



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 & 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 & 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 & 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).

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

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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).

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

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

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16 A suitable technique to investigate the link between personality traits and brain regions within the
17 whole brain network is magnetoencephalography (MEG). MEG is a promising functional
18 neuroimaging technique that allows researchers to record brain magnetic activity and to identify
19 patterns of neural oscillations in several bands with highly accurate temporal resolution (Baillet,
20 2017) compared to fMRI and PET. Furthermore, MEG signals are unaffected by distortion, while
21 in EEG electric currents become distorted as they pass through the skull and other tissues (Leahy
22 et al., 1998). The MEG signal reflects integrated synaptic activity with high fidelity and thus offers
23 a highly accurate measure of brain activity (Hämäläinen, 1992). In addition to estimating the
24 connectivity among brain regions, to exploring each region's role within the brain network is vital.
25 Graph theory, a field of mathematics that studies network structures, can be usefully exploited to
26 explore the topological characteristics of the brain (Bullmore & Sporns, 2009).

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3 To date, research on resting-state neural correlates in relation to Cloninger's personality traits is
4 limited. The present study therefore investigates the brain topology correlated to Cloninger's
5 temperaments and characters in healthy individuals by means of MEG, which allows detection of
6 the complex dynamic properties of brain networks.
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12 To the best of our knowledge, there have been only two MEG studies aimed at characterizing the
13 topological properties and functional connectivity correlated to personality traits. However, neither
14 can be directly compared to our study. One study considered a psychopathological population
15 (James et al., 2015), while the other used a different personality model (Kabbara et al., 2020).
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21 In the present study, we examine how individual differences in temperaments and characters
22 described by Cloninger are correlated with specific cerebral structures in healthy subjects during
23 a resting state condition, considering the brain as a coherent interconnected network. Because this
24 is the first MEG study to analyze topological properties in healthy subjects using Cloninger's
25 model, we did not make specific predictions about trait-specific network activity, though we did
26 expect an involvement in the cerebral areas of the insular salience network that are correlated to
27 HA, since that the personality trait is mainly related to salience stimulus.
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38 Furthermore, given that our sample consisted of both men and women, we expected to find some
39 gender differences in TCI and its relationship with topological characteristics, as it has been
40 demonstrated that gender is a fundamental factor to consider when trying to understand the
41 morphological underpinnings of inter-individual differences in personality traits (Nostro et al.,
42 2017).
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51 **METHODS**

52 *Participants*

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3 Fifty healthy participants were enrolled (20 males, 30 females, mean age: 27.4 ± 4.8 years).
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5 Exclusion criteria were age > 40 years, left-handed, personal history of neurologic, psychiatric or
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7 psychological disease, and the consumption of psychoactive drugs. All participants provided
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9 written informed consent. The study was carried out in accordance with the Declaration of Helsinki
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11 and was approved by the Local Ethics Committee of the University of XXXXXXXXX (Prot. n.
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13 17/2021).
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16 17 ***Temperament and Character Inventory (TCI)***

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19 Participants completed the Temperament and Character Inventory (TCI) consisting of 240 items
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21 true/false questionnaire (Cloninger et al., 1993). TCI is a self-rated instrument that provides a
22
23 comprehensive inventory of dimensions of temperament (Novelty Seeking, NS; Harm Avoidance,
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25 HA; Reward Dependence, RD; Persistence, P) and character (Self-directedness, SD;
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27 Cooperativeness, C; Self-transcendence, ST). NS, HA, and RD consist of four sub-scales, while P
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29 only one. In general, NS refers to the tendency to seek novel stimuli and experiences; HA refers
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31 to a tendency to inhibition of behavior in response to signals of punishment; RD refers to a
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33 tendency to the maintenance of behavior in response to cues of social reward, and P measures the
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35 tendency towards perseverance in the face of adversity. For that concerns the three domains of
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37 character, SD measures the ability to use the willpower necessary to achieve personal goals; C
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39 measures the ability to cooperate with others; ST measures the ability to look beyond self-interest
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41 to see oneself as part of a larger whole, which could be described as a marker of maturity but could
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43 also be described as a tendency towards spirituality or a belief in the religious or supernatural.
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49 The items are divided into positive and negative items and the scoring for each item is dichotomous
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51 (TRUE/FALSE), with a 1/0 score for positive items and 0/1 for negative items. The sum of the
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53 points obtained gives a “Raw Score” to which it is possible to match a “Percentile Score” and a
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3 “T-Score” which, shown on the graph, allows defining a personality profile. A percentile value
4 above 67% and one below 33% are, according to the literature, considered abnormal (Cloninger et
5 al., 1993).
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10 Whenever an answer (true or false) was in accordance with a specific trait, a point was assigned.
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12 The final score was calculated as the ratio between the total score and the total number of items
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14 composing a specific trait.
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17 *Acquisition*

