Eur. Phys. J. Spec. Top.
https://doi.org/10.1140/epjs/s11734-026-02251-9

THE EUROPEAN PHYSICAL JOURNAL SPECIAL TOPICS

Regular Article

Hidden nodes of personality: functional brain networks and their trait correlates

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Received 4 February 2026 / Accepted 4 March 2026

Abstract This study investigates the associations between personality traits and the topology of resting-state functional brain networks, aiming to identify trait-specific global, nodal, and predictive network markers. Graph-theoretical metrics of functional connectivity were related to psychometric measures of personality traits using correlational analysis, unsupervised clustering, principal component analysis (PCA), and predictive modeling. Nonlinear relevance vector machine (RVM) and linear regression models were applied to assess the predictability of traits from network measures. Psychopathic traits were moderately and negatively associated with global integration measures, including mean node strength ($r = -0.264$) and mean clustering coefficient ($r = -0.247$), indicating reduced local segregation and integration. Masochistic traits showed a negative correlation with mean betweenness centrality ($r = -0.230$), suggesting a more distributed network architecture. At the nodal level, eigenvector centrality was positively associated with masochistic traits in frontal mid regions ($r = 0.28$–0.32), left inferior frontal gyrus ($r = 0.27$–0.31), left postcentral gyrus ($r = 0.26$), and supramarginal gyrus ($r = 0.27$–0.31). Psychopathic traits were positively related to eigenvector centrality of Heschl's gyrus ($r = 0.25$–0.26). A replicable association was observed between oral traits, node strength, and the left nucleus accumbens ($r = 0.26$), indicating increased centrality of reward-related circuits. PCA revealed three latent components explaining 75% of total variance, separating psychopathic–masochistic, oral–rigid, and masochistic trait dimensions. In predictive analyses, RVM models achieved the lowest errors (mean RMSE < 0.4), with the highest accuracy for psychopathic traits using functional connectivity (RMSE $= 0.40$) and for masochistic traits using node strength (RMSE $= 0.346$). Linear regression yielded exceptionally low error for psychopathic traits predicted by betweenness centrality (RMSE $= 0.122$). Our work offers a modest contribution to the development of a nomological network of traits within the bioenergetic analytical paradigm in the domain of personality neuroscience. Personality traits are associated with distinct and partially nonlinear patterns of functional brain network organization. Both global topology and trait-specific nodal centrality contribute to the neural expression and prediction of personality dimensions, supporting a multilevel network-based model of personality.

1 Introduction

The research that has grown over the past two decades in the perspective of personality neuroscience and network neuroscience motivates a reevaluation of the methodologies for measuring personality traits and brain activity, which complement each other.

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In personality psychology, traits are considered as narrow and broad [1], structured in hierarchies [2]. This distinction is related to different levels of generalization in the description of personality. Broad traits, or higher-level traits, are stable characteristics of people that remain consistent over time and across contexts. Narrow traits, or lower-level traits, are continuous characteristics corresponding to personality tendencies toward specific behaviors and experiences, and at the same time to greater diversity and specificity in behavior [1]. The existing taxonomies of personality allow the assessment of groups of traits, or sets of traits, which requires consideration of the potential rank of a given trait within the hierarchies of traits when studying its neural mechanisms [2].

Neuroticism, for example, is one of the best-studied broad personality traits in the neuroscientific field. It is defined as a general tendency to experience various negative emotions and associated cognitions and behaviors. Neuroticism entails subtraits such as sadness, irritability, hopelessness, rumination, and self-consciousness [2], as well as anxiety, depression, tension, guilt [3], and worry and moodiness [4]. Neuroticism is associated with vulnerability to psychopathology and mental disorders (e.g., depression and anxiety) [5–7]. The neural basis of neuroticism has been described as involving various interconnected brain regions that participate in the generation and regulation of negative emotions. For example, it has been demonstrated that in individuals with high levels of neuroticism, the amygdala shows increased activity in response to negative stimuli [8], including socially emotional stimuli [9]. Moreover, neuroticism is linked to altered functional connectivity between the amygdala and other regions such as the prefrontal cortex [10, 11]. Neuroticism has also been associated with increased activity in the anterior cingulate cortex (ACC) and the anterior insular cortex during anticipation of threat [12], as well as with stronger connectivity between the ACC and regions involved in emotional processing such as the amygdala and medial prefrontal cortex [13]. Individuals with high levels of neuroticism demonstrate altered functional and structural connectivity of the hippocampus with prefrontal [14] and limbic regions [15]. Increased activity in the anterior insula has been observed in individuals with high neuroticism during risky or complex decision-making tasks in fMRI studies [16]. High neuroticism is associated with stronger effective connectivity between the insula and the amygdala according to resting-state fMRI data [17], as well as with increased spontaneous activity of the insula mediated by personality traits, specifically self-consciousness [18].

Through graph-theoretical analysis, significant positive associations were found between betweenness centrality (BC) and neuroticism (measured with Eysenck Personality Questionnaire-Revised Short Scale) in the right precentral gyrus (PreCG), the right olfactory cortex (OLF), the right caudate nucleus (CAU), and the bilateral amygdala, indicating more frequent participation of these regions in intranetwork information transfer and potentially lower excitation thresholds. In the same study, higher extraversion scores were correlated with greater area under the curve (AUC) of the normalized clustering coefficient (CC), which indicates more clustered functional brain networks and likely a higher excitation threshold and tolerance to excitation. Furthermore, extraversion correlated positively with BC in the right insula and negatively with BC in the bilateral middle temporal gyrus (MTG), suggesting that the relationship between extraversion and regional excitation is complex and nonlinear [19].

Extraversion is defined as a stable and heritable higher-order trait. Several brain regions associated with extraversion have been identified, with observed differences in gray matter in both cortical and subcortical areas. (1) Positive associations with the bilateral dorsal anterior cingulate cortex (dACC) and medial prefrontal cortex (mPFC)—regions that are part of the limbic emotional circuit and have been linked to the positive emotional characteristics of extraversion and a potential protective effect against affective disorders. (2) A positive association with the left angular gyrus (AG) and negative associations with the right parahippocampal gyrus/amygdala and the right middle frontal gyrus (MFG)—components of the frontal behavioral regulatory system. These areas are implicated in behavioral features of extraversion as well as in emotional differences between extraverts and introverts, particularly involving the amygdala. (3) The right supramarginal gyrus (SMG) and right angular gyrus/temporoparietal junction (AG/TPJ) are associated with extraversion through variations in gray matter volume. These findings align with the involvement of the parietal mirror neuron sociable system and the social processes characteristics of extraversion. Sex and age modulate these associations and may contribute to heterogeneity [20], which is an important consideration when selecting covariates in research on personality traits. In analyses of resting-state effective connectivity of the amygdala, extraversion has been found to be positively correlated with connectivity from the right inferior occipital gyrus (IOG) to the left amygdala and from bilateral IOG to the right amygdala. This suggests that extraversion is associated with a heightened influence of visual processing streams on the amygdala, considered a neural correlate of social interaction in extraverts. In the same study, neuroticism was positively correlated with effective connectivity from the right amygdala to the right MFG and negatively correlated with effective connectivity from the right precuneus (PCu) to the right amygdala. The latter pattern has been interpreted as reflecting suboptimal cognitive regulation and increased self-referential processes in individuals high in neuroticism [17].

