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Identifying neural network structures explained by personality traits: combining unsupervised and supervised machine learning techniques in translational validity assessment

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Abstract There have been studies previously the neurobiological underpinnings of personality traits in various paradigms such as psychobiological theory and Eysenck's model as well as five-factor model. However, there are limited results in terms of co-clustering of the functional connectivity as measured by functional MRI, and personality profiles. In the present study, we have analyzed resting-state connectivity networks and character type with the Lowen bioenergetic test in 66 healthy subjects. There have been identified direct correspondences between network metrics such as eigenvector centrality (EC), clustering coefficient (CC), node strength (NS) and specific personality characteristics. Specifically, N Acc L and OFCmed were associated with oral and masochistic traits in terms of EC and CC, while Insula R is associated with oral traits in terms of NS and EC. It is noteworthy that we observed significant correlations between individual items and node measures in specific regions, suggesting a more targeted relationship. However, the more relevant finding is the correlation between metrics (NS, CC, and EC) and overall traits. A hierarchical clustering algorithm (agglomerative clustering, an unsupervised machine learning technique) and principal component analysis were applied, where we identified three prominent principal components that cumulatively explain 76% of the psychometric data. Furthermore, we managed to cluster the network metrics (by unsupervised clustering) to explore whether neural connectivity patterns could be grouped based on combined average network metrics and psychometric data (global and local efficiencies, node strength, eigenvector centrality, and node strength). We identified three principal components, where the cumulative amount of explained data reaches 99%. The correspondence between network measures (CC and NS) and predictors (responses to Lowen's items) is 62% predicted with a precision of 90%.

1 Introduction

The psychometric constructs can be validated inductively, based on empirical data at the population level, or deductively, based on pre-formulated hypotheses. At the core of the methods for determining validity lies the correlation [1]. However, the validity is stabilized by many different criteria, that is why in psychological measurements, it is necessary to assess its separate dimensions, such as:

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(a) construct validity, or the extent to which a test is based on a theoretical model, the extent to which it measures a certain trait, or the extent to which test performance can be explained by underlying psychological constructs (latent variables);

(b) convergent validity, or the high correlations of the test with other variables with which it should theoretically correlate;

(c) divergent (discriminant validity), or the absence of significant correlations with variables from which the test should theoretically differ;

(d) obvious validity (face validity), which corresponds to the impression of the participants in the study or non-specialists that the test indeed measures what it is intended to measure;

(e) cross-validation, or the determination of the validity of a test for a new sample, different from the one for which the items were selected;

(f) content validity, the degree to which the items of a test are related to the construct, based on expert assessments;

(g) concurrent validity (cross-sectional validity), or the degree of agreement between two independent measures, one of which is already established as valid (e.g., scores from another test measuring similar characteristics);

(h) predictive validity, or the extent to which a test is an indicator of future achievements in a specific field, i.e., its ability to correlate with external criteria that are distant in time [1].

Possible criteria for validating a psychological test may include: academic achievements, performance in specialized training (tests for specific abilities), actual performance, group comparisons, and psychiatric diagnoses [2].

In multidisciplinary research, the issue of validity takes on new dimensions. The use of multiple measures in studying the same constructs within different areas of expertise (e.g., describing mental functions and their impairments in a clinical setting) is associated with disciplinarily diverse validation criteria. Discrepancies arise with the integration of the empirical data from different domains of knowledge. In fact, general principles of organization emerge, which transcend these discrepancies. Adherence to a certain position, for example, one based solely on neuroscientific principles, may lead to the conclusion that the obtained information is inauthentic, or conversely, that it is more real than psychological information. (e.g., self-assessment data) [3]. Objective scientific findings, based on the conventional assessment of validity in each field of research, carry both the limitations and the advantages of the corresponding scientific methodology. In other words, the linear integration of conventionally valid techniques can multiply both their imperfections and their strengths. It is claimed that neuroimaging (non-invasive techniques such as fMRI and EEG) shows low ecological validity, or the degree to which participants' perceptions and reactions in the experiment can be generalized to real-life settings [4–6]. Studies using virtual reality (VR) methods, especially in the field of medical training, enhance ecological validity by adding realism (three-dimensionality, simulated experience). This allows to the participants to be immersed in the stimuli rather than being passive observers. At the same time, VR techniques also face methodological limitations, such as poor and inadequate experimental design, relative differences between the real and virtual environments, small sample sizes, convenience sampling, and lack of transparency regarding the collection of the data. VR applications have significant advantages, such as creating and evaluating innovative IT artifacts that expand the human capabilities (applicability, satisfaction) and the organizational capabilities (cost reduction, productivity), as well as providing objective data collection opportunities (biometric sensors for real-time psychophysiological data, data on hemodynamic changes) [4]. Among the factors that compromise the ecological validity of neuroimaging studies are the highly controlled laboratory stimuli and the artificial and isolated environment of the research setting. In neurocognitive imaging studies, the participants perform tasks aimed at isolating a specific cognitive skill or cognitive process, using highly controlled, simplified stimuli that require multiple repetitions. The setting can be intimidating, and fMRI sessions can be long and exhausting. Therefore, it is believed that the developing of more naturalistic stimuli (e.g., VR in the scanner) or incorporating real-life interactions during the laboratory experiment would make it more ecologically valid [7, 8].

In addition, people with anxiety and somatoform disorders could aggravate symptoms related to other neurological disorders or simulate illnesses and deficits motivated by secondary benefits. It is also possible that the examined individuals might be disinterested or insufficiently engaged with the task, or simply tired [9]. However, even without recreating real-life conditions, capturing key characteristics in a way that allows conclusions from the experiment to be extrapolated to the studied phenomenon also increases the ecological validity of the measurement. It is crucial that these characteristics represent the core elements of the phenomenon in the reality [10, 11]. Brunswik defines ecological validity as the correlation between a proximal cue and a distal variable, or the potential utility of a proximal cue (source of information) available to the organism for inferring the state of a distal variable (e.g., an object). In the example from Brunswik's lens model, the judgment of a person determining another person's age is referred to as functional validity or achievement, while the distal variable is the age. The correlation between the proximal cue (such as hair color, skin condition, and posture) and age is referred to as ecological validity, while the correlation between the observer's judgment (central response) and the cues is referred to as the cue utilization coefficient. The observer might use relatively superficial cues with limited validity to determine age, and yet they may still be useful for the perception [12, 13]. Within the widely accepted concept of ecological validity, understood as the degree of correspondence between natural and laboratory contexts, certain variables remain artificially "tied" or "untied." In this way, both perfect correlation, known as functional dependence [1], and non-correlation are possible. Brunswik emphasizes the importance of representativeness in the design, precisely because differences exist between the natural ecology of a psychological experiment and the experimenter's construction, which are maintained by artificial systematic designs. Design representativeness requires researchers to carefully define a reference class of conditions (stimuli, tasks, and situations) to which they intend to generalize their results. In addition, participants should be selected from well-defined populations, and stimulation situations should be selected from well-defined natural-cultural ecologies. Whether experiments are conducted in laboratory or real-life settings, when a well-defined set of conditions is lacking, they are deprived of specificity [13, 14].

