons for this. First, there were some differences in the subjects between the two samples. Both the mean age and the SWB score of the subjects in dataset 1 are lower than those in dataset 2 ($t_{\text{age}} = -17.56$, $P_{\text{age}} < 0.001$; $t_{\text{SWB}} = -2.76$, $P_{\text{SWB}} < 0.01$). Second, the method we used in the present study may limit the direct comparison of the two samples. ICA is a data-driven method and requires no a priori hypothesis (Zuo et al., 2010). The ICs obtained from the ICA are based on the data for each sample. Though the SM showed high overlap, there were still small differences in the SMs of the components derived from ICA using different samples. Furthermore, the clustering method made it difficult to obtain the same states using different samples. To compare the results of the different samples, we used the same setup parameters in the GICA and dFNC analyses and further conducted a correlation analysis to examine the similarity between the patterns of SWB-related states across the two samples. We have found that the fraction of time spent in a specific state was negatively correlated with SWB score, and this was consistent across samples. Furthermore, the connectivity patterns of SWB-related states across samples showed high similarity. Taken together, these findings consistently suggested that dynamic interactions between the DMN, SN and FPN, which are involved in self-focused processing, emotional regulation and cognitive control, play an important role in SWB.

The correlation coefficient is small in our study ($r = 0.1$ to 0.2 range). Previous research has found that correlations can be unstable in small samples but converge to be stable with increasing sample size (Schönbrodt and Perugini, 2013). The present study explored the relationship between SWB score and functional connectivity between networks in two big samples. Although the correlation coefficient is small, it is consistent with previous studies which aimed to explore the relationship between the intrinsic brain activity and well-being using similar methods in a big sample (Feng et al., 2016; Kong et al., 2015b, 2016; Luo et al., 2015b). For example, the study of Kong et al. (2015b), which aimed to explore the neurobiological pathway linking personality and eudaimonic well-being in a big sample ($N = 286$), found that neuroticism is correlated with the fALFF in the posterior superior temporal gyrus (pSTG) ($r = -0.15$, $P = 0.048$; FDR corrected) and thalamus ($r = -0.20$, $P = 0.005$; FDR corrected) and the thalamic-insular connectivity ($r = 0.17$, $P = 0.021$; FDR corrected). These correlation coefficients also ranged from 0.1 to 0.2 . In addition, the relationship between behavior and brain seems to be complicated and may be influenced by other factors, such as other behavioral and genetic variables. The present study only explored the relationship between SWB score and functional connectivity between networks while the relationship may be mediated by other variables, such as personality and emotional intelligence (Kong et al., 2015a). So further studies could add multidimensional data to get a higher variance of SWB.

Finally, as noted earlier, well-being has hedonic and eudaimonic components. Previous research has found that there are different neural associations with hedonic and eudaimonic well-being (Kong et al., 2015b). Here, we focused on the dynamic FC of only the hedonic component of SWB. Future studies exploring the dynamic FC underlying the eudaimonic component will be needed to provide a complete understanding of the dynamic FC of SWB.

Conclusion

In summary, the current study extends previous studies attempting to examine the SWB-related functional connectivity between large-scale brain networks during rs-fMRI (both static and dynamic). We found that the strength of static functional connectivity between the SN and the aDMN was negatively correlated with SWB. In addition, SWB was negatively correlated with the fraction of the time that participants spent in a brain state characterized by weak cross-network connectivity (between the DMN, the SN and the FPN) and strong within-network connectivity (within the DMN and within the FPN). More importantly, we demonstrated the robustness of this relationship using different analysis parameters and in a new independent sample. These results suggest that the dynamic interactions between networks involved in self-focused processing, emotional regulation and the cognitive control process underlie SWB. Overall, these findings enriched the understanding of the neural correlates of SWB and provided insight into the dynamic neural underpinnings of SWB, which will be useful for future research.