Intelligence is reliably assessed with performance tests that are free from the subjective distortions and biases inherent in self-report instruments. It is also a trait with relatively well-reproduced neural correlates [2]. Human intelligence is viewed as fluid (problem-solving independent of prior knowledge) and crystallized (acquired, learned knowledge), based on different cognitive abilities. Fluid and crystallized intelligence show distinct morphometric profiles and shared neuroanatomical correlates. Fluid intelligence shows a stronger association with cortical surface area in the dorsolateral prefrontal and parietal cortex, whereas crystallized intelligence correlates primarily with reduced thickness and increased cortical surface in the temporal and frontal (left caudal middle frontal gyrus) regions. The cortical surface of the anterior temporal lobe (including the anterior inferior temporal gyrus) and the middle temporal lobe is associated with both fluid and crystallized intelligence. In support of the parietal–frontal integration theory of intelligence (P-FIT), fluid intelligence reflects the efficiency of information integration and processing, while crystallized intelligence is associated with experience-dependent structural cortical maturity [21]. There is compelling meta-analytic evidence for a positive relationship between brain volume and intelligence quotient [22], but brain size is not the only variable determining intelligence [2]. Recent findings in network neuroscience provide evidence that intelligence is better explained by global rather than local profiles of functional connectivity. Predictive modeling based on connectomes (CPM) has been applied to resting-state data, trained to include left and right functional edges so that associations between higher intelligence and significantly higher/lower connectivity could be tested. It has been found that including weak connections improves the accuracy of models predicting intelligence, in particular the global connectivity profiles defined by the network neuroscience theory (NNT). The results demonstrate that the networks supporting intelligence can be predicted from, but are not limited to, specific brain regions, i.e., they are characterized by a widely distributed functional organization in which weak connections contribute to the flexibility of the global network associated with general intelligence [23]. Recent studies in network neuroscience emphasize that both stronger connections (supporting integration between regions) and weaker connections/nodes (facilitating functional segregation) together jointly shape optimal cognitive function during sustained long-term reorganization of brain networks, for example during rest, task, or pathological states [24].

Theoretical models in personality neuroscience are expected to be compatible with multiple complementary levels of explanation [25]. A metatheoretical approach proposes formulating working definitions for a given trait across several analytical levels: (1) the cognitive level—both descriptive and explanatory, at which the psychological theoretical construct is situated; (2) the intermediate or subcognitive level—represented by connectionist theories and computational models that simulate brain processes (including neuromorphic computing); and (3) the neural level—primarily explanatory, where physiological theoretical constructs such as biochemical and neuroanatomical variables are located. At these levels, stable patterns of emotional, behavioral, cognitive, and motivational regulation, commonly referred to as ABCD models, are observed; these reflect personality structure and describe regularities in behavior and experience. Trait-like mechanisms, positioned at different levels of explanation and giving rise to personality characteristics, have motivated the definition of neural traits. These neural traits pertain to fundamental regularities of neural processing, or phylogenetically ancient mechanisms conserved in humans and other vertebrate species. For example, the brains' regulation of the hormonal system has been proposed as a neural trait in its capacity as a basic neural mechanism. It is well established that the hippocampus regulates physiological reactions to stress hormones, and the short-term release of adrenaline elicits immediate bodily and mental changes. Experiencing chronic stress can remodel brain circuits in the hippocampus, amygdala, and prefrontal cortex, leading to lasting, trait-like alterations such as anxiety, depressive states, or mood disorders. In this way, specific biological processes have the potential to account for individual variation in personality traits, which supports a reconsideration of the commonly reported heterogeneity in psychometric taxonomies of personality [25]. The manner in which the brain regulates stress and the hormonal response fits within the concept of neural traits as candidates for neurobiological variables. However, the study of personality is a matter of developing a nomological network [26] for traits through their relations with observable behavior, transient states, biological correlates, other personality constructs, and life outcomes. Well-documented links exist between personality traits, neurotransmitter systems, and genetic variations. Anxious personality traits are associated with imbalances in core emotional systems and neurotransmitters—specifically serotonin, norepinephrine, and gamma-aminobutyric acid (GABA)—as well as dysregulation of the stress-regulating HPA axis [27]. Dopaminergic genes have been linked to higher levels of extraversion and lower levels of neuroticism [28]. Variations in genes encoding receptors and transporters for dopamine, serotonin, and norepinephrine contribute to differences in personality profiles, particularly for traits related to affective reactivity and motivation such as extraversion and neuroticism [29]. Regularities of molecular and biological mechanisms are conceptually embedded in one of the most authoritative contemporary taxonomies of personality, namely, Robert Cloninger's psychobiological theory [30]. In the highest degree of concordance, research on temperament using the Temperament and Character Inventory (TCI) has provided explanatory models for personality at multiple levels of translation [31]. Nonlinear significant associations (NMF method) have been observed between 51 sets of single-nucleotide polymorphisms (SNPs) and sets of temperament profiles in three large independent samples (Finnish, German, and Korean), with the genes explaining nearly all of the expected heritability in each cohort, between 37 and 53% [32]. The nature of this prediction (PGMRA classifier) is represented by genophenotypic networks—sets of genes, organized into networks, are significantly associated with sets of temperament profiles organized into profiles (reliable, antisocial, and sensitive). These complex many-to-many relationships demonstrate pleiotropy (one gene influencing multiple traits) and heterogeneity. The SNP networks have been mapped to 736 genes involved in the regulation of synaptic plasticity and long-term memory based on associative conditioning. For example, conditioned impulsivity is often associated with a sensitive temperament profile, but sometimes with antisocial and reliable profiles, since multiple genes regulate behavioral disinhibition.

This means that genes predominantly determine the balance and coordination of traits within the individual, rather than isolated manifestations [32]. Therefore, profiles of temperament traits, rather than individual traits, are a more natural unit for measuring personality characteristics [31]. The nonadditive (noncumulative or nonlinear) influence of genes on personality is compelling evidence for hierarchies of traits at both the cognitive (phenotype) and neural (genotype) levels.

Configurations of large-scale resting-state networks represent the organization of personality [33]. Personality profiles measured with the TCI explain the majority of the possible variability in resting-state functional connectivity (35–67%), with the four top-down prefrontal networks (default mode network, DMN; cingulo-opercular network, CON; frontoparietal network, FPN; dorsal attention network, DAN) mediating mental self-regulation (character traits), and the two bottom-up prefrontal networks (ventral attention network, VAN; salience network, SN) mediating sensory and emotional reactivity (temperament traits). Together, resting-state connectivity and personality profiles represent the underlying phylogenetic systems for learning and memory that are metastable and trait-like, specifically associative conditioning (procedural system), intentionality (semantic system), and autonoetic learning (self-awareness) [34].

