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## Functional connectome of the five-factor model of personality

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### Abstract

A key objective of the emerging field of personality neuroscience is to link the great variety of the enduring dispositions of human behaviour with reliable markers of brain function. This can be achieved by analyzing large sets of data with methods that model whole-brain connectivity patterns. To meet these expectations, we exploited a large repository of personality and neuroimaging measures made publicly available via the Human Connectome Project.

Using connectomic analyses based on graph theory, we computed global and local indices of functional connectivity (e.g., nodal strength, efficiency, clustering, betweenness centrality) and related these metrics to the five-factor-model (FFM) personality traits (i.e., neuroticism, extraversion, openness, agreeableness, and conscientiousness). The maximal information coefficient was used to assess for linear and non-linear statistical dependencies across the graph 'nodes', which were defined as distinct brain circuits identified via independent component analysis. Multi-variate regression models and 'train/test' machine-learning approaches were also used to examine the associations between FFM traits and connectomic indices as well as to test for the generalizability of the main findings, whilst accounting for age and sex differences.

Conscientiousness was the sole FFM trait linked to measures of higher functional connectivity in the fronto-parietal and default mode networks. This might provide a mechanistic explanation of the behavioural observation that conscientious people are reliable and efficient in goal-setting or planning.

Our study provides new inputs to understanding the neurological basis of personality and contributes to the development of more realistic models of the brain dynamics that mediate personality differences.

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## Keywords

Big-five; individual differences; resting-state fMRI; connectome; graph analysis

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## Introduction

Personality neuroscience is a rapidly growing research field that aims at understanding the neural underpinnings of variability in cognitive and emotional functions as well as the brain basis of individual differences in behaviour (Corr, 2006; Colin G. DeYoung, 2010). Extensive research in personality has shown that the complexity of human behaviour can be described by an aggregate taxonomy termed the five-factor model (FFM)(Costa & McCrae, 1992; Digman, 1990; Robert R. McCrae & Terracciano, 2005), although other models of personality have also been developed to explain the high variability in a wide range of behaviours, including clinical disorders, occupational/educational performance, and economic behaviour (Ashton et al., 2004; Cloninger, 1999; Cloninger, Przybeck, & Svrakic, 1991; Cloninger, Svrakic, & Przybeck, 1993; Corr, 2006; H. Eysenck, 1983; H. J. Eysenck, 2012; J. A. Gray, 1970; J.A. Gray & McNaughton, 2003). The FFM posits that neuroticism, extraversion, openness, agreeableness, and conscientiousness are the universal descriptors of human enduring behavioural dispositions (R. R. McCrae, 1991; R. R. McCrae & Costa, 1987; R. R. McCrae & John, 1992; Robert R. McCrae & Terracciano, 2005).

However, *how* and *why* individuals differ in these traits remain an important open question. Recently, sophisticated brain imaging techniques and new analytical methods have become available to help formulating novel theories and models regarding the neurological origin of human personality, although it must be acknowledged that neuroimaging intrinsically remains an indirect and correlational measure of brain anatomy and function. Past research has linked the FFM traits to different indices of brain structure and function, although the presence of mixed and often conflicting results in the literature limits the conclusions that can be drawn from these studies (Canli, 2004; Canli, Sivers, Whitfield, Gotlib, & Gabrieli, 2002; H. Cremers et al., 2011; H. R. Cremers et al., 2010; C. G. DeYoung et al., 2010; Dima, Friston, Stephan, & Frangou, 2015; Fischer, Wik, & Fredrikson, 1997; Hu et al., 2011; Indovina, Riccelli, Staab, Lacquaniti, & Passamonti, 2014; Kapogiannis, Sutin, Davatzikos, Costa, & Resnick, 2012; Krebs, Schott, & Duzel, 2009; Liu et al., 2013; Lu et al., 2014; Passamonti et al., 2015; Riccelli, Indovina, et al., 2017; Rodrigo et al., 2016; Servaas et al., 2013; Wright, Feczko, Dickerson, & Williams, 2007; Wright et al., 2006). Several factors may explain the inconsistencies across previous findings, including the use of different analytic approaches and the fact that most of the earlier studies, with some notable exceptions (Bjornebekk et al., 2013; Holmes et al., 2012; Nostro, Muller, Reid, & Eickhoff, 2016; Riccelli, Toschi, Nigro, Terracciano, & Passamonti, 2017), have been conducted in small samples of participants.

Another important issue is the necessity to progress from accounts that describe personality differences in terms of anatomical and functional heterogeneity in isolated brain regions, to predictive frameworks that formally model the complexity of the connectivity patterns at the whole-brain level. Within this context, mathematical approaches based on graph theory have

been applied to measure the architecture ('topology') of the brain structural and functional connectivity patterns (i.e., 'connectomic' approaches) (Fornito & Bullmore, 2015). The graph theoretical approach provides a series of key indices to quantify different aspects of the brain 'connectome' (Fornito & Bullmore, 2015). For instance, the network's capacity to 'route' information across its distinct elements ('nodes') can be estimated by computing the efficiency of the paths ('edges') linking these nodes (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006). In other words, the network's efficiency is a quantitative representation of 'how easy' it is for an input to 'travel' across the graph's nodes. Consequently, increased efficiency reflects heightened capacity of a network to process and route relevant information across its nodes. Graph analyses also enable to quantify the degree of segregation of a network (modularity) and its capacity to integrate the information at a global or local level (i.e., global or local clustering coefficient) (Rubinov & Sporns, 2010).

