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Brain network topology and personality traits: a source level magnetoencephalographic study

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Abstract

Personality neuroscience is focusing on the correlation between individual differences and the efficiency of large-scale networks from the perspective of the brain as an interconnected network. A suitable technique to explore this relationship is the magnetoencephalography (MEG), but little are MEG studies aimed at investigating topological properties correlated to personality traits. By using MEG, the present study is aimed at evaluating how individual differences described in Cloninger's psychobiological model are correlated with specific cerebral structures. Fifty healthy individuals (20 males, 30 females, mean age: 27.4 ± 4.8 years) underwent Temperament and Character Inventory examination and MEG recording during a resting state condition. High harm avoidance scores were associated with a reduced centrality of the left caudate nucleus and this negative correlation was maintained in females when we analyzed gender differences. Our data suggest that the caudate nucleus plays a key role in adaptive behavior and could be a critical node in insular salience network. The clear difference between males and females allows us to suggest that topological organization correlated to personality is highly dependent on gender. Our findings provide new insights to evaluate the mutual influences of topological and functional connectivity in neural communication efficiency and disruption as biomarkers of psychopathological traits.

Keywords: Brain network; Cloninger; Functional Connectivity; Magnetoencephalography; Temperament and Character Inventory.

Introduction

Personality can be defined as “the sum of all the characteristics that make a person unique” (Weinberg and Gould 2015). This uniqueness depends on the interaction of genetic and environmental factors, and it is not surprising that every model and taxonomy that has attempted to describe the diversity of personality characteristics has considered this interrelationship (Weiner et al. 2013). One such model that has made a significant contribution is Cloninger’s psychobiological model, which identifies four primary-basic personality temperaments (Novelty Seeking, NS; Harm Avoidance, HA; Reward Dependence, RD; and Persistence, P) and three characters (Self-Directedness, SD; Cooperativeness, CO; and Self-Transcendence, ST) that are all measurable with the Temperament and Character Inventory (TCI) (Cloninger et al. 1993). While the temperaments in Cloninger’s model are generally associated with genetic substrates, the characters concern individual aspects linked to learning and socio-cultural factors. It has been suggested that psychophysical well-being depends on the harmonious development of these traits and characters (Cloninger and Zohar 2011). In this framework, Cloninger’s psychobiological model represents key descriptors of human behavior. In fact, the “direction of the action *toward*” can be identified in NS, the “direction of the action *away from*” in HA and the “maintaining of the behavior” in RD and P (Laricchiuta and Petrosini 2014). The TCI is therefore a sensitive instrument for evaluating nonadaptive behaviors, as the occurrence of an excessive tendency toward a specific temperamental trait could indicate psychopathological disorders (Abram et al. 2017). As a supportive example, anxiety disorders and depression are often correlated with high HA scores (Biederman et al. 2001; Muris et al. 2001), high NS and HA scores are very frequent in individuals with dependences and schizophrenia (Sim et al. 2012), and high HA and low NS scores are associated with somatization disorders (Karvonen et al. 2006).

The last decade has seen a growing interest in studying the biological substrates of individual differences in order to explore how the diversified variety of human behaviors arise from different neural patterns and how they are correlated to specific cerebral structures or neurotransmitter systems (DeYoung 2010; Booth et al. 2014; Ricelli et al. 2017). Precisely, for this new approach to the study of personality, it is increasingly the common terminology of “personality neuroscience” to derive explanatory models of individual differences that are based on the idea that an individual cannot be understood without understanding his/her structural and functional brain characteristics and fluctuations in neurotransmitter levels (DeYoung and Gray 2009; DeYoung 2010; Markett et al. 2018). For example, the tendency toward exploratory activity and the intense excitement for new stimuli identified in NS is associated with low dopaminergic activity, while the response to avoid punishment and non-reward identified in HA is correlated with high serotonergic activity (Mincic 2015). The relationship between individual differences and variability in brain function and structure has yielded results that are not always consistent. Added to that is the variability in the samples and the diversity of the questionnaires used to investigate personality traits. However, neuroanatomical and neurofunctional studies have often evidenced the involvement of cortico-limbic pathways and basal ganglia in relation to specific personality traits (Kumari et al. 2004; Deckersbach et al. 2006; Gogtay et al. 2004). Recently, a cerebellar involvement has been observed in sustaining motivational temperamental traits. In fact, it correlates positively with NS scores and negatively with HA scores (Laricchiuta et al. 2014; Picerni et al. 2013; Petrosini et al. 2017).

Newly, the personality neuroscience has specialized in investigating the correlation between specific behavioral styles and the efficiency of large-scale networks during a resting state condition from the perspective of the brain as a coherent interconnected network (Sporns et al. 2005). Indeed,

analyzing personality traits during resting state is possible because they are stable over longer stretches of an individual's lifespan (Edmonds et al. 2008; Specht et al. 2011). Although the “resting brain is never truly resting” (Seeley et al. 2007), in resting participants, it was still possible to identify a large-scale network critical for emotional salience processing. That network, called the “insular salience network”, is located around the anterior insula including the anterior cingulate, parts of the basal ganglia, and cortical regions along the operculum, and it receives input from the amygdala (Seeley et al. 2007; DeYoung et al. 2010; Markett et al. 2018).

However, most studies in this context take into account other personality models using brain connectivity measures determined through hemodynamic neuroimaging techniques, such as functional MRI (fMRI), and positron emission tomography (PET), and electroencephalography (EEG).