Improving the validity by adding new predictors to existing sets of measurements is noted in psychology as incremental validity. Determining incremental validity involves: first, capturing and identifying the validity of separately applied tests, and second, capturing and identifying the process of joint evaluation. Strong psychometric characteristics are a necessary, but insufficient, condition for ensuring incremental validity [3, 15]. Incremental validity refers to a measure's ability to add new information or improve the classification accuracy of another established measure in the assessment of the same construct. Incremental validity is regarded as a key form of validity and clinical utility; it relates to the usefulness of a measure in clinical practice. An interesting example is the simultaneous testing of the clinical application of two of the most respected methods in the assessment of personality psychopathology. It turns out that Rorschach indices[1] do not significantly improve the classification accuracy for depression and conduct behavior, diagnosed with MMPI-A in psychiatrically referred adolescents. At the same time, Rorschach indices do not significantly improve the classification accuracy for depression and conduct behavior diagnosed with the MMPI-A[2] in psychiatrically referred adolescents. At the same time, Rorschach data improve the classification accuracy of the MMPI-2 in identifying individuals with personality disorders according to DSM-IV criteria, specifically histrionic [18–20]. Demonstrating incremental validity does not necessarily prove improved prediction of the criterion variable through the use of a given measure. In evaluating incremental validity, certain risks are described, such as:

1. An unrecognized or unassessed artifact that influences one or more, but not all, predictor variables. This is similar to the so-called third-variable problem in correlation analyses, where the empirical relationship between two variables is a function of an unmeasured third variable.
2. Criterion contamination, when the same source informs both the predictor and the criterion, potentially artificially inflating their association, known as the source overlap artifact. The alternative is to extract data from independent sources in studies that share minimal method variance.
3. The non-cumulative nature of published studies. The replication of previous findings must be carefully conducted both conceptually and procedurally. Multiple variables should be introduced in a similar or the same order in regression analyses to ensure comparability. This is one of the reasons why researchers are encouraged to provide complete correlation matrices of all variables.
4. The findings from studies on incremental validity are in a more enhanced degree conditional. This is because any predictive variance that the test shares with previously introduced variables in the regression equation is not available to be allocated to the test.

Therefore, it is important to consider the order of variable introduction, the research context (e.g., how the diagnosis was formulated and how the treatment plan was developed), and the chosen clinical sample when assessing incremental validity [15]. Higher incremental validity has been reported for interviews, objective personality inventories, and self-report measures [21]. The merging of different fields in interdisciplinary work is based on the implicit norms embedded in each of them. In this way, certain sets of disciplinary norms may be privileged over others, which in turn explains the choice of sometimes inappropriate measurement methods. The interdisciplinary designs require an assessment of the quality, utility, and the accuracy of the selected methods within the same disciplinary field (internal validity), as well as the generalizability of the obtained results across two or more disciplinary fields (external validity) [22].

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[11]The Rorschach inkblot method is the most famous projective test, created in 1921 by psychiatrist and psychoanalyst Hermann Rorschach. It was initially conceived as an experiment for assessing perception. It involves presenting 10 symmetrical inkblots, some of which are achromatic (black-gray-white), while others are colored. The subjective perceptions of the participants are recorded and analyzed (apperception, interpretation, pure perception, projections, perceptual conflict). The reliability and validity of the method have been the subject of longstanding debate among scientific critics [16].

[22]The MMPI is the most widely used psychological test for assessing psychopathology and personality traits, created in 1942 by Stuart Hathaway and Charlie McKinley. The method is designed to capture the presence of psychiatric syndromes such as hypochondriasis, depression, hysteria, psychopathic deviation, masculinity-femininity, paranoia, psychasthenia or obsessive–compulsive tendencies, schizophrenia, mania, and social introversion. In addition to clinical psychology, it is effectively applied in criminology (for forensic psychological evaluations) and organizational psychology (for recruitment in human resources sectors) [17].

The development of clinical questionnaires for the assessment of psychopathological constructs is carried out within an exploratory-confirmatory measurement framework in two stages. The exploratory stage is based on the selection and revision of items, initial structural evaluation, and preliminary tests for convergent and discriminant/concurrent validity. The confirmatory stage is based on the reproduction of the factor structure using a more restrictive model, identification of areas of strain in the model, additional tests for concurrent validity, and an evaluation of the invariance of the study. The conceptual framework of psychopathology can be narrow, broad, or hierarchically organized, shaped by a hypothesis, theory, or nosology. In different cases, the psychopathological construct may be a theoretical model for assessing disorder-specific mechanisms or symptoms (e.g., in relation to the diagnostic criteria of the DSM) or a theoretical model for assessing a broader psychopathological category (e.g., personality psychopathology). Such phenomena are also defined as transdiagnostic constructs. In these cases, validity is established within the context of a nomological network, which should include at least one similar and one less related or unrelated construct [23].

In the field of translational neuroscience, particularly in the domain of clinical psychology, psychiatry, and neuroscience, the measurement of validity is known as the approach of translational validity. By its nature, this approach is unconventional and instrumental, relying on objective neuroimaging data [24]. His innovative perspective is largely guided by the following considerations:

1. Modern psychiatric nosology cannot reliably classify psychopathology based on the diagnostic units outlined in the DSM and ICD. They do not represent natural systematic classifications, do not form hierarchies, and do not contain higher organizational concepts, as observed in biological taxonomies;
2. The disorders in the DSM and ICD have a hybrid status. Some correspond to medical syndromes, while others to isolated symptoms, habitual behaviors, or personality traits that tend to occur simultaneously [25];
3. The conventional diagnostic concepts and tools lack phenomenological accuracy and prognostic value. The clinical assessment in psychiatry is based on fragmented narratives, interviews (conducted by professionals with patients, family members, or referential informative communities), or patients' self-assessment [25, 26];
4. The translational validity is a form of external validity that arises from the simultaneous integration of clinical and neurobiological measures. The translation of data emerges as a primary challenge in the dialogue between the various disciplinary languages [24, 26].

This also opens up the possibility of "falsification" of theories, which Popper defines as a key criterion for scientific progress [27]. The studies developing the approach of translational validity consider the investigation of clinical conditions as a more robust approach for transferring the neurobiological mechanisms of mental disorders into clinical reality, as opposed to stable psychological phenomena such as traits. Their rationale is that certain correlations are directly related and specific to variables of the current mental state [24, 28–31]. The traits and the states are the most significant concepts in personality psychology theory and research [32]. They are considered to be prototype-based categories with a graded internal structure and fuzzy boundaries. The traits are stable over time, long-lasting, and internally driven, while states are short-term, temporary responses to external circumstances. The concept of traits allows for the prediction of current personality characteristics from the past, while the concept of states enables the identification of behaviors that can be controlled by manipulating the situation [33]. The personality traits reflect conceptually corresponding/relevant states experienced in different situations; therefore, trait measures should closely correspond to the central tendency of the distribution of states (mean, median, and mode). On the other hand, the personality traits correspond to socio-cognitive mechanisms (goals, beliefs, values, life stories, expectations, etc.) that process incoming (environmental events, internal events) and outgoing personality states (increase or decrease in state, changes in state manifestations). The individual differences in socio-cognitive mechanisms can explain inter-individual variations in traits (i.e., the central tendency of the distribution of states, or standard deviation, range, minimum, maximum, skewness, kurtosis as viable indices of the trait), while the variations in input data from situation to situation can explain intra-individual variations in states [34]. The descriptive and explanatory models of traits, as well as the etiological aspects of traits (why people exhibit specific traits), are integrated into a more global model, postulated in the whole trait theory [35].

The existing explanatory gap between the significance of neuroimaging and self-report data has been articulated in neuroscience as a central issue of translational validity. The discovery of a hierarchy in the organization of brain functional connectivity, when jointly interpreted with data on genetic, developmental, and evolutionary characteristics of personality, may contribute to improving the translation, or the ability to convert neurobiological findings into meaningful and clinically significant descriptions of human behavior [36]. The fundamental unresolved problem is the precise approach for co-clustering psychometric and resting-state brain imaging data. The latter is assumed to reflect test-retest stable personality trait measures. Measures of resting-state functional connectivity (rsFC) in the human brain correspond to differences in human's perceptual, cognitive, emotional, and social functioning [36]., as opposed to mental, and respectively, neurophysiological states, which are highly dependent on variables such as brain hemodynamics. Some of the most recent attempts at co-clustering resting-state fMRI data with personality questionnaires have been conducted within the paradigm of the psychobiological theory of personality

[36–38]. Cloninger and colleagues found that the organization of temperament and character corresponds to configurations of resting-state functional connectivity in the brain, specifically, bottom-up prefrontal networks (VAN, SN) mediate sensory and emotional reactivity (temperament traits measured by TCI), while top-down prefrontal networks (DMN, CON, FPN, DAN) mediate mental self-regulation (character traits measured by TCI). In patients with psychosis and personality disorders, the functional connectivity networks are discordant, manifested by the prevalence of negative emotions and irrational thoughts over weak and dysfunctional self-regulation. Vulnerability to psychosis corresponds to disrupted connectivity of the prefrontal cortex with parietal, temporal, limbic, and cerebellar centers of the resting-state networks. Dysfunctions in these networks are associated with biopsychosocial aspects of psychosis, such as sensory hypersensitivity, negative emotional balance, impaired attentional control, avolition, and social mistrust [36, 37]. To this date, no attempts have been made to co-cluster other personality questionnaires commonly used in psychodiagnostics with nonlinear metrics for assessing brain connectivity in this context. One of the tests for assessing personality typology during the initiation of psychotherapy is Alexander Lowen's test. On the one hand, it is developed within the body psychotherapy paradigm and is presumed to reflect real biological processes. On the other hand, there are numerous concerns regarding the lack of stable evidence supporting the scientific basis of this assumption, which is derived from practical therapeutic experience [39].

