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RESEARCH PAPER

The Relationship Between Personality Traits and Well-Being via Brain Functional Connectivity

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Abstract
Different single personality traits have been found to be closely related to well-being, and single personality traits and well-being shared multiple neural substrates. Yet little is known about how the multi-trait profile, which better reflects individual differences in terms of taxonomy, is related to multi-faceted well-being, and whether the spontaneous brain activities of their common neural substrates can partially explain this relationship. To advance our understanding, we examined the relationships among personality traits, well-being, and brain functional connectivity generated in resting-state functional MRI among 729 healthy participants. We first identified a linear combination of personal traits (i.e., higher extraversion, conscientiousness, and agreeableness, but lower neuroticism) that was most relevant to a set of well-being indicators (i.e., positive affect, life satisfaction, and meaning of purpose) by considering their canonical correlational relation. Next, by using the network-based statistic method, we identified the sub-network associated with the well-being canonical variate. The subnetwork was formed by functional connectivity within and between multiple brain networks spanning from primary sensory networks to high-order networks. Moreover, the mediation analyses showed that the relationship between personality trait variate and well-being variate was explained by higher positive functional connectivity and higher global network efficiency within the identified sub-network. These findings suggest that effective functional communication within and between multiple brain networks can be a potentially important mechanism for promoting better well-being.

Keywords Personality trait · Well-being · Resting-state fMRI · Functional connectivity

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1 Introduction

Enhancing well-being becomes a non-negligible goal due to an increase in stress in contemporary society (Boman, 2018). Different theoretical frameworks have been proposed for well-being. One of the frameworks defines well-being as the extent to which people fulfill their potential and achieve their self-worth, i.e., psychological well-being (Linley et al., 2009). Another one defines well-being as the extent to which people satisfy with their life and experience positive affect, i.e., subjective well-being (Ryan & Deci, 2001). In both theoretical frameworks, well-being is considered as a complicated, multi-faceted construct. The scales measuring psychological well-being include self-acceptance, purpose in life, and personal growth (Linley et al., 2009), and the scales measuring subjective well-being include life satisfaction and positive/negative affect (Diener et al., 1997).

Well-being is found to relate to diverse outcomes, including health-related outcomes (Aspinwall & Tedeschi, 2010) and social relationships (Salsman et al., 2014). Given its significance, many studies tried to identify the factors that promote or impair well-being among individuals. Personality traits were involved in the tendency to perceive and interpret daily events and life circumstances (Brief et al., 1993), which, in turn, were substantially associated with the level of well-being among individuals (Diener et al., 2003). In general, lower neuroticism (Librán, 2006; Steel et al., 2008), higher extraversion (Lee et al., 2008; Soto, 2015), higher conscientiousness (Lightsey et al., 2014), and higher agreeableness (Zhang & Tsingan, 2014) are related to better well-being. In contrast, the effect of openness to new experiences (McCrae & Costa, 1991) on well-being is inconsistent and relatively weak.

Despite a wealth of research on the relation between personality traits and well-being, previous studies mostly analyzed the relationship between a single personality trait and a single dimension of well-being. This practice often ignored possible interactions among various personality traits and different dimensions of well-being (Mai & Ness, 1999), possibly leading to an oversimplified conclusion (DeNeve & Cooper, 1998). Importantly, it was found that a personality trait profile instead of single traits may better reflect individual differences from a biological perspective, which may facilitate the understanding of gene-environment interactions (Cloninger & Zwir, 2018). To address this concern, the present study examined how a multi-trait profile is related to multi-faceted well-being by identifying a personality profile that can be the most relevant to multi-faceted well-being.

To further enhance the understanding of the relationship between personality traits and well-being, we explored its underlying neural basis. We used data of resting-state functional magnetic resonance imaging (R-fMRI), which detects spontaneous fluctuation of blood oxygenation level-dependent (BOLD) signals from various brain regions and identifies co-activation patterns during rest (Damoiseaux et al., 2006). R-fMRI has been proved to be a useful tool to examine the neural basis of stable personal characteristics, including self-construal (Li et al., 2018), trait loneliness (Yi et al., 2018), and trait anxiety (Tian et al., 2016).

Abundant evidence is obtained to support that the brain is important for dealing with different processes related to well-being, including emotion recognition (Rickard & Vella-Brodrick, 2014), emotion regulation (Rolls, 2000), and evaluation of life satisfaction (Kagan, 2018). Yet, diverse brain regions were identified. For instance, greater happiness was associated with increased regional homogeneity within the prefrontal cortex and temporal lobe (Luo et al., 2014). Greater eudaimonic well-being was linked to weaker functional connectivity (FC) between the thalamus and insula (Kong et al., 2015a, 2015b). The amplitudes of low-frequency fluctuation in the left postcentral gyrus and bilateral posterior superior temporal gyrus were correlated with higher life satisfaction, and that in the right amygdala was associated with positive affect (Kong et al., 2015a, 2015b). The hyperconnectivity within the default mode network, including the inferior parietal lobule, medial prefrontal cortex, and posterior cingulate cortex, was more likely to be observed among individuals with lower scores in happiness (Luo et al., 2016). In line with the multi-faceted nature of well-being (Linley et al., 2009; Ryan & Deci, 2001), these findings showed that well-being is associated with diverse regions widely distributed in the brain. However, similar to the research on personality traits and well-being, previous work did not examine the brain mechanism related to well-being by considering its multiple facets simultaneously.

Moreover, these brain regions and networks related to well-being have also been found to be associated with personality traits. Specifically, a recent meta-analysis demonstrated that functional fluctuation of human brain spontaneous activity in the left middle temporal gyrus, left superior temporal gyrus, and right supramarginal gyrus was significantly correlated with neuroticism (Lin et al., 2023). The functional connectivity within the default mode network, particularly the left inferior parietal lobe, bilateral superior parietal lobe, and the right precuneus, was correlated with extraversion (Sampaio et al., 2014). The functional connectivity associated with extraversion was widely distributed among brain regions involved in emotion perception and primary sensory processing, such as amygdala, temporal pole (Aghajani et al., 2014), motor cortex, and occipital cortex (Hsu et al., 2018). And the functional connectivity between dorsolateral prefrontal cortex and inferior parietal lobule was positively associated with conscientiousness (Gao et al., 2021). The functional connectivity associated with agreeableness was distributed among areas involved in empathy and social information processing, such as precuneus and anterior cingulate cortex (Adelstein et al., 2011).

In summary, well-being and personality traits shared multiple neural substrates, such as superior and middle temporal gyrus, inferior parietal lobule, and motor cortices. Considering that previous studies showed that each of the five personality dimensions was associated with different resting state networks (Adelstein et al., 2011; Markett et al., 2018; Servaas et al., 2015), we speculated that the functional connectivity among the shared neural correlates might mediate the association between personality traits and well-being.

