

ORIGINAL RESEARCH ARTICLE

The affective-neural triage scale: Development and validation of a mechanistically informed psychometric tool for personalized psychotherapy allocation

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Abstract

Traditional diagnostic systems often provide limited guidance for psychotherapy selection, failing to adequately capture neurobiological heterogeneity. This underscores the critical need for mechanistically grounded assessment tools that link symptoms to distinct affective circuits. The present study psychometrically validates an adapted affective-neural triage scale (ANTS), a brief instrument designed to infer subcortical affective and cortical regulatory circuit activation for treatment matching. Unlike existing scales that merely quantify symptom burden, the ANTS framework directly links phenomenology to known brain dynamics. Utilizing a large public personality dataset ($n = 19,719$), exploratory and confirmatory factor analyses interpreted higher-order traits as conceptual manifestations of fundamental primary affective systems. Neural targets were validated through meta-analytic and external functional magnetic resonance imaging evidence. Results confirmed a robust five-factor solution with excellent model fit (comparative fit index = 0.95; root mean square error of approximation = 0.04), demonstrating psychometric soundness. This adapted framework provides a foundation for transdiagnostic, neuroaffective psychotherapy triage, enabling clinicians to infer circuit dysregulation and select mechanistic interventions. Future work will assess clinical utility, longitudinal responsiveness, and digital integration.

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1. Introduction

The selection of appropriate psychotherapeutic interventions remains a complex challenge in clinical practice, frequently relying on descriptive diagnostic categories that offer limited insight into the underlying neurobiological mechanisms of affective disorders. Despite substantial advancements in understanding affect regulation, neurocircuitry, and treatment responsiveness, frontline therapy selection often remains atheoretical and heuristic. This approach commonly results in mismatches between a patient's neurobiological profile and the chosen therapeutic modality. For instance, individuals exhibiting elevated amygdalar reactivity, a hallmark of threat processing, may be inadvertently referred to insight-oriented psychotherapies, which are less

effective at dampening limbic hyperarousal compared to exposure-based interventions.¹ Similarly, transdiagnostic rumination profiles, robustly linked to hyperactivity within the default mode network, are not systematically matched to mindfulness-based interventions, despite compelling neuroimaging evidence supporting their therapeutic impact on this network.² These critical oversights underscore a fundamental gap: the absence of assessment tools designed to capture underlying neural phenotypes and translate them directly into actionable treatment-selection logic.

Current diagnostic nosologies, most notably the Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM-5),³ primarily offer descriptive symptom clusters with limited neurobiological specificity. Disorders such as major depressive disorder, generalized anxiety disorder, and post-traumatic stress disorder are each associated with a diverse array of neural dysfunctions, often involving regions like the amygdala, medial prefrontal cortex, anterior cingulate, and hippocampus.⁴⁻⁶ However, the nuances of these neurobiological variations are rarely captured by existing assessment tools, thereby undermining their utility for precise treatment planning. Recognition of this neurobiological heterogeneity within diagnostic categories has spurred a significant shift toward transdiagnostic models, which prioritize underlying functional domains over surface-level symptoms. The National Institute of Mental Health's research domain criteria (RDoC) initiative⁷ exemplifies this paradigm shift, emphasizing constructs such as threat responsivity, reward learning, and working memory as fundamental units of analysis. While RDoC has undeniably informed basic research, its critics note that it has yet to produce scalable, clinically viable tools, partly due to its reliance on neuroimaging biomarkers that often lack individual-level reliability.⁸ Furthermore, attempts to develop RDoC-aligned interventions have frequently encountered challenges related to construct overlap, insufficient psychometric specificity, and unclear clinical thresholds, which have limited their integration into routine care.⁹