Acknowledgements

This research was supported by the National Natural Science Foundation of China (31470981; 31571137; 31500885; 31600878; 31771231), Project of the National Defense Science and Technology Innovation Special Zone, Chang Jiang Young

Scholar, National Program for Special Support of Eminent Professionals (National Program for Support of Top-notch Young Professionals), the Program for the Top-notch Young Professionals by Chongqing, the Fundamental Research Funds for the Central Universities (SWU1609177), Natural Science Foundation of Chongqing (cstc2015jcyjA10106), the Innovative Research Project for Postgraduate Student of Chongqing (CYS18129), Fok Ying Tung Education Foundation (151023) and the Research Program Funds of the Collaborative Innovation Center of Assessment toward Basic Education Quality at Beijing Normal University.

Conflict of interest. None declared.

References

- Abdel-Khalek, A.M. (2010). Quality of life, subjective well-being, and religiosity in Muslim college students. *Quality of Life Research*, 19(8), 1133–43.
- Abou-Elseoud, A., Starck, T., Remes, J., Nikkinen, J., Tervonen, O., Kiviniemi, V. (2010). The effect of model order selection in group PICA. *Human Brain Mapping*, 31(8), 1207–16.
- Abrol, A., Chaze, C., Damaraju, E., Calhoun, V.D. (2016). The chronnectome: evaluating replicability of dynamic connectivity patterns in 7500 resting fMRI datasets. In: *The 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'16)*.
- Achard, S., Bullmore, E. (2007). Efficiency and cost of economical brain functional networks. *PLoS Computational Biology*, 3(2), e17.
- Allen, E.A., Damaraju, E., Plis, S.M., Erhardt, E.B., Eichele, T., Calhoun, V.D. (2014). Tracking whole-brain connectivity dynamics in the resting state. *Cerebral Cortex*, 24(3), 663–76.
- Allen, E.A., Erhardt, E.B., Damaraju, E., et al. (2011). A baseline for the multivariate comparison of resting-state networks. *Frontiers in Systems Neuroscience*, 5, 2.
- Andrews-Hanna, J.R., Kaiser, R.H., Turner, A.E., et al. (2013). A penny for your thoughts: dimensions of self-generated thought content and relationships with individual differences in emotional well-being. *Frontiers in Psychology*, 4, 900.
- And, R.M.R., Deci, E.L. (2001). On happiness and human potentials: a review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, 52(1), 141–66.
- Bell, A.J., Sejnowski, T.J. (1995). An information-maximization approach to blind separation and blind deconvolution. *Neural Computation*, 7(6), 1129–59.
- Blackford, J.U. (2017). Leveraging statistical methods to improve validity and reproducibility of research findings. *JAMA Psychiatry*, 74(2), 119.
- Brunetti, M., Marzetti, L., Sepede, G., et al. (2017). Resilience and cross-network connectivity: a neural model for post-trauma survival. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, 77, 110–9.
- Buckner, R., Andrews-Hanna, J., Schacter, D. (2008). The brain's default network: anatomy, function, and relevance to disease. *Annals of the New York Academy of Sciences*, 1124, 1–38.
- Button, K.S., Ioannidis, J.P.A., Mokrysz, C., et al. (2013). Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, 14(5), 365–76.
- Cacioppo, S., Frum, C., Asp, E., Weiss, R.M., Lewis, J.W., Cacioppo, J.T. (2013). A quantitative meta-analysis of functional imaging studies of social rejection. *Scientific Reports*, 3, 2027.
- Calhoun, V., Yaesoubi, M., Rashid, B., Miller, R. (2013). Characterization of connectivity dynamics in intrinsic brain networks.

