Brain network dynamics correlates with personality traits

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Abstract

Identifying the neural substrates underlying the personality traits is a topic of great interest. On the other hand, it is now established that the brain is a dynamic networked system which can be studied using functional connectivity techniques. However, much of the current understanding of personality-related differences in functional connectivity has been obtained through the stationary analysis, which do not capture the complex dynamical properties of brain networks. In this study, we aimed to evaluate the feasibility of dynamic network measures to predict personality traits. Using the EEG-source connectivity method combined with a sliding window approach, dynamic functional brain networks were reconstructed from EEG data acquired from 45 subjects during resting state. Then, several dynamic functional connectivity metrics were evaluated. Results showed a negative correlation between neuroticism and the dynamic variability of temporal lobe regions in terms of strength. In addition, a positive correlation was found between agreeableness and centrality variability of the posterior cingulate, which is known as a key hub in resting state networks. Results also revealed that extraversion is positively correlated with the dynamics of the superior parietal region. These findings highlight the importance of tracking the dynamics of functional brain networks to improve our understanding about the neural substrates of personality.

Introduction

Personality refers to a characteristic way of thinking, behaving and feeling, that distinguishes one person from another (Back et al., 2009; Furr, 2009; Hong et al., 2008; Jaccard, 1974). Since personality traits are thought to be stable and broadly predictable (Canli and Amin, 2002; Deyoung, 2006), it is unsurprising that personality is linked to reliable markers of brain function (Yarkoni, 2014). In this context, the interest in the neural substrates underpinning personality is substantially increased in recent years. One of the most widely used and accepted taxonomy of personality traits is the factor five model (FFM), or big-five model, which covers different aspects of behavioral and emotional characteristics (McCrae and John, 1992). It represents five main factors: conscientiousness, openness to experience, neuroticism, agreeableness and extraversion.

On the other side, emerging evidence show that most cognitive states and behavioral functions depend on the activity of numerous brain regions operating as a large-scale network (Bressler, 1995; Edelman, 1993; Fuster, 2010; Goldman-Rakic, 1988; Greicius et al., 2003; Mesulam, 1990; Sporns et al., 2004). This dynamical behavior is even present in the pattern of intrinsic or spontaneous brain activity (i.e., when the person is at rest) (Allen et al., 2014; Baker et al., 2014; de Pasquale et al., 2015, 2012; Kabbara et al., 2017; O'Neill et al., 2017). In particular, the dynamics of brain connectivity patterns can be studied at the millisecond time scale, for example using electro-encephalography (EEG).

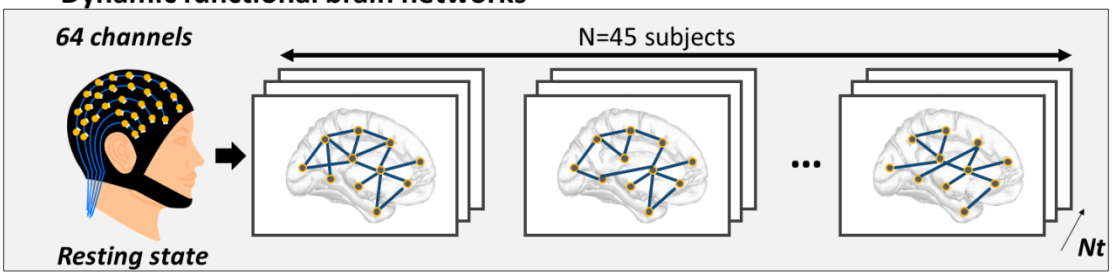
However, while multiple studies have been conducted to relate the FFM traits to functional patterns of brain networks (Beaty et al., 2016a; Li et al., 2017; Mulders et al., 2018; Tian et al., 2018; Tomeček and Androvičová, 2017; Toschi et al., 2018), we argue that the assessment of such relationships has been limited, in large part, due to an ignorance of networks variation throughout the measurement period. In the present study, we hypothesized that investigating the dynamic properties of the brain network reconfiguration over time will reveal new insights about the neural substrate of personality.

Here, we collected EEG data of 45 subjects during resting state. Dynamic brain networks were reconstructed using the EEG source connectivity approach (Hassan and Wendling, 2018) combined with a sliding window approach as in (Kabbara et al., 2017; Rizkallah et al., 2018). Then, based on graph theoretical approaches, several dynamic features were estimated. Correlations between individual FFM traits and network dynamics were assessed. Our findings reveal robust relationships between dynamic network measures and four of the big five personality traits (agreeableness, conscientiousness, extraversion and neuroticism).