The currently existing body of knowledge provides background in terms of links between certain personality traits and their underlying brain networks. Those are measured by means of different techniques, such as EEG or fMRI either at rest or with relevant to the construct (trait) tasks (stimuli). That is of particular interest in the psychobiological theory and Eysenck's model of personality. However, there still exists a gap in terms of identifying the so called "bridge laws" [40, 41]. Bridge laws are defined in order to facilitate inter-theoretic translation by determining biconditions which exist in the vocabulary of two disciplines, which are likely to share common terms and notions. In our context, a set or a cluster of personality traits may be explained in terms of neural circuits and vice versa. In such a way, the two conditions are likely to validate each other. In that perspective, the aim of our work is to investigate the premises for:

1. Existence of biconditions which can potentially bridge Lowen's personality types with functional MRI measures at rest. This, in turn, implies a) clarifying the extent to which measurements based on Lowen's bioenergetic typology correspond to real neurobiological processes, and b) specifying how well resting-state functional connectivity (rsFC) measurements of the human brain correspond to Lowen's personality profiles.
2. The resources of the two methods: psychometrics and functional neuroimaging cross-validate each other. We suggest a concept for revalidating (translational validity) trait-oriented personality scales and discuss unsupervised machine learning as a nonlinear method in personality assessment through neuroimaging measures.

2 Materials and methods

2.1 Sample and psychometrics

For the present study, 66 individuals (with a mean age of 29.8 $\pm$ 11 years, including 21 males and 41 females) were recruited for voluntary participation. Participants were classified as a clinically healthy population. Exclusion criteria were medical and/or psychoneurophysiological conditions contraindicated for neuroimaging sessions, such as pregnancy, impaired vision, claustrophobia, presence of neurological history, artifacts, and movements that could compromise their performance. Persons under the age of 18 were not admitted to the study. All participants provided written informed consent under the Declaration of Helsinki and the approval of the Scientific Ethics Committee of Medical University-Plovdiv (Protocol No. 1/25.01.2022). Within a week after the neuroimaging session, participants completed the Bulgarian adaptation of Alexander Lowen's scale Bioenergetic Character Type, which self-assesses schizoid, oral, masochistic, rigid, and psychopathic traits. The method was created as a bioenergetic analytical model for personality assessment, designed to measure character and temperament constellations from a specific typological perspective.

For the purposes of our study, we used Lowen's self-assessment questionnaire (Appendix 1), expanded with additional items following consultation with experts from BINAP-Bulgaria. The method is not intended to measure psychopathology, despite the names of the scales referring to psychological disorders, but it is sensitive to psychological instability and vulnerability to psychopathology. In the bioenergetic analytical paradigm, these five groups of traits describe the psychophysiological structure of personality, shaped by the earliest intrapersonal and interpersonal experiences [42, 43].

The schizoid traits are represented by the dominance of personality characteristics such as creativity, discovery, mysticism, narcissism, physical detachment, and imagination. The sensitive age for their formation is considered to be the prenatal period and the first 3–4 months, identified as the narcissistic evolutionary phase. The oral traits include stronger development of qualities such as intellect, preference for art, oratory, creativity, and dependency. Sensitive age for their formation is 3–12 months, known as the sensory phase of development. The masochistic traits imply qualities such as restraint, service, invasiveness, compliance, endurance, and care, and they form between the ages of 1–4 years, during the phase of the Ego. The psychopathic traits are represented by qualities such as extraversion, dominance, competitiveness, leadership, achievement, and risk-taking. They develop between the ages of 3–5 years, referred to as the rivalry phase. Rigid traits are associated with qualities such as control, morality, hesitation, and teaching. They develop and solidify as a lasting characteristic between the ages of 4–8 years, known as the sexual phase in bioenergetic terms. Schizoid and oral traits are associated with asthenic body morphology, masochistic traits with a pyknic body type, psychopathic traits with an athletic-pyknic body type, and rigid traits with an athletic body type [44]. It is assumed that individual results suggest a combination of traits. The interpretation of personality profiles within psychological assessment remains robustly descriptive and is in nomological alignment with other well-established methods for assessing personality traits such as TCI and Eysenck. The psychometric validity of the Lowen's scale was assessed with SPSS, version 28. Cronbach's Alpha reliability coefficient was 0.831 for the entire scale. For the separate subscales, Cronbach's Alpha values are lower than the recommended acceptable value of 0.7.

2.2 fMRI data analysis for experiment with Lowen test

The experimental protocol involved conducting structural scan on a 3T MRI system (GE Discovery 750w) using a Sag 3D T1 FSPGR sequence. The structural scan had slice thickness of 1 mm, matrix of 256 × 256, relaxation time (TR) of 7.2 ms, echo time (TE) of 2.3 ms, and flip angle of 12ø. In addition, a resting-state functional scan was performed using 2D echo-planar imaging (EPI) with slice thickness of 3 mm, matrix of 64 × 64, TR of 2000 ms, TE of 30 ms, 36 slices, flip angle of 90ø, and field of view (FOV) of 24, or a total of 192 volumes.

FMRI data were analyzed using the SPM 12 [45] running on MATLAB R2019b for Windows. Preprocessing consists of the following steps: realignment, coregistration with the high-resolution anatomical image, and normalization to standard MNI space. Parameters for the realignment step were the following: quality 0.9, separation 4, no smoothing, 2-nd degree B-spline interpolation, no wrap, 12 × 12 basis function, regularization 1 with medium factor, without Jacobian deformations, 5 iterations, average Taylor expansion point.

The preprocessed activity signals extracted with SPM12 from fMRI were divided into 165 parcellations according to the automatically matched AAL3 anatomical labeling atlas [46]. We chose the AAL atlas because it is the most commonly used parcellation scheme in functional network research [47].

2.3 Network measures

To assess the connectivity between the regions of interest, we calculated the average BOLD time series $x_i(t)$ (across voxels in each parcellation i) and the corresponding metrics for all pairs of average activities of each region. The analysis of the relationship between the sequence was based on the established Pearson's cross-correlation (Table 1). The following network measures from the Brain Connectivity Toolbox [48] were used to analyze the network structure: weighted undirected clustering coefficient, weighted undirected eigenvector node centrality, node strength, betweenness centrality, local efficiency, and global efficiency. The metric known as clustering coefficient assesses how interconnected all the nodes in a network are. The weighted clustering coefficient calculates how intense all the triangles related to each node are, on average [49]. Weighted undirected eigenvector centrality is a circular measure of importance when it comes to networking. A node's importance increases if it is connected to other significant nodes. The eigenvector centrality of node i is equal to the i-th element in the eigenvector that corresponds to the biggest eigenvalue in the adjacency matrix [50]. The node strength metric determines how tightly a node is directly connected to other nodes in the network by sum up all the absolute edge weights connected to it. All values are normalized and higher values indicate an increased centrality within the network

Table 1 Correlation between network statistics and trait statistics

Metric	Schizoid traits	Oral traits	Rigid traits	Psychopathic traits	Masochistic traits
Local efficiency	– 0.0244	– 0.0219	0.1270	– 0.0095	– 0.0056
Global efficiency	– 0.0183	– 0.0590	0.0925	– 0.0772	– 0.0948
Mean node strength	0.1641	0.0945	0.0330	– 0.0556	0.1142
Mean eigenvector centrality	– 0.1042	– 0.0597	0.0988	– 0.1180	0.2420
Mean betweenness centrality	– 0.0928	0.0654	– 0.0221	0.2349	0.0800
Mean clustering coefficient	0.0562	0.1429	– 0.0009	– 0.0413	0.2692

[51]. The betweenness centrality metric is a ratio that considers all the shortest paths passing through the given node in a network. Nodes with greater values of betweenness centrality participate in the highest numbers of short routes [52, 53].