- In: *Global Conference on Signal and Information Processing (Global-SIP)*, 2013 IEEE, IEEE.
- Calhoun, V.D., Adali, T., Pearlson, G.D., Pekar, J. (2001). A method for making group inferences from functional MRI data using independent component analysis. *Human Brain Mapping*, **14**(3), 140–51.
- Calhoun, V.D., Miller, R., Pearlson, G., Adali, T. (2014). The chronnectome: time-varying connectivity networks as the next frontier in fMRI data discovery. *Neuron*, **84**(2), 262–74.
- Campbell, A. (1976). Subjective measures of well-being. *American Psychologist*, **31**(2), 117.
- Cloninger, C.R. (2006). The science of well-being: an integrated approach to mental health and its disorders. *World Psychiatry*, **5**(2), 71.
- Cox, C.L., Uddin, L.Q., Di Martino, A., Castellanos, F.X., Milham, M.P., Kelly, C. (2011). The balance between feeling and knowing: affective and cognitive empathy are reflected in the brain's intrinsic functional dynamics. *Social Cognitive and Affective Neuroscience*, **7**(6), 727–37.
- Craig, A.D. (2009). How do you feel—now? The anterior insula and human awareness. *Nature Reviews Neuroscience*, **10**(1), 59–70.
- Cunningham, W.A., Kirkland, T. (2013). The joyful, yet balanced, amygdala: moderated responses to positive but not negative stimuli in trait happiness. *Social Cognitive and Affective Neuroscience*, **9**(6), 760–6.
- Damaraju, E., Allen, E., Belger, A., et al. (2014). Dynamic functional connectivity analysis reveals transient states of dysconnectivity in schizophrenia. *NeuroImage: Clinical*, **5**, 298–308.
- Dennis, E.L., Gotlib, I.H., Thompson, P.M., Thomason, M.E. (2011). Anxiety modulates insula recruitment in resting-state functional magnetic resonance imaging in youth and adults. *Brain Connectivity*, **1**(3), 245–54.
- Diener, E. (2013). The remarkable changes in the science of subjective well-being. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, **8**(6), 663.
- Diener, E., Biswas-Diener, R. (2011). *Happiness: Unlocking the Mysteries of Psychological Wealth*. John Wiley & Sons.
- Diener, E., Emmons, R.A., Larsen, R.J., Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, **49**(1), 71–5.
- Diener, E., Oishi, S., Lucas, R.E. (2003). Personality, culture, and subjective well-being: emotional and cognitive evaluations of life. *Annual Review of Psychology*, **54**(1), 403–25.
- Diener, E., Oishi, S., Lucas, R.E. (2015). *Subjective well-being: the science of happiness and life satisfaction*, 187–94.
- Diener, E., Suh, E.M., Lucas, R.E., Smith, H.L. (1999). Subjective well-being: three decades of progress. *Psychological Bulletin*, **125**(2), 276–302.
- Dosenbach, N.U.F., Nardos, B., Cohen, A.L., et al. (2010). Prediction of individual brain maturity using fMRI. *Science*, **329**(5997), 1358–61.
- Eisenberger, N.I., Lieberman, M.D., Williams, K.D. (2003). Does rejection hurt? An fMRI study of social exclusion. *Science*, **302**(5643), 290.
- Etkin, A., Egner, T., Kalisch, R. (2011). Emotional processing in anterior cingulate and medial prefrontal cortex. *Trends in Cognitive Sciences*, **15**(2), 85–93.
- Fair, D.A., Dosenbach, N.U., Church, J.A., et al. (2007). Development of distinct control networks through segregation and integration. *Proceedings of the National Academy of Sciences*, **104**(33), 13507–12.
- Feng, K., Wang, X., Song, Y., Liu, J., et al. (2016). Brain regions involved in dispositional mindfulness during resting state and their relation with well-being. *Social Neuroscience*, **11**(4), 331–343.