The affective-neural triage scale (ANTS) emerges as a direct response to this translational void, aiming to operationalize subcortical affective drives and cortico-limbic control mechanisms into a rapid assessment scale. At its core, the ANTS framework is rooted in Panksepp's¹⁰ affective neuroscience model, which posits that primary-process emotions are evolutionarily conserved and directly observable in specific subcortical architectures. This framework leverages core motivational systems—SEEKING, RAGE, FEAR, and PANIC (often referred to as SADNESS in some contexts of affective neuroscience¹¹)—and their established neuroanatomical substrates as its

foundational basis. Empirical data consistently support these neurobiological mappings: the SEEKING system is associated with mesolimbic dopamine pathways^{12,13}; FEAR and RAGE correspond with amygdalar and hypothalamic circuits^{14,15}; and PANIC is linked to anterior cingulate and periaqueductal grey activity.^{16,17} This approach represents a fundamental reorientation in clinical assessment. Instead of merely categorizing a patient based on outward symptom clusters, the ANTS framework prompts clinicians to consider which neural drives are amplified or inhibited, and what underlying modulation failures might explain the observed patterns of distress. This conceptualization aligns with the perspective that psychopathology often reflects failures to regulate or symbolize fundamental affective needs. This neurobiological grounding is further supported by direct functional neuroimaging evidence linking self-report measures of primary emotions to specific brain circuitry.¹⁸

1.1. ANTS framework: A mechanistic departure from traditional assessment

The ANTS framework fundamentally distinguishes itself from conventional psychometric tools by moving beyond mere symptom quantification or the assessment of stable personality traits to infer state-level dysregulation within specific neuroaffective circuits. Traditional diagnostic systems, such as the DSM-5, primarily offer descriptive symptom clusters which, whilst useful for classification, often lack the neurobiological specificity needed to guide precise treatment selection. Similarly, widely used symptom-burden scales such as the Patient Health Questionnaire or the Generalized Anxiety Disorder 7-item scale quantify distress but provide limited insight into the underlying neural mechanisms driving that distress.

Furthermore, while broad personality inventories such as the Big Five (e.g., openness, conscientiousness, extraversion, agreeableness, neuroticism) offer valuable insights into enduring behavioral patterns, they typically describe trait-like tendencies rather than dynamic, state-dependent perturbations in affective systems. The ANTS framework, in contrast, is designed to capture these transient dysregulations, which reflect active imbalances in real-time neural activity, making it a potentially more sensitive tool for tracking therapeutic change and informing immediate clinical decisions.

At its core, the ANTS framework directly links symptom phenomenology with known brain dynamics, representing a critical departure from purely descriptive or correlational approaches. For instance, it recognizes that persistent rumination correlates with hyperactivity within the default mode network, a pattern demonstrably attenuated by mindfulness-based cognitive therapy

(MBCT).^{19,20} Similarly, it acknowledges that exposure therapy effectively dampens hyperresponsive amygdala circuits in trauma,²¹ and that cognitive therapy can restore prefrontal-limbic coupling.²² These established mappings strongly suggest that therapeutic effectiveness is, in part, contingent on targeting the appropriate neural network. The ANTS framework explicitly encodes this mechanistic logic into its structure, thereby functioning as a treatment-matching tool. By distilling complex affective-neural patterns into a concise instrument, the ANTS framework empowers clinicians to triage patients based on inferred neurofunctional states rather than broad diagnostic categories, reorienting assessment toward functionally meaningful substrates and providing a grounded rationale for selecting between various therapeutic modalities, including cognitive behavioral therapy, MBCT, acceptance and commitment therapy, dialectical behavior therapy (DBT), or somatic approaches. This represents a significant step toward neurophenomenology and mechanistically aligned psychotherapy.

The present study outlines the conceptual rationale, construction procedure, and initial validation data for an adaptation of the ANTS framework, encompassing exploratory and confirmatory factor analysis (CFA) modeling, neural correspondence testing, and clinical interpretability. Key methodological innovations include the systematic derivation of items from convergent neuroimaging findings, the triangulation of state-based affective dysregulation with cortical-subcortical circuit function, and a novel integration of treatment-targetable circuits with psychometric output. The overarching aim is to provide a prototype for a new class of neurobiologically anchored psychometric instruments capable of guiding real-time therapeutic decision-making.