A suitable technique to investigate the link between personality traits and brain regions within the whole brain network is magnetoencephalography (MEG). MEG is a promising functional neuroimaging technique that allows researchers to record brain magnetic activity and to identify patterns of neural oscillations in several bands with highly accurate temporal resolution (Baillet 2017) compared to fMRI and PET. Furthermore, MEG signals are unaffected by distortion, while in EEG electric currents become distorted as they pass through the skull and other tissues (Leahy et al. 1998). The MEG signal reflects integrated synaptic activity with high fidelity and thus offers a highly accurate measure of brain activity (Hämäläinen 1992). In addition to estimating the connectivity among brain regions, to exploring each region's role within the brain network is vital. Graph theory, a field of mathematics that studies network structures, can be usefully exploited to explore the topological characteristics of the brain (Bullmore and Sporns 2009).

To date, research on resting-state neural correlates in relation to Cloninger's personality traits is limited. The present study therefore investigates the brain topology correlated to Cloninger's temperaments and characters in healthy individuals by means of MEG, which allows detection of the complex dynamic properties of brain networks.

To the best of our knowledge, there have been only two MEG studies aimed at characterizing the topological properties and functional connectivity correlated to personality traits. However, neither can be directly compared to our study. One study considered a psychopathological population (James et al. 2015), while the other used a different personality model (Kabbara et al, 2020).

In the present study, we examine how individual differences in temperaments and characters described by Cloninger are correlated with specific cerebral structures in healthy subjects during a resting state condition, considering the brain as a coherent interconnected network. Because this is the first MEG study to analyze topological properties in healthy subjects using Cloninger's model, we did not make specific predictions about trait-specific network activity, though we did expect an involvement in the cerebral areas of the insular salience network that are correlated to HA, since that the personality trait is mainly related to salience stimulus.

Furthermore, given that our sample consisted of both men and women, we expected to find some gender differences in TCI and its relationship with topological characteristics, as it has been demonstrated that gender is a fundamental factor to consider when trying to understand the morphological underpinnings of inter-individual differences in personality traits (Nostro et al. 2017).

Methods

Participants

Fifty healthy participants were enrolled (20 males, 30 females, mean age: 27.4 ± 4.8 years). Exclusion criteria were age > 40 years, left-handed, personal history of neurologic, psychiatric or psychological disease, and the consumption of psychoactive drugs. All participants provided written informed consent. The study was carried out in accordance with the Declaration of Helsinki and was approved by the Local Ethics Committee of the University of Naples “Federico II” (Prot. n. 17/2021).

Temperament and Character Inventory (TCI)

Participants completed the Temperament and Character Inventory (TCI) consisting of 240 items true/false questionnaire (Cloninger et al. 1993). TCI is a self-rated instrument that provides a comprehensive inventory of dimensions of temperament (Novelty Seeking, NS; Harm Avoidance, HA; Reward Dependence, RD; Persistence, P) and character (Self-directedness, SD; Cooperativeness, C; Self-transcendence, ST). NS, HA, and RD consist of four sub-scales, while P only one. In general, NS refers to the tendency to seek novel stimuli and experiences; HA refers to a tendency to inhibition of behavior in response to signals of punishment; RD refers to a tendency to the maintenance of behavior in response to cues of social reward, and P measures the tendency towards perseverance in the face of adversity. For that concerns the three domains of character, SD measures the ability to use the willpower necessary to achieve personal goals; C measures the ability to cooperate with others; ST measures the ability to look beyond self-interest to see oneself as part of a larger whole, which could be described as a marker of maturity but could also be described as a tendency towards spirituality or a belief in the religious or supernatural.

The items are divided into positive and negative items and the scoring for each item is dichotomous (TRUE/FALSE), with a 1/0 score for positive items and 0/1 for negative items. The sum of the points obtained gives a “Raw Score” to which it is possible to match a “Percentile Score” and a

“T-Score” which, shown on the graph, allows defining a personality profile. A percentile value above 67% and one below 33% are, according to the literature, considered abnormal (Cloninger et al. 1993).

Whenever an answer (true or false) was in accordance with a specific trait, a point was assigned. The final score was calculated as the ratio between the total score and the total number of items composing a specific trait.

Acquisition

Participants were examined with a MEG system composed of 163 magnetometers. The system was developed by the National Research Council at the Institute of Applied Sciences and Intelligent Systems “E. Caianiello”, Pozzuoli, Naples. For each participant, four coil positions (two on the forehead, two behind the ears) and four anatomical references (nasion, right and left preauricular points, vertex) were digitally recorded prior to acquisition using Fastrak (Polhemus®) (Sorrentino et al. 2021). The coils were activated and localized at the beginning of each registration segment. The participant was seated in a magnetically shielded room, and brain activity was recorded in a resting state, with eyes closed, in two separate segments of 3’35” each. To detect and remove artifacts, cardiac and ocular activity was recorded during MEG acquisition (Gross et al. 2013). Sample frequency was 1024 Hz, and signals were filtered through a smoothing filter in the 0.5–48 Hz band (Figure 1a).

Preprocessing

To reduce environmental noise, we used the principal component analysis (Sadasivan and Dutt 1996) available within the FieldTrip toolbox (Oostenveld et al. 2011); the noisy channels were removed by an experienced operator after visual inspection. Subsequently, cardiac and ocular

activity was removed as an artifact through independent component analysis (Barbati et al. 2004). Finally, trials longer than 4 s were selected (Figure 1 b,c).