2.4 Clustering methods

We employed two distinct data clustering methodologies to effectively organize and categorize our dataset. These techniques were specifically chosen for their ability to uncover patterns and group similar data points together, thereby providing valuable insights into the structure of our information. The first method we utilized was agglomerative clustering, which is a hierarchical clustering approach [54]. This technique begins by treating each data point as an individual cluster and then progressively merges the closest clusters together. The process continues iteratively until all data points are grouped into a single, overarching cluster or until a predetermined number of clusters is reached. This bottom-up approach allows for the creation of a tree-like structure, often visualized as a dendrogram, which can reveal hierarchical relationships within the data.

The second technique we implemented was self-organized maps (SOMs), also known as Kohonen maps. This is an unsupervised machine learning method that uses artificial neural networks to produce a low-dimensional representation of high-dimensional input data. SOMs are particularly effective at preserving topological properties of the input space, making them useful for visualizing complex datasets. In this process, neurons compete to best represent the input data, and the winning neurons and their neighbors are adjusted to better match the input, resulting in a map where similar data points are grouped together.

Self-organization maps were used as a first step to test the partitioning of the feature options [55]. Self-organizing maps are powerful visual exploration techniques capable of mapping large amounts of data onto small areas. It organizes a large quantity of information into compact two-dimensional grids or arrays. The basic idea was proposed by Kohonen and revolves around C cells or grid points (we used 5×5 since only 66 samples available and not more than 5 clusters expected with “Batch weight” training rules and performance improvement based on mean squared error (MSE)), which are organized in specific maps. These grids act as a medium, where the data are distributed through neighborhood functions, as defined in Ref. [56].

2.5 Principal component analysis

Principal component analysis is a statistical procedure that transforms a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The primary goal of PCA is to reduce the dimensionality of the data while retaining as much of the original variability as possible. We applied the principal component analysis method to reduce the volume of the factors. To implement PCA, we utilized the standard singular value decomposition (SVD) algorithm [57].

2.5.1 RVM regression

Following our initial data preprocessing and dimensionality reduction steps, we proceeded to implement machine learning technique known as relevance vector machine (RVM) regression on our dataset. This step was crucial in our analysis pipeline, aimed at modeling the relationships within our data and making predictions. relevance vector machine is a Bayesian sparse kernel technique for regression and classification. RVM has several advantages, including the ability to use fewer kernel functions and avoid the need to estimate a regularization parameter. We implemented the RVM regression on the network and connectivity measure matrices with 30% holdout cross-validation [58] with the SPARSEBAYES Matlab toolbox and package RVM 2.1 [59], averaged results for 100 iterations.

2.6 Support vector machine analysis

Support vector machine is a supervised machine learning algorithm used for classification and regression analysis [60]. It works by finding the optimal hyperplane or boundary that separates data points of different classes with the maximum margin. Employing support vector machine analysis (in Classification Learner toolbox, Matlab), we explored the accuracy of classification (considering classes obtained through agglomerative clustering) based on different connectivity measures. Parameters including the enforced amount of regularization or prior probabilities were not applied. For validation, K-fold with 5-fold over 100 iterations was used.

3 Results

To begin, we note that the correlation of psychological traits between subjects can be seen in Fig. 1.

As first step, we used self-organizing maps (SOM) on the psychological traits distribution using answers for the Lowen test (Fig. 2). The result suggests possibility of existing two macro-types with core of 20 persons each.

Comparing the network metrics of individual nodes to differentiate by specific issues and types indicates the most pronounced correlations ($p < 0.025$ for all network measures) for the nodes presented in Tables S1 and Fig. 3.

The distribution of the participants in agglomerative clustering based on the predictors (pairwise traits) as depicted in Fig. S1 can be described as "strong versus weak". The results indicate that one of the clusters holds a greater tendency for higher values on four out of the five traits, while the psychopathic trait is comparatively more evenly distributed. We applied the principal component analysis method to reduce the volume of the factors and achieved the goal. By utilizing the standard singular value decomposition (SVD) algorithm, three prominent principal components (PCs) were extracted with the cumulative amount of data explained reaching 76%. The first PC (PCA1) was heavily driven by rigid and schizoid traits, the second (PCA2) leaned towards oral and psychopathic, while the third (PCA3) was influenced by masochistic and rigid factors simultaneously (more details in Table 2). Displays the distribution of the agglomerative clusters based on the principal components, as depicted in Fig. 4. As seen, one cluster is made up of a higher number of points that hold lower values of PCA scores, while the second cluster leans more toward the opposite corner of the diagram with higher PCA values. Another option for space reduction was to compute principal components on network measures, the details are shown in Tables 3 and S2.

We used MATLAB "clusterdata" function with cutoff parameter equal to two. Results of clustering for the full correlation matrix and different network measures are shown in Fig. 5. For one of the clustering approaches, we used the following technique: we took matrices only binary matrices of significant correlations ($p < 0.05$), then

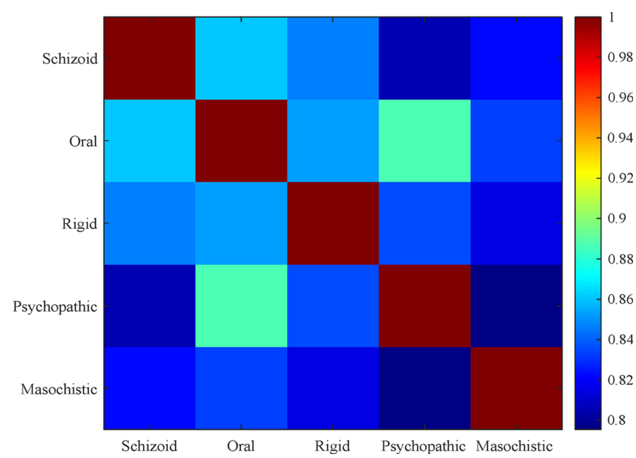


Fig. 1 Correlation matrix for psychological traits between subjects

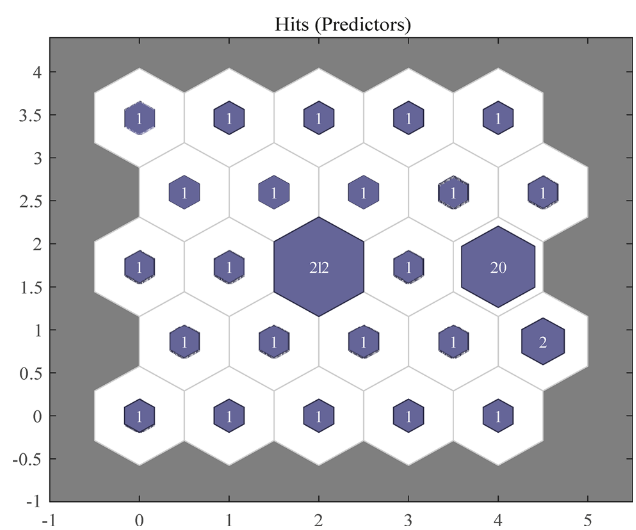


Fig. 2 Self-organizing maps for the psychological traits (answers)