- Gan-Qi, T., Huang, M.-E. (2012). Diverse consequences of negative emotional responses between high and low happiness people. *Acta Psychologica Sinica*, **8**, 11.
- Geng, X.W., Zhang, F., Zheng, Q.Q. (2009). A study of the predictive validity of explicit and implicit self-esteem for subjective well-being of university students. *Psychological Development and Education*, **1**, 97–12.
- Goodman, R., Ford, T., Richards, H., Gatward, R., Meltzer, H. (2000). The development and well-being assessment: description and initial validation of an integrated assessment of child and adolescent psychopathology. *The Journal of Child Psychology and Psychiatry and Allied Disciplines*, **41**(5), 645–55.
- Goulden, N., Khusnulina, A., Davis, N.J., et al. (2014). The salience network is responsible for switching between the default mode network and the central executive network: replication from DCM. *Neuroimage*, **99**, 180–90.
- Heller, A.S., van Reekum, C.M., Schaefer, S.M., et al. (2013). Sustained striatal activity predicts eudaimonic well-being and cortisol output. *Psychological Science*, **24**(11), 2191–200.
- Hooker, C.I., Knight, R.T. (2006a). In the inhibitory control of emotion. *The Orbitofrontal Cortex*, 307.
- Hooker, C.I., Knight, R.T. (2006b). *The role of lateral orbitofrontal cortex in the inhibitory control of emotion. The Orbitofrontal Cortex*, 307.
- Hu, T., Zhang, D., Wang, J. (2015). A meta-analysis of the trait resilience and mental health. *Personality and Individual Differences*, **76**, 18–27.
- Ioannidis, J.P.A. (2005). Why most published research findings are false. *PLoS Medicine*, **8**(2), e124.
- Jafri, M.J., Pearlson, G.D., Stevens, M., Calhoun, V.D. (2008). A method for functional network connectivity among spatially independent resting-state components in schizophrenia. *Neuroimage*, **39**(4), 1666–81.
- Kaiser, R.H., Andrews-Hanna, J.R., Wager, T.D., Pizzagalli, D.A. (2015). Large-scale network dysfunction in major depressive disorder: a meta-analysis of resting-state functional connectivity. *JAMA Psychiatry*, **72**(6), 603–11.
- Keilholz, S.D. (2014). The neural basis of time-varying resting-state functional connectivity. *Brain Connectivity*, **4**(10), 769–79.
- Kim, D.I., Manoach, D.S., Mathalon, D.H., et al. (2009). Dysregulation of working memory and default-mode networks in schizophrenia using independent component analysis, an fBIRN and MCIC study. *Human Brain Mapping*, **30**(11), 3795–811.
- Kong, F., Ding, K., Yang, Z., et al. (2014). Examining gray matter structures associated with individual differences in global life satisfaction in a large sample of young adults. *Social Cognitive and Affective Neuroscience*, **10**(7), 952–60.
- Kong, F., Hu, S., Wang, X., Song, Y., Liu, J. (2015a). Neural correlates of the happy life: the amplitude of spontaneous low frequency fluctuations predicts subjective well-being. *Neuroimage*, **107**, 136–45.
- Kong, F., Liu, L., Wang, X., Hu, S., Song, Y., Liu, J. (2015b). Different neural pathways linking personality traits and eudaimonic well-being: a resting-state functional magnetic resonance imaging study. *Cognitive, Affective & Behavioral Neuroscience*, **15**(2), 299–309.
- Kong, F., Xue, S., Wang, X. (2016). Amplitude of low frequency fluctuations during resting state predicts social well-being. *Biological Psychology*, **118**, 161–8.
- Kringelbach, M.L., Berridge, K.C. (2009). Towards a functional neuroanatomy of pleasure and happiness. *Trends in Cognitive Sciences*, **13**(11), 479–87.