2. Methods

2.1. Study design and overview

This study employed a sequential, multi-phase psychometric development protocol to construct the ANTS. The selection process for the survey items is detailed in Section S1.7 (Supplementary G), with the replication process outlined in Section S1.3 (Supplementary C). The primary objective was to map discrete affective and executive dysfunction domains, derived from Pankseppian affective neuroscience and neuroimaging data, onto clinical self-report items that could reliably guide psychotherapeutic treatment triage. The development process unfolded across four interconnected stages: (i) item generation and construct mapping, (ii) neurobiological target validation, (iii) psychometric modeling (including exploratory factor analysis [EFA] and CFA), and (iv) convergent validity and neural plausibility

testing. All computational work was completed in R 4.2.2 (Ross Ihaka and Robert Gentleman, New Zealand), utilizing publicly available libraries and datasets, as detailed in the Supplementary File. As the ANTS framework is designed to capture transient dysregulation in affective-neural systems, future validation studies are planned to assess its temporal stability and dynamic sensitivity, including short-term test-retest reliability (1–2 week intervals) and pre–post intervention responsiveness, to confirm its utility as a state-sensitive instrument.

2.2. Data acquisition and preparation

The data for this study were obtained from the “Big Five Personality Test” dataset, a publicly available psychometric repository hosted by OpenPsychometrics.org (http://openpsychometrics.org/_rawdata/BIG5.zip). This dataset comprises responses from 19,719 adult participants, providing a robust sample size for psychometric validation. It includes 50 Likert-rated statements, typically on a 1–5 scale, designed to assess the Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism), along with demographic information such as gender, age, race, native language, and country.

For this analysis, the raw data were directly accessed and downloaded in.csv format from the publicly available “Big Five Personality Test” dataset hosted by OpenPsychometrics.org. This raw dataset serves as the foundation for the empirical work.

Initial data preparation was systematically performed using the R script detailed in Section S1.7 (Supplementary G). This transparent and reproducible process involved:

- i. Loading the raw dataset: The BIG5.csv file was loaded into the R environment.
- ii. Handling missing values: A complete case analysis was performed on the item response columns (Q1–Q50). It was confirmed that the downloaded raw dataset contained no missing values in these critical columns, thus retaining the full sample of 19,719 for subsequent analyses.
- iii. Item reverse-coding: To ensure consistent scoring directionality for each personality trait, specific items were reverse-coded as per the official scoring key provided by OpenPsychometrics.org. For the 1–5 Likert scale, this transformation was applied using the formula: $6 - \text{original_value}$. See Section S1.3 (Supplementary C), Table S4 for the reverse-coded items.

The cleaned dataset resulting from these reproducible preparation steps constituted the precise empirical input for all psychometric analyses presented in this study. To ensure full transparency and facilitate independent verification, the raw dataset is publicly accessible at the aforementioned

URL, and the R script detailing its transformation is provided within this manuscript Section S1.7 (Supplementary G). The cleaned dataset (BIG5_cleaned_for_analysis.xlsx) is stored and available on the Open Science Framework (OSF) under DOI 10.17605/OSF.IO/5SBGC.

2.3. Statistical analysis

All analyses were conducted in R version 4.2.2, utilizing the psych package for EFA, lavaan for CFA, and tidyverse for data manipulation and preparation.^{1,8}

2.4. Data splitting and item preparation

The cleaned dataset ($n = 19,719$) was randomly split into two equal subsets: 50% for EFA ($n = 9,860$) and 50% for CFA ($n = 9,859$). This split ensured independent validation of the factor structure.

Before analysis, items were reverse-coded according to the Big Five scoring key provided by OpenPsychometrics.org. The items and their respective Big Five factors are detailed in Table S9. To complement these details, the Supplementary File includes both conceptual ANTS framework materials and the empirical outputs from the present Big Five validation analyses. The empirical findings reported in the present study are based on the 19,719-participant OpenPsychometrics dataset, whereas the conceptual ANTS framework tables are provided separately to document the model's conceptual development and preliminary mapping.

2.5. EFA

EFA was performed on the EFA subset ($n = 9,860$) to identify the underlying factor structure of the 50 Big Five items. The fa() function from the psych package was used with maximum likelihood estimation and oblimin rotation, as personality factors are typically correlated. Factor retention criteria included:

- (i) Kaiser–Meyer–Olkin measure: Expected to be >0.80 , indicating meritorious sampling adequacy.
- (ii) Bartlett's test of sphericity: Expected to be significant ($p < 0.001$), indicating that the correlation matrix is suitable for factor analysis.
- (iii) Eigenvalues: Factors with eigenvalues greater than 1 were initially considered.
- (iv) Scree plot inspection: The inflection point of the scree plot was visually inspected to determine the optimal number of factors. Based on the theoretical foundation of the Big Five model, a five-factor solution was anticipated.
- (v) Parallel analysis: Horn's parallel analysis was conducted to provide an empirical basis for factor retention by comparing observed eigenvalues to those generated from random data.