There were two major goals in the present study. The first goal was to identify a personality profile that can be the most relevant to multi-faceted well-being. We utilized canonical correlation analysis (CCA) to analyze the interrelated relationship between the two sets of variables (i.e., multiple personality traits and multi-faceted well-being). CCA weighs the set of outcome variables (i.e., the well-being canonical variate) that are the most associated with a weighted combination of the predictor set (i.e., the personality trait canonical variate). It can be achieved through linear transformations based on the maximum correlation method (Conrod et al., 2011). In other words, the results provided by CCA reveal a well-being-oriented personality profile. The second goal was to explore the brain basis for the relationship between personality traits and well-being by examining the information transmission ability across brain regions. We first used the network-based statistic method (Zalesky et al., 2010) to detect the sub-networks associated with the well-being canonical variate. Next, we examined whether the information transmission ability of identified sub-networks, which was indicated by mean FC strength and global efficiency, would explain the relationship between personality traits and well-being. The schematic for the analytical procedures utilized in this study is presented in Fig. 1.

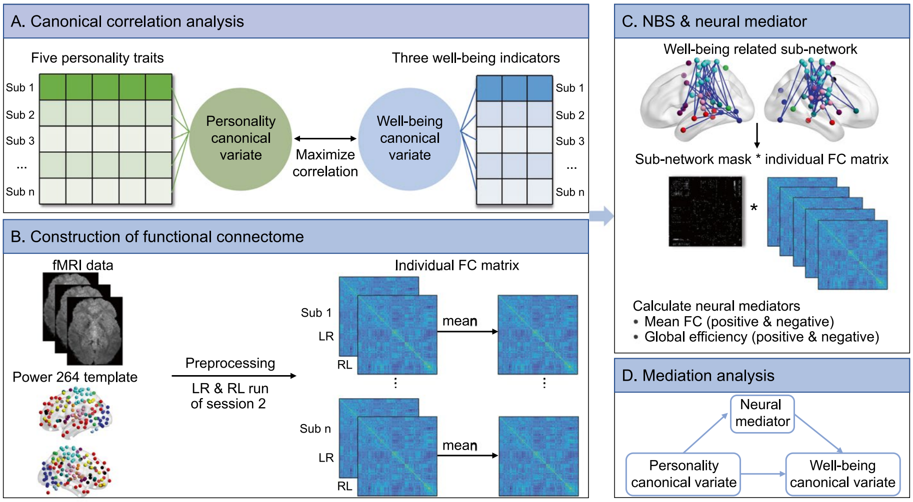

Fig. 1 Schematic diagram of study design and methodology. **A** Using canonical correlation analysis (CCA) to analyze the interrelated association between multiple personality traits and multi-faceted well-being. **B** Applying the Power 264 brain parcellation template (Power et al., 2011) to construct functional connectome based on the resting-state fMRI data from LR and RL run of session 2. **C** Utilizing network-based statistic (NBS) to identify the well-being related sub-network that were significantly correlated with well-being canonical variate obtained from CCA. Then the mean FC strength (positive or negative edge) and global network efficiency (positive or negative sub-network) of the identified sub-network were calculated as neural mediators. **D** Mediation analysis for testing the relationships among personality canonical variate, neural mediator, and well-being canonical variate

2 Method

2.1 Participants

The R-fMRI data, corresponding personality trait, and well-being scores of 970 participants were acquired from the human connectome project S900 public repository that was led by the WU-Minn HCP consortium (HCP; https://db.humanconnectome.org) (Van Essen et al., 2013). Given that the image data of 970 participants were from the secondary dataset, we did not set the sample size before conducting analyses. Among them, 136 participants were discarded for their missing complete imaging data of session 2, 97 were excluded due to excessive head motion in either run of session 2 with the exclusion criteria of mean frame-wise head motion above 0.14 mm (Finn et al., 2015; Yi et al., 2018), and eight were excluded because of incomplete personality scores or demographic information including age, gender, income, educational level. So, 729 participants were included for further analysis (28.67 ± 3.70 years old; 405 females, 324 males). These participants did not have neuropsychiatric disorders, neurodevelopmental or neurologic disorders, or any other contraindications of MRI (Van Essen et al., 2013). Each participant signed informed consent before the scan, and the study was carried out under the permission of the local institutional review board of Washington University. Sensitivity analysis conducted with the G*Power analysis program (Faul et al., 2009) showed that the current sample size (729 participants) would allow us to detect a minimum effect size of $\rho = 0.10$ with 80% power and an alpha level of 0.05.

2.2 Measures for Well-Being and Personality Traits

Well-being and personality traits were measured through the NIH toolbox (http://www.nihtoolbox.org) (Kupst et al., 2015). Well-being was measured by three scales, including Positive Affect Scale, General Life Satisfaction Scale, and Meaning and Purpose Scale. The 34-item Positive Affect scale captures the affective component of well-being (Ryan & Deci, 2001). A sample item includes, "I generally enjoyed the things I did in the past 7 days". Both the 10-item General Life Satisfaction Scale and the 17-item Meaning and Purpose Scale capture the cognitive component of well-being. A sample item of the Life Satisfaction Scale includes, "My life situation is excellent". A sample item of the Meaning and Purpose Scale includes, "My life has a clear sense of purpose". Each item of the Positive Affect Scale and Meaning and Purpose Scale was rated on a 5-point scale ranging from 1 (not at all or strongly disagree) to 5 (very much or strongly agree). For the General Life Satisfaction Scale, five items were rated on a 5-point scale (1: strongly disagree; 5: strongly agree), while the remaining items were rated on a 7-point scale (1: strongly disagree; 7: strongly agree). The total score of each scale was converted to the T-score with the mean of 50 and *SD* of 10 based on item response theory methods (for details, see http://www.healthmeasures.net/score-and-interpret/interpret-scores/nih-toolbox).

Personality traits were measured by the 60-item NEO Five Factor Inventory (NEO-FFI), which was shown great reliability and validity (Egan et al., 2000; Rolland et al., 1998). Each item was rated on a 5-point scale ranging from 1 (strongly disagree) to 5 (strongly agree) [Neuroticism: e.g., "I often get angry at the way people treat me"; Extraversion: e.g., "I really enjoy talking to people"; Agreeableness: e.g., "I would rather cooperate with others than compete with them"; Openness: e.g., "Sometimes when I am reading poetry or liking at a work of art, I feel a chill or wave of excitement"; and Conscientiousness: e.g., "I try to perform all the tasks assigned to me conscientiously"]. The sum score of each personality trait was used for the final analysis.