Studying how 'communications' across large-scale brain circuits relate to each of the FFM traits has thus the potential to significantly improve our understanding of the neurological roots of human personality. The rationale behind this study was to reliably associate each of the FFM traits with functional connectivity patterns across large-scale brain networks. Although the relationship between the blood-oxygen-level dependant (BOLD) activity in single regions and the whole-brain network measures is highly complex, there is compelling evidence that 'holistic' neuroimaging approaches are able to predict individual variability in multiple behavioural, demographic, and life-style measures (S. M. Smith et al., 2015). However, it remains to be determined whether graph-based metrics can be reliably associated with individual differences in the FFM personality traits. To take a step in this direction, we studied the brain functional connectome in relation to the FFM in a large sample of young and healthy individuals drawn from the Human Connectome Project (HCP) (n=818, age-range: 22–37 years). The HCP is an international project that has granted open access to an unprecedented large set of demographics, personality, and neuroimaging data with high spatial and temporal resolution (McNab et al., 2013).

By using robust and highly validated methods to analyze resting-state functional magnetic resonance imaging (rsfMRI) data, we tested how individual differences in neuroticism, extraversion, openness, agreeableness, and conscientiousness are associated to global and local indices of brain functional connectivity (e.g., nodal strength, efficiency, clustering). A machine-learning validation approach based on a "training" and "testing" split of the total dataset was also employed to assess for the replicability of our main findings. We hypothesized that the FFM traits linked to less favorable outcomes (e.g., risk of developing psychiatric disorders) like neuroticism are associated to reduced brain functional connectivity (e.g., low nodal strength, low clustering, and low efficiency). Conversely, FFM traits like openness, extraversion, agreeableness, and conscientiousness (which have been linked to curiosity, social skills, and life success) were expected to be associated to measures of heightened functional connectivity (e.g., high nodal strength, high clustering, and high efficiency).

These predictions are based upon a recent study which found that functional connectomic metrics strongly relate to a 'single-axis' co-variation (ranging from 'positive' to 'negative' measures) in behavioural traits (S. M. Smith et al., 2015). In other words, those individuals

scoring high on the ‘positive’ end of the behavioural axis linking lifestyle, demographic, and other psychometric measures (e.g., fluid intelligence) displayed stronger functional connectivity patterns than low-scoring subjects (S. M. Smith et al., 2015). Interestingly, the brain regions that most contributed to these increased functional connectivity patterns included those areas that belong to the default mode network (DMN) (e.g., the medial prefrontal and parietal cortices, temporo-parietal junction, and anterior insula). Although the precise role of each region within the DMN is still matter of debate (Leech, Kamourieh, Beckmann, & Sharp, 2011), there is robust evidence that the DMN *as a whole* is involved in several aspects of human cognition and behaviour, including episodic and semantic memory, imagination, decision-making, and theory of mind (R. P. Roberts et al., 2017; Schacter, 2012; Schacter et al., 2012; Schacter, Benoit, De Brigard, & Szpunar, 2015). It is thus reasonable to expect that enhanced functional connectivity patterns within and across the DMN is linked with FFM personality traits that predict ‘positive’ and favorable behavioural outcomes, although caution is always warranted when making reverse inferences in interpreting neuroimaging findings (Poldrack, 2006).

## Participants & Methods

### Participants

The demographic and personality variables of the HCP sample are summarized in Table 1.

In brief, all participants were young and healthy adults with no obesity, hypertension, alcohol or tobacco misuse, anxiety, depressive or other psychiatric and neurologic disorders, or history of behavioural problems. Most participants were right-handed white Americans with a non-Hispanic or Latinos background.

### Personality assessment

The FFM personality traits were assessed via the NEO five-factors inventory (NEO-FFI) (Costa & McCrae, 1992; Terracciano, 2003). The NEO-FFI is composed by 60 items, 12 for each of the five factors. For each item, participants reported their level of agreement on a 5-points Likert scale, from strongly disagree to strongly agree. The NEO instruments have been previously validated in USA and several other countries (Robert R. McCrae & Terracciano, 2005).

### MRI scanning protocol and pre-processing

Resting-state fMRI (rs-fMRI) data were acquired using a 3T scanner (Siemens AG, Erlangen, Germany) (Van Essen et al., 2012). Four runs of 15 minutes each were acquired. Subjects lied within the scanner with open eyes and while fixating a bright central cross projected on a dark background. Oblique axial acquisitions were alternated between phase encoding in a right-to-left direction in one run and phase encoding in a left-to-right direction in the other run. Gradient-echo echo-planar imaging used the following parameters: TR=720 ms, TE=33.1 ms, flip angle=52°, FOV=208×180 mm, Matrix 104×90, Slice thickness=2.0 mm; 72 slices; 2.0 mm isotropic voxels, Multiband factor=8, Echo spacing=0.58 ms, BW=2290 Hz/Px. This resulted in 4800 rs-fMRI volumes in total per subject, subdivided in

4 runs of 1200 volumes each. Structural (T1-weighted) images and field maps were also acquired to aid data pre-processing.