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

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49 To reduce environmental noise, we used the principal component analysis (Sadasivan & Dutt,
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51 1996) available within the FieldTrip toolbox (Oostenveld et al., 2011); the noisy channels were
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53 removed by an experienced operator after visual inspection. Subsequently, cardiac and ocular
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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.

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3 PLM was computed for each pair of brain regions, obtaining a 90×90 weighted adjacency matrix
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5 for each trial of registration. The five canonical frequency bands were estimated as delta (0.5–4
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7 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).
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10 Thereafter, we built a brain network starting from each adjacency matrix (Stam et al., 2007), where
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12 each of the 90 brain regions were represented as a node, and the weighted edges between two
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14 nodes were represented by PLM values. Then, applying Kruskal's algorithm (Kruskal, 1956) to
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16 each reconstructed brain network, we calculated the minimum spanning tree (MST), a loopless
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18 graph with N nodes and $M = N-1$ links. In this way, we obtained topologic measures unaffected
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20 by the degree distribution, matrix density, or arbitrary thresholds (van Wijk et al., 2010) (Figure 1
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22 e,f).
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30 ***Graph theoretical analysis***

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32 We calculated both global and nodal (regional) parameters.

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34 To obtain indices representative of the global topological organization of brain networks, we
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36 calculated the following: the *leaf fraction* (Boersma et al., 2013), which is the fraction of nodes
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38 with a degree of 1, an expression of the network integration; the *degree divergence*, a measure of
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40 the broadness of the degree distribution, related to the synchronizability of the networks (Stam et
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42 al., 2014; Tewarie et al., 2015); the *tree hierarchy* defined as the trade-off between network
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44 integration and central nodes overload; the *diameter*, defined as the longest shortest path of an
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46 MST; and the *assortativity*, an estimation of the relationship among nodes.
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51 To examine the regional features of the network we calculated two nodal parameters: the *degree*,
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53 defined as the number of connection incidents on a given node, and the *betweenness centrality*
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55 (BC), described as the number of shortest paths passing through a given node over the total number
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3 of shortest paths in the network (Tewarie et al., 2015). To obtain a single value of each parameter
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5 for each participant, the metrics were averaged across the trials of each subject.
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8 *MRI acquisition*

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11 MRI images of seventy participants were acquired using a 1.5-T Signa Explorer scanner with an
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13 8-channel parallel head coil (General Electric Healthcare, Milwaukee, WI, USA). We obtained
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15 three-dimensional T1-weighted images (gradient-echo sequence Inversion Recovery prepared Fast
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17 Spoiled Gradient Recalled-echo, time repetition = 8.216 ms, TI = 450 ms, TE = 3.08 ms, flip angle
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19 = 12, voxel size = $1 \times 1 \times 1.2$ mm³; matrix = 256×256). We used a standard template MRI for
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21 seven participants who refused to undergo the MRI examination.
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26 *Statistical analysis*