2.3 MRI Data Acquisition

All participants were scanned on a Siemens 3.0 Tesla MRI Connectome scanner (Smith et al., 2013). Before scanning, participants were required to keep their eyes open and fixate on a white cross on the black screen without thinking or falling asleep. The R-fMRI data were collected with the following scanning parameters: repetition time = 720 ms, echo time = 33.1 ms, flip angle = 52°, field of view = 208×108 mm^2, matrix = 104×90, slices number = 72, slice thickness = 2 mm, and voxel size = $2 \times 2 \times 2$ mm^3. The R-fMRI data were collected in two sessions on two consecutive days. Each session consisted of two runs acquired with a left-to-right (LR) and a right-to-left (RL) phase encoding direction, resulting in 4 resting-state run scans for each participant. Since participants' perceived well-being and functional connectivity were both state-dependent (Machell et al., 2015; Senden et al., 2017), we chose to analyze R-fMRI data from both LR and RL run of session 2, which was collected on the same day as the scales were completed, in order to strengthen the correspondence between neural activity and subjective reports.

2.4 Image Pre-Processing

The HCP minimal pre-processing pipelines for R-fMRI data were conducted in order to avoid duplicate work and ensure the basic quality of collected images (Glasser et al., 2013). The minimal pre-processing pipelines included the steps of removing spatial distortions, correcting the head motion of each participant, and co-registering functional images into standard space. As mentioned above, 97 participants were excluded for severe head motion that was over 0.14 mm mean framewise head motion (Finn et al., 2015). Further pre-processing steps were conducted with a MATLAB toolbox, named as Data Processing & Analysis of Brain Imaging (DPABI) [http://rfmri.org/dpabi; (Yan et al., 2016)], including removing linear trends and regressing out nuisance factors and temporal band-pass filtering (0.01–0.1 Hz). Nuisance factors included cerebrospinal fluid signals, white matter signals, global signals, and head motion with Friston 24-parameters (Friston et al., 1996). We performed the same preprocessing procedure for the data of the LR and RL run.

2.5 Detection of a Well-Being-Oriented Personality Profile

To identify a well-being-oriented personality profile, we used the CCA method to generate possible pairs of personality trait canonical variates and well-being canonical variates that had the maximum correlation with each other (Hotelling, 1936). In the present study, observed scores of big-five personality traits and well-being were first converted in Z score form to get standardized weights and prevent errors in measuring units of different scales (Sherry & Henson, 2005). Then, the Pearson correlation coefficient was calculated between the canonical variates and observed scores to find the size of the contribution of each component in the CCA. The CCA was implemented by the Matlab function “canoncorr.m” in MATLAB R2018b. For statistical inference, we permuted the indices of participants for the well-being canonical variate scores by 10,000 times, and ran CCA for each permutation to build a null distribution for correlation value between canonical variates.

2.6 Construction of Functional Brain Networks

To explore the underlying neural basis of well-being, the functional brain network was constructed based on the toolbox of graph theoretical network analysis (GRETNA, http://www.nitrc.org/projects/gretna/) (Wang et al., 2015a). We used the Power 264 template to divide the whole brain into 264 regions of interest (ROIs) (Power et al., 2011). The mean time series of each ROI was calculated by averaging the time series of the voxels within the ROI for the preprocessed R-fMRI data of each run, respectively. The two functional connectivity matrices of each participant were then obtained by calculating the Pearson correlation coefficients between the time series of the possible pair of ROIs. After that, Fisher’s z-transformation was performed on the functional connectivity matrix to make the Pearson correlation more normally distributed. Last, the two Fisher’s z-transformed functional connectivity matrices derived from two runs were averaged for each participant. Hence, for each participant, we obtained a 264 by 264 symmetric correlation matrix. In the present study, we used fully connected and weighted functional connectivity matrices to identify the well-being related sub-network and calculate its mean FC strength as well as global efficiency for two reasons. First, the functional connectivity values of these edges in the identified sub-network were all significantly correlated to well-being, which suggested the importance of these connections to well-being. Second, the processes of arbitrary thresholding and binarization in graph theory analysis may induce loss of information (Rubinov & Sporns, 2011), especially for the negative connectivity that was found to have a potential neurophysiological basis and cognitive significance (Keller et al., 2015; Spreng et al., 2016).

2.7 Brain Regions Associated with Well-Being Canonical Variate

Network-based statistic (NBS) was utilized to find out the sub-networks that were correlated with well-being canonical variate obtained from CCA. NBS is designed to identify the connected components that are significantly correlated with interested behavioral measures with controlling for family-wise error rate in the multiple comparisons (Zalesky et al., 2010). NBS was conducted with the network-based statistic (NBS) toolbox (Version 1.2; https://www.nitrc.org/projects/nbs/; Zalesky et al., 2010).

Utilizing the NBS methods, we set the well-being canonical variate score as the variable of interest while controlling for the effects of participants' age, gender, household income, and educational level (i.e., years of education completed). In the first step of NBS, *t*-test was carried out between FC value of any pair of two brain regions and the well-being canonical variate, and then stored the edges that survived the chosen *t*-threshold. An initial threshold of *t*-value was set to be 3.1 (corresponding to the edge-level *p*-value threshold to be 0.001), and the edges that survived 3.1 formed connected sub-network.

Next, to examine the significance of empirically identified sub-network, we randomized the score of well-being canonical variate to repeat NBS analyses for 5000 times, recording the maximal sub-network size above the chosen threshold in each permutation to generate the null distribution. The network-level *p*-value was calculated by dividing the number of permutations in which the maximal sub-network size was greater than the empirical size by the total number of permutations, i.e., 5000 (significance level: $\alpha = 0.05$).

Further, the resulting significant sub-network was defined as a mask to apply to individual fully connected and weighted functional connectomes, which were then directly used to calculate the mean FC strength and global efficiency of identified sub-network. To examine the impact of different initial *t*-threshold, another two thresholds of *t*-value were set to be 2.58 and 3.2 in the validation analysis.

2.8 Neural Basis Underlying the Relation Between Personality Trait Canonical Variate and Well-Being Canonical Variate

To examine whether the identified brain sub-network could explain the relationship between personality traits and well-being, we examined the role of mean FC and global network efficiency of the identified sub-network, which reflect an overall information transmission capability of the sub-network. Specifically, we separated the positive and negative edges within the significant sub-network of each participant's functional connectomes, and then calculated the mean FC of positive edges and the mean FC of the absolute values of negative edges, respectively. A higher mean FC value suggests stronger average positive or negative connections in the sub-network. The following equation was utilized for the computation of the global efficiency of the sub-network (Rubinov & Sporns, 2010):

$$E = \frac{1}{N(N-1)} \sum_{i,j \in N, i \neq j} \frac{1}{l_{ij}}$$

where N is the number of nodes that is the remaining brain regions in the well-being associated sub-network; l_{ij} is the shortest path length between node i and j. Also, the global efficiency calculation was performed basing positive and negative edges, respectively. Specifically, we divide the significant sub-network into a positive sub-network that only included positive edges and a negative sub-network that only included negative edges, and set the strengths of all edges in the negative sub-network as absolute values. Then, the global efficiency of the positive sub-network and negative sub-network was calculated, respectively. The global efficiency of the network indicates the mean inverse shortest path, and higher global efficiency reflects a better ability to transfer efficient information (Toschi et al., 2018).