- Leber, A.B., Turk-Browne, N.B., Chun, M.M. (2008). Neural predictors of moment-to-moment fluctuations in cognitive flexibility. *Proceedings of the National Academy of Sciences*, **105**(36), 13592–7.
- Leonardi, N., Richiardi, J., Gschwind, M., et al. (2013). Principal components of functional connectivity: a new approach to study dynamic brain connectivity during rest. *Neuroimage*, **83**, 937–50.
- Lewis, G.J., Kanai, R., Rees, G., Bates, T.C. (2013). Neural correlates of the ‘good life’: Eudaimonic well-being is associated with insular cortex volume. *Social Cognitive and Affective Neuroscience*, **9**(5), 615–8.
- Li, X., Zhu, D., Jiang, X., et al. (2014). Dynamic functional connectomics signatures for characterization and differentiation of PTSD patients. *Human Brain Mapping*, **35**(4), 1761–78.
- Liu, F., Wang, Y., Li, M., et al. (2017a). Dynamic functional network connectivity in idiopathic generalized epilepsy with generalized tonic-clonic seizure. *Human Brain Mapping*, **38**(2), 957–73.
- Liu, W., Wei, D., Chen, Q., et al. (2017b). Longitudinal test-retest neuroimaging data from healthy young adults in southwest China. *Scientific Data*, **4**, 170017.
- Luo, Y., Huang, X., Yang, Z., Li, B., Liu, J., Wei, D. (2014). Regional homogeneity of intrinsic brain activity in happy and unhappy individuals. *PLoS ONE*, **9**(1), e85181.
- Luo, Y., Kong, F., Qi, S., You, X., Huang, X. (2015a). Resting-state functional connectivity of the default mode network associated with happiness. *Social Cognitive and Affective Neuroscience*, **11**(3), 516–24.
- Luo, Y., Li, B., Liu, J., Bi, C., Huang, X. (2015b). Amplitude of low-frequency fluctuations in happiness: a resting-state fMRI study. *Chinese Science Bulletin*, **60**(2), 170–8.
- Luo, Y., Qi, S., Chen, X., You, X., Huang, X., Yang, Z. (2017). Pleasure attainment or self-realization: the balance between two forms of well-beings are encoded in default mode network. *Social Cognitive and Affective Neuroscience*, **12**(10), 1678–86.
- Luthar, S.S., Cicchetti, D., Becker, B. (2000). The construct of resilience: a critical evaluation and guidelines for future work. *Child Development*, **71**(3), 543–62.
- Lyubomirsky, S. (2001). Why are some people happier than others? The role of cognitive and motivational processes in well-being. *American Psychologist*, **56**(3), 239.
- Lyubomirsky, S., Boehm, J.K., Kasri, F., Zehm, K. (2011). The cognitive and hedonic costs of dwelling on achievement-related negative experiences: implications for enduring happiness and unhappiness. *Emotion*, **11**(5), 1152.
- Lyubomirsky, S., King, L., Diener, E. (2005). The benefits of frequent positive affect: does happiness lead to success? *Psychological bulletin*, **131**(6), 803.
- Marusak, H.A., Calhoun, V.D., Brown, S., et al. (2017). Dynamic functional connectivity of neurocognitive networks in children. *Human Brain Mapping*, **38**(1), 97–108.
- Menon, V. (2011). Large-scale brain networks and psychopathology: a unifying triple network model. *Trends in Cognitive Sciences*, **15**(10), 483.
- Moore, A., Malinowski, P. (2009). Meditation, mindfulness and cognitive flexibility. *Consciousness and Cognition*, **18**(1), 176–86.
- Niendam, T.A., Laird, A.R., Ray, K.L., Dean, Y.M., Glahn, D.C., Carter, C.S. (2012). Meta-analytic evidence for a superordinate cognitive control network subserving diverse executive functions. *Cognitive, Affective, & Behavioral Neuroscience*, **12**(2), 241–68.
- Nolen-Hoeksema, S., Wisco, B.E., Lyubomirsky, S. (2008). Rethinking rumination. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, **3**(5), 400.