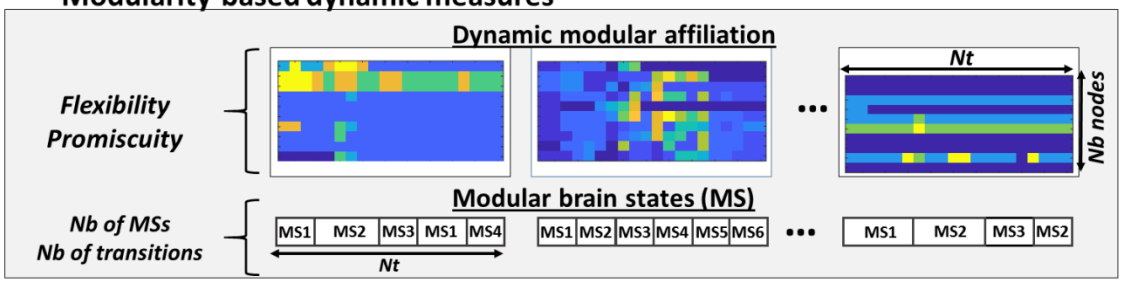
Materials and methods

The full pipeline of the current study is summarized in Figure 1.

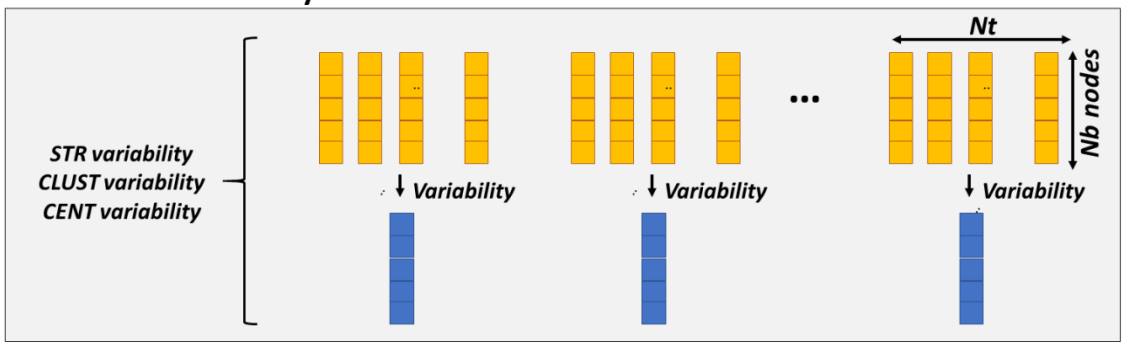
Dynamic functional brain networks



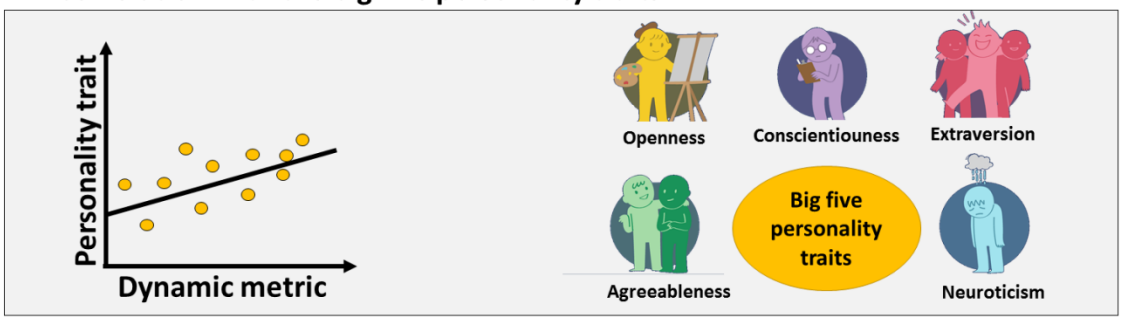
Modularity-based dynamic measures



Network- based dynamic measures



Correlation with the big five personality traits



Out of sample test

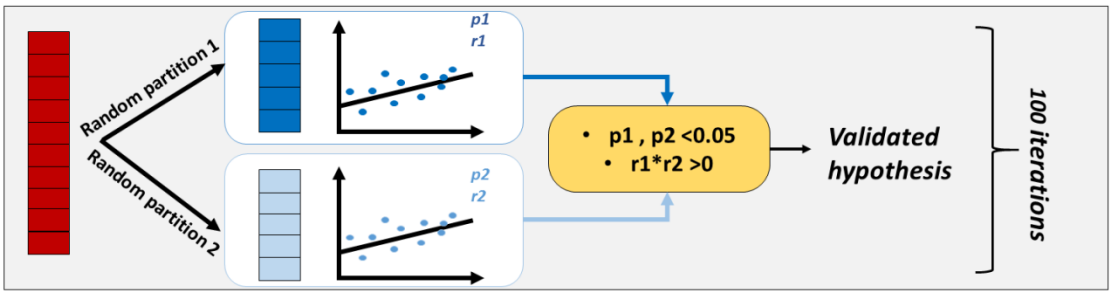


Figure 1. Full study pipeline. First, dynamic brain networks were reconstructed from 45 participants from a 64-channel EEG system. Then, for each subject, dynamic features were extracted (modularity-based features and graph-based features). Correlations between FFM personality traits (agreeableness, extraversion, neuroticism, openness, conscientiousness) and the dynamic features were then evaluated. Finally, statistical tests were assessed using a randomized out of sample test. STR = strength, CLUST=clustering coefficient, CENT=betweenness centrality.