Four mediation analyses were conducted with personality trait canonical variate as the independent variable, well-being canonical variate as the dependent variable, and mean FC (positive or negative edge) and global network efficiency (positive or negative sub-network) of the identified sub-network as the mediator, separately. Meanwhile, the effects of participants' age, gender, household income, and educational level were controlled as covariates in these four mediation models. We employed the PROCESS macro in SPSS for the mediation analyses using the bootstrap approach with 5000 resamples (Hayes, 2017). The indirect effect of the mediator was considered significant when the bootstrapped 95% confidence intervals (CI) did not include zero (Hayes, 2017).

To quantify the unique and shared variance in the contributions of personality canonical variate and neural mediators calculated based on brain functional connectivity to well-being and eliminate the influence of multicollinearity between them, we conducted a commonality analysis following the previous studies (Nathans et al., 2012; Nimon & Reio, 2011) using the R package *yhat* 2.0–3 (Nimon et al., 2021; https://CRAN.R-project.org/package=yhat). Commonality analysis is an effective technique for uncovering the relative importance of multiple individual predictors to an outcome variable, by partitioning the total explained variance (R^2) in the outcome variable into the unique and common variance accounted by each predictor and each predictor combination (i.e., overlap) (Mullarkey & Schleider, 2020; Nathans et al., 2012; Nimon & Reio, 2011). The unique and common variance partition estimates outputted by commonality analysis, known as commonality coefficients, represent the variance uniquely explained by every single predictor (i.e., unique to personality canonical variate or neural mediator in the present study) and shared variance explained by two or more predictors (i.e., common to personality canonical variate and neural mediator in the present study). The detailed formulas for calculating the commonality coefficients can be found in the Supplementary materials. The partition estimate can be interpreted in terms of effect size (e.g., < 1% negligible, > 1% small, > 9% moderate, and > 25% large) (Cohen, 2013; Mullarkey & Schleider, 2020; Slattery et al., 2021). Moreover, a bootstrapping analysis (5000 bootstraps) was performed to calculate 95% CI for measuring the precision of the partition estimates, and we can inspect whether the 95% CI extends into the negligible range.

3 Results

3.1 The Well-Being-Oriented Personality Trait Profile

In the CCA model, the maximum number of canonical variates that can be extracted is usually equal to the minimal number of variates in the two original sets (e.g., personality and well-being variables set here), and the extracted canonical variates would be generated through the linear transformation of original variables (Dattalo, 2014; Sherry & Henson, 2005). Hence, the CCA yielded three pairs of canonical variates because there were three indicators for well-being. The first pair of canonical variates established the maximum association between personality trait canonical variate and well-being canonical variate ($r = 0.578$, $p < 0.001$, 10,000 permutations), which showed that personality trait canonical variate is appropriate to function as the predictor variate of the well-being canonical variate. Thus, only the first CCA model was used in the present study. The correlation coefficients of remaining two CCA models were $r = 0.177$ ($p < 0.001$, 10,000 permutations) and $r = 0.132$ ($p < 0.001$, 10,000 permutations) respectively.

The canonical structure coefficient, referring to the Pearson correlation between canonical variates and observed scores, was generally utilized to differentiate the size of the contribution of each component (Joshanloo et al., 2012). A cutoff of 0.3 was applied to the canonical structure coefficient to differentiate between large and small contributions (Buckley, 2018; Liu et al., 2009). In the first model, the structure coefficients ($\boldsymbol{r_s}$) of extraversion, neuroticism, conscientiousness, agreeableness, and openness were 0.758, −0.846, 0.551, 0.486, and 0.002, respectively. It suggested that individuals with higher extraversion, higher conscientiousness, higher agreeableness, and lower neuroticism were more likely to report better well-being, while openness had minimal impact on well-being. Besides, all three indicators of well-being, i.e., life satisfaction ($\boldsymbol{r_s} = 0.779$), positive affect ($\boldsymbol{r_s} = 0.871$), and meaning and purpose ($\boldsymbol{r_s} = 0.848$), were significant criteria for the well-being canonical variate. The detailed results of canonical

Table 1 Canonical correlation analysis of well-being and personality traits

Variate	Canonical coefficient	r_s	r_s^2
Personality traits			
Agreeableness	0.132	**0.486**	0.236
Openness	−0.042	0.002	0.000
Conscientiousness	0.159	**0.551**	0.303
Neuroticism	−0.579	**−0.846**	0.715
Extraversion	0.473	**0.758**	0.574
Well-being			
Life satisfaction	0.221	**0.779**	0.606
Meaning and purpose	0.455	**0.848**	0.719
Positive affect	0.508	**0.871**	0.759
r_c	0.578		
r_c^2	0.334		

r_s = canonical structure coefficient, and it represents the Pearson correlation between canonical variates and observed scores. Canonical structure coefficient > .30 are in bold. r_c = canonical correlation coefficient, and it refers to the Pearson correlation between personality canonical variate and well-being canonical variate correlation analysis between big-five personality traits and well-being are shown in Table 1.

To verify the relationship between each personality trait and well-being, Pearson correlation coefficients were computed between observed scores of five personality traits and well-being canonical variate. Extraversion ($r=0.438$, $p<0.001$), conscientiousness ($r=0.318$, $p<0.001$), agreeableness ($r=0.281$, $p<0.001$) and neuroticism ($r=-0.489$, $p<0.001$) were found to be significant predictors of the well-being variate. In contrast, the correlation between well-being canonical variate and openness ($r=0.001$, $p=0.980$) were non-significant.

3.2 Brain Regions Associated with Well-Being Canonical Variate

As mentioned above, NBS was performed to detect the associated sub-networks with the well-being canonical variate. The results of NBS showed that only one significant sub-network consisted of 136 edges positively correlated with the well-being canonical variate ($p=0.0004$, t-threshold$=3.1$, 5000 permutations). All of these 136 edges were positively associated with well-being canonical variate, defined as the well-being related brain network. To visualize the edges, BrainNet Viewer (http://www.nitrc.org/projects/bnv/) (Xia et al., 2013) was employed to locate the ROIs and the 264 ROIs were further assigned into eight functional modules (Fig. 2, Power et al., 2011). We found that the well-being related brain network was mainly distributed within primary sensory networks such as the somatosensory-motor network (SMN), auditory network (AUD), and visual network (VIS) and between the high-order networks and primary sensory networks, such as between default network (DMN) and VIS, SMN; dorsal attention network (DAN) and AUD, SMN; ventral attention network (VAN) and AUD, SMN (Fig. 2). This well-being related brain network included only a small proportion of negative edges that appeared between the primary sensory networks and the default network as well as the ventral attention network (Fig. 2).