Each 15-minute (1200 volume) run of each subject's rs-fMRI data was pre-processed using FSL and it was minimally pre-processed according to the latest version (3.1) of the HCP pipeline (Glasser et al., 2013). Each dataset was then temporally de-meant and had variance normalization applied according to Beckmann and colleagues (Beckmann & Smith, 2004). Group-PCA output was generated by MIGP (MELODIC's Incremental Group-PCA), a technique that approximates full temporal concatenation of all subjects' data, from all 820 participants. This comprises the top 4500 weighted spatial eigenvectors from a group-averaged PCA (Stephen M Smith, Hyvärinen, Varoquaux, Miller, & Beckmann, 2014). The MIGP output was then fed into group-ICA using FSL's MELODIC tool (Beckmann & Smith, 2004), applying spatial-ICA at dimensionality of 15. Successively, the ICA maps were dual-regressed into each subject's 4D dataset to give a set of 15 time-courses of 4800 time points per subject. Further details regarding data acquisition and processing can be found in the HCP S900 Release reference manual available at <https://www.humanconnectome.org/>.

### Estimation of functional connectivity

To quantify the resting-state functional connectivity among the 15 circuits ('nodes'), the maximum information coefficient (MIC) between the time-series of each pair of circuits was computed (Reshef et al., 2011). MIC is a powerful statistic sensitive to both linear and nonlinear associations of arbitrary shape between paired variables (Reshef et al., 2011). This method was recently applied to investigate the functional connectivity patterns in patients with schizophrenia (Su, Wang, Shen, Feng, & Hu, 2013; Zhang, Sun, Yi, Wu, & Ding, 2015). The basic idea underlying MIC is that, when a relationship between two variables exists, it can be quantified via creating a grid on the scatterplot that creates a partition of the data. More formally, the MIC between two variables  $x$  and  $y$  is defined as:

$$I(x, y) = \sum_{i=1}^{n_x} p(x_i) \log_2 \frac{1}{p(x_i)} + \sum_{j=1}^{n_y} p(y_j) \log_2 \frac{1}{p(y_j)} - \sum_{i=1}^{n_x} \sum_{j=1}^{n_y} p(x_i, y_j) \log_2 \frac{1}{p(x_i, y_j)}$$

where  $n_x$  and  $n_y$  are the number of bins of the partition of the x- and y-axis. Therefore, the MIC of two variables  $x$  and  $y$  is calculated as:

$$MIC = \max \left\{ \frac{I(x, y)}{\log_2 \min\{n_x, n_y\}} \right\}$$

where the maximum is taken over all the possible  $n_x$  by  $n_y$  grids. The MIC between each pair of networks' time-series was calculated using the MINEPY toolbox (Albanese et al., 2013) implemented in MATLAB (<https://github.com/minepy/minepy>). These analytical steps generated a  $15 \times 15$  full and symmetric subject-specific matrix of functional connectivity data. These matrices were then treated as weighted networks to calculate the graph-related measures.

### Local network analyses

All graph measures were computed via the Brain Connectivity Toolbox (Rubinov & Sporns, 2010) in MATLAB (<https://sites.google.com/site/bctnet/>). For each independent components analysis (ICA) and at the subject level, we calculated the graph measures that quantify the centrality of a node within a network (local strength and betweenness centrality) as well as its integration and segregation properties (clustering coefficient and local efficiency respectively). Local strength and betweenness centrality are two indices of centrality that measure the relative importance of a node within a network (Zuo et al., 2012). Nodes with high levels of centrality are thought to facilitate information routing in the network with a key role in the overall communication efficiency of a network. The node's strength is the simplest measure of centrality and is defined as the sum of all the edge weights between a node and all the other nodes in the network. Regions with a high nodal strength indicate high connectivity with other nodes. Betweenness centrality of a node is defined as the fraction of all shortest paths in the network that contain a given node. If a node displays a high value of betweenness centrality, it participates in a large number of shortest paths and has an important role in the information transfer within a network. Along with centrality measures, the nodes of a network could display different levels of segregation and integration of information (Sporns, 2013). Also, the clustering coefficient is a commonly used metric to assess the segregation properties of a network. It reflects the ability of a node to communicate with other nodes with which it shares direct connections; in other words, it represents the fraction of triangles around an individual node. It is equivalent to the fraction of the node's neighbours that are also neighbours of each other (Watts & Strogatz, 1998) and in the case of weighted networks it is calculated as the geometric mean of all triangles associated with each node (Onnela, Saramäki, Kertész, & Kaski, 2005). Finally, the ability of an efficient information transfer across distributed nodes (i.e., nodes that are not directly connected) can be quantified via local path length and local efficiency. In the case of a binary network, the local path length is the minimum number of edges that must be traversed to go from one node to another, while in a weighted network high levels of correlations are interpreted as short distances. The local efficiency is therefore the average of the inverse local path length. Local efficiency is calculated as the global efficiency of the subgraph formed by the node's neighbours (Boccaletti et al., 2006). It measures the ability of parallel information transfer at local level.

### Global network analyses

Global graph metrics describe the topology of a network in a single number which characterizes the overall organization of a network. As global measures, we computed the global strength, the global clustering coefficient and global efficiency (Boccaletti et al., 2006; Rubinov & Sporns, 2010). These measures were calculated as the average of the local strength, local clustering coefficient and the local efficiency of all nodes, respectively.