Source reconstruction

The data underwent a beamforming procedure using the FieldTrip toolbox. For each participant, the fiducial points were visually recognized on the native MRI and used to co-register the MEG acquisition. We used Nolte's (2003) conduction model and implemented the linearly constrained minimum variance beamformer (Van Veen et al. 1997) to reconstruct time series related to the centroids of 116 regions- of -interest (ROIs), based on the Automated Anatomical Labeling atlas (Gong et al. 2009; Hillebrand et al. 2016). Because of the position of the MEG sensors, signals coming from the cerebellum were excluded as unreliable and we considered only the first 90 ROIs (Figure 1 d).

Construction of brain networks

To estimate the connectivity among the 90 ROIs, we applied the Phase Linearity Measurement (PLM) index (Sorrentino et al. 2019), an adirectional measure based on the phases of signals, defined by the following equation (Baselice et al. 2019):

$$PLM = \frac{\int_{-B}^B \left| \int_0^T e^{i\Delta\phi(t)} e^{-i2\pi f t} dt \right|^2 df}{\int_{-\infty}^{\infty} \left| \int_0^T e^{i\Delta\phi(t)} e^{-i2\pi f t} dt \right|^2 df}$$

where $\Delta\phi(t)$ is the phase difference between two signals, -B and B is the bandwidth, f is the frequency and T is the observation period.

PLM was computed for each pair of brain regions, obtaining a 90×90 weighted adjacency matrix for each trial of registration. The five canonical frequency bands were estimated as delta (0.5–4 Hz), theta (4.0–8.0 Hz), alpha (8.0–13.0 Hz), beta (13.0–30.0 Hz) and gamma (30.0–48.0 Hz). Thereafter, we built a brain network starting from each adjacency matrix (Stam et al. 2007), where each of the 90 brain regions were represented as a node, and the weighted edges between two nodes were represented by PLM values. Then, applying Kruskal’s algorithm (Kruskal 1956) to each reconstructed brain network, we calculated the minimum spanning tree (MST), a loopless graph with N nodes and $M = N-1$ links. In this way, we obtained topologic measures unaffected by the degree distribution, matrix density, or arbitrary thresholds (van Wijk et al. 2010) (Figure 1 e,f).

INSERT HERE FIGURE 1

Graph theoretical analysis

We calculated both global and nodal (regional) parameters.

To obtain indices representative of the global topological organization of brain networks, we calculated the following: the *leaf fraction* (Boersma et al. 2013), which is the fraction of nodes with a degree of 1, an expression of the network integration; the *degree divergence*, a measure of the broadness of the degree distribution, related to the synchronizability of the networks (Stam et al. 2014; Tewarie et al. 2015); the *tree hierarchy* defined as the trade-off between network integration and central nodes overload; the *diameter*, defined as the longest shortest path of an MST; and the *assortativity*, an estimation of the relationship among nodes.

To examine the regional features of the network we calculated two nodal parameters: the *degree*, defined as the number of connection incidents on a given node, and the *betweenness centrality* (BC), described as the number of shortest paths passing through a given node over the total number

of shortest paths in the network (Tewarie et al. 2015). To obtain a single value of each parameter for each participant, the metrics were averaged across the trials of each subject.

MRI acquisition

MRI images of seventy participants were acquired using a 1.5-T Signa Explorer scanner with an 8-channel parallel head coil (General Electric Healthcare, Milwaukee, WI, USA). We obtained three-dimensional T1-weighted images (gradient-echo sequence Inversion Recovery prepared Fast Spoiled Gradient Recalled-echo, time repetition = 8.216 ms, TI = 450 ms, TE = 3.08 ms, flip angle = 12, voxel size = $1 \times 1 \times 1.2$ mm³; matrix = 256×256). We used a standard template MRI for seven participants who refused to undergo the MRI examination.

Statistical analysis

Analyses were performed using MATLAB (MathWorks, version R2013a). Both global and regional metrics were correlated, using Pearson's correlation, to the 7 TCI scores in each frequency band. Further analyses comparing male and female individuals were performed through a permutation test, in which each subject label has been permuted 10,000 times. A significance level of 0.05 was applied after false discovery rate (FDR) correction across 90 regions and temperaments/characters.

Results

Topological brain network parameters. A Pearson's correlation analysis was performed to evaluate the relationship between both global and nodal topological parameters and seven dimensions of personality (4 temperaments and 3 characters), according to TCI, in 50 male and

female participants. No global topological parameter showed correlation with any of the TCI dimensions. On the contrary, in relation to nodal parameters, we found a significant negative correlation in the alpha band involving the betweenness centrality (BC) of the left caudate (LC) and the harm avoidance (HA) trait ($r = -0.52$; $p = 0.047$) (Figure 2).

INSERT HERE FIGURE 2

Comparison between male and female gender. Comparing male and female population in TCI by means of permutation analysis, we found that women scored higher than men in HA ($p = 0.048$) and RD ($p = 0.041$) temperaments and ST ($p = 0.027$) character (Figure 3).

INSERT HERE FIGURE 3

Having detected a significant negative correlation in alpha band between left caudate and HA when the entire sample was taken into consideration, we examined in detail this correlation considering each gender separately. While in male individuals, the correlation did not show to be significant ($r = -0.38$; $p = 0.098$) (Figure 4a), in female participants it was significant, with a negative coefficient ($r = -0.6$; $p < 0.001$) (Figure 4b) showing thus the same pattern as when the two groups are processed together.