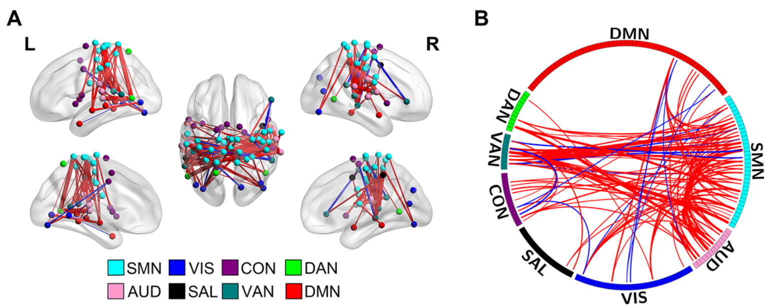

Fig. 2 Definitions of the sub-network. A total of 136 edges in the sub-network were found to be positively correlated with well-being canonical variate. **A** Visualization of the functional connectivity patterns of sub-network, with the nodes color-coded according to the original Power et al. (2011) parcellation template. **B** Circular visualization of average functional connectivity patterns calculated based on all participants, with the positive and negative connections colored in red and blue, respectively. The thickness of lines indicates the strength of the association between functional connectivity with the well-being canonical variate (i.e., the thicker the line, the greater the positive correlation). Abbreviations: SMN, somatosensory-motor network; AUD, auditory; VIS, visual; SAL, salience; CON, cingulo-opercular network; VAN, ventral attention network; DAN, dorsal attention network; DMN, default-mode network

Table 2 Pearson correlations among key variables

	1	2	3	4	5	6
1. PerCCA	–					
2. WelCCA	0.578**	–				
3. meanPosFC	0.150**	0.235**	–			
4. meanNegFC	−0.108**	−0.208**	0.086*	–		
5. GE_PosNet	0.141**	0.232**	0.945**	−0.024	–	
6. GE_NegNet	−0.103**	−0.167**	−0.111**	0.782**	−0.286**	–

PerCCA Personality canonical variate; WelCCA Well-being canonical variate; meanPosFC: the mean FC values of positive connections; meanNegFC: mean absolute FC values of negative connections; GE_PosNet: global efficiency of the positive sub-network; GE_NegNet: global efficiency of the negative sub-network. $^{*}p<0.05$, $^{**}p<0.01$

3.3 Neural Basis Underlying the Relationship of Personality Trait Canonical Variate and Well-Being Canonical Variate

The Pearson correlations between personality canonical variate, well-being canonical variate, and four neural indicators calculated based on functional connectivity within the sub-network are displayed in Table 2. The results of these correlational analyses showed that the four neural indicators were all significantly related to personality and well-being canonical variate simultaneously, and the absolute values of the correlation coefficients were all greater than 0.10. Then four mediation analyses were conducted to examine

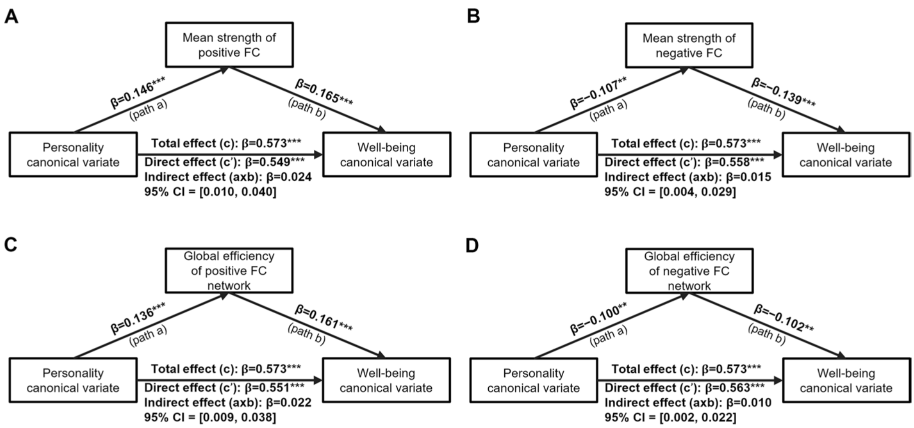

Fig. 3 Mediation analyses regarding the roles of mean FC value and global efficiency of the identified sub-network with controlling the effects of participants' age, gender, income, and educational level. **A** The relationship between personality trait canonical variate and well-being canonical variate was mediated by mean FC values of positive connections in the sub-network. **B** The relationship between personality trait canonical variate and well-being canonical variate was mediated by mean absolute FC values of negative connections in the sub-network. **C** The global efficiency of the positive sub-network mediated the relationship between personality trait canonical variate and well-being canonical variate. **D** The global efficiency of the negative sub-network also mediated the relationship between personality trait canonical variate and well-being canonical variate. Standardized regression coefficients are presented. $^{**}p<0.01$, $^{***}p<0.001$

the role of mean FC (positive or negative edge) and global efficiency of the identified sub-networks (positive or negative sub-network), separately, in explaining the relationship between two sets of canonical variates. When the mean strength of positive FC of the well-being related sub-network was entered as the mediator, the results showed that a stronger well-being-oriented personality trait profile was linked to greater mean positive FC, $b = 0.146$, $p < 0.001$, which was positively correlated with higher well-being canonical variate, $b = 0.165$, $p < 0.001$. Considering the effect of mean positive FC, the relationship between personality trait canonical variate and well-being canonical variate became weakened, $b = 0.549$, $p < 0.001$ (from $b = 0.573$, $p < 0.001$). More importantly, the indirect effect via the mean positive FC was significant, 95% CI = [0.010, 0.040] (Fig. 3A). When the mean absolute value of negative FC of the well-being related sub-network was entered as the mediator, the results showed that a stronger well-being-oriented personality trait profile was linked to lesser mean negative FC (i.e., the smaller the absolute value of negative connection strength), $b = -0.107$, $p = 0.004$, which was negatively correlated with higher well-being canonical variate, $b = -0.139$, $p < 0.001$. Considering the effect of mean negative FC, the relationship between personality trait canonical variate and well-being canonical variate was weakened, $b = 0.558$, $p < 0.001$ (from $b = 0.573$, $p < 0.001$). More importantly, the indirect effect via the mean negative FC was significant, 95% CI = [0.004, 0.029] (Fig. 3B).