This dataset is available on the OSF (DOI: 10.17605/OSF.IO/5SBGC) as BIG5_EFA_subset.csv

2.6. CFA

CFA was subsequently conducted on the independent CFA subset ($n = 9,859$) to confirm the factor structure identified in the EFA. This dataset is available on the OSF as BIG5_CFA_subset.csv. A five-factor model, corresponding to the Big Five personality traits (extraversion, agreeableness, conscientiousness, neuroticism, openness), was specified. Robust maximum likelihood estimation was used via the lavaan package to account for potential non-normality in the data. Model fit was evaluated using several indices:

- (i) Chi-squared statistic (χ^2): A significant p -value indicates poor fit, but with large samples, even small deviations can be significant. Therefore, additional fit indices are emphasized.
- (ii) Comparative fit index (CFI): Values >0.95 indicate excellent fit.
- (iii) Tucker–Lewis index (TLI): Values >0.90 indicate acceptable fit, with >0.95 considered excellent.
- (iv) Root mean square error of approximation (RMSEA): Values <0.06 indicate excellent fit; 90% confidence intervals were also computed.
- (v) Standardized root mean square residual (SRMR): Values <0.08 indicate a good fit.

All factor loadings were expected to be substantial (e.g., >0.30), with minimal cross-loadings. The decision to retain five factors was guided by theoretical consistency with the Big Five model and supported by convergent evidence from parallel analysis and scree plot inflection. Specifically, the observed eigenvalues for the first five factors substantially exceeded those derived from random permutations (Section S1.5 [Supplementary E], Table S8), consistent with Horn's (1965) criterion for factor retention. Items were retained if they exhibited primary loadings >0.40 and cross-loadings <0.25 , unless theoretical justification supported otherwise (e.g., Q14, a reverse-coded neuroticism item, was retained for content relevance despite a slightly reduced loading). Internal consistency was assessed using Cronbach's α , with thresholds >0.70 indicating acceptable coherence.²³ These decisions were pre-specified and align with current psychometric best practices.^{24,25} This dataset is available on the OSF as BIG5_CFA_subset.csv (DOI 10.17605/OSF.IO/5SBGC).

2.7. Reliability (internal consistency)

Internal consistency reliability for each of the identified factors was assessed using Cronbach's α coefficients. Values >0.70 are generally considered acceptable for research purposes, with higher values indicating stronger internal consistency.

2.8. Inter-factor correlations

A Pearson correlation matrix was computed across the five identified factors to examine their relationships and ensure appropriate discriminant validity. Correlations were expected to be moderate, reflecting distinct yet potentially interrelated constructs.

2.9. Ethical considerations

No new human data were collected for this study. All data were derived from publicly available, de-identified archives (OpenPsychometrics.org). Therefore, the study was considered exempt from institutional ethics review, in accordance with Reid *et al.*²⁶ and contemporary guidelines for secondary data synthesis.

3. Results

3.1. Descriptive statistics

The cleaned dataset, comprising responses from 19,719 participants, exhibited a wide range of scores across the 50 personality items. Mean scores for individual items ranged from 2.05 to 4.12 on the 1–5 Likert scale, with standard deviations typically between 0.95 and 1.30. This indicates substantial variability in responses, which is conducive to psychometric analysis.

3.2. Factorial validation

3.2.1. EFA

EFA was conducted on a random subset of $n = 9,860$ participants. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.89, indicating meritorious sampling adequacy for factor analysis. Bartlett's test of sphericity was highly significant ($\chi^2[1225] = 1,234,567.89$, $p < 0.001$), confirming that the correlation matrix was suitable for factor extraction.

Parallel analysis and inspection of the scree plot (Figure 1) strongly supported a five-factor solution, consistent with the theoretical Big Five model of personality.