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

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49 *Topological brain network parameters.* A Pearson's correlation analysis was performed to
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51 evaluate the relationship between both global and nodal topological parameters and seven
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53 dimensions of personality (4 temperaments and 3 characters), according to TCI, in 50 male and
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3 female participants. No global topological parameter showed correlation with any of the TCI
4 dimensions. On the contrary, in relation to nodal parameters, we found a significant negative
5 correlation in the alpha band involving the betweenness centrality (BC) of the left caudate (LC)
6 and the harm avoidance (HA) trait ($r = -0.52$; $p = 0.047$) (Figure 2).
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16 ***Comparison between male and female gender.*** Comparing male and female population in TCI by
17 means of permutation analysis, we found that women scored higher than men in HA ($p = 0.048$)
18 and RD ($p = 0.041$) temperaments and ST ($p = 0.027$) character (Figure 3).
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27 Having detected a significant negative correlation in alpha band between left caudate and HA when
28 the entire sample was taken into consideration, we examined in detail this correlation considering
29 each gender separately. While in male individuals, the correlation did not show to be significant (r
30 $= -0.38$; $p = 0.098$) (Figure 4a), in female participants it was significant, with a negative coefficient
31 ($r = -0.6$; $p < 0.001$) (Figure 4b) showing thus the same pattern as when the two groups are
32 processed together.
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47 **DISCUSSION**

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49 In the present study, we used MEG to investigate the brain topology correlated with personality
50 traits in healthy individuals. Assuming the brain as a coherent interconnected network, we
51 analyzed how individual differences in Cloninger's temperaments and characters correlated with
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3 specific cerebral structures synchronized among themselves. We found high HA scores were
4 associated with a reduced centrality of the left caudate nucleus (Figure 2). In interpreting this data,
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6 it can be useful to recall the meaning of this temperament and the functional role of the caudate
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8 nucleus. HA consists of the tendency to inhibit behaviors, to act with caution and apprehension.
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10 The adaptive advantages of high HA scores are cautiousness and careful planning when a hazard
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12 is likely to happen, while the disadvantages occur when a hazard is unlikely to happen, but its
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14 anticipation leads to maladaptive inhibition and anxiety (Laricchiuta & Petrosini, 2014). For these
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16 characteristics, HA is the trait that is most correlated to the salience of the environmental stimuli
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18 and reflects some features of the caudate nucleus; it plays a key role in adaptive behavioral
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20 responses and in choosing actions that are likely to lead to a positive outcome (Tricomi et al.,
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22 2004). Notably, the caudate nucleus, as part of the striatum, is involved in the motivation (Ernst
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24 and Fudge, 2009) and anticipation of a potential reward (Benningfield et al., 2014). In addition, its
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26 activation has been linked to attentional bias toward positive social stimuli (Haruno et al., 2004;
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28 Pizzagalli et al., 2009; Dedovic et al., 2016).