- Pavot, W., Diener, E. (1993). Review of the satisfaction with life scale. *Psychological Assessment*, **5**(2), 164.
- Pe, M.L., Koval, P., Kuppens, P. (2013). Executive well-being: updating of positive stimuli in working memory is associated with subjective well-being. *Cognition*, **126**(2), 335–40.
- Poldrack, R.A., Baker, C.I., Durnez, J., et al. (2017). Scanning the horizon: towards transparent and reproducible neuroimaging research. *Nature Reviews Neuroscience*, **18**(2), 115.
- Power, J.D., Barnes, K.A., Snyder, A.Z., Schlaggar, B.L., Petersen, S.E. (2012). Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *Neuroimage*, **59**(3), 2142–54.
- Raichle, M.E., MacLeod, A.M., Snyder, A.Z., Powers, W.J., Gusnard, D.A., Shulman, G.L. (2001). A default mode of brain function. *Proceedings of the National Academy of Sciences*, **98**(2), 676–82.
- Rashid, B., Arbabshirani, M.R., Damaraju, E., et al. (2016). Classification of schizophrenia and bipolar patients using static and dynamic resting-state fMRI brain connectivity. *Neuroimage*, **134**, 645.
- Rubinov, M., Sporns, O. (2010). Complex network measures of brain connectivity: uses and interpretations. *Neuroimage*, **52**(3), 1059–69.
- Rudie, J.D., Shehzad, Z., Hernandez, L.M., et al. (2011). Reduced functional integration and segregation of distributed neural systems underlying social and emotional information processing in autism spectrum disorders. *Cerebral Cortex*, **22**(5), 1025–37.
- Ryff, C.D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality & Social Psychology*, **57**(6), 1069–81.
- Ryff, C.D., Keyes, C.L. (1995). The structure of psychological well-being revisited. *Journal of Personality and Social Psychology*, **69**(4), 719–27.
- Sakoğlu, Ü., Pearlson, G.D., Kiehl, K.A., Wang, Y.M., Michael, A.M., Calhoun, V.D. (2010). A method for evaluating dynamic functional network connectivity and task-modulation: application to schizophrenia. *Magnetic Resonance Materials in Physics, Biology and Medicine*, **23**(5–6), 351–66.
- Schönbrodt, F.D., Perugini, M. (2013). At what sample size do correlations stabilize? *Journal of Research in Personality*, **47**(5), 609–12.
- Scott, W.A. (1962). Cognitive complexity and cognitive flexibility. *Sociometry*, 405–14.
- Seligman, M.E., Csikszentmihalyi, M. (2000). Special issue on happiness, excellence, and optimal human functioning. *American Psychologist*, **55**(1), 5–183.
- Sheline, Y.I., Price, J.L., Yan, Z., Mintun, M.A. (2010). Resting-state functional MRI in depression unmasks increased connectivity between networks via the dorsal nexus. *Proceedings of the National Academy of Sciences*, **107**(24), 11020.
- Shine, J.M., Bissett, P.G., Bell, P.T., et al. (2016). The dynamics of functional brain networks: integrated network states during cognitive task performance. *Neuron*, **92**(2), 544–54.
- Shirer, W., Ryali, S., Rykhlevskaia, E., Menon, V., Greicius, M. (2012). Decoding subject-driven cognitive states with whole-brain connectivity patterns. *Cerebral Cortex*, **22**(1), 158–65.
- Singer, T., Critchley, H.D., Preuschoff, K. (2009). A common role of insula in feelings, empathy and uncertainty. *Trends in Cognitive Sciences*, **13**(8), 334–40.
- Smith, S.M., Fox, P.T., Miller, K.L., et al. (2009). Correspondence of the brain’s functional architecture during activation and rest. *Proceedings of the National Academy of Sciences*, **106**(31), 13040–5.
- Sripada, R.K., King, A.P., Welsh, R.C., et al. (2012). Neural dysregulation in posttraumatic stress disorder: evidence for disrupted