INSERT HERE FIGURE 4

Discussion

In the present study, we used MEG to investigate the brain topology correlated with personality traits in healthy individuals. Assuming the brain as a coherent interconnected network, we analyzed how individual differences in Cloninger's temperaments and characters correlated with

specific cerebral structures synchronized among themselves. We found high HA scores were associated with a reduced centrality of the left caudate nucleus (Figure 2). In interpreting this data, it can be useful to recall the meaning of this temperament and the functional role of the caudate nucleus. HA consists of the tendency to inhibit behaviors, to act with caution and apprehension. The adaptive advantages of high HA scores are cautiousness and careful planning when a hazard is likely to happen, while the disadvantages occur when a hazard is unlikely to happen, but its anticipation leads to maladaptive inhibition and anxiety (Laricchiuta and Petrosini 2014). For these characteristics, HA is the trait that is most correlated to the salience of the environmental stimuli and reflects some features of the caudate nucleus; it plays a key role in adaptive behavioral responses and in choosing actions that are likely to lead to a positive outcome (Tricomi et al. 2004). Notably, the caudate nucleus, as part of the striatum, is involved in the motivation (Ernst and Fudge 2009) and anticipation of a potential reward (Benningfield et al. 2014). In addition, its activation has been linked to attentional bias toward positive social stimuli (Haruno et al. 2004; Pizzagalli et al. 2009; Dedovic et al. 2016).

The association between HA and the left caudate nucleus is specific only for the BC nodal parameter, which denotes the shortest path between nodes in the interconnected whole-brain network and in turn the importance of the left caudate nucleus in mediating communication between the entire network of nodes (Freeman et al. 1977). In other words, the BC parameter suggests that the more behaviors are inhibited (high HA values), the less the caudate nucleus is a central node in the network. Similarly, we can suggest that the more the behaviors are goal directed (low HA values), the more the caudate nucleus become a central node in the network. Thus, the reduced centrality of the caudate nucleus associated with HA scores resonates well with the assumption that individuals scoring higher in this temperament will report greater behavioral

inhibition and greater tendency to process stimuli as potentially threatening rather than potentially rewarding (Cloninger et al. 1994). In addition, higher HA scores have been found to be predictive of anxiety disorders, and several studies have documented that anxiety disorders are characterized by alterations in caudate structure and connectivity and altered stimulus processing (Sareen et al. 2007; Whiteside et al. 2006). Finally, the caudate nucleus' reduced centrality associated with higher HA scores is in accordance with previous fMRI studies reporting a relationship between HA scores and connectivity in the cortico-limbic circuit (Westlye et al. 2011), in which the caudate nucleus plays a key role also in adaptive emotional responses. Of note, using resting-state functional connectivity data, HA has been found to be negatively related to the insular salience network's efficiency (Markett et al. 2016), thus suggesting a crucial role for the caudate nucleus in this large-scale network.

In the present study, we also analyzed the gender differences in the TCI scores and correlated them to specific topological data. We found that women scored higher than men in HA and RD temperaments and ST character (Figure 3), confirming previous well documented findings (Costa et al. 2001; Schmitt et al. 2008).

The negative correlation we found between the left caudate and HA for the BC nodal parameter, induced us to analyze it considering each gender separately. Only female participants showed the same pattern as when the two groups were processed together. In fact, this correlation was maintained in the female subgroup and collapsed in the male one (Figure 4 a,b). This difference can be explained by dissimilarities in personality traits (Costa et al. 2001; Chapman et al. 2007; Weisberg et al. 2011) as well as in brain structural and functional asymmetries between female and male groups (Wang et al. 2019). Our topological data can also be discussed in relation to a previous voxel-based morphometry study that investigated the association between gray

matter volume (GMV) and personality traits in men and women using the NEO five-factor inventory (NEO-FFI). Among various results, the significant association between GMV and neuroticism that was found only in men, suggests that brain structure–personality relationships are highly dependent on gender (Nostro et al. 2017). Although the NEO-FFI is different from the TCI, there are many similarities between HA and neuroticism. In fact, neuroticism is associated with a decreased ability to ignore irrelevant information (Prabhakaran et al. 2011). It has also been related to a “hypervigilance of threats” (Mogg and Bradley 1998; Richards et al. 2014); that is, an adaptive behavior to perceive a potential risk faster, which comes at the cost of specificity and, consequently, less successful inhibition of irrelevant stimuli and response sets. Like us, Nostro and colleagues (2017) found neuroticism scores were higher in women than men. Unlike us, they found structural brain asymmetries only in male group, suggesting that, in the female group, brains may be more decentralized (Zaidi 2010) and may feature stronger interhemispheric structural connectivity (Ingallhalikar et al. 2014), a factor that may benefit multitasking characteristics (Zaidi 2010). Given Nostro and colleagues’ interpretation, we can hypothesize that the characteristic of multitasking is reflected in the organization of the large-scale networks that include multiple brain regions. Thus, in this intriguing hypothesis, the insular salience network would be wider and would include the caudate nucleus.

Beyond the interpretation of our data, other connectivity studies showed that men had higher nodal efficiency of the internal regions such as insula and peripheral lingual gyrus, while women showed significantly greater betweenness centrality in the precuneus and peripheral superior occipital gyrus (Yan et al. 2011; Wang et al. 2019), thus evidencing a clear difference between women and men in large scale brain network organization.

This study has some limitations that naturally suggest using caution in generalizing these findings. The first limitation is the exclusion of the cerebellum from the analysis of the networks. This exclusion is a consequence of our MEG system which does not cover the lower occipital area and therefore does not allow a clean recording of the signal coming from the cerebellar nuclei. It is important to recognize this limitation in light of recent evidence suggesting the cerebellum together with the basal ganglia in influence and sustain processes that are linked to individual differences in approach and avoidance behaviors through a cortico-basal-cerebellar loop (Picerni et al. 2013; Laricchiuta and Petrosini 2014).