We believe that what may enhance the interpretation of associations between personality traits and brain connectivity is, above all, a methodology focused on functional connections and grounded in a nomological network. Network centrality metrics used in the analysis of complex networks or graphs provide information about the functional organization of the brain [24, 35]. There are still relatively few studies that compare how metrics of integration and metrics of segregation of brain networks are related to individual differences in personality. For example, one study reported a significant negative correlation between openness to experience (measured with the NEO Five-Factor Inventory) and global efficiency (a measure of integration, GE) in an analysis of structural characteristics of neural networks associated with the trait. It was concluded that openness to experience is associated with a lower capacity of the brain to integrate information from different regions [36].

Another study investigated how psychopathic traits (population variation of general psychopathy in young women with subsyndromal scores) are associated with local and global network topology based on the Psychopathy Checklist-Revised and resting-state fMRI. Changes were found at the level of nodes and hubs—nodes within the DMN and hubs connecting different resting-state networks—suggesting local abnormalities. No significant associations were found between psychopathic traits and global topological measures (e.g., overall connectivity, global efficiency). It was concluded that abnormal specificity in information processing and integration may explain general psychopathy [37]. A recent study on individual differences according to Cloningers' model reported that personality traits are associated more at the nodal level than at the global level. Specifically, a significant negative correlation was found between BC of the left caudate nucleus and the temperament trait Harm Avoidance (HA). Reduced betweenness centrality (BC) of the left caudate nucleus at higher HA values suggests a lower role of this structure as a "bridge" node in the network. It was concluded that individuals with higher HA scores may have more limited integration of the caudate nucleus within the large-scale brain network. HA generally describes inhibited behaviors and a tendency for stimuli to be processed as threatening. This finding aligns with data on the involvement of the caudate nucleus in adaptive behaviors, motivation, expectation of potential reward, and the orientation of attention toward positive social stimuli [38]. A study of dynamic network measures based on the Five-Factor Model demonstrated a stable relationship of neurophysiological indicators with the trait of neuroticism. Specifically, the following were found: (1) negative correlations between neuroticism and the number of transitions between modules and promiscuity (β-band), as well as with flexibility in the θ-band; (2) negative correlations between neuroticism and the variability of nodal measures in the left middle temporal gyrus (MTG), left superior temporal gyrus (STG), and temporal–temporal region (TT) (θ-band, EEG); (3) a negative association between neuroticism and variability of node strength in the δ-band, as well as variations of strength in the left temporal pole (α-band) and right supramarginal area (SMAR) (θ- and β-bands); and (d) a negative association between neuroticism and flexibility of the right STG (θ-band, MEG). Most significant effects were observed in the "slow" frequency bands (δ, θ, α), which are associated with the integration of activity across distributed brain regions. The conclusion is that at higher levels of neuroticism, resting-state functional brain networks are more static and less dynamic. This suggests that temporal changes in networks are also associated with personality traits [39].

As evident, integration metrics have been reported more frequently as the most consistent results in the reviewed literature examining the associations between network measures and personality traits. Functional segregation of individual brain networks increases during planning and execution of motor activity, as the brain selectively and adaptively reorganizes networks to meet changing cognitive demands, achieving an optimal balance between segregation and integration [24, 40]. In the context of personality neuroscience, the distinction between integration and segregation metrics carries a specific interpretation. Integration metrics, such as global efficiency, node strength, and centrality, reflect the degree of global coordination and information exchange across distant regions. Consequently, they are more sensitive to the presence and stability of functional networks supporting broad personality traits that integrate diverse emotional, cognitive, and motivational processes. Segregation metrics, such as the clustering coefficient and local efficiency, characterize the local specialization and functional density of subsystems engaged in specific aspects of behavior and experience relevant to the trait [35, 41, 42]. The primary goal in the research field of personality neuroscience is to identify and map the functional network—the conceptual nervous system—that constitutes a trait and organizes multiple stimuli in a manner that produces a functionally equivalent, consistent, and meaningful response [35].

In this direction, we set the following primary objectives: first, to investigate how integration and segregation metrics are related to personality traits, and second, in continuation of our previous work, to identify the network structure associated with traits in accordance with the concept of functional networks that constitute traits.

2 Materials and methods

2.1 Participants

In the current study, 86 volunteers (mean age = 29.2 years, SD = 10.2) were recruited and classified as a clinically healthy population. Of these participants, 36 were men and 50 were women. Exclusion criteria encompassed medical and/or psychoneurophysiological conditions that are contraindications for neuroimaging sessions—for example, pregnancy, visual impairment, claustrophobia, a history of neurological disorders, artifacts, or movements that could compromise data quality. Individuals under the age of 18 years were not permitted to participate. All participants provided written informed consent in accordance with the Declaration of Helsinki, and the study was approved by the Scientific Ethics Committee of the Medical University-Plovdiv (Protocol No. 1/25.01.2022).

2.2 Instrument and scoring

Lowens' Questionnaire Bioenergetic Character Type is a self-assessment scale for schizoid, oral, masochistic, rigid, and psychopathic traits. Participants completed the Bulgarian adaptation of this questionnaire within 1 week following the neuroimaging session. The method is based on the bioenergetic–analytical paradigm and is designed to measure fixed behavioral patterns corresponding to broad personaity traits. In this paradigm, character is defined as a stable, preconscious, and fixed psychobodied structure (formed by neuro-psychic processes, bodily manifestations, social influences, and early developmental factors), and personality type refers to the specific dynamic expression of this character structure—or the trait that is being measured [43].

Participants responded to each item using a four-point Likert scale, with the following values assigned: 3 = completely true, 2 = somewhat true, 1 = partly true, and 0 = false. The items are presented in Appendix 1. The four-point format was used to encourage choice without a neutral midpoint, supporting greater discrimination among response tendencies—a well-recognized practice in questionnaire research that can enhance psychometric performance by maximizing variance captured in responses.

2.3 Psychometric properties

The method is not intended for clinical diagnosis, but it is sensitive to variations associated with pathological conditions [43]. Reliability of the Bulgarian adaptation of Lowens' Questionnaire was assessed using IBM SPSS Statistics 28. Cronbachs' alpha indicated good internal consistency for the total scale ($\alpha = 0.831$), while subscale coefficients did not reach the conventional threshold ($alpha \geq 0.70$)—a pattern not uncommon in typological instruments with broad trait constructs.

2.4 Trait descriptions

The following descriptions reflect theoretical constructs as embedded within the questionnaire:

2.4.1 Schizoid type

Behavioral pattern: Fixation on planning, imagination, and process of thinking; difficulty synchronizing thought, emotion, and action. Psychological traits: introversion, narcissism, rich imagination, and genius tendencies.

2.4.2 Oral type

Behavioral pattern: excessive intellectualization, dependence on external support, and constant need for attention and security. Psychological traits: attachment, pursuit of pleasure, egocentrism, fear of abandonment, and tendency to talkativeness.

2.4.3 Masochistic type

Behavioral pattern: retroflection—directing aggression toward oneself instead of others; dynamics between compliance and manipulation. Psychological traits: self-sacrifice, masochism, and tendency to provoke punishment.