When global efficiency of the positive sub-network (i.e., only included positive edge) was entered as the mediator, the results showed that a stronger well-being-oriented personality trait profile was related to greater global efficiency of the identified positive sub-network, $b = 0.136$, $p < 0.001$, which was positively associated with higher well-being canonical variate, $b = 0.161$, $p < 0.001$. With considering the effect of global efficiency of the identified positive sub-network, the relationship between personality trait canonical variate and well-being canonical variate was weakened, $b = 0.551$, $p < 0.001$ (from $b = 0.573$, $p < 0.001$). The results showed that the indirect effect was significant, 95% CI = [0.009, 0.038] (Fig. 3C). When global efficiency of the negative sub-network (i.e., only included negative edge) was entered as the mediator, the results showed that a stronger well-being-oriented personality trait profile was related to less global efficiency of the identified negative sub-network, $b = -0.100$, $p = 0.008$, which was negatively associated with higher well-being canonical variate, $b = -0.102$, $p = 0.001$. With considering the effect of global efficiency of the identified negative sub-network, the relationship between personality trait canonical variate and well-being canonical variate was weakened, $b = 0.563$, $p < 0.001$ (from $b = 0.573$, $p < 0.001$). The indirect effect via global efficiency of the negative sub-network was significant, 95% CI = [0.002, 0.022] (Fig. 3D).

The detailed results of four commonality analyses, which correspond to four mediation models, are presented in Table S1. The results showed that the unique variance explained by personality canonical variate was 28.9–30.8% of the variance in well-being, while the unique variance explained by neural indicators based on brain functional connectivity was 1.0–2.6% of the variance in well-being. And the shared variance explained by personality canonical variate and neural indicators was 1.4–3.3% of the variance in well-being. In summary, the personality canonical variate explained the largest amount of variance in well-being (i.e., all effects were in the large effect size range, > 25%), and the unique effects of the four neural indicators were relatively small but should not be negligible (i.e., all effects were in the small effect size range, > 1%; Cohen, 2013; Mullarkey & Schleider, 2020; Slattery et al., 2021).

3.4 Replication Results with Different Initial Thresholds

To examine the reproducibility of the results, we set another initial threshold ($t=2.58$ and $t=3.2$) in the NBS and re-ran the analyses. Under the threshold $t=2.58$, one significant positive sub-network was identified ($p=0.0006$, 5000 permutations), which involved widely distributed brain networks (Fig. S1). The results of mediation analyses showed that the indirect effect via mean positive FC value of the identified sub-network, 95% CI = [0.010, 0.037] (Fig. S2A), mean absolute negative FC values of the identified sub-network, 95% CI = [0.012, 0.046] (Fig. S2B), the global network efficiency of the identified positive sub-network, 95% CI = [0.014, 0.046] (Fig. S2C), and the global efficiency of the negative sub-network, 95% CI = [0.035, 0.080] (Fig. S2D) remained significant. Under the threshold $t=3.2$, one significant positive sub-network was also identified ($p=0.0008$, 5000 permutations), and brain functional connectivity associated with the well-being canonical variate was also embedded in primary sensory networks and high-order networks (Fig. S3). The results of mediation analyses showed that the indirect effect via mean positive FC value of the identified sub-network, 95% CI = [0.011, 0.042] (Fig. S4A), mean absolute negative FC values of the identified sub-network, 95% CI = [0.004, 0.025] (Fig. S4B), and the global network efficiency of the identified positive sub-network, 95% CI = [0.009, 0.039] (Fig. S4C), and the global efficiency of the negative sub-network, 95% CI = [0.001, 0.017] (Fig. S4D), remained significant. Therefore, the results were similar when applying a different initial threshold.

4 Discussion

The present study using CCA found that a personality profile with lower neuroticism, higher extraversion, conscientiousness, and agreeableness was most associated with a set of three well-being indicators (i.e., positive affect, life satisfaction, and meaning and purpose). In addition, we found that the sub-network, which was formed by functional connectivity (FC) within and between multiple brain networks spanning from primary sensory networks to high-order networks, was associated with scores of the set of well-being indicators. Moreover, the mediation analyses showed that greater mean FC and global network efficiency of positive connections, and less mean FC and global network efficiency of negative connections in well-being related brain network helped explain the relationship between personality traits and well-being canonical variates. Of note, the unique effects of the four neural indicators were relatively small, although they should not be negligible following statistical recommendations (Cohen, 2013; Mullarkey & Schleider, 2020; Slattery et al., 2021).

4.1 Well-Being-Oriented Personality Trait Profile

In the CCA model, all three indicators for well-being were strongly and positively correlated with well-being canonical variates (i.e., all canonical structure coefficients were greater than 0.77), which suggests that these three indicators were all contributing to cultivating the well-being profile and the well-being-oriented personality trait profile was not driven by a single dimension of well-being. Thus, we mainly discuss the relationship between different dimensions of personality and well-being profile rather than a single dimension of well-being. Previous studies mostly focused on the effect of certain personality traits on an overall score of well-being (Schmutte & Ryff, 1997). Thus, the complex interaction between multiple personality traits and multiple dimensions of well-being was easily neglected (DeNeve & Cooper, 1998; Mai & Ness, 1999).

The present study showed that a personality profile with higher extraversion, conscientiousness and agreeableness but lower neuroticism was closely related to a higher score in a set of well-being indicators. These findings were consistent with previous findings (Fors Connolly & Johansson Sevä, 2021; Lightsey et al., 2014; Soto, 2015; Steel et al., 2008). The greater significance of extraversion and neuroticism highlighted the importance of emotional information processing for well-being (Rusting, 1998), which might explain why most empirical work in well-being has focused on these two personality traits (Diener et al., 2003). Some studies suggested that extraversion may share the same neurological structure with positive affect (e.g., Larsen & Ketelaar, 1991), while neuroticism makes people more vulnerable to psychological distress and negative affect (DeNeve & Cooper, 1998; Gale et al., 2013). Thus the levels of extraversion and neuroticism have a prolonged influence on well-being, in which they predict the level of well-being 40 years later (Gale et al., 2013). Consistent with previous work (e.g., DeNeve & Cooper, 1998; Hayes & Joseph, 2003), the present study found that conscientiousness, which is suggested to facilitate positive experience in goal-setting situations (DeNeve & Cooper, 1998), is highly relevant to people's well-being. Concerning agreeableness, previous studies found that a high level of agreeableness contributes to the development and maintenance of harmony in interpersonal relationships, which is important for positive emotions and well-being (Kwan et al., 1997; Zhang & Tsingan, 2014). Besides, agreeableness was found to positively correlate with activity in the midline core regions of the DMN (Sampaio et al., 2014). These regions are considered to serve important cognitive and emotional functions, such as self-referential decision making and emotion processing (Andrews-Hanna et al., 2010; Sampaio et al., 2014), which are closely related to well-being. In contrast, we did not find a significant effect of openness to new experience, which was consistent with previous work showing non-significant or inconsistent relationships between openness and well-being (DeNeve & Cooper, 1998; Kokko et al., 2013).