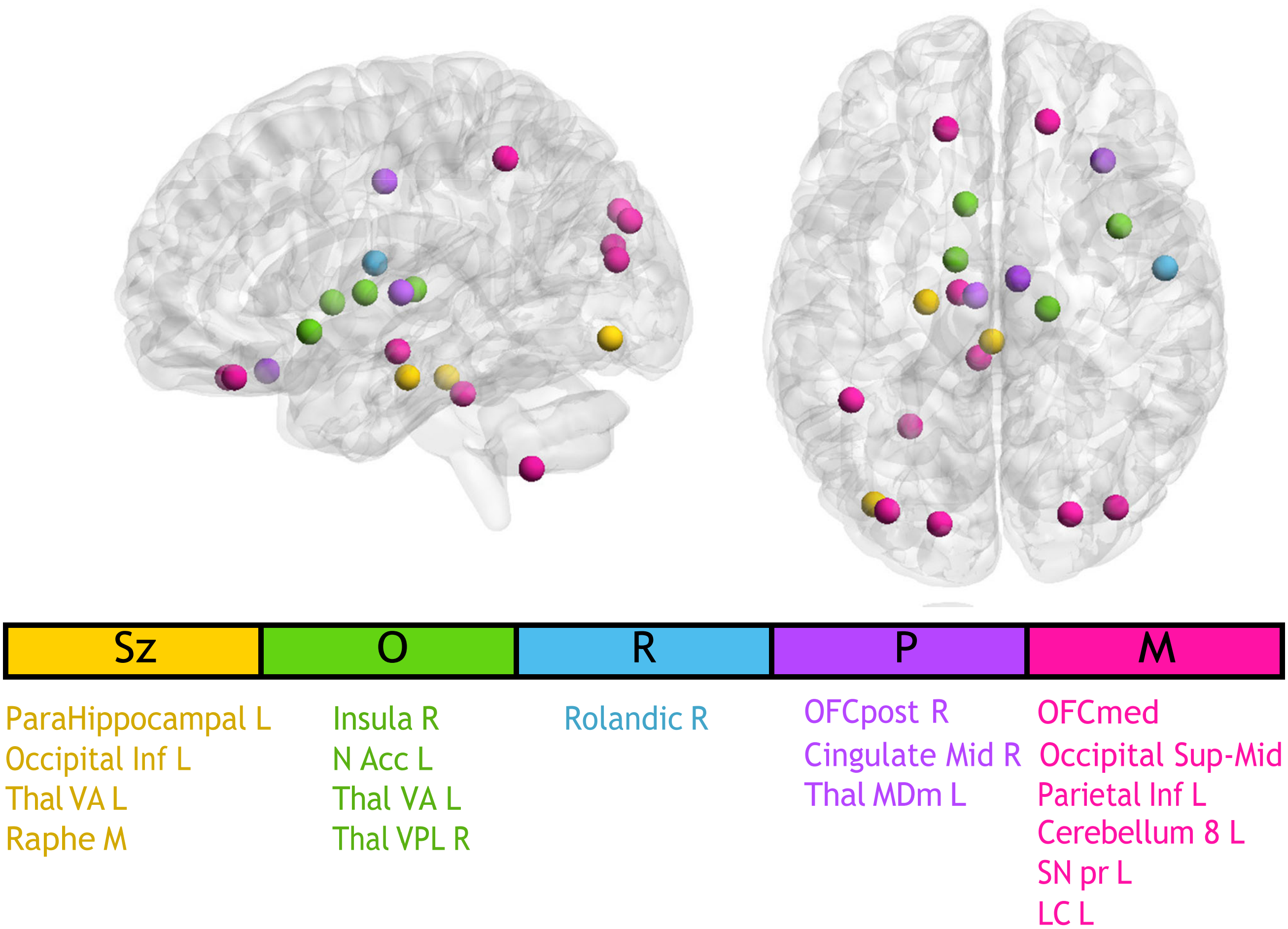


Fig. 3 Most pronounced nodes correlated by traits ($p < 0.05$). Nodes corresponding to the Schizoid traits—Sunglow yellow, Oral—Orchid green, Rigid—Reef blue, Psychopathic—Purple, Masochistic—Magenta

Table 2 Weight of traits in respective principal components (PCAs)

Traits	PCA1	PCA2	PCA3
Schizoid	0.3578	– 0.3035	0.1682
Oral	0.2462	0.3926	0.2828
Rigid	0.7097	0.2623	– 0.6384
Psychopathic	– 0.2477	0.8253	0.0793
Masochistic	0.49613	0.0608	0.6912

excluded all connections common for all of the subjects, and used clustering on the remaining data, results are shown in Fig. 6 under "Pval" row. Such approach gave results very close to obtained from the node strength (64/66).

The RVM regression averaged results for 100 iterations are shown in Table 4. Best regression coefficients are shown by clustering coefficient and eigenvector centrality for schizoid and oral traits. Lastly, we applied linear regression for the network and connectivity measures fitting traits and principal components. Results are shown in Table 5. In addition, correlation between network measures and principal components is presented in Table 6

Since all RMSE values for both regression types are greater than 1, we cannot speak of a good fit. Moreover, although it is possible to compare measures and traits combinations between each other, for each of the methods, the difference is insignificant, which seems to indicate the low prospectivity of this approach.

The chance level of the SVM classification for the considered problem is 50%. As seen in Table 7, correspondence between trait-obtained classes and network measures in not very high, although distribution agglomerative clusters

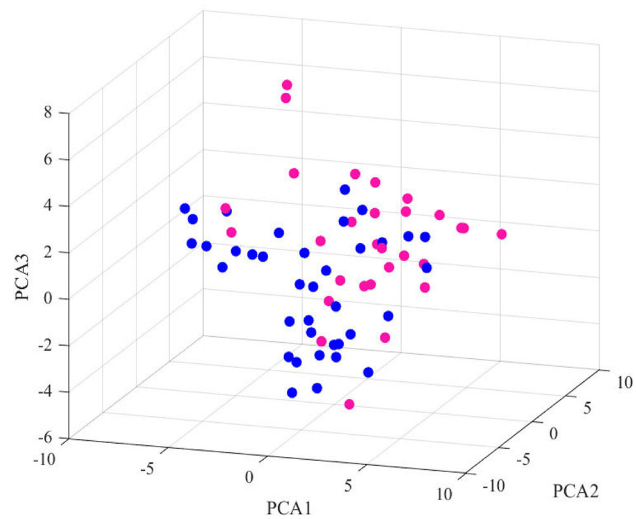


Fig. 4 Distribution agglomerative clusters by principal components of traits

Table 3 Weight of network measures in respective principal components (PCAsn)

Mean network measures	PCA1n	PCA2n	PCA3n
Local efficiency	– 1.046e–08	0.0002	7.62626e–05
Global efficiency	0.0002	0.9893	0.1411
Node strength	0.9939	0.0006	– 0.0055
Eigenvector centrality	0.0002	0.0001	0.2411
Clustering coefficient	0.0056	– 0.1454	0.9601

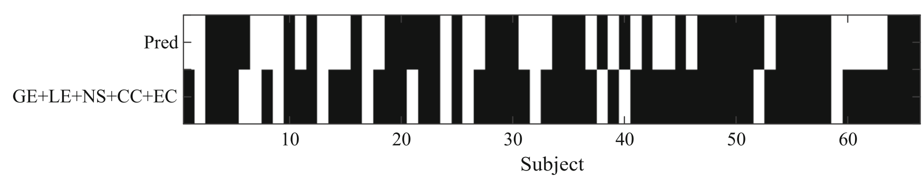


Fig. 5 Results of unsupervised clustering for different network measures, color of the cell represents cluster

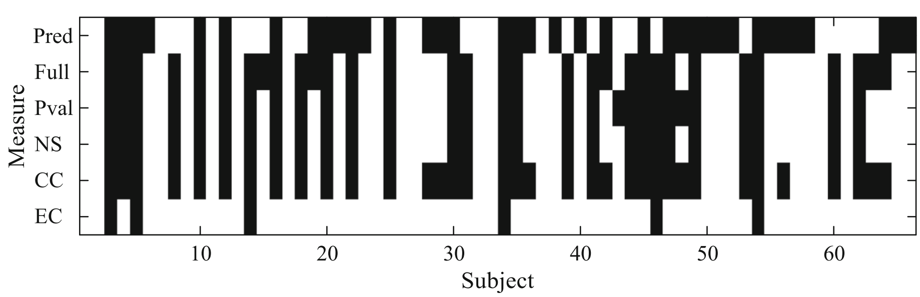


Fig. 6 Results of unsupervised clustering for different network measures, color of the cell represents cluster. "Pred" denotes predictors (answers) matrix, "Full"—full correlation matrix, "Pval"—matrices thresholded by p-value (without average), NS—node strength, CC—clustering coefficient, EC—eigenvector centrality

by principal components of network measures shows potential possibility on dividing by the first component (Fig. 7 and Table S2).