Participants

A total of 45 healthy subjects were recruited (22 women). The mean age was 34.7 years old (*SD* = 9.1 years, range = 18–55). Education ranged from 10 years of schooling to a PhD degree. None of the volunteers reported take any medication or drugs, nor suffered from any past or present neurological or psychiatric disease.

Evaluating the FFM personality traits

The Five-Factor Model (FFM) represents five major personality traits: 1) *conscientiousness* which describes an organized and detailed-oriented nature, 2) *agreeableness* which is associated to kindness and cooperativeness, 3) *neuroticism* which indexes the tendency to have negative feelings, 4) *openness* is related to intellectual curiosity and imagination, 5) *extraversion* refers to the energy drawn from social interactions. In the present study, personality traits were assessed with the French Big Five Inventory (BFI-Fr) (Plaisant et al., 2010). The BFI-Fr is composed by 45 items in which respondents decide whether they agree or disagree with each question, on a 1 (strongly disagree) to 5 (strongly agree) Likert scale. Responses are then summed to determine the scores for the five personality constructs..

Data Acquisition and Preprocessing

Each EEG session consisted in a 10-min resting period with the participant's eyes closed (Paban et al., 2018). Participants were seated in a dimly lit room, were instructed to close their eyes, and then to simply relax until they were informed that they could open their eyes. Participants were informed that the resting period would last approximately 10 min. The eyes-closed resting EEG recordings protocol was chosen to minimize movement and sensory input effects on electrical brain activity. EEG data were collected using a 64-channel Biosemi ActiveTwo system (Biosemi Instruments, Amsterdam, The Netherlands) positioned according to the standard 10–20 system montage, one electrocardiogram, and two bilateral electro-oculogram electrodes (EOG) for horizontal movements. Nasion-inion and preauricular anatomical measurements were made to locate each individual's vertex site. Electrode impedances were kept below 20 kOhm. EEG signals are frequently contaminated by several sources of artifacts, which were addressed using the same preprocessing steps as described in several previous studies dealing with EEG resting-state data (Kabbara et al., 2017; Kabbara et al., 2018; Rizkallah et al., 2018). Briefly, bad channels (signals that are either completely flat or contaminated by movement artifacts) were identified by visual inspection, complemented by the power spectral density. These bad channels were then recovered using an interpolation procedure implemented in Brainstorm (Tadel et al., 2011) by using neighboring electrodes within a 5-cm radius. Epochs with voltage fluctuations between +80 μV and −80 μV were kept. Five artifact-free epochs of 40-s lengths were selected for each participant. This epoch length was used in a previous study, and was considered as a good compromise between the needed temporal resolution and the results reproducibility (Kabbara et al., 2017).

Dynamic brain networks construction

Dynamic brain networks were reconstructed using the "EEG source connectivity" method (Hassan and Wendling, 2018), combined with a sliding window approach as detailed in (Kabbara et al., 2017; Kabbara et al., 2018; Rizkallah et al., 2018). "EEG source connectivity" involves two main steps: i) solving the EEG inverse problem in order to estimate the cortical sources and reconstruct their temporal dynamics, and ii) measuring the functional connectivity between the reconstructed time-series.

Briefly, the steps performed are the following:

1- EEGs and MRI template (ICBM152) were coregistered through the identification of anatomical landmarks by using Brainstorm (Tadel et al., 2011).
2- A realistic head model was built using the OpenMEEG (Gramfort et al., 2010) software.
3- A Desikan-Killiany atlas-based segmentation approach was used to parcellate the cortical surface into 68 regions (Desikan et al., 2006).
4- The weighted minimum norm estimate (wMNE) algorithm was used to estimate the regional time series (Hamalainen and Ilmoniemi, 1994).
5- The reconstructed regional time series were filtered in different frequency bands (delta: 1–4 Hz; theta: 4–8 Hz; alpha: 8–13 Hz; beta: 13–30 Hz and gamma: 30-45 Hz)
6- The filtered regional time series were segmented into non-overlapping time windows of length L, which depends on the frequency band. As recommended in Lachaux et al.(Lachaux et al., 2000), L is the smallest window length which is equal to $\frac{6}{Central\ frequency}$, where 6 is the number of "cycles" at the given frequency band.

7- For each temporal window, the functional connectivity was computed between the regional time series using PLV. This yields to a connectivity matrix and thus a network for each window.

8- To ensure equal density between time windows, a proportional (density-based) threshold of 10% was applied.

Dynamic measures

While functional connectivity provides crucial information about how the different brain regions are connected, graph theory offers a framework to characterize the network topology and organization. In practice, many graph measures can be extracted from networks to characterize static and dynamic network properties. Here, we focused on measures quantifying the dynamic aspect of the brain networks/modules/regions and their reconfiguration over time.