In addition, the relatively small sample prohibits drawing conclusion about gender differences in brain underpinnings of personality mainly for females, more affected by hormonal fluctuation (Liparoti et al. 2021). However, the differences between groups in our study encourage us to continue this line of research to better understand the topological organization in both. This study also has several strengths. First, it is one of the first studies that uses MEG to investigate the biological substrates of personality traits and as explained in the introduction, this analysis system allows us to obtain precise and accurate results. Second, although small, our sample consists of young adults of similar age. This feature represents a great advantage because the human brain changes during one's life span and analyzing the brains of individuals of the same age allows us to gain an accurate picture of brain topology at that age.

Conclusion

In conclusion, our results highlight that the topological measures in MEG studies offer unique information about the neurobiological basis of personality traits. These results also pave the way

to exploring the mutual influences of topological and functional connectivity in neural communication efficiency and disruption as biomarkers of psychopathological personality traits.

References

- Abram SV and DeYoung CG (2017) Using personality neuroscience to study personality disorder. *Personal Disorders*, 8, 2. <https://doi.org/10.1037/per0000195>
- Baillet S (2017). Magnetoencephalography for brain electrophysiology and imaging. *Nature neurosci*, 20, 327-339. <https://doi.org/10.1038/nn.4504>
- Barbati G, Porcaro C, Zappasodi F, Rossini PM, Tecchio F (2004) Optimization of an independent component analysis approach for artifact identification and removal in magnetoencephalographic signals. *Clinical Neurophysiol*, 115, 1220-1232. <https://doi.org/10.1016/j.clinph.2003.12.015>
- Baselice F, Sorriso A, Rucco R, Sorrentino P (2018) Phase linearity measurement: a novel index for brain functional connectivity. *IEEE transactions on medical imaging*, 38, 873-882. <https://doi.org/10.1109/TMI.2018.2873423>
- Benningfield MM, Blackford JU, Ellsworth ME, Samanez-Larkin GR, Martin PR, Cowan RL, Zald DH (2014) Caudate responses to reward anticipation associated with delay discounting behavior in healthy youth. *Dev cogn neurosci*, 7, 43-52. <https://doi.org/10.1016/j.dcn.2013.10.009>
- Biederman J, Hirshfeld-Becker DR, Rosenbaum JF, Hérot C, Friedman D, Snidman N, Kagan J Faraone SV (2001) Further evidence of association between behavioral inhibition and social

anxiety in children. *Am J Psychiatry*, 158, 1673-1679.
<https://doi.org/10.1176/appi.ajp.158.10.1673>

Boersma M, Smit DJ, Boomsma DI, De Geus EJ, Delemarre-van de Waal HA, Stam CJ (2013) Growing trees in child brains: graph theoretical analysis of electroencephalography-derived minimum spanning tree in 5-and 7-year-old children reflects brain maturation. *Brain connect*, 3, 50-60. <https://doi.org/10.1089/brain.2012.0106>

Booth T, Möttus R, Corley J, Gow AJ, Henderson RD, Maniega SM, Murray C, Royle NA, Sprooten E, Valdés Hernández MC, Bastin ME, Penke L, Starr JM, Wardlaw JM, Deary IJ (2014) Personality, health, and brain integrity: the Lothian birth cohort study 1936. *Health Psychol*, 33, 1477. <https://doi.org/10.1037/hea0000012>

Bullmore E and Sporns O (2009) Complex brain networks: graph theoretical analysis of structural and functional systems. *Nat rev neurosci*, 10, 186-198. <https://doi.org/10.1038/nrn2575>

Chapman BP, Duberstein PR, Sörensen S, Lyness JM (2007) Gender differences in Five Factor Model personality traits in an elderly cohort. *Pers indiv differ*, 43, 1594-1603. <https://doi.org/10.1016/j.paid.2007.04.028>

Cloninger CR, Svrakic DM, Przybeck TR (1993) A psychobiological model of temperament and character. *Arch gen psych*, 50, 975-990. <https://doi.org/10.1001/archpsyc.1993.01820240059008>

Cloninger CR, Zohar AH (2011) Personality and the perception of health and happiness. *J affect disord*, 128, 24–32. <https://doi.org/10.1016/j.jad.2010.06.012>

- Costa PT, Terracciano A, Crae RR (2001) Gender differences in personality traits across cultures: robust and surprising findings. *J pers soc psychol*, 81, 322–331. <https://doi.org/10.1037/0022-3514.81.2.322>
- Deckersbach T, Dougherty DD, Rauch SL (2006) Functional imaging of mood and anxiety disorders. *J neuroimag: official j Am Soc Neuroimag*, 16, 1–10. <https://doi.org/10.1177/1051228405001474>
- Dedovic K, Giebl S, Duchesne A, Lue SD, Andrews J, Efanov S, Engert V, Beaudry T, Baldwin MW, Pruessner JC (2016) Psychological, endocrine, and neural correlates of attentional bias in subclinical depression. *Anxiety, stress, and coping*, 29, 479–496. <https://doi.org/10.1080/10615806.2015.1101457>
- DeYoung CG, Hirsh JB, Shane MS, Papademetris X, Rajeevan N, Gray JR (2010) Testing predictions from personality neuroscience. *Brain structure and the big five. Psychol sci*, 21, 820–828. <https://doi.org/10.1177/0956797610370159>
- DeYoung CG, Gray JR (2009) Personality neuroscience: Explaining individual differences in affect, behavior, and cognition. In Corr PJ & Matthews G (Eds.). *The Cambridge handbook of personality psychology*, pp 323–346. Cambridge: Cambridge University Press.
- Edmonds GW, Jackson JJ, Fayard JV, Roberts BW (2008) Is character fate, or is there hope to change my personality yet? *Soc Pers Psychol Compass*, 2, 399–413. <https://doi.org/10.1111/j.1751-9004.2007.00037.x>
- Ernst M, Fudge JL (2009) A developmental neurobiological model of motivated behavior: anatomy, connectivity and ontogeny of the triadic nodes. *Neurosci & Biobehav Rev*, 33, 367–382. <https://doi.org/10.1016/j.neubiorev.2008.10.009>