2.4.4 Psychopathic type

Behavioral pattern: drive for control and approval; separation of emotions, sexuality, and thought; instrumental manipulation of others. Psychological traits: extraversion, egocentrism, power orientation, ambition, charisma, and rationalism.

2.4.5 Rigid type

Behavioral pattern: fixation on doubt, ambivalence, control, and perfectionism; difficulty relaxing after achieving a goal. Psychological traits: rigidity, distrust, ambition, fear of evaluation, and nationalism [43].

2.5 fMRI data analysis for Lowen's experiment

Structural imaging was performed on a 3T MRI system (GE Discovery 750w) using a Sag 3D T1 FSPGR sequence with 1 mm slice thickness, 256 × 256 matrix, TR = 7.2 ms, TE = 2.3 ms, and flip angle = 12ø. Resting-state functional scans were acquired using 2D EPI with 3 mm slice thickness, 64 × 64 matrix, TR = 2000 ms, TE = 30 ms, 36 slices, flip angle = 90ø, and FOV = 24, totaling 192 volumes. fMRI data were preprocessed in SPM12 (MATLAB R2019b) including realignment, co-registration to the high-resolution anatomical image, and normalization to MNI space. Realignment parameters were: quality 0.9, separation 4, no smoothing, second-degree B-spline interpolation, no wrap, 12 × 12 basis functions, regularization 1 (medium factor), no Jacobian deformations, five iterations, and average Taylor expansion point. (a). Because our primary outcome measure was ROI-to-ROI functional connectivity based on anatomically defined regions, spatial smoothing was intentionally omitted to avoid artificial signal mixing across adjacent regions. Data from 86 healthy participants who completed the Lowens' Questionnaire [44] were analyzed. Preprocessed signals were parcellated into 165 regions using the AAL3 anatomical atlas [45], chosen for its widespread use in functional network research [46].

2.6 Network measures

Functional connectivity (FC) between regions of interest was evaluated by extracting the mean BOLD time series $x_i(t)$ from all voxels within each parcellation i and computing pairwise correlation metrics among these regional signals. Pearsons' cross-correlation was used to assess inter-regional relationships. For the negative edges of the connectivity matrices, the absolute value was taken. The connectivity matrices were thresholded by retaining only significant Pearson correlation values. To examine the network structure, we applied metrics from the Brain Connectivity Toolbox [47], including weighted undirected clustering coefficient (CC), weighted undirected eigenvector centrality (EC), node strength (NS), betweenness centrality (BC), local efficiency (LE), and global efficiency (GE). The clustering coefficient quantifies the extent to which nodes are interconnected, with the weighted variant reflecting the average intensity of all triangles associated with each node [48]. Weighted undirected eigenvector centrality evaluates a node's importance based on its connections to other highly central nodes. For node i, eigenvector centrality corresponds to the i-th element of the eigenvector linked to the largest eigenvalue of the adjacency matrix [49]. Node strength represents the total connectivity of a node, computed as the sum of absolute edge weights attached to it. Higher normalized values indicate greater centrality within the network [50]. Betweenness centrality measures the proportion of all shortest paths passing through a given node, with higher values highlighting nodes that serve as key conduits within the network [51, 52].

2.7 Data clustering

To identify latent structures within the neuroimaging data, we applied **agglomerative hierarchical clustering**, a data-driven method that organizes observations based on pairwise similarity across multidimensional features derived from brain connectivity metrics. Each subject was initially treated as a separate unit, and clusters were iteratively merged according to minimal inter-cluster distance until a defined hierarchical organization was obtained. This bottom-up procedure produces a dendrogram representation that illustrates the nested relationships among clusters and enables the detection of coherent subgroups within the dataset.

2.8 Principal component analysis (PCA)

Principal component analysis (PCA) was conducted to reduce dimensionality and minimize noise while preserving the majority of the data's variance. PCA transforms correlated neuroimaging features into a smaller set of orthogonal principal components, facilitating a more efficient and interpretable representation of the data in a reduced feature space. Dimensionality reduction was implemented using the singular value decomposition (SVD) algorithm.

2.9 Relevance vector machine (RVM) regression

Following the clustering and dimensionality reduction procedures, we employed a relevance vector machine (RVM) regression model to examine predictive relationships between brain connectivity features and personality trait scores. RVM is a Bayesian sparse kernel method that provides probabilistic predictions while maintaining high model sparsity. Compared to traditional support vector approaches, it requires fewer kernel functions and does not rely on manual estimation of a regularization parameter, allowing for more efficient and interpretable modeling of individual-level variability in functional connectivity patterns. Lastly, we applied RVM regression to the network and connectivity-measure matrices using 30% holdout cross-validation averaged over 100 random splits [53], via the SparseBayes MATLAB toolbox and RVM 2.1 package.

3 Results

Figure 1 illustrates the correlations between psychological traits across participants, indicating slightly stronger associations between oral and rigid traits, as well as between psychopathic and masochistic traits.

Significant negative correlations were observed between brain network metrics and personality traits (Table 1). Mean node strength was negatively correlated with psychopathic traits ($r = -0.264$, $p = 0.014$), which suggests that individuals with higher psychopathic traits tend to exhibit lower overall connectivity strength within the brain network. Mean betweenness centrality was negatively correlated with masochistic traits ($r = -0.230$, $p = 0.033$), suggesting that stronger masochistic tendencies are associated with fewer or less central network hubs mediating information flow. Finally, mean clustering coefficient was negatively correlated with psychopathic traits ($r = -0.247$, $p = 0.022$), suggesting that higher psychopathic traits are linked to reduced local interconnectedness or weaker local network segregation. For further analysis of the network metrics, we applied agglomerative clustering, a type of hierarchical clustering algorithm. This unsupervised machine learning method groups data points based on similarity measures. Initially, each data point is treated as an individual cluster, and the algorithm iteratively merges the most similar clusters until all points are combined into a single final cluster. As a result, data points within the same cluster exhibit greater similarity to each other than to points in other clusters, making this approach well suited for exploring large datasets and uncovering meaningful patterns [3, 54]. Comparison of network metrics across individual nodes to differentiate specific traits revealed the most pronounced correlations ($p<0.025$ for all network measures) for the nodes presented in Table 2 and Fig. 2.