Graph-based dynamic measures:

Most previous studies attempt to average the graph measures derived from temporal windows (de Pasquale et al., 2015; Kabbara et al., 2017). However, such strategy constrains the dynamic analysis. Distinctively, we aimed here at quantifying the dynamic variation of node's characteristics inferred from graph measures (including strength, centrality and clustering). The graph measure's variation (GM) of the node i across time windows is defined as:

$$V(GM_i) = \sum_{k=1}^{L-1} \left| W_{i,tw} - W_{i,tw+1} \right|$$

Where i is the considered node, GM is the considered graph measure, L denotes the number of time windows and tw and $tw + 1$ refer to two consecutive time windows. A node with high V reflects that the node is dynamic in terms of the given GM.

In this study we focused on three graph measures:

1- **Strength:** The node's strength is defined as the sum of all edges weights connected to a node (Barrat et al., 2004). It indicates how influential the node is with respect to other nodes.
2- **Clustering coefficient:** The clustering coefficient of a node evaluates the density of connections formed by its neighbors (Watts & Strogatz, 1998). It is calculated by dividing the number of existing edges between the node's neighbors to the number of possible edges that can exist between them. The clustering coefficient of a node is an indicator of its segregation within the network.
3- **Betweenness centrality:** The betweenness centrality calculates the number of shortest paths that pass through a specific node (Rubinov and Sporns, 2011). The importance of a node is proportional to the number of paths in which it participates.

An illustrative example of strength variability on a toy dynamic graph is presented in Figure 2.B.

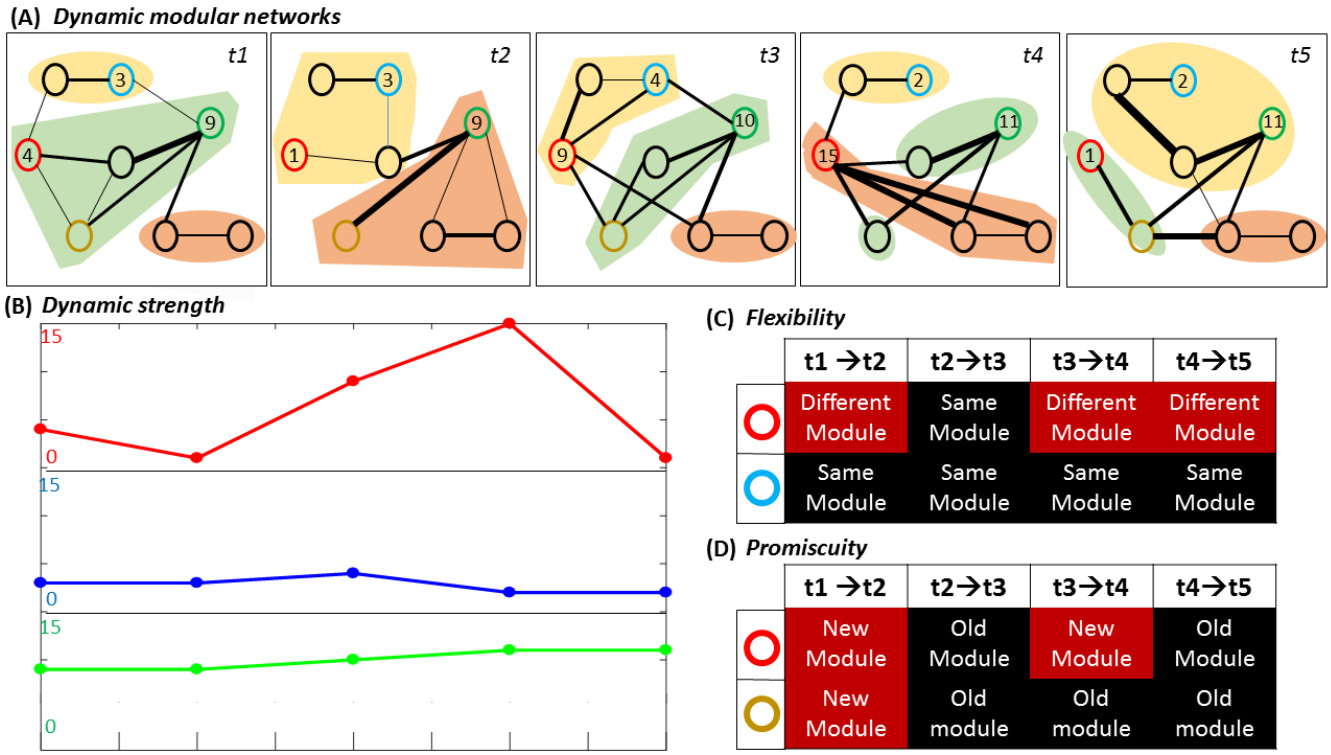


Figure 2. An illustrative example of the dynamic features extracted from a toy dynamic graph. A) The dynamic modular networks. B) The strength variation. C) Flexibility of red and blue nodes. D) Promiscuity of red and yellow nodes.