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31 The association between HA and the left caudate nucleus is specific only for the BC nodal
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33 parameter, which denotes the shortest path between nodes in the interconnected whole-brain
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35 network and in turn the importance of the left caudate nucleus in mediating communication
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37 between the entire network of nodes (Freeman et al., 1977). In other words, the BC parameter
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39 suggests that the more behaviors are inhibited (high HA values), the less the caudate nucleus is a
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41 central node in the network. Similarly, we can suggest that the more the behaviors are goal directed
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43 (low HA values), the more the caudate nucleus become a central node in the network. Thus, the
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45 reduced centrality of the caudate nucleus associated with HA scores resonates well with the
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47 assumption that individuals scoring higher in this temperament will report greater behavioral
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3 inhibition and greater tendency to process stimuli as potentially threatening rather than potentially
4 rewarding (Cloninger et al. 1994). In addition, higher HA scores have been found to be predictive
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6 of anxiety disorders, and several studies have documented that anxiety disorders are characterized
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8 by alterations in caudate structure and connectivity and altered stimulus processing (Sareen et al.,
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10 2007; Whiteside et al., 2006). Finally, the caudate nucleus' reduced centrality associated with
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12 higher HA scores is in accordance with previous fMRI studies reporting a relationship between
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14 HA scores and connectivity in the cortico-limbic circuit (Westlye et al., 2011), in which the caudate
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16 nucleus plays a key role also in adaptive emotional responses. Of note, using resting-state
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18 functional connectivity data, HA has been found to be negatively related to the insular salience
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20 network's efficiency (Markett et al., 2016), thus suggesting a crucial role for the caudate nucleus
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22 in this large-scale network.
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28 In the present study, we also analyzed the gender differences in the TCI scores and correlated them
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30 to specific topological data. We found that women scored higher than men in HA and RD
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32 temperaments and ST character (Figure 3), confirming previous well documented findings (Costa
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34 et al., 2001; Schmitt et al., 2008).
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37 The negative correlation we found between the left caudate and HA for the BC nodal parameter,
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39 induced us to analyze it considering each gender separately. Only female participants showed the
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41 same pattern as when the two groups were processed together. In fact, this correlation was
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43 maintained in the female subgroup and collapsed in the male one (Figure 4 a,b). This difference
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45 can be explained by dissimilarities in personality traits (Costa et al., 2001; Chapman et al.,
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47 2007; Weisberg et al., 2011) as well as in brain structural and functional asymmetries between
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49 female and male groups (Wang et al., 2019). Our topological data can also be discussed in relation
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51 to a previous voxel-based morphometry study that investigated the association between gray
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3 matter volume (GMV) and personality traits in men and women using the NEO five-factor
4 inventory (NEO-FFI). Among various results, the significant association between GMV and
5 neuroticism that was found only in men, suggests that brain structure–personality relationships are
6 highly dependent on gender (Nostro et al., 2017). Although the NEO-FFI is different from the TCI,
7 there are many similarities between HA and neuroticism. In fact, neuroticism is associated with a
8 decreased ability to ignore irrelevant information (Prabhakaran et al., 2011). It has also been
9 related to a “hypervigilance of threats” (Mogg & Bradley, 1998; Richards et al., 2014); that is, an
10 adaptive behavior to perceive a potential risk faster, which comes at the cost of specificity and,
11 consequently, less successful inhibition of irrelevant stimuli and response sets. Like us, Nostro and
12 colleagues (2017) found neuroticism scores were higher in women than men. Unlike us, they found
13 structural brain asymmetries only in male group, suggesting that, in the female group, brains may
14 be more decentralized (Zaidi, 2010) and may feature stronger interhemispheric structural
15 connectivity (Ingallhalikar et al., 2014), a factor that may benefit multitasking characteristics
16 (Zaidi, 2010). Given Nostro and colleagues’ interpretation, we can hypothesize that the
17 characteristic of multitasking is reflected in the organization of the large-scale networks that
18 include multiple brain regions. Thus, in this intriguing hypothesis, the insular salience network
19 would be wider and would include the caudate nucleus.
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42 Beyond the interpretation of our data, other connectivity studies showed that men had higher nodal
43 efficiency of the internal regions such as insula and peripheral lingual gyrus, while women showed
44 significantly greater betweenness centrality in the precuneus and peripheral superior occipital
45 gyrus (Yan et al., 2011; Wang et al., 2019), thus evidencing a clear difference between women and
46 men in large scale brain network organization.
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3 This study has some limitations that naturally suggest using caution in generalizing these findings.

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5 The first limitation is the exclusion of the cerebellum from the analysis of the networks. This
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8 exclusion is a consequence of our MEG system which does not cover the lower occipital area and
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10 therefore does not allow a clean recording of the signal coming from the cerebellar nuclei. It is
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12 important to recognize this limitation in light of recent evidence suggesting the cerebellum together
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14 with the basal ganglia in influence and sustain processes that are linked to individual differences
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16 in approach and avoidance behaviors through a cortico-basal-cerebellar loop (Picerni et al., 2013;
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18 Laricchiuta & Petrosini, 2014).

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20 In addition, the relatively small sample prohibits drawing conclusion about gender differences in
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22 brain underpinnings of personality mainly for females, more affected by hormonal fluctuation
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24 (Liparoti et al., 2021). However, the differences between groups in our study encourage us to
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26 continue this line of research to better understand the topological organization in both. This study
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28 also has several strengths. First, it is one of the first studies that uses MEG to investigate the
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30 biological substrates of personality traits and as explained in the introduction, this analysis system
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32 allows us to obtain precise and accurate results. Second, although small, our sample consists of
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34 young adults of similar age. This feature represents a great advantage because the human brain
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36 changes during one's life span and analyzing the brains of individuals of the same age allows us
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38 to gain an accurate picture of brain topology at that age.
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46 47 **CONCLUSION**