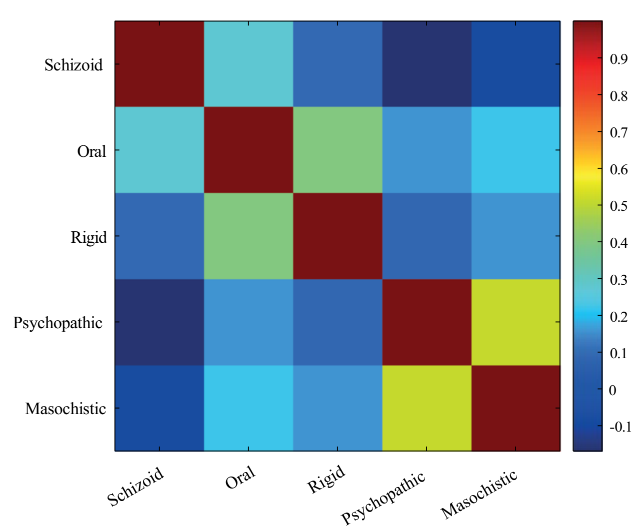

Fig. 1 Correlation matrix for psychological traits between subjects

Table 1 Correlation between network statistics and trait statistics

Metric	Schizoid traits	Oral traits	Rigid traits	Psychopathic traits	Masochistic traits
Local efficiency	$r = -0.1090$ $p = 0.3176$	$r = -0.1093$ $p = 0.3165$	$r = 0.1110$ $p = 0.3091$	$r = 0.1256$ $p = 0.2491$	$r = 0.0767$ $p = 0.4828$
Global efficiency	$r = 0.0031$ $p = 0.9770$	$r = -0.1861$ $p = 0.0863$	$r = 0.0733$ $p = 0.5025$	$r = 0.0256$ $p = 0.8147$	$r = -0.0215$ $p = 0.8446$
Mean node strength	$r = 0.0487$ $p = 0.6560$	$r = -0.0840$ $p = 0.4418$	$r = -0.0596$ $p = 0.5854$	$r = -0.2638$** $p = 0.0141$	$r = -0.0288$ $p = 0.7924$
Mean eigenvector centrality	$r = 0.0478$ $p = 0.6618$	$r = -0.1448$ $p = 0.1834$	$r = 0.0724$ $p = 0.5075$	$r = -0.1581$ $p = 0.1460$	$r = -0.0044$ $p = 0.9681$
Mean betweenness centrality	$r = -0.1290$ $p = 0.2367$	$r = -0.2108$ $p = 0.0514$	$r = 0.0599$ $p = 0.5840$	$r = -0.0685$ $p = 0.5312$	$r = -0.2298$** $p = 0.0333$
Mean clustering coefficient	$r = 0.0485$ $p = 0.6573$	$r = -0.0835$ $p = 0.4445$	$r = -0.0582$ $p = 0.5946$	$r = -0.2469$** $p = 0.0219$	$r = -0.0405$ $p = 0.7113$

Sign ** denotes significance

Table 2 Most pronounced nodes correlated by traits ($p < 0.05$)

№	Area	r	Metric	correlated with
5, 6	Frontal Mid	0.28–0.32	EC	Masochistic traits
7, 9	Frontal Inf L	0.27–0.31	EC	Masochistic traits
59	Postcentral L	0.26	EC	Masochistic traits
65, 66	Supramarginal	0.27–0.31	EC	Masochistic traits
79, 80	Heschl	0.25–0.26	EC	Psychopathic traits
85	Temporal Mid L	0.25	EC	Schizoid traits
132–135	Thal MDL, LGN	0.25	EC	Rigid traits
152	N Acc L	0.26	NS	Oral traits

The distribution of participants in the agglomerative clustering, based on pairwise trait predictors (A), is depicted in Fig. 3 and can be characterized as "strong versus weak," reflecting a more pronounced distinction along psychopathic and masochistic traits. Principal component analysis (PCA) was applied to reduce the dimensionality of the factors. Using the standard singular value decomposition (SVD) algorithm, three prominent principal components (PCs) were extracted, explaining a substantial portion of the dataset's variance [12], with a cumulative amount of data explained reaching 75%. In our dataset, the first component (PCA1) was primarily influenced by psychopathic and masochistic traits, the second (PCA2) by oral and rigid traits, and the third (PCA3) by masochistic traits. The distribution of agglomerative clusters based on these principal components (B) is also shown in Fig. 3. One cluster contains a larger number of points with lower PCA scores, while the other cluster occupies the opposite region of the diagram, corresponding to higher PCA values.

The weights of personality traits on the three principal components are summarized in Table 3. PCA1 is primarily associated with psychopathic (0.748) and masochistic (0.592) traits. PCA2 is mainly driven by oral (0.686) and rigid (0.541) traits, whereas PCA3 is dominated by masochistic traits (0.802). Schizoid traits contributed moderately to PCA2 (0.380) and minimally to PCA1 (−0.064) and PCA3 (−0.040).

To evaluate the predictive relationship between individual traits and functional network topology, we performed regression analyses using two distinct models: a nonlinear relevance vector machine (RVM) (see Table 4) [53] and a classical linear regression (Table 5). The performance of each model was assessed using the root mean square error (RMSE), with lower values indicating better predictive accuracy. The RVM model, capable of capturing nonlinear relationships, showed robust predictive performance for most trait–network pairs, with the majority of RMSE values above 0.4. However, two specific pairs were notable exceptions: The model performed best when