Modularity-based dynamic measures:

Modularity describes the tendency of a network to be partitioned into modules or communities of high internal connectivity and low external connectivity (Sporns and Betzel, 2016). To explore how brain modular networks reshape over time, we detected the dynamic modular states that fluctuate over time using our recent proposed algorithm (Kabbara et al., 2019). Briefly, it attempts to extract the main modular structures (known as modular states) that fluctuate repetitively across time. Modular states reflect unique spatial modular organization, and are derived as follows:

- Decompose each temporal network into modules using the consensus modularity approach (Bassett et al., 2013; Kabbara et al., 2017). This approach consists of generating an ensemble of partitions acquired from the Newman algorithm (Girvan and Newman, 2002) and Louvain algorithm (Blondel et al., 2008) repeated for 200 runs. Then, an association matrix of N x N (where N is the number of nodes) is obtained by counting the number of times two nodes are assigned to the same module across all runs and algorithms. The association matrix is then compared to a null model association matrix generated from a permutation of the original partitions, and only the significant values are retained (Bassett et al., 2013). To ultimately obtain consensus communities, we re-clustered the association matrix using Louvain algorithm.
- Assess the similarity between the temporal modular structures using the z-score of Rand coefficient, bounded between 0 (no similar pair placements) and 1 (identical partitions) as proposed by (Traud et al., 2008). This yielded a T x T similarity matrix where T is the number of time windows.
- Cluster the similarity matrix into "categorical" modular states (MS) using the consensus modularity method. This step combines similar temporal modular structures into the same community. Hence, the association matrix of each "categorical" community is computed using the modular affiliations of its corresponding networks.

Once the modular states (MS) were computed, two metrics were extracted:

1- *The number of MSs*

2- *The number of transitions:* It measures the number of switching between MSs.

In addition, after obtaining the dynamic modular affiliations, two dynamic nodal measures were calculated:

1. *Flexibility:* It is defined as the number of times that a brain region changes its module across time, normalized by the total number of changes that are possible. We considered that a module was changed if more than 50% of its nodes have changed (Figure 2.C).
2. *Promiscuity:* It is defined as the number of modules a node participate during time (Figure 2.D)

Statistical analysis:

In order to investigate the associations between the dynamic network measures and FFM personality traits, Pearson's correlation analysis was assessed. A Bonferroni correction was applied for multiple comparisons across regions and frequency bands (Bland and Altman, 1995).

To avoid data dredging problem, we conducted randomized out-of-sample tests repeated 100 times. The out of sample test consists of randomly dividing data into two random subsets. If significant correlations were obtained from the two subsets for all the iterations, the correlation is considered statistically significant on the whole distribution.

Results

For each subject, the dynamic functional networks were reconstructed using a sliding window approach. Then, dynamic measures were extracted at the level of each brain region

(node-wise analysis), and at the level of the whole network. At the network-level, flexibility, promiscuity, strength variation, clustering variation and centrality variation were averaged over all brain regions. At the node-level, the values of each node were kept.

The correlation between FFM personality traits and the network-level parameters are presented in Figure 3. Agreeableness was found to be positively correlated with the overall centrality variation in the alpha band ($p_{Bonferroni\ corrected} < 0.05; r = 0.35$). Neuroticism showed a negative correlation with the number of transitions ($p_{Bonferroni\ corrected} < 0.05; r = -0.33$) and the overall promiscuity ($p_{Bonferroni\ corrected} < 0.05; r = -0.39$) in the beta band, as well as the flexibility in the theta band ($p_{Bonferroni\ corrected} < 0.05; r = -0.32$). Results also depict a negative correlation between conscientiousness and the overall clustering variation in the alpha band ($p_{Bonferroni\ corrected} < 0.05; r = -0.46$). No significant relationship was observed at the network-level between any of the dynamic measures with neither openness nor extraversion.