### Statistical analyses

To evaluate the replicability of our inference framework, the initial sample of  $n=818$  participants was randomly split into two sub-samples: a "training" sample (70% of participants,  $n=573$ ) and a "test" sample (30% of participants,  $n=245$ ). The "training"



sample was used to examine the association between each of the graph measures (both global and local metrics) and the FFM personality traits. Conversely, the “test” sample was employed to assess whether the multivariate model based on the “training” sample was able to predict outcomes in the “test” sample (i.e., in an ‘unseen’ group of subjects to which the model was completely ‘agnostic’). More specifically, to test the associations between graph measures and personality differences, general linear models (GLMs), including each of the FFM traits as well as age and gender as nuisance covariates, were fitted using the “training” sample. The resulting P values were corrected for multiple comparisons using a false discovery rate (FDR) procedure. Associations surviving a stringent threshold of  $P < 0.01$  FDR were considered statistically significant. The GLMs fitted in the former procedure were then used to estimate the graph measures resulting in the “test” sample using the demographic variables and personality scores of the “test” sample only as inputs (in other words, the rsfMRI data of the “train” sample was not employed in this procedure). The similarity between ‘real’ graph measures (i.e., computed using rsfMRI data from the “test” sample) and ‘estimated’ graph indices (i.e., predicted using the GLM fitted on “training” data only) was assessed using the relative root mean square error (RRMSE). This approach is typically referred as external validation and tests for generalizability of the findings beyond the study population. The image analysis workflow is summarized in Figure 1.

## Results

### Independent components analysis (ICA)

The fifteen brain networks identified via ICA were represented by a series of circuits that have been consistently reported in past rs-fMRI studies (e.g., the sensory-motor circuit, the visual circuits, the default-mode network, the left and right fronto-parietal circuits, the salience network, etc.) (Raichle, 2015; Toschi, Duggento, & Passamonti, 2017) (Figure 2 and Supplementary Table 1 for a detailed list of the anatomical regions involved in each network node).

### Correlations between *global* graph indices and FFM traits

No significant associations were found between any of the FFM personality traits and: (i) the global strength ( $R^2 < 0.084$ ,  $P > 0.14$ ); (ii) global clustering coefficient ( $R^2 < 0.081$ ,  $P > 0.15$ ), and (iii) global efficiency ( $R^2 < 0.083$ ,  $P > 0.17$ ).

### Correlations between *local* graph indices and FFM traits

**Neuroticism**—No associations, either positive and negative, were found between neuroticism scores and: (i) the nodal strength ( $R^2 < 0.07$ ,  $P > 0.75$ ); (ii) local clustering coefficient ( $R^2 < 0.06$ ,  $P > 0.88$ ); (iii) local efficiency ( $R^2 < 0.07$ ,  $P > 0.82$ ), and (iv) betweenness centrality ( $R^2 < 0.09$ ,  $P > 0.59$ )

**Extraversion**—As for neuroticism, no statistically significant association was found between extraversion scores and: (i) the nodal strength ( $R^2 < 0.11$ ,  $P > 0.09$ ); (ii) local clustering coefficient ( $R^2 < 0.12$ ,  $P > 0.04$ ); (iii) local efficiency ( $R^2 < 0.12$ ,  $P > 0.09$ ), and (iv) betweenness centrality ( $R^2 < 0.11$ ,  $P > 0.09$ ).

**Openness**—No positive or negative association was detected between openness scores and: (i) the nodal strength ( $R^2 < 0.07$ ,  $P > 0.97$ ); (ii) local clustering coefficient ( $R^2 < 0.06$ ,  $P > 0.96$ ); (iii) local efficiency ( $R^2 < 0.06$ ,  $P > 0.99$ ), and (iv) betweenness centrality ( $R^2 < 0.09$ ,  $P > 0.27$ ).

**Agreeableness**—No positive or negative association was detected between Agreeableness scores and: (i) the nodal strength ( $R^2 < 0.10$ ,  $P > 0.13$ ); (ii) local clustering coefficient ( $R^2 < 0.10$ ,  $P > 0.12$ ); (iii) local efficiency ( $R^2 < 0.10$ ,  $P > 0.15$ ), and (iv) betweenness centrality ( $R^2 < 0.08$ ,  $P > 0.25$ ).

**Conscientiousness**—A schematic representation of the statistically significant associations between conscientiousness scores and the local graph measures is reported in Figure 3, while the statistical details are included in Table 2. In summary, significantly *positive* correlations were found between conscientiousness scores and the nodal strength, local clustering coefficient, and local efficiency in the left fronto-parietal network (FPN) ( $R^2 > 0.14$ ,  $P < 0.01$ , FDR). Furthermore, increased local clustering coefficient and betweenness centrality in the default mode network (DMN) and right FPN were associated with higher levels of conscientiousness ( $R^2 > 0.14$ ,  $P < 0.005$ , FDR). External validation showed good replicability, with RRMSE values of around 0.15 in the “test” sample.

To further explore which specific aspects of conscientiousness were linked to local graph measures, we conducted *post-hoc* analyses that included conscientiousness facets (i.e., C2-Order, C3-Dutifulness, C4-Achievement striving; C5-Self-Discipline) as main outcome measures. As in the previous analyses, age, sex, and the other FFM traits were also included in the GLM as nuisance covariates. We found that the betweenness centrality in the DMN was positively associated with C3 ( $P = 0.01$ , FDR, RRMSE=0.17) and C4 ( $P = 0.01$ , FDR, RRMSE=0.16). Finally, the betweenness centrality in the right FPN was positively associated with C3 ( $P = 0.01$ , FDR, RRMSE=0.16).

## Discussion

This study provides compelling new evidence that ‘local’ graph metrics based on resting state functional imaging are significantly associated with conscientiousness in a sample of 818 young and healthy adults drawn from the Human Connectome Project (HCP). More specifically, we found higher nodal strength, local clustering, and local efficiency in the left fronto-parietal network (FPN) in people scoring high in conscientiousness. Likewise, higher local clustering and betweenness centrality in the right FPN and default mode network (DMN) were positively related to conscientiousness scores. A validation approach based on a “training” and “test” split of the total dataset strongly supported the robustness, replicability, and ‘cross-validity’ of these findings.