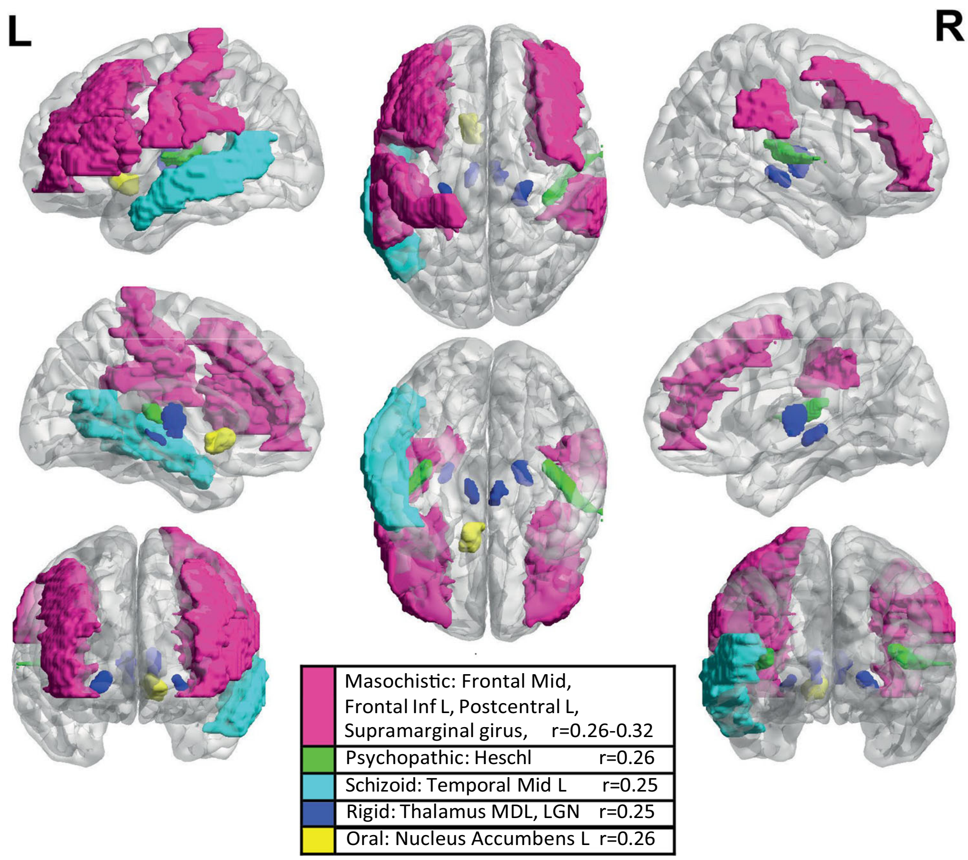

Fig. 2 Nodes corresponding to traits

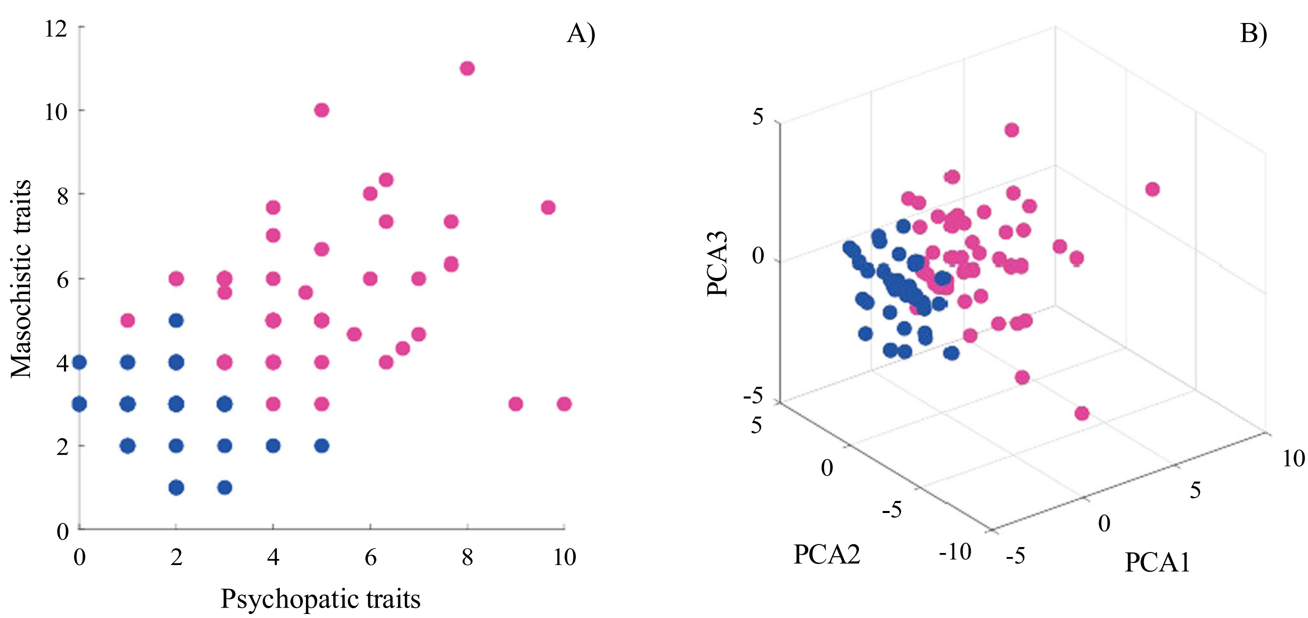

Fig. 3 Distribution agglomerative clusters by **A** traits and **B** principal components of traits

Table 3 Weight of traits in the respective principal components (PCAs)

Traits	PCA1	PCA2	PCA3
Schizoid	−0.064	0.380	−0.040
Oral	0.241	0.686	−0.169
Rigid	0.165	0.541	−0.073
Psychopathic	0.748	−0.305	−0.567
Masochistic	0.592	−0.004	0.802

Table 4 Mean RMSE regression predictors versus traits (RVM)

Traits	FC	NS	CC	EC	BC
Schizoid	0.7483	0.8000	0.4480	0.4473	0.6325
Oral	0.7746	0.6000	0.5026	0.5163	0.6325
Rigid	0.7211	0.6633	0.4901	0.5004	0.6928
Psychopathic	**0.4000**	0.4899	0.4889	0.5025	0.4899
Masochistic	0.4899	**0.3464**	0.4944	0.5076	0.6000

These are the values of the Root Mean Square Error (RMSE), with lower values indicating better predictive accuracy (in bold)

Table 5 Mean RMSE regression predictors versus traits (linear regression)

Traits	FC	NS	CC	EC	BC
Schizoid	0.4706	0.4914	0.4969	0.5047	0.7677
Oral	0.5129	0.4791	0.5350	0.4833	0.5789
Rigid	0.5609	0.4730	0.5390	0.5093	0.5968
Psychopathic	0.4299	0.5159	0.4728	0.4308	**0.1220**
Masochistic	0.5209	0.5140	0.4345	0.4609	**0.3866**
PCA1	2.6856	2.8131	2.2687	3.1827	2.1053
PCA2	2.3348	1.7634	1.4397	2.1250	1.9029
PCA3	1.1192	1.2614	1.6328	1.6314	1.4338

These are the values of the Root Mean Square Error (RMSE), with lower values indicating better predictive accuracy (in bold)

predicting psychopathic traits using full connectivity (RMSE = 0.4). The lowest prediction error was observed for masochistic traits when using node strength as the predictor (RMSE = 0.3464).

The linear regression model revealed a different outlook. Predictive performance for the majority of trait–network combinations was maintained (RMSE $>$ 0.4). A stark contrast was found for predictions involving betweenness centrality. The model showed its ability to predict psychopathic traits (RMSE = 0.122) and masochistic traits (RMSE = 0.3866).

4 Discussion

Personality traits in our study showed interesting moderate, but significant associations with network metrics. The negative correlation we found between mean node strength and psychopathic traits ($r = -0.264$) indicates that a higher level of psychopathic traits is associated with lower average node strength. The negative correlation between mean clustering coefficient and psychopathic traits ($r = -0.247$) suggests that individuals whose network structures are less clustered may exhibit stronger psychopathic traits. Conversely, higher clustering implies a more segregated, locally better integrated network that is associated with lower psychopathic traits. Similar results have been observed by Lindner et al. (2018), who identified topology abnormalities at the level of nodes and hubs—including nodes of the default mode network and hubs linking multiple resting state networks—suggesting local disruptions and impaired information integration in association with psychopathic traits [37]. Their study applied the Psychopathy Checklist Revised, which implies partial nomological correspondence between the constructs (with reference to the items on Lowen's psychopathic scale and, for comparison, the scales of the Psychopathy Checklist-Revised).

The found correlation between mean betweenness centrality and masochistic traits ($r = -0.230$) suggests a network configuration in which there are no few key nodes, but rather a more widely distributed brokerage of nodes, corresponding to high masochism. In a similar manner, higher harm avoidance (TCI) values are associated with lower BC of the left caudate nucleus, which likewise implies limited local integration of nodes without significant changes in global network topology. These results support the nomological conclusion that both constructs—the masochistic trait and Ham—manifest through local network changes related to inhibited or self-suppressing behavioral tendencies [38].