- equilibrium between salience and default mode brain networks. *Psychosomatic Medicine*, **74**(9), 904.
- Stawarczyk, D., Majerus, S., Van der Linden, M., D'Argembeau, A. (2012). Using the daydreaming frequency scale to investigate the relationships between mind-wandering, psychological well-being, and present-moment awareness. *Frontiers in Psychology*, **3**, 363.
- Stevens, M.C., Pearson, G.D., Calhoun, V.D. (2009). Changes in the interaction of resting-state neural networks from adolescence to adulthood. *Human Brain Mapping*, **30**(8), 2356–66.
- Tagliazucchi, E., Laufs, H. (2014). Decoding wakefulness levels from typical fMRI resting-state data reveals reliable drifts between wakefulness and sleep. *Neuron*, **82**(3), 695–708.
- Takeuchi, H., Taki, Y., Nouchi, R., et al. (2014). Anatomical correlates of quality of life: evidence from voxel-based morphometry. *Human Brain Mapping*, **35**(5), 1834–46.
- Taylor, T.E. (2016). Happiness explained. *Erasmus Journal for Philosophy & Economics*, **9**(2), 196–202.
- Tian, L., Li, Q., Wang, C., Yu, J. (2018). Changes in dynamic functional connections with aging. *Neuroimage*, **172**, 31–9.
- Urry, H.L., Nitschke, J.B., Dolski, I., et al. (2004). Making a life worth living: neural correlates of well-being. *Psychological Science*, **15**(6), 367–72.
- Van Reekum, C.M., Urry, H.L., Johnstone, T., et al. (2007). Individual differences in amygdala and ventromedial prefrontal cortex activity are associated with evaluation speed and psychological well-being. *Journal of Cognitive Neuroscience*, **19**(2), 237–48.
- Vincent, J.L., Kahn, I., Snyder, A.Z., Raichle, M.E., Buckner, R.L. (2008). Evidence for a frontoparietal control system revealed by intrinsic functional connectivity. *Journal of Neurophysiology*, **100**(6), 3328.
- Wang, X.D., Wang, X.L., Ma, H. (1999). *Rating Scales For Mental Health*, Beijing: Chinese Mental Health Journal.
- Waytz, A., Hershfield, H.E., Tamir, D.I. (2015). Mental simulation and meaning in life. *Journal of Personality and Social Psychology*, **108**(2), 336.
- Wells, K.B., Stewart, A., Hays, R.D., et al. (1989). The functioning and well-being of depressed patients: results from the medical outcomes study. *JAMA*, **262**(7), 914–9.
- Xinhua, D. (2004). Wang Jisheng (Institute of Psychology, Chinese Academy of Sciences, Beijing); A Review on the Researches about Subjective Well-Being of Adolescents [J], *Advances in Psychological Science*, **1**.
- Xu, J., Zhang, S., Calhoun, V.D., et al. (2013). Task-related concurrent but opposite modulations of overlapping functional networks as revealed by spatial ICA. *Neuroimage*, **79**, 62–71.
- Yan, C., Zang, Y. (2010). DPARSF: a MATLAB toolbox for 'pipeline' data analysis of resting-state fMRI. *Frontiers in Systems Neuroscience*, **4**, 13.
- Yerys, B.E., Herrington, J.D., Satterthwaite, T.D., Guy, L., Schultz, R.T., Bassett, D.S. (2017). Globally weaker and topologically different: resting-state connectivity in youth with autism. *Molecular Autism*, **8**(1), 39.
- Yin, Y., Jin, C., Hu, X., et al. (2011). Altered resting-state functional connectivity of thalamus in earthquake-induced post-traumatic stress disorder: a functional magnetic resonance imaging study. *Brain Research*, **1411**, 98–107.
- Yue, S.H., Zhang, W., Huang, H.Q., Li, D.P. (2006). The adolescent's subjective well-being and mental health and relationships with stress coping. *Psychological Development and Education*, **3**, 93–8.
- Zhou, Y., Lui, Y.W., Zuo, X.N., et al. (2014). Characterization of thalamo-cortical association using amplitude and connectivity of functional MRI in mild traumatic brain injury. *Journal of Magnetic Resonance Imaging*, **39**(6), 1558.
- Zuo, X.-N., Kelly, C., Adelstein, J.S., Klein, D.F., Castellanos, F.X., Milham, M.P. (2010). Reliable intrinsic connectivity networks: test-retest evaluation using ICA and dual regression approach. *Neuroimage*, **49**(3), 2163–77.