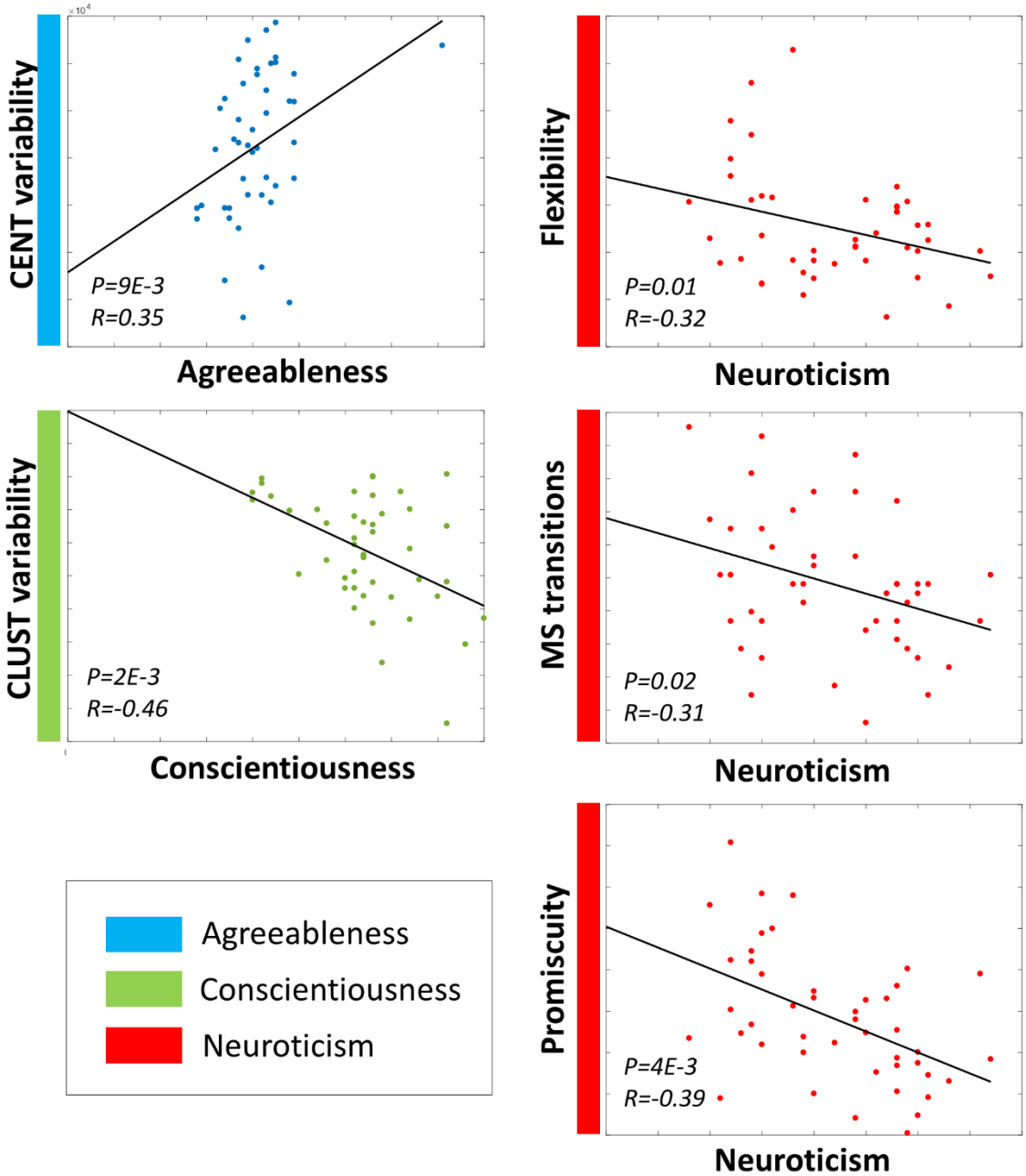


Figure 3. Significant correlations between the FFM traits and the dynamic graph measures computed on the network-level.

Figure 4 illustrates the correlation between FFM traits and nodal characteristics in terms of dynamic features. Agreeableness was positively correlated with the flexibility of the right fusiform in delta band ($p_{Bonferroni\ corrected} < 0.05; r = 0.48$), and the centrality

variation of the left posterior cingulate in the alpha band ($p_{Bonferroni\ corrected} < 0.05; r = 0.5$). Results also show that higher extraversion was correlated with higher clustering variability of superior parietal lobule in the theta band ($p_{Bonferroni\ corrected} < 0.05; r = 0.5$). In contrast, neuroticism was negatively correlated with strength variation of the left middle temporal gyrus ($p_{Bonferroni\ corrected} < 0.05; r = -0.56$), left superior temporal gyrus ($p_{Bonferroni\ corrected} < 0.05; r = -0.48$) and transverse temporal region ($p_{Bonferroni\ corrected} < 0.05; r = -0.57$) in the theta band.