Table 4 Mean RMSE regression predictors versus traits (RVM)

Traits	FC	Pval	NS	CC	EC	BC
Schizoid	5.8017	5.6452	5.7452	2.3519	2.3801	5.7201
Oral	5.6914	5.6682	5.6659	2.3547	2.2826	5.7326
Rigid	7.2258	7.2171	7.2197	3.0028	3.0054	7.2127
Psychopathic	7.6718	7.5673	7.6956	2.7087	2.6879	7.5966
Masochistic	5.4773	5.5413	5.5307	2.7106	2.7294	5.4454
PCA1	3.3546	3.3746	3.3278	3.3965	3.4225	3.3944
PCA2	2.9973	2.8594	2.9105	2.9004	2.9042	2.8883
PCA3	2.6366	2.6706	2.6619	2.6421	2.7004	2.6900

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

Traits	FC	Pval	NS	CC	EC	BC
Schizoid	2.4262	2.4245	2.4253	2.4255	2.4250	2.3984
Oral	2.3489	2.3459	2.3433	2.3435	2.3470	2.3595
Rigid	3.1021	3.1027	3.1007	3.1000	3.0916	3.0973
Psychopathic	2.7446	2.7611	2.7471	2.7505	2.7620	2.7342
Masochistic	2.7876	2.8028	2.7973	2.7936	2.7334	2.8090
PCA1	3.4004	3.4064	3.4045	3.4049	3.3519	3.4133
PCA2	2.9735	2.9787	2.9742	2.9755	2.9755	2.9261
PCA3	2.7065	2.7160	2.7076	2.7026	2.7068	2.7338

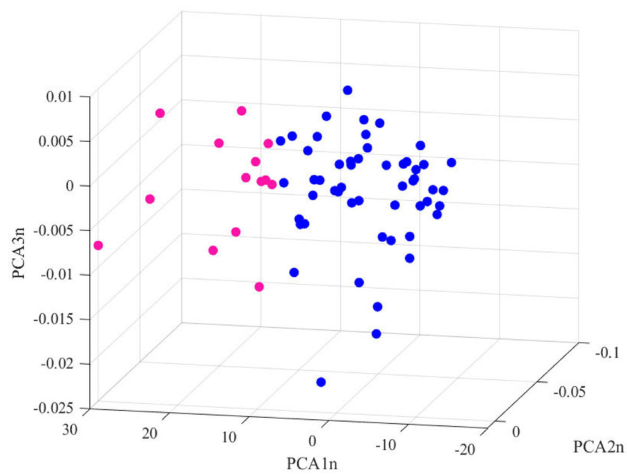
Table 6 Correlation between network measures and principal components

Metric	PCA1	p	PCA2	p	PCA3	p
Local efficiency	0.0217	0.8630	0.0264	0.8336	– 0.1579	0.2055
Global efficiency	0.0716	0.5677	– 0.0531	0.6719	– 0.1058	0.3978
Mean node strength	0.0723	0.5641	– 0.0549	0.6617	0.1383	0.2680
Mean eigenvector centrality	0.1890	0.1286	0.0467	0.7098	0.1404	0.2610
Mean betweenness centrality	– 0.0086	0.9451	– 0.1871	0.1325	– 0.0031	0.9802
Mean clustering coefficient	0.0704	0.5745	– 0.0461	0.7135	0.1507	0.2271

Table 7 Classification accuracy of different connectivity features for the agglomerative clustering classes of the psychological traits

	Feature vector	Accuracy (Mean ± SD)	Sensitivity	Specificity	Precision	F1 score
1	Full FC matrices	0.5042 ± 0.0432	55%	42%	60%	0.58
2	Pval matrices	0.5598 ± 0.0455	59%	50%	73%	0.65
3	Node strength	0.5036 ± 0.0450	55%	43%	59%	0.57
4	Cluster coefficient	0.5805 ± 0.0273	58%	62%	94%	0.72
5	Eigenvector centrality	0.5606 ± 0.0149	56%	49%	98%	0.72
6	5 mean network measures (GE LE NS EC CC)	0.5739 ± 0.0269	58%	56%	90%	0.71

Fig. 7 Distribution agglomerative clusters by principal components of network measures



4 Discussion

In the present study, by means of analysis of resting-state connectivity networks, we identified direct correspondences between network metrics such as EC, CC, NS and specific personality characteristics. Specifically, N Acc L and OFCmed were associated with oral and masochistic traits in terms of EC and CC, while Insula R is associated with oral traits in terms of NS and EC. It is noteworthy that we observed significant correlations between individual items and node measures in specific regions, suggesting a more targeted relationship. However, the more relevant finding is the correlation between metrics (NS, CC, and EC) and overall traits. A hierarchical clustering algorithm (agglomerative clustering, an unsupervised machine learning technique) and principal component analysis were applied, where we identified three prominent principal components that cumulatively explain 76% of the psychometric data. PC1 is driven by schizoid and rigid traits, PC2 by oral and psychopathic traits, and PC3 by masochistic and rigid traits simultaneously. The methodological steps so far constitute the first part of the clustering, based on psychometric data. Furthermore, we managed to cluster the network metrics (by unsupervised clustering) to explore whether neural connectivity patterns could be grouped based on combined average network metrics and psychometric data (global and local efficiencies, node strength, eigenvector centrality, and node strength). We identified three principal components, where the cumulative amount of explained data reaches 99%. PCA1n is strongly driven by node strength, PCA2n is driven by global efficiency, and PCA3n is driven by the clustering coefficient. In this way, we revealed significantly associated connectivity patterns in the FPN, DMN, and DAN, measured via node strength and clustering coefficient in PCA1n. Specifically, the correspondence between network measures (CC and NS) and predictors (responses to Lowen's items) is 44/66 (in a sample N=66), corresponding to regions such as the Insula L, Calcarine, Cuneus L, Angular Precuneus, and Thal VL. In an expanded interpretation of the personality profile, which assumes a non-homogeneous representation of all traits according to Lowen, this result is convergent with Cloninger's findings on the correspondence between the organization of character (character traits measured by TCI) and top-down prefrontal networks (DMN, CON, FPN, DAN), mediating mental self-regulation [36, 37]. Our results are also relevant to the finding of a positive correlation between extraversion and the precuneus in resting state, in the aspect of reduced need for emotional regulation, typical of extraverts [61]. The role of the left insula as a node in resting-state connectivity in our study is also intriguing. The insula has been initially described as a paralimbic or limbic integration cortex. As a network center, it coordinates information across multiple cognitive domains and processes. The insula is conceptualized primarily as a visceral-somatic area due to its involvement in visceral sensations, autonomic control, and interoception. The anterior insula is linked to empathy and social cognition, with the anterior right insula associated with the affective-perceptual component of empathy, and the left insula with both the affective-perceptual and cognitive-evaluative aspects of empathy [62]. In the context of our data, the insula could be associated to neurotic traits, but this assumption is speculative as this relationship likely reflects a more complex pattern of functional neuronal organization. Thal VL is another region that appears to be significantly important in overall connectivity at the group level. The thalamus is vital for mediating sensation, motor activities, cortical arousal, memory, and learning. Thal VL is a substructure involved in motor movements and is part of the final dopamine pathway [63]. Variations in DA functioning are considered a neurobiological substrate for the personality dimension of psychoticism. There is evidence for the dopaminergic basis of psychoticism. In a non-clinical sample, it was found that spontaneous eye movements/EBR, a marker of striatal dopaminergic functioning (DA), predict the level of psychoticism [64]. Here, we can also speculate on the extent to which the role of Thal VL in resting-state data refers to functional connectivity explained by traits. The thalamus is part of the visceral/limbic system, which, together with the autonomic nervous system and individual arousal characteristics, corresponds to neuroticism in Eysenck's model [65, 66]. Cloninger's finding of a complex hierarchical organization of personality [36, 37, 67], and evidence of the link between dopaminergic activity and heritable traits such as novelty seeking from TCI. Cloninger C. R. further support our hypotheses in this direction [68].