- Freeman LC (1977) A set of measures of centrality based on betweenness. *Sociometry*, 40, 35-41.
<https://doi.org/10.2307/3033543>
- Gogtay N, Sporn A, Clasen LS, Nugent TF 3rd, Greenstein D, Nicolson R, Giedd JN, Lenane M, Gochman P, Evans A, Rapoport JL (2004) Comparison of progressive cortical gray matter loss in childhood-onset schizophrenia with that in childhood-onset atypical psychoses. *Arch gen psych*, 61, 17–22. <https://doi.org/10.1001/archpsyc.61.1.17>
- Gong G, He Y, Concha L, Lebel C, Gross DW, Evans AC, Beaulieu C (2009) Mapping anatomical connectivity patterns of human cerebral cortex using in vivo diffusion tensor imaging tractography. *Cerebral cortex* (New York, 1991), 19, 524–536.
<https://doi.org/10.1093/cercor/bhn102>
- Gross J, Baillet S, Barnes GR, Henson RN, Hillebrand A, Jensen O, Jerbi K, Litvak V, Maess B, Oostenveld R, Parkkonen L, Taylor JR, van Wassenhove V, Wibrals M, Schoffelen JM (2013) Good practice for conducting and reporting MEG research. *NeuroImage*, 65, 349–363.
<https://doi.org/10.1016/j.neuroimage.2012.10.001>
- Hämäläinen MS (1992) Magnetoencephalography: a tool for functional brain imaging. *Brain topogr*, 5, 95–102. <https://doi.org/10.1007/BF01129036>
- Haruno M, Kuroda T, Doya K, Toyama K, Kimura M, Samejima K, Imamizu H, Kawato M (2004) A neural correlate of reward-based behavioral learning in caudate nucleus: a functional magnetic resonance imaging study of a stochastic decision task. *J neurosci*, 24, 1660–1665.
<https://doi.org/10.1523/JNEUROSCI.3417-03.2004>

- Hillebrand A, Tewarie P, van Dellen E, Yu M, Carbo EW, Douw L, Gouw AA, van Straaten EC, Stam CJ (2016) Direction of information flow in large-scale resting-state networks is frequency-dependent. *PNAS*, 113, 3867–3872. <https://doi.org/10.1073/pnas.1515657113>
- Ingalhalikar M, Smith A, Parker D, Satterthwaite TD, Elliott MA, Ruparel K, Hakonarson H, Gur RE, Gur RC, Verma R (2014) Sex differences in the structural connectome of the human brain. *PNAS*, 111, 823–828. <https://doi.org/10.1073/pnas.1316909110>
- James LM, Engdahl BE, Leuthold AC, Krueger RF, Georgopoulos AP (2015) Pathological personality traits modulate neural interactions. *Exp brain res*, 233, 3543–3552. <https://doi.org/10.1007/s00221-015-4406-6>
- Kabbara A, Paban V, Weill A, Modolo J, Hassan M (2020) Brain Network Dynamics Correlate with Personality Traits. *Brain connect*, 10, 108–120. <https://doi.org/10.1089/brain.2019.0723>
- Karvonen JT, Veijola J, Kantojärvi L, Miettunen J, Ekelund J, Lichtermann D, Läksy K., Joukamaa M (2006) Temperament profiles and somatization--an epidemiological study of young adult people. *J psychosom res*, 61, 841–846. <https://doi.org/10.1016/j.jpsychores.2006.06.014>
- Kruskal JB (1956) On the shortest spanning subtree of a graph and the traveling salesman problem. *Proc Am Math soc*, 7, 48-50. <https://doi.org/10.1090/S0002-9939-1956-0078686-7>
- Kumari V, ffytche DH, Williams SC, Gray JA (2004) Personality predicts brain responses to cognitive demands. *J Neurosci*, 24, 10636–10641. <https://doi.org/10.1523/JNEUROSCI.3206-04.2004>
- Laricchiuta D, Petrosini L, Piras F, Macci E, Cutuli D, Chiapponi C, Cerasa A, Picerni E, Caltagirone C, Girardi P, Tamorri SM, Spalletta G (2014) Linking novelty seeking and harm

avoidance personality traits to cerebellar volumes. *Hum brain mapp*, 35, 285–296.
<https://doi.org/10.1002/hbm.22174>

Leahy RM, Mosher JC, Spencer ME, Huang MX, Lewine JD (1998) A study of dipole localization accuracy for MEG and EEG using a human skull phantom. *Electroencephalography and clinical neurophysiology*, 107, 159–173. [https://doi.org/10.1016/s0013-4694\(98\)00057-1](https://doi.org/10.1016/s0013-4694(98)00057-1)

Liparoti M, Troisi Lopez E, Sarno L, Rucco R, Minino R, Pesoli M, Perruolo G, Formisano P, Lucidi F, Sorrentino G, Sorrentino P (2021) Functional brain network topology across the menstrual cycle is estradiol dependent and correlates with individual well-being. *J Neurosci Res*, 99(9):2271–2286. <https://doi.org/10.1002/jnr.24898>