Overall, our results demonstrate the value of applying connectomic approaches to study the brain functional connectivity in relation to the FFM of personality. The multi-variate analyses also show that the positive association between the FPN/DMN connectivity patterns and conscientiousness is not dependent on other FFM personality traits (i.e., neuroticism, extraversion, openness, and agreeableness) or potentially confounding factors



like gender and age variability. Similarly, the non-significant correlations with global connectomic measures (e.g., global clustering and efficiency) suggests that individual differences in conscientiousness are mediated by specific functional dynamics across distinct cognitive nodes. In the following sections, we discuss the implication of our findings to improve the understanding of the neural underpinnings of conscientiousness as well as the main strengths and limitations of our study.

### FPN and DMN connectivity patterns mediate conscientiousness

The higher nodal strength in the left fronto-parietal network (FPN) in people scoring high in conscientiousness reflects the fact that this specific circuit ‘node’ has heightened ‘communications’ with the other nodes. Highly conscientious people also show higher local clustering in the left FPN, which implies that the FPN is densely inter-connected to its neighbours and formed an elevated number of local aggregates (‘triangles’) with its most adjacent nodes. At the same time, the local efficiency in the left FPN and the betweenness centrality in the right FPN are higher in people scoring high in conscientiousness.

The FPN includes cito-architecturally complex and evolutionarily recent cortices that have been associated with inter-subject variance in several cognitive measures (Mueller et al., 2013; Zilles, Armstrong, Schleicher, & Kretschmann, 1988). Furthermore, a recent study in n=126 people from the HCP database reported that the functional connectivity patterns involving the FPNs were the most distinguishing features (‘fingerprints’) to predict variability in cognitive functioning across different individuals (Finn et al., 2015). Although the FPNs are particularly engaged during tasks that require high levels of attention and cognitive control, their connectivity patterns *at rest* can also predict subject-specific performance with a high degree of precision (Finn et al., 2015; Miranda-Dominguez et al., 2014). This may depend on the fact the FPN ‘nodes’ act as flexible ‘hubs’ and therefore play a critical role in coordinating the activity and functioning of several other brain regions (Finn et al., 2015; Miranda-Dominguez et al., 2014).

The enhanced connectivity patterns in FPNs in people scoring high in conscientiousness can therefore be interpreted as a ‘sign’ of increased cognitive control and flexible behaviour in these individuals, bearing in mind the shortcomings of making reverse inference in cognitive neuroscience (Poldrack, 2006). This is in keeping with several observations showing that conscientious people are efficient in pursuing their objectives and planning, which are *themselves* critical predictors of academic or occupational success, healthy life-styles, and ultimately longevity (Nofle & Robins, 2007; Ozer & Benet-Martinez, 2006; B. W. Roberts, Lejuez, Krueger, Richards, & Hill, 2014; Sutin et al., 2016). Our data are also consistent with past neuroimaging studies that have implicated the dorsolateral prefrontal cortex (DLPFC) and other PFC areas (e.g., the anterior cingulate cortex-ACC, which is also part of the FPN) in conscientiousness (Bunge & Zelazo, 2016; C. G. DeYoung et al., 2010; Forbes et al., 2014; Jackson, Balota, & Head, 2011; Kapogiannis et al., 2012; Matsuo et al., 2009; Whittle et al., 2009). Nevertheless, it is important to emphasize that our results show that it is the FPN *connectivity patterns* with the other ‘nodes’ which is linked with conscientiousness rather than the activity in the DLPFC/ACC in isolation. This is a key issue, especially when considering the necessity to progress from models of personality that

consider the function of single brain regions, to more naturalistic frameworks that aim at describing individual differences in behavioural traits in terms of large-scale networks dynamics.

Last but not least, we found that the default mode network (DMN) showed higher local clustering and betweenness centrality in relation to high conscientiousness scores. This finding was predicted on the basis of recent data showing that connectivity patterns involving the DMN strongly predict variability in a single ‘positive-to-negative’ behavioural axis (S. M. Smith et al., 2015). There is also evidence that the DMN significantly contributes to working memory performances via the dynamic reconfiguration of its interactions with other networks, which suggests that the DMN is actively involved during the execution of cognitive demanding tasks (Vatansever, Menon, Manktelow, Sahakian, & Stamatakis, 2015). Overall, high-level cognitive functioning is critical in human evolution and is likely to be central in the life of conscientious people. Hence, we speculate that the enhanced DMN ‘interplay’ with other nodes may help explaining, in mechanistic terms, why conscientious individuals are able to efficiently elaborate complex plans like imaging and planning future scenarios. This hypothesis is corroborated by our *post-hoc* analyses showing that local measures in the DMN (i.e., local clustering and betweenness centrality) are respectively linked to the C3-Dutifulness facet (i.e., reliable, dependable, careful, scrupulous and strictly adherent to rules) and C4-Achievement Striving facet (i.e., industrious, enterprising, ambitious, purposeful, and driven) of conscientiousness.

### Strengths & limitations

The main strengths of our study are: (i) the large, homogeneous, and well-characterized sample of participants in terms of FFM personality traits, demographic variables, and neuroimaging data, which *in itself* offers greater statistical power compared to several previous studies, and (ii) the fact that we employed robust statistical approaches (i.e., machine-learning) to show specificity and replicability of our main findings. We note, however, that the effects sizes were relatively small ( $T$ 's~3.5), although in the typical range of other recent studies using similar sample sizes in healthy individuals (Mackey et al., 2016; S. M. Smith et al., 2015). There was also a relatively high number of statistical tests, although we strived to attenuate this potential problem with the use of stringent statistical procedures to correct for multiple comparisons ( $P < 0.01$ , FDR).