Calcarine is a field of the visual cortex [69], and Cuneus L is involved in primary visual processing [70]. The Angular Precuneus is linked to self-awareness processes [71] and is anatomically the seat of mental self-images [72]. On a superficial level, these regions, significantly associated with network measures, could likely relate to the neuroimaging experimental situation on both experiential and/or self-assessment levels. In all cases, a deeper interpretation requires a connectivity measurement methodology based on the understanding that both personality and the brain operate within a complex hierarchy of connections, sharing common mechanisms. Furthermore, not localized centers but multiple distributed and complex adaptive networks collaborate in the brain's functioning. These distributed functional connectivity networks, composed of neuronal ensembles, work synchronously and collaboratively through a combination of neurobiological and psychosocial mechanisms [36, 37].

Lastly, an interesting finding in our study is the "failure" of linear regression analysis (RVM regression) to measure the correspondence between traits and principal components based on connectivity measures. No significant overlap was found between them. Moreover, the correspondence between the classes derived from traits and network measures was 50%, or not very high, when applying Employing Support Vector Machine Analysis to assess classification accuracy after agglomerative clustering. The last results are again consistent with the work and views of Cloninger, who argued that linear methods do not adequately capture the nonlinear and dynamic nature of intrapsychic processes, and thus personality traits [73].

To put our research in broader context, we should outline earlier efforts in the field. The connections between the functions and structure of specific brain areas and personality traits have projections in the neurobiological foundations of individual differences. However, studying their aspects requires sufficiently robust personality and cognitive theories, as well as sophisticated methods of analysis [74], which expand and deepen beyond established linear interdependencies. Previous attempts have been made to intercorrelate neuroimaging findings with the assessment of personality traits, which we are trying to further develop methodologically. The contemporary scientific psychology operates with established taxonomies of personality traits, resulting from the contributions of prominent personality theorists in the development of descriptive and explanatory models of individual differences.

For example, Eysenck's model is essentially biological, accounting for the dominant influence of heredity on individual differences, based on psychophysiological variables. According to this model, personality is described by three orthogonal dimensions, or dispositions: neuroticism-stability, introversion–extroversion, and psychoticism. Neuroticism corresponds to individual characteristics of the arousal of the autonomic nervous system and formations of the visceral/limbic system (hippocampus, amygdala, cingulate, septum, and hypothalamus). High neuroticism indicates emotional lability, while low neuroticism indicates emotional stability. People with high neuroticism are easily and more persistently aroused at the behavioral level (e.g., poor performance on a given experimental test), physiologically (e.g., changes in heart rate, galvanic skin response, or other electrophysiological indicators), and introspectively (subjective self-report).

Introversion–extroversion axis corresponds to individual characteristics of cortical excitability. In introverts, the threshold for arousal in the ascending reticular activating system (ARAS) is lower, and they exhibit higher levels of arousal tension than extroverts [66, 67]. The cortical overstimulation determines avoidance behavior (in the broadest sense) in introverts, typically associated with anxiety. Conversely, insufficient cortical stimulation in extroverts leads to a need for increased stimulation, usually associated with impulsivity [75]. Psychoticism corresponds to the predisposition toward psychosis as a dispositional source of normal (typical) personality variations. High psychoticism is associated with impulsivity, hostility, aggressiveness, and psychopathy, as well as schizoid tendencies, unipolar depression, affective disorders, schizoaffective disorders, and schizophrenia, risk-taking, irresponsibility, manipulativeness, sensation-seeking, tough-mindedness, and practicalness. In Eysenck's model, psychoticism encompasses a wide range of psychotic phenomena and symptoms, from non-clinical levels to those characterizing individuals with schizophrenia. Due to this fact, the psychoticism scale in Eysenck's questionnaire is a controversial dimension in terms of its construct and predictive validity, especially when applied to healthy populations [76]. When analyzing resting-state/RSFC data, where spontaneous brain activity is observed, revealing intrinsic and temporally stable patterns of connectivity, negative correlations have been found between neuroticism and regional activity in the middle frontal gyrus and precuneus, and positive correlations between extraversion and regional activity in the striatum, precuneus, and superior frontal gyrus [74, 77]. It is suggested that an emotional regulation mechanism for coping with the disposition toward negative affect explains the negative relationship between neuroticism and the precuneus in the brain's resting state, while the positive relationship between the precuneus and extraversion reflects a reduced need for emotion regulation. A recent study on the relationship between personality traits and the dynamic functional network connectivity (DFNC) method in the resting brain found low modularity, hyperconnectivity of regions responsible for sensory processing and the default mode network (DMN), and weak connections between the cortex and subcortical areas such as the hippocampus and ventral striatum (VS) in healthy individuals compared to patients with major depressive disorder (MDD). This corresponds to high extraversion and low neuroticism scores. Such connectivity was not observed in depressed individuals, which is associated with deficits in sensory processing, reduced positive emotions, and decreased activity [61]. An earlier study on the resting-state functional connectivity of the salience network, located in the anterior insula and anterior cingulate cortex, and psychoticism measured by Eysenck's questionnaire in a neurologically healthy sample reported a connection between psychoticism and the surface area of the salience network. Specifically, higher psychoticism was linked to smaller cortical volume and surface area (SA) in these regions. The salience network is also known as the network for switching between significant (salient) stimuli (serves information processing when we are in a potentially threatening situation, for example). Anomalies in its function are described as proximal markers specific to the development of psychotic symptoms [78]. Reduced functional connectivity in the salience network (SN) in the resting state has been found in individuals at high risk for psychosis [79]. Moderately high psychoticism often characterizes individuals who demonstrate peak performance levels [80]. In addition, psychoticism is linked to creativity [81, 82]. In studies of resting-state functional connectivity data of the thalamus, it has been found that it negatively correlates with intelligence scores, with FC between the left thalamus and left amygdala significantly mediating the correlation between psychoticism and full-scale IQ. The authors interpret this finding as a weaker tendency of intelligent individuals toward psychoticism [83].