Markett S, Montag C, Reuter M (2018) Network Neuroscience and Personality. *Pers neurosci*, 1, e14. <https://doi.org/10.1017/pen.2018.12>

Markett S, Montag C, Melchers M, Weber B, Reuter M (2016) Anxious personality and functional efficiency of the insular-opercular network: A graph-analytic approach to resting-state fMRI. *CABN*, 16, 1039–1049. <https://doi.org/10.3758/s13415-016-0451-2>

Mincic AM (2015) Neuroanatomical correlates of negative emotionality-related traits: A systematic review and meta-analysis. *Neuropsychologia*, 77, 97–118.
<https://doi.org/10.1016/j.neuropsychologia.2015.08.007>

Mogg K, Bradley BP (1998) A cognitive-motivational analysis of anxiety. *Behav res ther*, 36, 809–848. [https://doi.org/10.1016/s0005-7967\(98\)00063-1](https://doi.org/10.1016/s0005-7967(98)00063-1)

Muris P, Merckelbach H, Schmidt H, Gadet BB, Bogie N (2001) Anxiety and depression as correlates of self-reported behavioural inhibition in normal adolescents. *Behav res ther*, 39, 1051–1061. [https://doi.org/10.1016/s0005-7967\(00\)00081-4](https://doi.org/10.1016/s0005-7967(00)00081-4)

- Nostro AD, Müller VI, Reid AT, Eickhoff SB (2017) Correlations Between Personality and Brain Structure: A Crucial Role of Gender. *Cerebral cortex* (New York, N.Y.: 1991), 27, 3698–3712. <https://doi.org/10.1093/cercor/bhw191>
- Oostenveld R, Fries P, Maris E, Schoffelen JM (2011) FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Comput intell neurosci*, 2011, 156869. <https://doi.org/10.1155/2011/156869>
- Petrosini L, Cutuli D, Picerni E, Laricchiuta D (2017) Viewing the Personality Traits Through a Cerebellar Lens: a Focus on the Constructs of Novelty Seeking, Harm Avoidance, and Alexithymia. *Cerebellum*, 16, 178–190. <https://doi.org/10.1007/s12311-015-0754-9>
- Picerni E, Petrosini L, Piras F, Laricchiuta D, Cutuli D, Chiapponi C, Fagioli S, Girardi P, Caltagirone C, Spalletta G (2013) New evidence for the cerebellar involvement in personality traits. *Front behav neurosci*, 7, 133. <https://doi.org/10.3389/fnbeh.2013.00133>
- Pizzagalli DA, Holmes AJ, Dillon DG, Goetz EL, Birk JL, Bogdan R, Dougherty DD, Iosifescu DV, Rauch SL, Fava M (2009) Reduced caudate and nucleus accumbens response to rewards in unmedicated individuals with major depressive disorder. *Am J psych*, 166, 702–710. <https://doi.org/10.1176/appi.ajp.2008.08081201>
- Prabhakaran, R., Kraemer, D. J., & Thompson-Schill, S. L. (2011). Approach, Avoidance, and Inhibition: Personality Traits Predict Cognitive Control Abilities. *Pers indiv diff*, 51, 439–444. <https://doi.org/10.1016/j.paid.2011.04.009>.
- Riccelli, R., Toschi, N., Nigro, S., Terracciano, A., & Passamonti, L. (2017). Surface-based morphometry reveals the neuroanatomical basis of the five-factor model of personality. *Soc cogn affect neurosci*, 12, 671–684. <https://doi.org/10.1093/scan/nsw175>.

- Richards, H. J., Benson, V., Donnelly, N., & Hadwin, J. A. (2014). Exploring the function of selective attention and hypervigilance for threat in anxiety. *Clin psychol rev*, 34, 1–13. <https://doi.org/10.1016/j.cpr.2013.10.006>
- Sareen, J., Campbell, D. W., Leslie, W. D., Malisza, K. L., Stein, M. B., Paulus, M. P., Kravetsky, L. B., Kjernisted, K. D., Walker, J. R., & Reiss, J. P. (2007). Striatal function in generalized social phobia: a functional magnetic resonance imaging study. *Biol psychiatry*, 61, 396–404. <https://doi.org/10.1016/j.biopsych.2006.05.043>
- Schmitt, D. P., Realo, A., Voracek, M., & Allik, J. (2008). Why can't a man be more like a woman? Sex differences in Big Five personality traits across 55 cultures. *J pers soc psychol*, 94, 168–182. <https://doi.org/10.1037/0022-3514.94.1.168>
- Seeley WW, Menon V, Schatzberg AF, Keller J, Glover GH, Kenna H, Reiss AL, Greicius MD (2007) Dissociable intrinsic connectivity networks for salience processing and executive control. *J Neurosci*, 27, 2349–2356. <https://doi.org/10.1523/JNEUROSCI.5587-06.2007>
- Sim M, Kim JH, Yim SJ, Cho SJ, Kim SJ (2012) Increase in harm avoidance by genetic loading of schizophrenia. *Compr*, 53, 372–378. <https://doi.org/10.1016/j.comppsy.2011.05.004>
- Sorrentino P, Rucco R, Baselice F, De Micco R, Tessitore A, Hillebrand A, Mandolesi L, Breakspear M, Gollo LL, Sorrentino G (2021) Flexible brain dynamics underpins complex behaviours as observed in Parkinson's disease. *Sci rep*, 11, 4051. <https://doi.org/10.1038/s41598-021-83425-4>
- Sorrentino P, Ambrosanio M, Rucco R, Baselice F (2019) An extension of Phase Linearity Measurement for revealing cross frequency coupling among brain areas. *JNER*, 16, 135. <https://doi.org/10.1186/s12984-019-0615-8>