Our most significant finding is the relationships between traits and network metrics at the nodal level. Specifically, we found weak, but significant positive correlations between eigenvector centrality and masochistic traits corresponding to the frontal mid region ($r = 0.28$–0.32), left inferior frontal region ($r = 0.27$–0.31), left postcentral gyrus ($r = 0.26$), and supramarginal region ($r = 0.27$–0.31), as well as between eigenvector centrality, psychopathic traits, and Heschl's gyrus ($r = 0.25$–0.26). The most notable finding is the correlation between NS, oral traits, and left NAcc ($r = 0.26$), which replicates in accordance with our previous work [55]. The left NAcc appears to be sensitive to the oral traits region. The NAcc is a structure that participates in the cognitive processing of reward, explaining subjective reactions of preference for certain pleasant stimuli, motivational significance, and positive reinforcement [56–58]. Within a small compartment in the medial NAcc shell lies a pleasure center responsible for the pleasurable component of some intrinsic rewards [59]. The nucleus accumbens (NAcc) mediates the so-called general Pavlovian–instrumental transfer, that is, in situations in which a stimulus that has acquired significance through classical conditioning influences operant behavior [60]. The neurobiological mechanisms are considered in behavior supported/motivated by the anticipation of reward, described both in drug and substance addictions [61] and in the pleasure derived from food and sex [57]. A recent meta-analysis reports on the localization of different types of rewards in the left and right hemispheres and, more specifically, the involvement of the nucleus accumbens (NAcc): processing of food rewards shows a preference for the right hemisphere; erotic rewards favor the right lateral globus pallidus and the left caudate body; monetary rewards activate the basal ganglia bilaterally (both left and right), including the most anterior part of the basal ganglia, the NAcc. Common to all reward types is concordance in the nuclei of the basal ganglia [62]. The association we found between NS and left NAcc identifies this structure as more functionally connected in individuals with more pronounced oral traits, which corresponds to the literature on the functions of the NAcc. This correlation suggests greater centrality of the left nucleus accumbens (NAcc L) within the functional network—even with the possibility that this region may serve as a hub. It is also necessary to note the nomological consistency between the finding and the trait: the oral personality type, according to neo-Reichian analytic psychotherapy (which operates with bioenergetic typology) is characterized by attachment, craving for pleasure and enjoyment, generally emotional hunger, and behaviors relevant to this characteristic. Moreover, the psychopathological terrain that may develop in individuals of this type includes depression, melancholy, hypomania, mania, hyper-consumption disorders, and toxic addictions [43]. There is clinical evidence that functional alterations of NAcc subregions mediate the relationship between major depressive disorder (MDD) and anhedonia in patients with MDD, who exhibit neurobiological underpinnings of reward systems that differ from those of healthy controls (HCs) [63]. In patients with recurrent MDD, reduced func tional connectivity of the nucleus accumbens (NAcc) within the reward network has also been observed [64].

Returning to the correlations between eigenvector centrality (EC) and masochistic traits corresponding to the frontal midregion ($r = 0.28$–0.32), left inferior frontal gyrus ($r = 0.27$–0.31), left postcentral gyrus ($r = 0.26$), and supramarginal gyrus ($r = 0.27$–0.31), higher EC in these regions associated with masochistic traits may indicate that these nodes are more central for local and global integration within a network related to cognitive control, emotional regulation, impulse control, and social behavior [63]. These regions are part of top-down prefrontal networks—CON, FPN, and DMN—which mediate mental self-regulation and represent character traits in the psychobiological model of personality [34]. Our findings allow us to hypothesize—within the framework of nomological consistency between Cloninger's character constructs and Lowen's bioenergetic typology—that in individuals with more pronounced masochistic traits, primary centrality may be located in the frontal and somatosensory regions associated with control, social regulation, and bodily processing.

The correlation between EC, psychopathic traits, and Heschl's gyrus ($r = 0.25$–0.26) suggests a key centrality (a possible hub) in Heschl's gyrus, known as an auditory–language hub. This region also receives and primarily processes auditory information (e.g., acoustic characteristics of sound such as frequency and temporal modulations) before it is transmitted to higher auditory and language functional areas responsible for interpretation, significance, and meaning [65, 66].

In the literature, there are no data on an association between psychopathic traits and Heschl's gyrus. Theoretically, this correlation should reflect a network structure of spontaneous brain connectivity that is relevant to the psychopathic trait in a healthy population. However, there are recent promising data on shared neural mechanisms of narcissistic and antisocial personality traits in which the right Heschl's gyrus appears. More specifically, alterations have been established in the functional organization of the triple network, including DMN (self-reflection and internal thought), SN (detection of salient stimuli and emotional evaluation), and FPN (cognitive control, planning, and strategic thinking). The visual and sensorimotor networks were used as controls to ensure that the observed results are specific to the DMN, SN, and FPN, as they did not show prediction of traits. The three networks together predict narcissistic and antisocial traits, and Heschl's gyrus is part of functional network connections (especially with the lateral prefrontal cortex (LPFC), part of the FPN) that differ in individuals with higher scores for these traits. Moreover, in this study Heschl's gyrus is a region significantly associated with narcissistic outcomes (which is consistent with the description of the psychopathic trait in the bioenergetic analytic paradigm), while high local efficiency in the LPFC is associated with both traits [67]. On the other hand, pathologically disrupted fronto-parietal connectivity has been reported in patients with antisocial personality disorder. In these individuals, reduced intra- and inter-modular functional connectivity and a specific weakened subnetwork of connections involving frontal and parietal regions have been observed, reflecting impaired integration and segregation of this network compared with healthy control participants [68]. These findings [37, 67, 68], and our own [55] with regard to the psychopathic trait, allow us to speculate that there is a functional connection of Heschl's gyrus with parts of the fronto-parietal control network that may explain psychopathic patterns in human behavior (both clinical and subclinical).

Using agglomerative hierarchical clustering (an unsupervised machine learning technique), we identified three natural groups of participants with similar personality trait profiles. We visualized the data structure and found subgroups with distinct behavior. We applied principal component analysis (PCA) for dimensionality reduction and identified three independent principal components that cumulatively explain 75% of the total variance in the original psychometric data. The first component (PCA1) is primarily associated with psychopathic (0.748) and masochistic (0.592) traits; the second component (PCA2) mainly comprises oral (0.686) and rigid (0.541) traits; and the third component (PCA3) is dominated by masochistic traits (0.802). Schizoid traits have a moderate contribution to PCA2 (0.380) and minimal contributions to PCA1 (−0.064) and PCA3 (−0.040). These components reveal clusters of traits that share joint variation and can be considered separate latent dimensions of the personality structure.

Finally, in the analysis of predictive models, we found that the model using the nonlinear relevance vector machine (RVM) algorithm demonstrated significantly lower RMSE values for most combinations of "personality trait–network metric," indicating relatively good performance (mean error below approximately 0.4). More specifically, the highest predictive accuracy was achieved for psychopathic traits using functional connectivity (FC) (RMSE = 0.40), and the smallest prediction error occurred for masochistic traits when node strength (NS) served as the predictor (RMSE = 0.3464). It appears that functional connectivity (FC) and NS are the most informative network metrics for predicting the respective traits, compared with the other metrics and models used. These results support the hypothesis that topological characteristics of functional brain networks—such as full connectivity and node strength—may have a predictive relationship with certain personality traits. Furthermore, they indicate that for some traits a very good prediction is possible using a relatively simple model. Our last supposition "for some traits" aligns with the concept of neural [25], according to which trait-like mechanisms located at different levels of explanation shape personality characteristics (e.g., hormones and neurotransmitter systems). Our results are in accordance with the view that the relationships between personality traits and network topology are complex and nonlinear in nature [19, 31]. Compared to our previous work, we observe a substantial reduction in RMSE for the traits in the current sample when using RVM [55]. This indicates that the expanded dataset has led to better models for the traits, with the larger sample size likely reducing overfitting in the RVM models.