The fact that conscientiousness was the sole personality trait related to ‘connectomic’ metrics *does not* necessarily imply that the other FFM traits *do not* have such brain correlates. Several reasons why the other FFM traits were not related to functional connectomic indices may be speculated—even if not resolved by our dataset. These include: (i) type II errors; (ii) non-linear relationships between personality traits and brain connectomic metrics; (iii) the fact that our models were multivariate rather than univariate, which means that the shared variance explained by the other FFM traits was factored out while analyzing the effect of each FFM trait; (iv) the possibility that correlations between brain functional connectomic measures and other personality traits *do exist* but can only be revealed by ‘meta-trait’ measures (C. G. DeYoung, Peterson, & Higgins, 2002) or traits from other models of personality, not the FFM.

Perhaps more importantly, our study suggests that different neuroimaging modalities and analytical techniques may be able to reveal the unique and exquisite nature of *how* the brain mediates each of the FFM traits. Consistent with this idea, we have recently found in  $n=509$  individuals from the same HCP dataset that measures of cortical anatomy (i.e., cortical thickness, folding, and surface area) were strongly and differently associated with each of the FFM traits (Riccelli, Toschi, et al., 2017). Hence, brain structural heterogeneity is likely to be an underlying substrate of variability in all FFM traits while the same may not be true for functional measures that assess more transient ‘communication’ patterns. Different functional connectivity approaches (e.g., time-variant connectivity methods) are thus warranted to reveal in more detail the complexity of the neural dynamics mediating individual differences in personality (Riccelli, Passamonti, Duggento, Guerrisi, Indovina, Terracciano, et al., 2017; Riccelli, Passamonti, Duggento, Guerrisi, Indovina, & Toschi, 2017).

### Summary & conclusions

To summarize, we found robust and specific associations between conscientiousness and graph measures of local connectivity in the FPN and DMN. These highly integrated circuits include different parts of the prefrontal and parietal cortices, a set of brain regions that have significantly evolved in human beings and have been consistently implicated in goal-setting and planning, two high-order cognitive functions in which conscientious people excel.

### Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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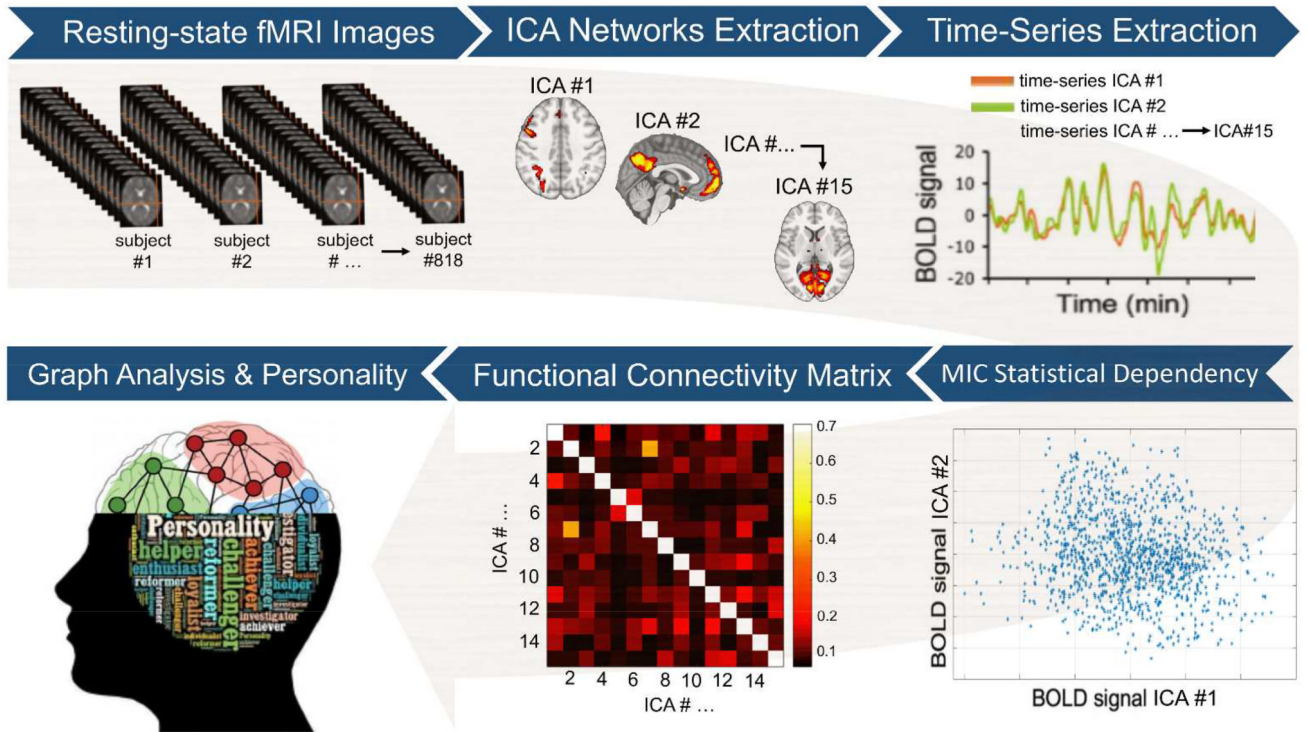
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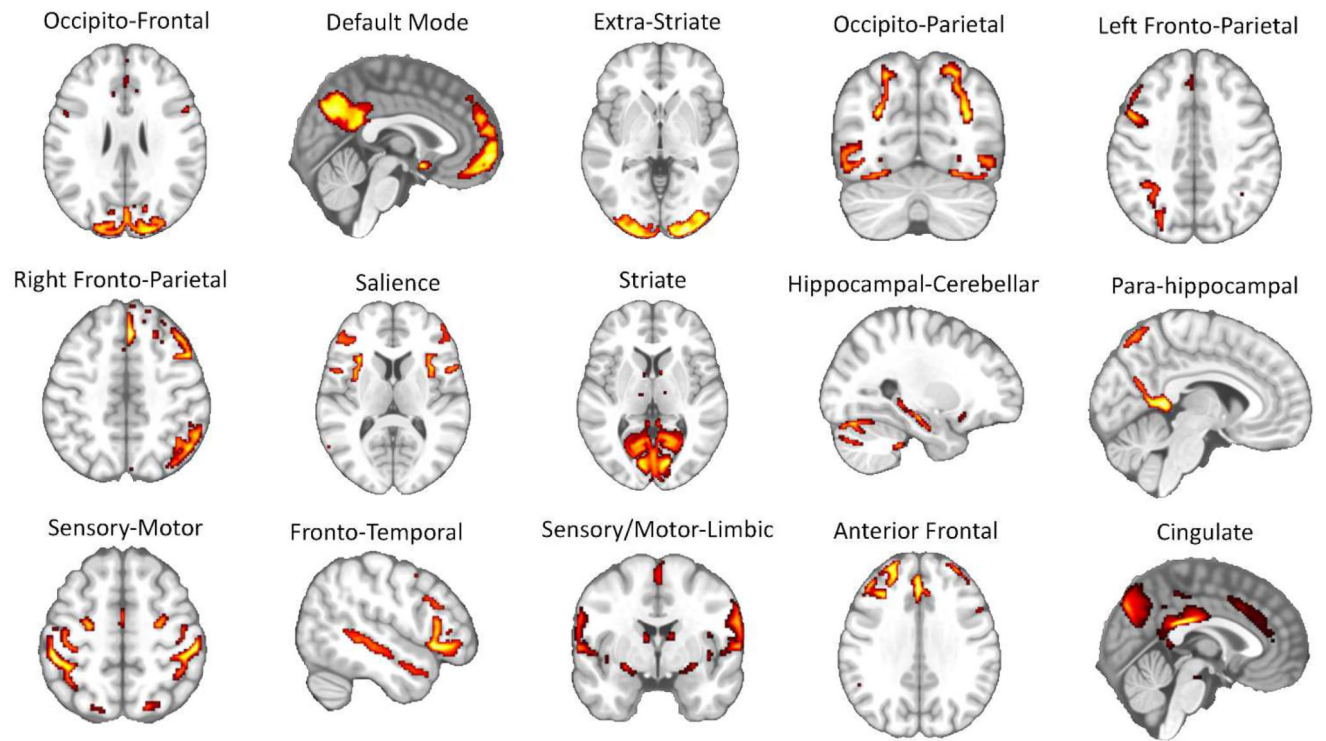
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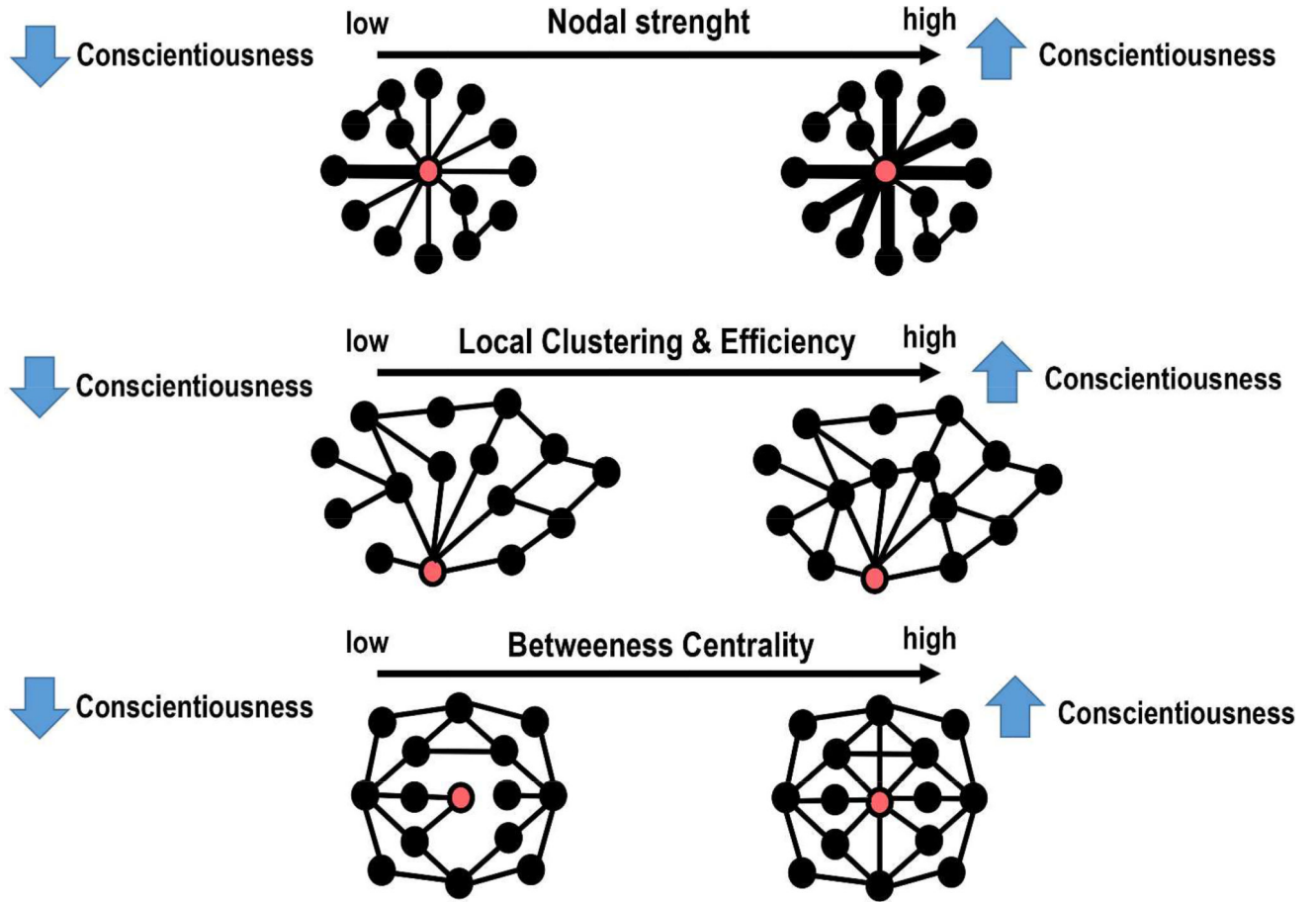
**Figure 1. Image analysis workflow**