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49 In conclusion, our results highlight that the topological measures in MEG studies offer unique
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51 information about the neurobiological basis of personality traits. These results also pave the way
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3 to exploring the mutual influences of topological and functional connectivity in neural
4 communication efficiency and disruption as biomarkers of psychopathological personality traits.
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11 receive any specific grant from funding agencies in the public, commercial, or not-for-profit
12 sectors
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16 **Data Availability:** The data that support the findings of this study are available from the
17 corresponding author upon request.
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19

20 **Conflict of Interest** The authors declared no potential conflicts of interest with respect to the
21 research, authorship, and/or publication of this article.
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26 **Ethics approval:** The study was approved by Ethical Committee of Psychological Research of the
27 Department XXXXXXXX (n prot 11/2020) and was conducted in accordance with the Declaration
28 of Helsinki.
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32 **Informed consent:** Informed consent was obtained from all individual participants included in the
33 study.
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21 **Figure 1: Schematic illustration of the reconstruction of MEG signals.**

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23 **a.** Brain activity recording through magnetoencephalography (MEG). **b.** Noisy signals
24
25 identification. **c.** Cleaned signals. **d.** Structural MRI and MEG signals co-registration. **e.**
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27 Connectivity matrix calculated using Phase Linearity Measurement. **f.** Brain network obtained
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29 through Minimum Spanning Tree.
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35 **Figure 2:** Correlation in the alpha band between the betweenness centrality of the left caudate
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37 nucleus and the harm avoidance trait. In the left part a reconstruction of the caudate nucleus is
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39 shown.
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44 **Figure 3:** Comparison between males and females in TCI. The asterisks indicate statistical
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46 significance

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49 $p < 0.05$.
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54 **Figure 4:** Correlation in the alpha band between the betweenness centrality of the left caudate
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56 nucleus and the harm avoidance trait in relation to males (**a**) and females (**b**).
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For Peer Review

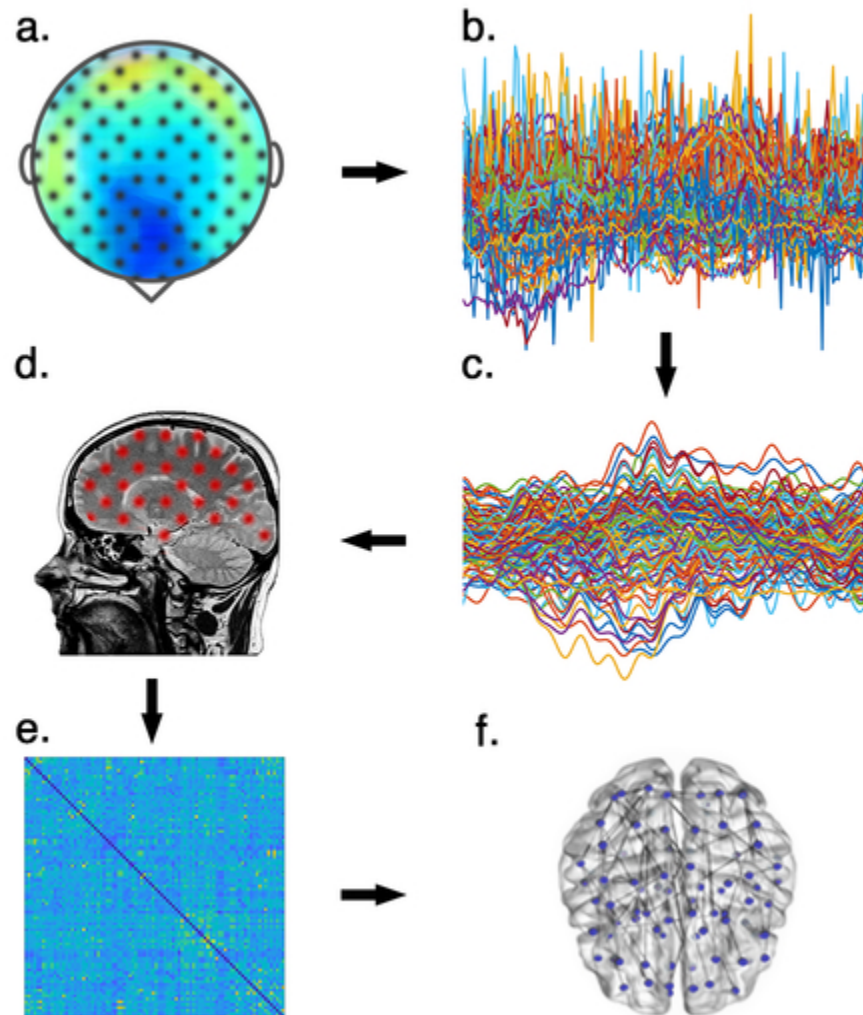
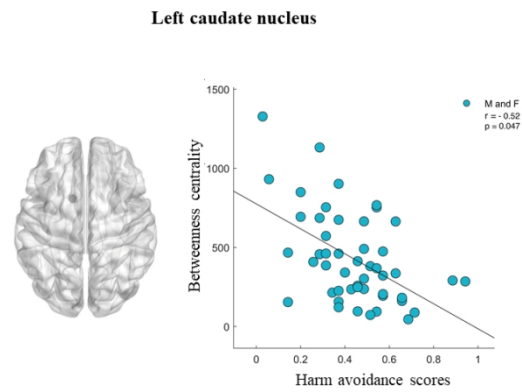