Classical linear regression models demonstrated surprisingly good RMSE values (mean error < 0.4) for the p sychopathic traits–betweenness centrality combination, for which the RMSE reaches 0.122—an exceptionally low value that indicates that linear modeling is adequate for this specific relationship, as well as for the masochistic traits–betweenness centrality combination, for which the RMSE is 0.387. Although the network structure and its interactions are complex and often nonlinear, the linear model captures enough of this complexity to make a prediction. This suggests that not only the degree of connectedness, but also the position of certain nodes as bridges/intermediaries in the network is a relevant predictor of individual differences. In this way, the structural role of key nodes may reflect important neural mechanisms that support the expression of these traits.

5 Conclusions

Our work investigates the associations between the topological characteristics of resting-state functional brain networks (resting-state fMRI) and personality traits, using analytical approaches from graph theory and statistical predictive models (including RVM and linear regression). The main results indicate that specific graph-theoretical metrics such as node strength, clustering coefficient, and betweenness centrality demonstrate significant, albeit moderate, correlations with certain personality traits—in our case, psychopathic and masochistic tendencies. This suggests that the local and global organization of the functional network may reflect individual differences in the psychobiological aspects of personality.

Our results support the idea that models of brain functional connectivity can be linked to psychological traits, as suggested by concepts from the neuroscience of personality and network neuroscience theory, according to which individual differences can be mapped onto interconnected brain systems. Methodologically, the combination of resting-state fMRI, graph-theoretic measures, and regression techniques—including RVM-type models and linear analyses—expands the traditional approach that considers the individual neural correlates of personality solely through local changes in function or structure. The application of cluster analysis and PCA also made it possible to uncover latent structures in the data that link specific neural profiles with trait configurations.

The results achieved are largely consistent with our previous research and demonstrate commensurability between the empirical measurements and the theoretical explanations of two heterogeneous scientific systems: personality psychology and neuroscience. In this way, premises are satisfied for the establishment of bridge or bi-condition laws, which facilitate inter-theoretical reduction between the taxonomic apparatus of the two scientific systems, taking into account their complex organization [69]. In turn, reduction is a prerequisite for more adequate integration of psychodiagnostic assessment methods into medical scientific knowledge and thereby for optimizing standards for psychological assessment and psychotherapy.

5.1 Limitations

Despite significant statistical associations between some graph-theoretic measures and personality traits, the observed correlation coefficients are of moderate strength ($r \approx -0.23$ to -0.27). This suggests that a large portion of the variance in personality traits is not directly explained by functional network topology as measured by rs-fMRI. Moderate effects are common in the literature on individual differences and rs-fMRI, highlighting the need for larger samples, more reliable measures, and replications to clarify the true nature and magnitude of these relationships. Furthermore, their investigation ought to be encompassed with a more complex panel of multimodal methods and techniques for investigation of brain systems at biochemical and biophysical level, including the mapping of essential metabolism and receptor density in the defined regions, thereby potentially increasing the explanatory power of the model. It should be noted that the concepts used by the bioenergetic typology of personality are to a large extent produced by psychotherapeutic practice, which lies within the field of intersubjectivity and can hardly be captured solely and exclusively through brain measurements. Bioenergetic personality types have been conceptualized as broad traits, but they are not sufficiently studied as such.

Acknowledgements The primary gratitude is to the people who believed in this project—Professor Drozdstoy Stoyanov, the mediator and mentor, the colleagues, coauthors from Russia who gave meaning to and analyzed the data, and the people who voluntarily participated in this study.

Funding This research was funded by the “Strategic Research and Innovation Program for the Development of MU—Plovdiv (SRIPD MUP)—Creation of a Network of Research Higher Schools”, under the National Recovery and Resilience Plan, cofinanced by the European Union—NextGenerationEU, contract No. BG RRP 2.004 0007 C01.

Availability of data and materials The data presented in this study are available on request from the corresponding author.

Declarations

Conflict of interest The authors declare no conflict of interest.

Ethics approval and consent to participate All participants provided written informed consent. The research was approved by the Committee on Scientific Ethics of Medical University Plovdiv (Protocol No. 1/25.01.2022).

Consent for publication All authors have read and agreed to the published version of the manuscript.

Appendix A

Alexander Lowen's Questionnaire: Bioenergetic Character Type (Bulgarian adaptation)

1. I feel comfortable when I am alone.
2. I often feel dependent on other people.
3. My father played a very important role in my upbringing.
4. I rarely feel afraid.
5. My mother is often grumbling and obsessive, but she is very caring.
6. Sometimes I feel inexplicable fear and anxiety.
7. It find it unpleasant to be alone.
8. I am more afraid to be wrong than others seem to be.
9. I enjoy being in a guideline/leadership role.
10. It is hard for me to say no.
11. I often feel rejected and unwanted.
12. I often focus more what is missing than what is available.
13. I separate sex from feelings.
14. I would like to be a hero.
15. I am afraid to be the first to react in a conflict situation.
16. I enjoy daydreaming.
17. I like to display my knowledge in front of others.
18. I strictly adhere to commonly accepted rules and norms.
19. I like to flirt using my charm.
20. I let others "use" me.
21. I am often told that I am quiet and distant.
22. My biggest fear is being abandoned.
23. I want to experiment with sex, but I rarely allow myself to do so.
24. I have an alert gaze and often observe people.
25. My skin flushes more easily from emotion than other people's.
26. I have an issue with my eyes (high diopters, illness).
27. I have a tight and tense jaw.
28. I find it difficult to relax and enjoy what I have achieved.
29. I fear failure more than others.
30. I often feel pressured by others and circumstances.
31. I often have cold hands and feet.
32. People say me often that I am like a child compared with others.
33. I have a tight back and posture.
34. I easily make contact and communicate with others.
35. I am prone to gaining weight.
36. I am described as a strange and withdrawn person.
37. My chest is somewhat sunken.
38. I think and hesitate for a long time before making a decision.
39. I look confident.
40. People say that I am slow and deliberate in my movements.
41. I have a powerful imagination.
42. I like to talk.
43. I comply with the authoritative persons.
44. I love being on a stage.
45. I am very resilient.
46. My body has reduced sensitivity.
47. I am drawn to the world of ideas and intellect.
48. It is hard to change established habits and attitudes for me.
49. People consider me attractive and sexy.
50. I can obey.
51. Physical intimacy with another person worries me.
52. I find it very difficult to ask someone for something.
53. It is important to me to be correct and disciplined.
54. I feel upset if I am not the center of attention.
55. After being humiliated, I have a desire for revenge.
56. It is difficult for me to work in a team.

57. I am waiting for others to recognise what I want.
58. I love orderliness in all its aspects.
59. I easily recognize the wishes of others.
60. My relatives say that I complain.

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