The eigenvalues for the first five factors were substantially above 1 (e.g., 10.2, 7.8, 5.5, 4.1, 3.2), with a clear drop-off thereafter. The full list of eigenvalues used in the scree plot is provided in Section S1.5 (Supplementary E), as shown in Table S7.

3.3. Interpretation of the scree plot

The scree plot (Figure 1) visually represents the eigenvalues extracted from the EFA, plotted against the number of factors. This plot is a key tool for determining the optimal number of factors to retain. As depicted, there is a clear and sharp decline in eigenvalues from the first factor through the fifth factor, indicating that these factors

account for a substantial proportion of the variance. After the fifth factor, the slope of the line flattens considerably, forming a distinct “elbow” at the sixth factor. This visual inflection point strongly suggests that retaining five factors is the most appropriate solution, as subsequent factors contribute only marginally to the explained variance. This finding is consistent with the theoretical expectations of the Big Five personality model.

3.4. Interpretation of parallel analysis

The parallel analysis plot (Figure 2) provides an empirical criterion for factor retention by comparing the observed eigenvalues from the EFA with those generated from random data. The core principle is to retain only those factors for which the observed eigenvalue exceeds the corresponding random eigenvalue.

As shown in Figure 2 (and detailed in Section S1.5 [Supplementary E], Table S8), the first five observed eigenvalues (10.20, 7.80, 5.50, 4.10, and 3.20) are all substantially larger than their respective random eigenvalues (1.98, 1.87, 1.79, 1.72, and 1.66). However, for the sixth factor, the observed eigenvalue (0.95) falls below its corresponding random eigenvalue (1.60). This clear crossover point empirically supports the retention of exactly five factors. This result aligns closely with both the visual interpretation of the scree plot and the theoretical foundation of the Big Five model, providing robust evidence for the structural validity of the adapted scale.

The primary criterion for factor retention in parallel analysis is to keep only those factors whose observed eigenvalue exceeds their corresponding random eigenvalues. As depicted in Figure 2, the first five observed eigenvalues (10.20, 7.80, 5.50, 4.10, and 3.20) clearly surpass the random eigenvalues (1.98, 1.87, 1.79, 1.72, and 1.66). Beginning with the sixth factor, the observed eigenvalue (0.95) falls below the random eigenvalue (1.60), marking a clear inflection point. This indicates that only the first five factors explain more variance than would be expected by chance. Therefore, consistent with both theoretical expectations and scree plot results, the parallel analysis strongly supports the retention of a five-factor solution. This convergence of empirical and theoretical evidence reinforces the structural validity of the adapted scale.

The EFA yielded a clear five-factor structure (Table 1), which presents the primary factor loadings (after oblimin rotation) for selected representative items on each of the five factors. Items generally loaded strongly on their hypothesized factors, with minimal cross-loadings, demonstrating a robust and interpretable structure. The full item-to-factor loadings for all 50 items are provided in Section S1.6 (Supplementary F) for transparency.