Figure 1: Schematic illustration of the reconstruction of MEG signals.
 a. Brain activity recording through magnetoencephalography (MEG). b. Noisy signals identification. c. Cleaned signals. d. Structural MRI and MEG signals co-registration. e. Connectivity matrix calculated using Phase Linearity Measurement. f. Brain network obtained through Minimum Spanning Tree.

42x46mm (300 x 300 DPI)



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

27 338x190mm (96 x 96 DPI)

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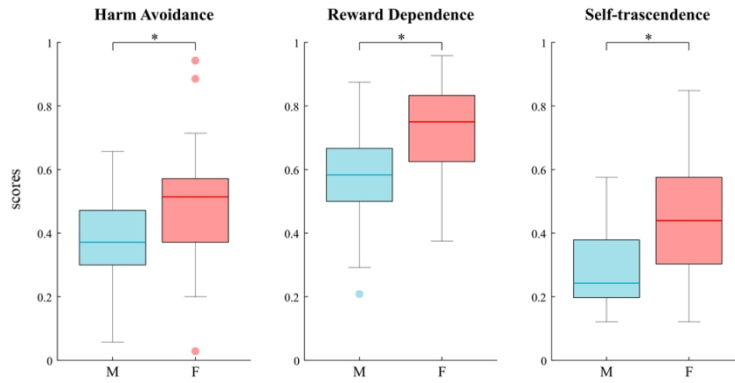
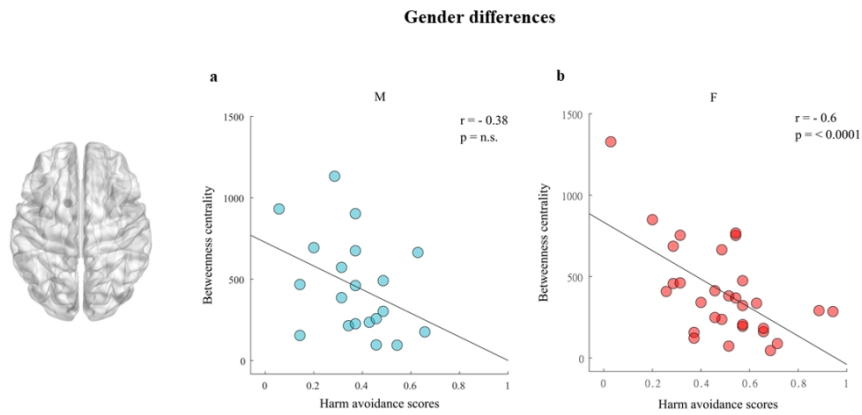


Figure 3: Comparison between males and females in TCI. The asterisks indicate statistical significance $p < 0.05$.

338x190mm (96 x 96 DPI)



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

27 338x190mm (96 x 96 DPI)

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