4.2 Neural Basis of the Relationship between Personality Traits and Multiple-Faceted Well-Being

4.2.1 The Functional Connections Within Primary Sensory Networks

The present study found that well-being was associated with functional connectivity connected to several primary sensory networks, especially the somatosensory-motor network, which might imply a role of primary sensory information processing in well-being. The somatosensory-motor network, which was primarily composed of somatosensory (postcentral gyrus), motor (precentral gyrus) regions and the supplementary motor areas (Chenji et al., 2016; Power et al., 2011), plays a crucial role in receiving various external and internal sensory signals, selecting and conveying relevant signals to the attention or control systems to generate reasonable responses (Wang et al., 2015b). Recently, increasing literature demonstrated that the somatosensory-motor network also plays an important role in multiple stages of emotional processing, including detection of emotional significance in a stimulus, generation of emotional experience, and emotion regulation (Kropf et al., 2018; Satpute et al., 2015). The significant association between the functional connectivity linked to the somatosensory-motor network and well-being might suggest that the effectiveness and correctness of sensory information processing is related to higher levels of well-being. As the important region of the somatosensory-motor network, the postcentral gyrus was found to associate with higher scores in the set of well-being indicators since there were 49 edges involved in bilateral postcentral gyrus, which were all positively correlated with the well-being canonical variate (t statistic values > 3.107, ps < 0.002), which was consistent with previous work (Kong et al., 2015a, 2015b). The function of postcentral gyrus reflects sensitivity to different senses (Ploner et al., 2000) and perception of internal bodily signals (Craig, 2002), which is closely related to emotional experiences (Northoff, 2008). Another brain region significantly associated with well-being was precentral gyrus, which is important during emotion regulation (Goldin et al., 2008). Compared with passive viewing, greater activation of precentral gyrus was observed when participants actively regulated their emotion using cognitive reappraisal (Belden et al., 2014; Kim et al., 2013), which was found to promote better well-being (Haga et al., 2009). Thus, these findings hint at a potential relationship that greater sensitivity and readiness to interpret internal and external sensory signals are important for better well-being.

4.2.2 The Functional Connections Between Primary Sensory and High-Order Cognitive Networks

Our findings demonstrated that well-being was associated with the functional connectivity between primary sensory networks and DMN, DAN as well as VAN, suggesting that the interaction between primary sensory networks and high-order cognitive networks might be closely associated with well-being. The DMN is one of the important high-order cognitive networks, which is involved in various important cognitive and emotional processing of the human brain. In terms of cognitive processing, the default network engaged in semantic and episodic memory as well as abstract thought (Smallwood et al., 2021). Within the domain of emotional processing, the DMN was involved in a wide range of self-related mental processes, such as self-referential processing (Andrews-Hanna et al., 2010), reflection on emotional states of one's self and others (Frith & Frith, 2003) and emotion regulation (Pan et al., 2018), which were all closely related to well-being. The above-mentioned psychological processes are all involved in the normal inter-network interaction between the default mode network and primary sensory networks. Moreover, previous studies have found that the human brain tends to hierarchically transmit and integrate internal and external signals received by primary sensory networks to the high-order cognitive network that includes DMN, and ultimately aids individuals in generating adaptive responses (Huntenburg et al., 2018; Margulies et al., 2016; Smallwood et al., 2021). These studies suggested that the effective information communication among primary sensory networks and default mode network may be potential neural correlates of well-being, and the level of perceived well-being may be related to the advanced emotional processing such as emotion experience and regulation that the default mode network participated in. As a key region of the default mode network, the middle temporal gyrus has been found to contribute to multi-modal sensory integration (Mesulam, 1998) and semantic control (Whitney et al., 2011) along with emotional and social cognition processes (Qi et al., 2021), which could be essential for better perceived well-being. The inferior parietal lobe was also found to be associated with well-being in the current study, which was in line with previous work (Luo et al., 2016). The inferior parietal lobe has been found to be a crucial neural substrate serving diverse mental processes spanning from basic attention to language and advanced social cognition (Numssen et al., 2021), all of which seemed to be associated with the formation of well-being.

In addition to the default mode network, the functional connectivity derived from dorsal attention and ventral attention network was also associated with well-being. The dorsal attentional network was recruited in the top-down attentional processes, in which the attention resource was voluntarily oriented onto goal-relevant signals coming from the sensory cortex (Corbetta & Shulman, 2002). While the ventral attention network was employed in the stimulus-driven/bottom-up attention process, in which the attention resource was distributed to unexpected but behaviorally relevant stimuli (Weissman & Prado, 2012). Previous studies found that the dynamic cooperation between the two attention networks is the cornerstone of the human brain to respond flexibly to various complex cognitive tasks (Vossel et al., 2014; Zhao et al., 2022). Hence, we speculated that rational attention allocation to the stimulus conveyed by sensorimotor areas and better dynamic cooperation between the two attention networks might be related to better well-being. Consistent with the previous study (Kong et al., 2015a, 2015b), bilateral superior temporal gyrus was found to be positively associated with well-being. Superior temporal gyrus was found to play a crucial role in cognitive control of attention (Ramezanpour & Fallah, 2022), processing speech comprehension (Holle et al., 2010), analyzing social information conveyed by eye gaze and body movement and social perception (Allison et al., 2000; Grosbras et al., 2012). These findings may suggest that the readiness for processing interpersonal social communication, which may facilitate positive social outcomes such as social support (Albrecht et al., 1992) and social acceptance (Mallett 2007; Odom et al., 2006), could be a mechanism for promoting higher levels of well-being (Potochnick et al., 2012). There were a few negative functional connections between the attention networks and the primary sensory networks, which may be because the human brain needs to simultaneously inhibit the processing of goal-irrelevant information while focusing on goal-relevant information (Geng, 2014; Hasher et al., 2007). Moreover, the strengths of these negative functional connections were negatively correlated with well-being, which suggested that the interaction between different regions of attention and sensory networks may be associated with well-being through different pathways.