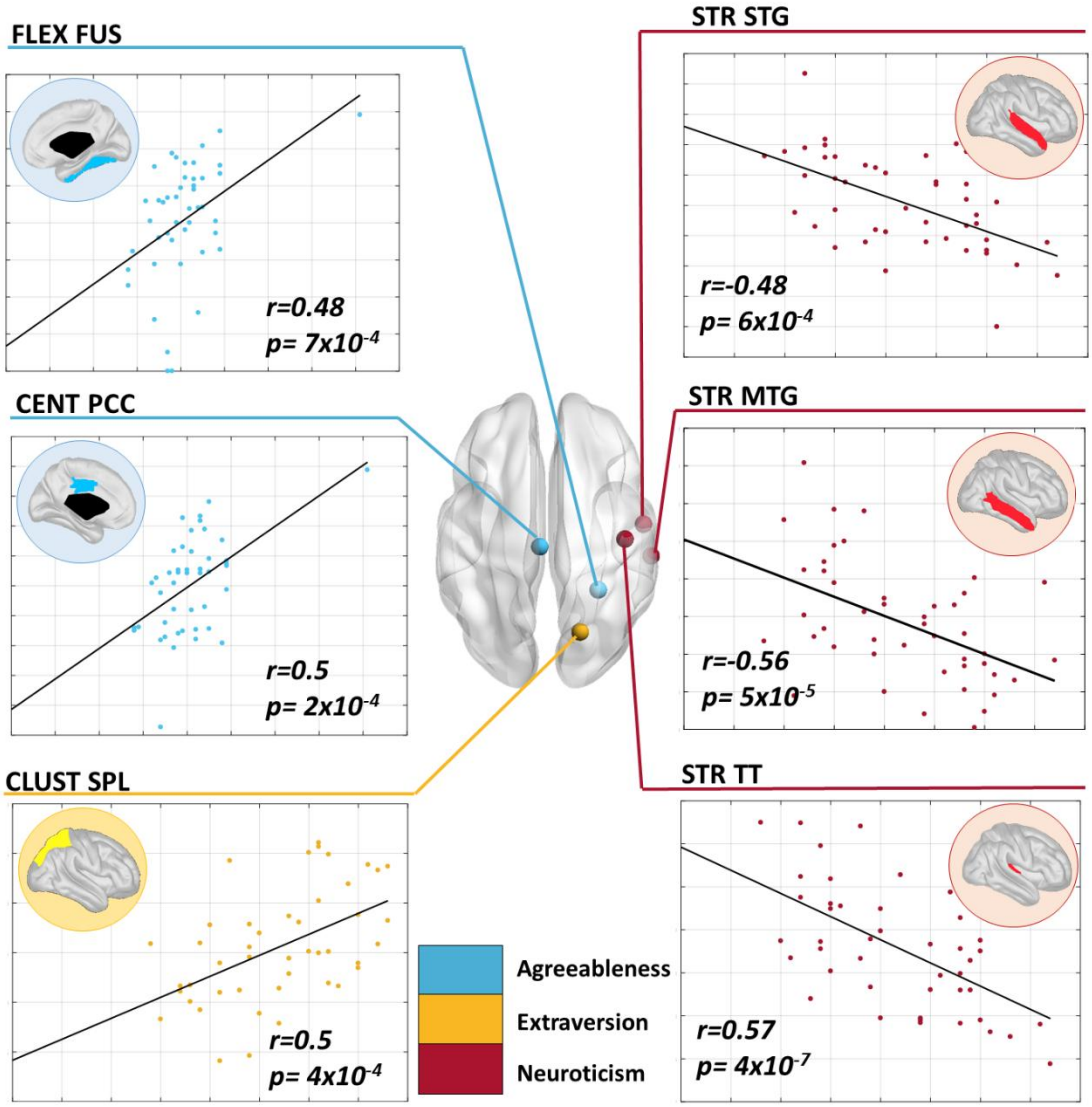


Figure 4. The cortical surface illustrating the brain regions for which the dynamic measures significantly correlated with FFM traits. STR = strength, CLUST=clustering coefficient, CENT=betweenness centrality, FLEX: flexibility, FUS=Fusiform, PCC: posterior cingulate cortex SPL=superior parietal lobule, STG= superior temporal gyrus, MTG=middle temporal gyrus, TT= transverse temporal.

Discussion

The present study provides evidence that dynamic features (derived from graph measures) based on resting-state EEG data are significantly associated with FFM personality traits (derived from the BFI-Fr questionnaire).

The majority of studies in personality has mainly examined the interaction between neuropsychological traits and brain features in a static way. In particular, multiple previous studies focused on investigating how personality traits are linked to differences in morphological brain properties (DeYoung, 2010; Gray et al., 2018; Liu et al., 2013; Omura et al., 2005; Riccelli et al., 2017). Another traditional way was to perform brain activation analysis to understand the neural basis of personality (Cooper et al., 2015; Falk et al., 2015). However, these strategies ignore useful information about the way in which brain regions interact with each other (Markett et al., 2018). Moving forward, multiple connectivity studies have been recently conducted to understand the neural substrates of human personality (Adelstein et al., 2011; Aghajani et al., 2013; Beaty et al., 2016b; Bey et al., 2015, 2015; Dubois et al., 2018; Gao, 2013; Kyeong et al., 2014; Markett et al., 2016, 2013; Tompson et al., 2018). Interestingly, graph theoretical assessment derived from networks were applied to link topological brain features to the Big Five personality traits (Beaty et al., 2016b; Bey et al., 2015; Gao, 2013; Toschi et al., 2018). As an example, (Toschi et al. 2018) shows that conscientiousness is linked to nodal properties (clustering coefficient, betweenness centrality and strength) of fronto-parietal and default mode network regions. Nevertheless, recent evidence revealed that dynamic analysis of functional data provides a more comprehensive understanding of neural implementation in personality (Tompson et al., 2018). The main originality of the current work is that it extends the traditional static view of brain networks to explore the time-varying characteristics associated to FFM traits.