After initial pre-processing, the resting-state functional magnetic imaging (fMRI) data were used to extract a set of 15 separate brain circuits via independent components analysis (ICA). Next, subject-specific time-series from each ICA brain circuit were obtained. The maximal information coefficient (MIC), an index that assesses for linear and non-linear relationships in big data-sets, was used to measure statistical dependency between each pair of time-series. This led to a 15×15 functional connectivity matrix at the single-subject level. The subject-specific connectivity matrices were then used to compute local and global graph measures (i.e., strength, clustering, efficiency, and betweenness centrality). Each of these graph measures, which quantify different aspects of the brain topological organization, was finally correlated with the five-factor-model personality traits at the group level.



**Figure 2. Results of independent component analysis (ICA)**

Fifteen separate brain functional circuits were identified during the ICA step of the image analysis pipeline (Figure 1 and methods section in the main text for further details). Each of these circuits was successively used as “node” in the graph analysis. The list of the brain areas belonging to each individual network is reported in Supplementary Table 1.



**Figure 3. Schematic representation of the main results**

Depending on the graph metric (Table 2), the red circle represents either the left or right fronto-parietal network (FPN) or default mode network (DMN), whilst the black circles represents the 14 remaining network nodes. **Top row.** The thicker lines in individuals with high levels of conscientiousness indicate the existence of higher strength in the ‘communications’ between the FPN and the other brain networks. **Middle row.** People scoring higher in conscientiousness show a higher degree of inter-connectedness between the FPN or DMN and the local networks consisting of direct neighbours of the FPN or DMN. **Bottom row.** The DMN has higher betweenness centrality in individuals with high levels of conscientiousness. This means that the DMN is a “hub” node in conscientious people.

**Table 1**

Demographic and personality variables in the HCP sample (n=818 healthy volunteers).

<b>Demographic variables</b>		
Gender (males / females)	367 / 451	
Age (years)	28.7 ± 3.7 [22–37]	
Handedness (Right / Left / Both)	743 / 73 / 2	
Education (years)	14.9 ± 1.8 [11–17]	
Ethnicity (%)	Hispanic / Latino	8.6 %
	Not Hispanic / Latino	90.5 %
	Unknown / Not Reported	0.9 %
<b>Personality scores (NEO-FFI)</b>		
Neuroticism	16.3 ± 7.2 [0–43]	
Extraversion	30.7 ± 5.9 [11–47]	
Openness	28.3 ± 6.1 [12–45]	
Agreeableness	32.0 ± 5.0 [13–45]	
Conscientiousness	34.5 ± 5.9 [12–48]	

Key to table. Age, education, and personality data are expressed as mean ± standard deviation while the range in parentheses [] is expressed as minimum-maximum. NEO five-factors inventory questionnaire, NEO-FFI.



**Table 2**

Positive correlations between *local* graph metrics and conscientiousness scores.

Local graph metric	Circuit	Mean ( $\pm$ SD)	T score	Pearson's <i>R</i>	P (FDR)	RRMSE
<b>Nodal strength</b>	Left FPN	2.37 $\pm$ 0.11	3.46	0.14	0.009	0.16
<b>Local clustering</b>	DMN	0.15 $\pm$ 0.008	3.40	0.14	0.008	0.15
	Left FPN	0.13 $\pm$ 0.007	3.26	0.14	0.008	0.14
<b>Local efficiency</b>	Left FPN	0.09 $\pm$ 0.007	3.53	0.15	0.006	0.15
<b>Betweenness-centrality</b>	DMN	2.17 $\pm$ 2.44	3.68	0.15	0.002	0.16
	Right FPN	0.23 $\pm$ 0.79	3.66	0.15	0.002	0.16

Key to Table. Standard deviation (SD); FPN, fronto-parietal network; DMN, default mode network. FDR, false discovery rate; RRMSE: Relative root mean square error.