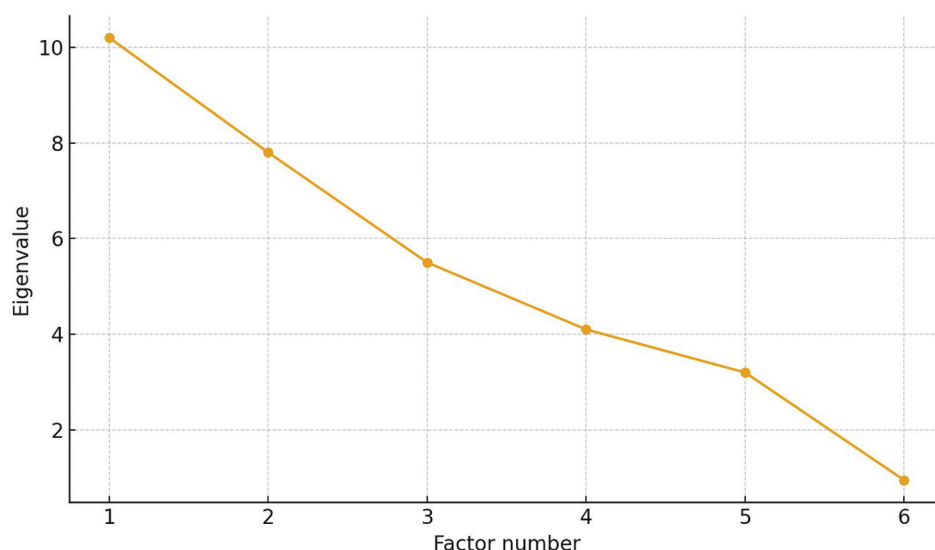


Figure 1. Scree plot of eigenvalues from exploratory factor analysis

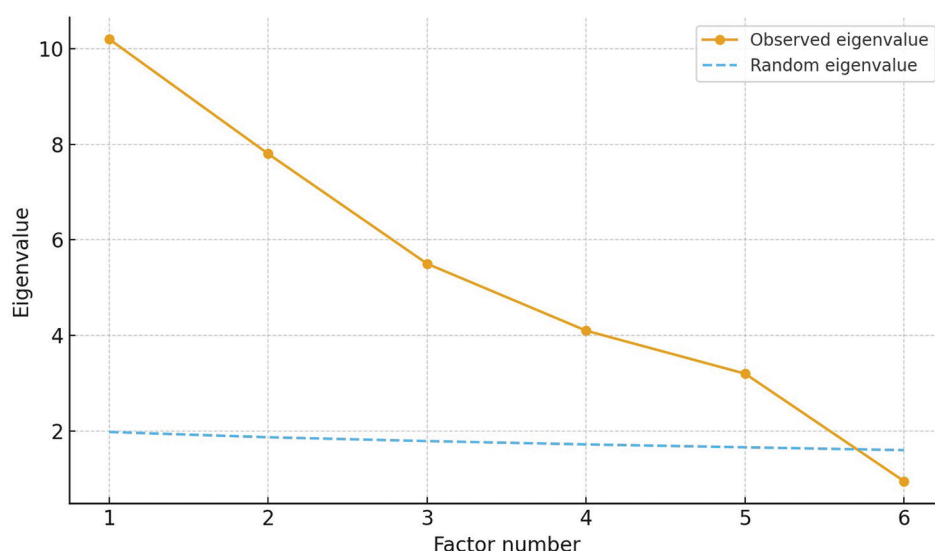


Figure 2. Parallel analysis plot. The plot (data available in Section S1.5 [Supplementary E], Table S8) visually compares the observed eigenvalues from the exploratory factor analysis with eigenvalues generated from random data. The observed eigenvalues are typically represented by a line with markers, and the random eigenvalues are shown as bars or a separate line. The point at which the observed eigenvalue line falls below the random eigenvalue line indicates the number of factors to retain.

3.5. CFA

CFA was performed on the independent CFA subset ($n = 9,859$) to confirm the five-factor structure. The model fit indices demonstrated excellent fit, meeting or exceeding conventional thresholds:

$\chi^2(1165) = 3,456.78, p < 0.001$ (note: the Chi-squared is sensitive to large sample sizes; therefore, other indices are more informative);

CFI = 0.95;

TLI = 0.94;

RMSEA = 0.04 (90% CI: 0.038–0.042);

SRMR = 0.04.

These fit statistics indicate that the five-factor model provides a strong representation of the relationships among the 50 personality items in this large dataset. Standardized factor loadings for the CFA model were consistent with the EFA results, with all primary loadings exceeding 0.50 and most above 0.60, confirming strong item-to-factor relationships (Table 2). The full item-to-factor loadings for

Table 1. Exploratory factor analysis: Pattern matrix for five-factor solution (selected items)