Results show that among the five frequency bands studied, changes were observed only within slow oscillations (namely, delta, theta, and alpha bands). As suggested by (Knyazev, 2012), these oscillations might play a major role in integration across diverse cortical sites

by synchronizing coherent activity and phase coupling across spatially distributed neural assemblies, so that it might be not surprising that network properties related to personality traits were affected only within slower frequency bands.

At the level of the whole network, our data revealed that not all the five personality traits were correlated with the dynamic measures, but only agreeableness, conscientiousness and neuroticism. This latter personality trait appeared to be the most sensitive to the analysis through dynamic approaches. Importantly, our study showed a negative correlation between neuroticism and centrality variation, number of transitions, promiscuity, and flexibility. This suggests that the more individuals had a strong tendency to experience negative affection, such as anxiety, worry, fear, and depressive mood (Ormel et al., 2013), the less their brain showed dynamic characteristics in terms of modular organization over time. In other words, one may speculate that individuals with low dynamic measures of brain networks did not have enough capacity to get over their tendency to experience negative emotions and their psychological distress.

At a node level, if conscientiousness and openness did not reveal significant correlation with dynamic metrics, interestingly our results highlight the involvement of various brain regions in the three others personality traits. Agreeableness was associated to increased dynamics in left PCC centrality variation and right FUS flexibility. Interestingly, FUS is known to be crucial in visual processing of faces (Kanwisher et al., 1997). This suggests a prominent role of FUS in agreeable individuals where visual processing is supposed to be more efficient. Moreover, multiple studies revealed the importance of the PCC as a key hub in resting state (de Pasquale et al., 2015; Kabbara et al., 2017; van den Heuvel and Sporns, 2013; Zhang et al., 2009), and also in episodic memory retrieval (Nielsen et al.,

2005). This may explain the correlation obtained between the centrality variation of this region with agreeableness. Our results are also found to be in line with (Sheu et al., 2011; Sofie L., Valk et al., 2019), that show a significant association between PCC and agreeableness using MRI approaches.

Concerning extraversion, a positive correlation was established with the clustering variation of superior parietal lobule (SPL), which is involved in attention and visuomotor integration (Iacoboni and Zaidel, 2004). In line with (Suslow et al., 2010) showing that extraverts displayed enhanced sensitivity and efficiency in sensory information processing compared with introverts, our data add to our neurobiological underpinning knowledge of extraversion highlighting the involvement of the SPL in such processes. Thus, SPL would play a central role promoting segregation within the network of extraverted individuals.

The degree of neuroticism was associated with low strength variation of temporal regions (mainly STG, MTG and TT). Importantly, the temporal lobe is known to be involved in processing sensory input related to visual memory, language comprehension, and emotion association (Kosslyn, 2007). In particular, the STG is involved in the interpretation of other individuals' actions and intentions (Pelphrey and Morris, 2006). Others stated that STG plays an important role in emotional processing and effective responses to social cues, such as facial expressions and eye direction (Pelphrey and Carter, 2008; Singer, 2006). These findings are in agreement with a recent study showing that neurotic individuals present delayed detection of emotional and facial expressions (Sawada et al., 2016).

The present study adds to our recent paper (Paban et al. 2019) in providing new evidence that the dynamic reconfiguration of brain networks is of particular importance in shaping behavior.

Methodological considerations:

First, let us mention that we used a template generated from MRIs of healthy controls, instead of a native MRI for EEG source connectivity. Recently, a study showed that there is no potential bias of the use of a template MRI as compared to individual MRI co-registration (Douw et al., 2018). In this context, a considerable number of EEG/MEG connectivity studies have used the template-based method due to the unavailability of native MRIs (Hassan et al., 2017; Kabbara et al., 2018; Lopez et al., 2014). However, we are aware that the use of subject-specific MRI is more recommended in clinical studies.

Second, choosing the suitable window width is a crucial issue in constructing the dynamic functional networks. On one hand, choosing short windows may underlie errors in the generated networks. On the other hand, large windows may fail to capture the temporal changes of the brain networks. Hence, the ideal is to choose the shortest window that guarantees a sufficient number of data points over which the connectivity is calculated. This depends on the frequency band of interest that affects the degree of freedom in time series. In this study, we adapted the recommendation of Lachaux et al. (Lachaux et al., 2000) in selecting the smallest appropriate window length that is equal to where 6 is the number of ‘cycles’ at the given frequency band. The reproducibility of resting state results whilst changing the size of the sliding window was validated in a previous study (Kabbara et al., 2017).

Acknowledgments

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