The nomological network of the most influential contemporary personality typology includes two components—temperament and character. TCI (temperament and character inventory) is an operationalization of the psychobiological theory of personality developed by R. Cloninger. The dimensions of temperament correspond to genetic tendencies in the expression of basic emotions and are linked to individual differences in prelogical brain functions for associative conditioning of habits, attachments, and emotional reactivity. The temperament traits in the psychobiological model are four—novelty seeking, harm avoidance, reward dependence, and persistence. The dimensions of character correspond to processes of intentionality and self-awareness (cognitive self-regulation) and are related to individual differences in mental self-management concerning executive functions (intrapersonal, such as planning and foresight), legislative functions (interpersonal, such as empathy and norms for cooperation), and judicial functions (transpersonal, such as insight and intuitive assessment of what is meaningful and good). The character traits in the psychobiological model are three—self-directedness, cooperativeness, and self-transcendence. Structurally, the character traits in TCI are related to the local volumes of gray and white matter in brain areas involved in self-reflection, empathy, and religious beliefs [84]. According to Cloninger, factor analysis as a linear method cannot adequately assess the nonlinear and dynamic nature of intrapsychic processes that are reflected in personality [73]. He finds that even biologically based traits, such as temperament, are problematically defined, as human beings possess three phylogenetically developed systems underlying learning and memory [85], each biologically and genetically determined. These include: (1) associative conditioning of habits and skills, or the procedural system (qualitative properties: prelogical, emotion-laden, quantitative (variable strength), not self-aware); (2) declarative learning of facts, or the semantic system (qualitative properties: logical, algorithmic, hierarchical, not self-aware); and (3) Autonoetic learning of personal narrative throughout life, or the autonoetic system (qualitative properties: self-aware, holistic, biographical, creative and freely willed, self-awareness). Thus, evolutionary newer processes of self-regulation and attention, which develop in adulthood, are included in the organization of temperament and, consequently, personality, in response to individual experiences and social norms. The maturation and integration of these three interconnected learning systems determine individual differences in both vulnerability to psychopathology and the development of a healthy personality [86, 87]. Genes do not code for individual traits but for profiles of multiple traits that describe the whole person. Cloninger argues for a method of unsupervised machine learning, strictly data-driven, with extended clustering. The phenotypic architecture of personality includes phenotypic networks, or associations/relationships between sets of character and temperament, which in turn are associated with sets of genetic variations (SNP sets). The three phenotypic networks described by Cloninger are prototypes of the three main learning and memory systems in modern humans: the creative-reliable network (self-awareness of autobiographical memory), the organized-reliable network (intentional self-regulation), and the emotional-unreliable network (associative conditioning for emotional reactivity), based on non-negative matrix factorization (NMF) to identify naturally emerging associations of patterns across different data types. The remarkable longitudinal work by him and his team, which focused on uncovering joint gene–phenotype associations and personality profiles in three independent samples (Finnish, German, and South Korean populations) using a deep NMF learning method, revealed significant relationships between gene-phenotype networks [88] temperament and character [67, 86]. The results demonstrate the non-additive (non-cumulative or nonlinear) action of genes. Specifically, SNP sets explain 37% to 53%, or nearly the entire expected heritability in three independent samples under conditions of epistasis. The process of complex gene interactions shapes the phenotypic diversity and complexity of human traits by modulating genetic variation. One epistatic gene can enhance the expression of another gene (antagonistic epistasis) or amplify the expression of another (synergistic epistasis). [89]. The SNP sets show complex relationships with phenotypic sets based on traits (TCI), involving multifinality and equifinality. Individuals with the same antecedent traits can exhibit different outcomes (multifinality), while individuals with different antecedent traits can exhibit the same outcome (equifinality) [86]. Moreover, a complex hierarchical organization of human personality has been demonstrated, ascending through the following levels:

1. individual scales and subscales of temperament and character;
2. sets of multiple subscales of temperament and character;
3. profiles of sets of temperament and character.

The genetic building elements of the phenotypic hierarchy encode the profiles of temperament and character, or representing the most complex structure in the organization of personality. Furthermore, the genes encode the profiles of temperament and the profiles of the character initially separately, and then integratively through gene–environment interactions in complex adaptive networks [67]. The applied method demonstrates the robustness of unsupervised machine learning techniques through the ability to deconstruct and reintegrate the complex architecture of personality on one hand, and on the other, through the focus of data-driven clustering on patterns of relationships within individuals, rather than on average differences between groups of individuals [86]. We emphasize that the analytical method discussed is nonlinear, just as the development of personality is nonlinear, dynamic, and complex. Such an approach proves to be more sensitive and tolerant in measuring the natural variability and heterogeneity of individual traits.

Through the discussion of the validity of psychological constructs, both within and outside the framework of multidisciplinary studies, as well as well-established personality assessment methods such as TCI and Eysenck's Personality Questionnaire (EPQ), this work aims to identify a precise methodology for assessing translational validity in the study of personality traits. Our focus is on the methodology of validation in the translation process during the joint analysis of psychometric and neuroimaging data. It is easy to establish the nomological correspondence between Lowen's and Eysenck's constructs regarding introversion and extraversion, as well as between them and some of the scales in TCI. For example, the schizoid traits correspond to characteristics of introversion, while psychopathic traits correspond to extraversion. Similarly, harm avoidance implies schizoid traits, while novelty seeking and reward dependence imply oral and/or psychopathic traits (see Appendix 1). This nomological correspondence supports the hypothesis of a common direction in neurofunctional connectivity.

The psychometric characteristics of EPQ traditionally show good internal consistency, high reliability, and validity, both in the original and revised shortened versions, across culturally diverse populations. However, as previously mentioned, the assessments for psychoticism are low and inconsistent [90–94]. Studies using the TCI have accumulated an impressive volume and content of scientific publications, demonstrating its utility and validity in assessing personality in international, clinical, and non-clinical populations [95–104]. The correlations between TCI and other personality scales (e.g., Zuckerman–Kuhlman Personality Questionnaire (ZKPQ) and EPQ confirm its construct and convergent validity [105]. For example, the ZKPQ impulsive sensation-seeking scale is positively correlated with the novelty seeking scale in TCI; the ZKPQ anxiety scale and EPQ neuroticism are positively correlated with harm avoidance in TCI; and psychoticism (EPQ) is negatively correlated with novelty seeking, reward dependence, and cooperativeness in TCI (77). A study of Cloninger's model and the Five-Factor Model of Personality (FFM) in a psychiatric sample found considerable overlap between all TCI scales and at least one domain scale of NEO-PI-R, with TCI significantly predicting all NEO-PI-R domains (78). In some samples, the factor structure of TCI could not be reproduced in confirmatory factor analyses and/or showed unsatisfactory Cronbach's alpha values, which is often a point of criticism for future revision [106–109]. In our study, the reliability of the entire Lowen scale, measured by Cronbach's alpha coefficient, is 0.831, indicating very good internal consistency of the items. However, for the individual subscales, the coefficient values are lower, ranging from 0.476 to 0.652. In psychological measurements, researchers perceive this as an imperfection of the test, signaling a lack of covariance, which is usually addressed by removing, correcting, or adding items. Some researchers argue that relying solely on Cronbach's alpha as an index of reliability is not sufficiently justified, as it is analytically limited in capturing important measurement errors and scale dimensionality. It is also not invariant to variations in scale length, inter-item correlations, and sample characteristics [110, 111]. Lowen's construct is conceptualized as a typology designed to assess personality traits corresponding to psychophysiological constellations of characteristics. As we discussed earlier, it is not expected that the natural variability and heterogeneity of traits can be adequately captured by linear metrics [74, 86]. Therefore, in our effort in the field of translational validity, building upon and testing the advantages of nonlinear analytical methods, such as unsupervised machine learning, we are guided by the understanding that psychometric validity and neuroimaging data can provide valid results based on complementary methodologies.

5 Conclusions

The current study adds further insights into the complex and non-linear relations of brain dynamics and personality organization. It is convergent upon existing body of evidence collected in the psychobiological paradigm and Eysenck's personality model. However, our findings also add incremental value in terms of trans-disciplinary validation of a character type inventory actively employed in psychotherapy and non-linear measures of brain functional connectivity. It paves the way forward for further explorative machine learning investigations of the co-clustering of the epistemic constructs and measures across psychopathology and neuroscience. There are some limitations to be acknowledged as well. The complex non-linearity of both fields—personality psychology and neuroimaging certainly requires greater sample to provide more robust inference. Psychometric standardization of Lowen's test in representative population and establishing its intra-domain validity properties is another caveat, that we intend to address in further studies.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1140/epjs/s11734-024-01411-z.

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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 Informed consent was obtained from all the subjects involved in the study. The study was approved by the Committee on Scientific Ethics of Medical University-Plovdiv with protocol No. 1/25.01.2022.

Appendix 1

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's 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'm 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 recognise the wishes of others.
60. My relatives say that I complain.

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