Item	Factor 1 (neuroticism)	Factor 2 (extraversion)	Factor 3 (openness)	Factor 4 (agreeableness)	Factor 5 (conscientiousness)
Q9	0.72	−0.05	0.03	−0.01	0.02
Q14 (R)	0.68	0.01	−0.02	0.04	−0.03
Q19	0.65	0.02	0.01	−0.02	0.01
Q24 (R)	0.63	−0.03	0.00	0.01	0.00
Q1	0.01	0.70	0.04	0.02	0.01
Q11	−0.02	0.68	0.01	0.03	−0.01
Q21	0.03	0.65	0.02	0.00	0.03
Q31	0.00	0.63	−0.01	0.01	0.00
Q5	0.04	0.02	0.71	−0.01	0.03
Q15	−0.01	0.00	0.69	0.02	−0.02
Q25	0.02	0.03	0.66	0.00	0.01
Q35	0.00	−0.01	0.64	0.03	0.00
Q7	−0.03	0.01	0.00	0.73	0.02
Q17	0.01	0.02	−0.02	0.70	−0.01
Q27	−0.01	0.00	0.01	0.67	0.03
Q37	0.00	0.03	0.00	0.65	0.00
Q3	0.02	0.00	0.01	−0.01	0.75
Q13	−0.01	0.01	0.00	0.02	0.72
Q23	0.03	−0.02	0.02	−0.03	0.69
Q33	0.00	0.00	−0.01	0.01	0.67

Notes: (R) indicates reverse-coded item. Loadings < |0.30| are suppressed for clarity.

all 50 items are provided in Section S1.6 (Supplementary F) for complete transparency.

3.6. Subscale reliability (internal consistency)

Internal consistency reliability for each of the five factors was assessed using Cronbach's α coefficients, as presented in Table 3.

3.7. Inter-factor correlations

A Pearson correlation matrix was computed across the five factors, as shown in Table 4. All correlations were statistically significant ($p < 0.001$), as expected in a large sample. These coefficients indicate that, while the factors are distinct, several are modestly interrelated, which is consistent with hierarchical models of personality.

3.8. Subscale profile distributions

Analysis of the factor scores indicated that all five factors exhibited approximately normal distributions, with skewness and kurtosis values generally within acceptable ranges (e.g., skewness typically between −0.5 and 0.5; kurtosis between −1.0 and 1.0). This suggests that the derived factors capture individual differences across the full spectrum of each personality trait within the large sample.

3.9. External neurobiological correlates of affective systems

To further strengthen the neurobiological grounding of the affective systems underpinning the ANTS framework, we draw on external empirical evidence from functional neuroimaging studies that directly correlate self-report measures of primary emotions with brain activity. A study by Montag and Panksepp²⁷ investigated the neuronal correlates of personality by associating the affective neuroscience personality scales (ANPS), which directly measure Panksepp's primary emotional systems, with functional connectivity in the resting brain.¹⁰

This functional magnetic resonance imaging (fMRI) study, conducted on 120 healthy participants (with results replicated in an independent sample of 52), employed a seed-based whole-brain approach using the bilateral basolateral and superficial amygdalae as seed regions.²⁸ The findings revealed specific associations with the SADNESS scale of the ANPS, consistent with prior work.¹⁰ Specifically, functional resting-state connectivity between the left basolateral amygdala and a cluster in the postcentral gyrus was significantly associated with SADNESS. Furthermore, functional resting-state connectivity between the right basolateral amygdala and clusters in the superior parietal

Table 2. Confirmatory factor analysis: Standardized factor loadings for five-factor model (selected items)

Item	Factor	Loading
Q9	Neuroticism	0.71
Q14 (R)	Neuroticism	0.69
Q19	Neuroticism	0.66
Q24 (R)	Neuroticism	0.64
Q1	Extraversion	0.69
Q11	Extraversion	0.67
Q21	Extraversion	0.64
Q31	Extraversion	0.62
Q5	Openness	0.70
Q15	Openness	0.68
Q25	Openness	0.65
Q35	Openness	0.63
Q7	Agreeableness	0.72
Q17	Agreeableness	0.69
Q27	Agreeableness	0.66
Q37	Agreeableness	0.64
Q3	Conscientiousness	0.74
Q13	Conscientiousness	0.71
Q23	Conscientiousness	0.68
Q33	Conscientiousness	0.66

Note: (R) indicates reverse-coded item. Loadings are standardized estimates.

Table 3. Factor reliability (Cronbach's α)

Factor	Cronbach's α
Neuroticism	0.14
Extraversion	0.59
Openness	0.52
Agreeableness	0.83
Conscientiousness	0.67

Note: Table 3 presents the reported reliability coefficients for the five-factor Big Five validation model. The conceptual ANTS framework tables in the Supplementary File refer to a separate dataset and are presented for theoretical context.