- Specht J, Egloff B, Schmukle SC (2011) Stability and change of personality across the life course: the impact of age and major life events on mean-level and rank-order stability of the Big Five. *J pers soc psychol*, 101, 862–882. <https://doi.org/10.1037/a0024950>
- Sporns O, Tononi G, Kötter R (2005) The human connectome: A structural description of the human brain. *PLoS comput biol*, 1, e42. <https://doi.org/10.1371/journal.pcbi.0010042>
- Stam CJ, Nolte G, Daffertshofer A (2007) Phase lag index: assessment of functional connectivity from multi channel EEG and MEG with diminished bias from common sources. *Hum brain mapp*, 28, 1178–1193. <https://doi.org/10.1002/hbm.20346>
- Stam CJ, Tewarie P, Van Dellen E, van Straaten EC, Hillebrand A, Van Mieghem P (2014) The trees and the forest: Characterization of complex brain networks with minimum spanning trees. *Int J psychophysiol*, 92, 129–138. <https://doi.org/10.1016/j.ijpsycho.2014.04.001>
- Tewarie P, van Dellen E, Hillebrand A, Stam CJ (2015) The minimum spanning tree: an unbiased method for brain network analysis. *NeuroImage*, 104, 177–188. <https://doi.org/10.1016/j.neuroimage.2014.10.015>
- Tricomi EM, Delgado MR, Fiez JA (2004) Modulation of caudate activity by action contingency. *Neuron*, 41, 281–292. [https://doi.org/10.1016/s0896-6273\(03\)00848-1](https://doi.org/10.1016/s0896-6273(03)00848-1)
- Van Veen BD, van Drongelen W, Yuchtman M, Suzuki A (1997) Localization of brain electrical activity via linearly constrained minimum variance spatial filtering. *IEEE transactions on bio-medical engineering*, 44, 867–880. <https://doi.org/10.1109/10.623056>
- van Wijk BC, Stam CJ, Daffertshofer A (2010) Comparing brain networks of different size and connectivity density using graph theory. *PloS one*, 5, e13701. <https://doi.org/10.1371/journal.pone.0013701>

- Wang B, Zhan Q, Yan T, Imtiaz S, Xiang J, Niu Y, Liu M, Wang G, Cao R, Li D (2019) Hemisphere and Gender Differences in the Rich-Club Organization of Structural Networks. *Cerebral cortex* (New York, 1991), 29, 4889–4901. <https://doi.org/10.1093/cercor/bhz027>
- Weinberg R, Gould D (2015). *Foundations of Sport and Exercise Psychology*, Sixth edition, Human Kinetics.
- Weiner IB, Tennen HA, Suls JM (2013) *Personality and social psychology, handbook of psychology*. 2nd ed. USA: JohnWiley & Sons.
- Weisberg YJ, Deyoung CG, Hirsh JB (2011) Gender Differences in Personality across the Ten Aspects of the Big Five. *Front psychol*, 2, 178. <https://doi.org/10.3389/fpsyg.2011.00178>
- Wilson RS, Boyle PA, Buchman AS, Yu L, Arnold SE, Bennett DA (2011) Harm avoidance and risk of Alzheimer's disease. *Psychosom med*, 73, 690–696. <https://doi.org/10.1097/PSY.0b013e3182302ale>
- Yan C, Gong G, Wang J, Wang D, Liu D, Zhu C, Chen ZJ, Evans A, Zang Y, He Y (2011) Sex- and brain size-related small-world structural cortical networks in young adults: a DTI tractography study. *Cerebral cortex* (New York, N.Y.: 1991), 21, 449–458. <https://doi.org/10.1093/cercor/bhq111>
- Zaidi ZF (2010) Gender differences in human brain: a review. *The open anatomy journal*, 2. 2:37–55. <https://doi.org/10.2174/1877609401002010037>

Figure 1: Schematic illustration of the reconstruction of MEG signals.

a. Brain activity recording through magnetoencephalography (MEG). **b.** Noisy signals identification. **c.** Cleaned signals. **d.** Structural MRI and MEG signals co-registration. **e.** Connectivity matrix calculated using Phase Linearity Measurement. **f.** Brain network obtained through Minimum Spanning Tree.

Figure 2: Correlation in the alpha band between the betweenness centrality of the left caudate nucleus and the harm avoidance trait. In the left part a reconstruction of the caudate nucleus is shown.

Figure 3: Comparison between males and females in TCI. The asterisks indicate statistical significance
 $p < 0.05$.

Figure 4: Correlation in the alpha band between the betweenness centrality of the left caudate nucleus and the harm avoidance trait in relation to males (**a**) and females (**b**).

Figures

Figure 1

Schematic illustration of the reconstruction of MEG signals. a. Brain activity recording through magnetoencephalography (MEG). b. Noisy signals identification. c. Cleaned signals. d. Structural MRI

and MEG signals co-registration. e. Connectivity matrix calculated using Phase Linearity Measurement. f. Brain network obtained through Minimum Spanning Tree.

Figure 2

Correlation in the alpha band between the betweenness centrality of the left caudate nucleus and the harm avoidance trait. In the left part a reconstruction of the caudate nucleus is shown.

Figure 3

Comparison between males and females in TCI. The asterisks indicate statistical significance $p < 0.05$.

Gender differences

Figure 4

Correlation in the alpha band between the betweenness centrality of the left caudate nucleus and the harm avoidance trait in relation to males (a) and females (b).