To sum up, the well-being related sub-network gathered a set of key brain regions from primary sensory networks and high-order networks, such as the superior temporal gyrus, middle temporal gyrus, inferior parietal lobule, motor cortex, and occipital cortex. Interestingly, these relevant brain regions detected based on the well-being canonical variate were also found to be associated with five personality dimensions in previous studies (Gao et al., 2021; Hsu et al., 2018; Lin et al., 2023; Sampaio et al., 2014). More importantly, despite the relatively small effect sizes, we found that the mean strength of positive FC and global network efficiency of the identified sub-network partially mediated the association between the personality profile and well-being profile, and the stronger positive FC and greater network efficiency were associated with higher scores in multi-faceted well-being. The brain regions, common to well-being and personality traits, were implicated in emotional awareness, cognitive control, and advanced mental processes, including self-referential processing, emotion regulation, and social cognition (Allison et al., 2000; Kropf et al., 2018; Numssen et al., 2021; Qi et al., 2021). The results of mediation analyses might suggest that multi-faceted personality traits are associated with multi-faceted well-being through a set of abilities, including processing emotional sensory signals, allocating attention resources, integrating multi-modal sensory information, and executing high-order cognitive and emotional functions like social perception and emotion regulation. Taken together, we may have found a potential neural mechanism bridging the personality traits profile with multi-faceted well-being; however, the results should be interpreted with caution due to the small effect sizes of the neural mediators.

When we linked the present findings to previous personality research, some consistent patterns emerged. Extraversion is found to be associated with better emotional regulation (Kokkonen & Pulkkinen, 2001) and better social communication skills (Fleeson et al., 2002). Conscientiousness is found to be associated with better emotion perception (Bommer et al., 2011) and better emotion regulation (Jensen-Campbell et al., 2007). Agreeableness is found to be associated with better perceptions of others' emotions (Hughes et al., 2020) and more positive subjective evaluations of emotional events (Komulainen et al., 2014). And neuroticism is found to be associated with poorer emotional regulation (Ng & Diener, 2009) and poorer social communication ability (Richmond et al., 1989). Taking together, the present study provides preliminary evidence suggesting that emotion perception, emotion regulation, and social communication skills would be crucial for enhancing well-being, combining the findings from the behavioral and neural levels.

4.3 Implications, Limitations and Further Considerations

The present study suggested that the relationship between personality and well-being may be associated with the ability to integrate personally relevant sensory information via the primary sensory networks, attention networks, and default mode networks. These findings may have important possible therapeutic implications. Cognitive behavioral therapies may be considered to focus on enhancing cognitive control of attention and facilitating significant internal and external sensory information integration, which may help promote well-being and alterations in personality. For instance, past work investigating the relationship between the practice of mindfulness meditation and personality traits alteration suggests that increased self-awareness and enhanced attention control learned through mindfulness meditation intervention was related to increased extraversion, decreased neuroticism, and more experience of positive affect (van den Hurk et al., 2011). Hence, the present study might provide neural evidence for the importance of developing self-awareness and attention control skills in improving well-being. Future research may explore how to develop neural interventions (e.g., non-invasive brain stimulation), which can modulate individual's emotional awareness and attention control abilities and thus influence personality and promote well-being. Additionally, the brain networks engaged in the relationship between personality and well-being in the present study have been associated with a wide range of psychiatric illnesses, which often manifest as higher levels of neuroticism, lower levels of extraversion, and lower levels of well-being. For example, recent transdiagnostic studies revealed that some alterations in the modular architecture of primary and high-order networks, including VIS, DMN, DAN, and VAN, were simultaneously related to multiple psychiatric disorders, such as schizophrenia, bipolar disorder, and major depressive disorder (Ma et al., 2020; Sha et al., 2018). Hence, the key regions located in these brain networks may be relevant targets for biological treatments for multiple mental illnesses. In summary, investigating the neural correlates of the relationship between personality and well-being may not only help us to move toward a better understanding of this complex relationship but also provide insights for developing appropriate interventions and treatments.

There were some limitations in the present study. First, all participants were relatively young (age: 22–35). Previous work demonstrated age-related changes in brain structure (Seidler et al., 2010) and brain function (Mattay et al., 2002). Thus, future studies should recruit participants in a wide range of age to confirm the generalizability of the present findings. Second, the responses for well-being and personality traits were self-reported, which could be vulnerable to self-presentation biases (Ryff & Keyes, 1995). To address this concern, future studies can measure participants' well-being and personality traits through the evaluation of the surrounding individuals, such as their friends, to increase the objectiveness of the rating (Sandvik et al., 1993). Third, the present study explored the relationship between personality traits and well-being based on correlational data, which did not draw causal conclusions. Cross-sequential designs could be applied to examine their causal relationship (Beck & Wilson, 2000). Fourth, in addition to the big five personality factors, other environmental factors such as social participation and sense of community were also found to be significant predictors of well-being (Cicognani et al., 2008); thus, future studies are invited to incorporate other important environmental factors into the analysis while exploring the neural basis of well-being. Fifth, the present study only focused on the possible contribution of brain functional activity to well-being. A recent review (Andò et al., 2021) suggested that the non-invasive brain stimulation techniques such as transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS) over specific brain regions including the posterior superior temporal sulcus and somatosensory cortex may help to improve the well-being of individuals, providing support the rationality of our focus on the effect of brain functional activity on well-being. However, the relationship between brain activity and well-being may be bi-directional, i.e., well-being may also, in turn, affect brain functional connectivity. To fully address this important question, longitudinal studies are necessary. Last, the effect sizes of four neural mediators are relatively small, although their indirect effects are statistically significant. To examine the unique and shared variance in the contributions of personality canonical variate and four neural mediators to well-being, we conducted four commonality analyses (for details, see Table S1 and Supplementary materials). These results of commonality analyses showed that the unique effects of the four neural mediators were small but not negligible following statistical recommendations (Cohen, 2013; Mullarkey & Schleider, 2020; Slattery et al., 2021). Previous brain-behavior cross-sectional mediation analysis studies also reported relatively small effect sizes (Kong et al., 2015a, 2015b; Mulders et al., 2018). The small effect sizes might be due to the joint involvement of multiple systems of the human brain in the cultivation of individuals' well-being, which might be reflected in other forms of brain activities (Jung et al., 2022; King, 2019). Specifically, the present study relied exclusively on the measure of resting-state functional connectivity; however, the association between brain regions or networks and well-being might be implicated in other types of brain function (e.g., dynamic functional connectivity and task-based functional MRI) and brain structure (e.g., gray matter volume). Future multimodal neuroimaging studies are needed to explore the relationship between the interaction of multiple attributes of the human brain and well-being. Nevertheless, we suggest caution when interpreting the findings of mediation analyses. In summary, the present study focused on identifying the brain regions associated with multi-faceted well-being scores that were most relevant to the personality profile. Cautions are needed, as the obtained findings may be restricted to the aspects of well-being that are related to personality traits.

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Data Availability The HCP dataset used in this study is publicly available in the database of Human Connectome Project (Van Essen et al., 2013): https://db.humanconnectome.org/data/projects/HCP_1200.

Declarations

Conflict of interest All the authors declare that they have no conflict of interest.

Ethical Approval The HCP project was approved by the Institutional Review Board of Washington University in St. Louis.

Informed Consent All the participants in this study signed informed consent before the data collection.

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