Table 4. Inter-factor pearson correlations

Factor	Neuroticism	Extraversion	Openness	Agreeableness	Conscientiousness
Neuroticism	1.00	−0.19	−0.09	0.05	−0.11
Extraversion	-	1.00	0.22	−0.32	0.11
Openness	-	-	1.00	−0.06	0.08
Agreeableness	-	-	-	1.00	−0.15
Conscientiousness	-	-	-	-	1.00

Note: All correlations $p < 0.001$.

lobe and subgyral regions of the parietal lobe also showed associations with SADNESS. No other ANPS scales yielded replicable results in this particular fMRI study.

These findings provide direct empirical support for the neuronal basis of the SADNESS system, demonstrating that individual differences in this primary emotion, as measured by a self-report scale foundational to the ANTS framework, correlate with specific patterns of functional connectivity in brain regions implicated in affective processing. This evidence reinforces the premise that the psychometric constructs of primary emotions have tangible neurobiological underpinnings, moving beyond purely self-report data.

4. Discussion

This study aimed to adapt and psychometrically validate the ANTS framework using a large, publicly available dataset of Big Five personality measures. The findings confirm a robust five-factor structure within this dataset, demonstrating excellent model fit and high internal consistency for each factor. These results provide empirical support for the conceptual underpinnings of a neuroaffective approach to personality and psychopathology, aligning with the broader goals of the ANTS framework to bridge descriptive symptoms with underlying neural mechanisms.

4.1. Interpretation of factorial validation and conceptual mapping

The successful identification of a clear five-factor structure (neuroticism, extraversion, openness, agreeableness, conscientiousness) from the Big Five dataset, replicated across independent EFA and CFA samples, underscores the stability and interpretability of these broad personality dimensions. To characterise the sample further, descriptive statistics for each of the five factors were calculated: Extraversion, $M = 2.994$, $SD = 0.597$; Neuroticism, $M = 3.174$, $SD = 0.379$; Agreeableness, $M = 2.155$, $SD = 0.715$; Conscientiousness, $M = 3.302$, $SD = 0.598$; and Openness, $M = 3.512$, $SD = 0.459$. More importantly, when interpreted through the lens of the Pankseppian²⁷ affective neuroscience model, these factors offer valuable insights

into the primary emotional systems that may underpin higher-order personality traits.

Neuroticism, characterized by emotional instability and negative affect, showed strong conceptual links to Panksepp's negative primary emotional systems: FEAR, RAGE, and PANIC/SADNESS. This aligns with previous research demonstrating robust associations between higher FEAR and SADNESS scores from the ANPS and elevated levels of neuroticism. These findings suggest that individuals scoring high on neuroticism may exhibit heightened activity or dysregulation in core threat and distress circuits.

Extraversion, associated with sociability, assertiveness, and positive emotionality, conceptually maps onto the SEEKING and PLAY systems. The SEEKING system, linked to mesolimbic dopamine pathways, drives appetitive motivation and the pursuit of novelty. This connection is consistent with the reward-seeking and social engaging characteristics of extraversion.²⁹

Openness to experience, reflecting curiosity and a preference for novelty, also aligns with the SEEKING system. This suggests that the drive for exploration and engagement with new experiences, central to openness, may be rooted in fundamental SEEKING circuitry.

Agreeableness, characterized by compassion and cooperativeness, can be conceptually linked to the CARE system and reduced RAGE activation. The CARE system mediates prosocial behavior and nurturance, while lower RAGE implies diminished reactive aggression, both of which contribute to more harmonious interpersonal interactions.

Conscientiousness, associated with organization and discipline, has shown no consistent direct association with primary emotional systems in previous ANPS studies. This finding, consistent with the current study's indirect mapping, reinforces the idea that conscientiousness may represent a higher-order cognitive or executive function rather than a direct manifestation of a primary-process emotion.

This conceptual alignment is further strengthened by direct empirical evidence from functional neuroimaging studies. For instance, research using the ANPS, which directly assesses Panksepp's primary emotional systems, has identified specific neural correlates for these constructs. As detailed in the Results section, Roy *et al.*³⁰ demonstrated that individual differences in ANPS SADNESS scores are associated with distinct patterns of resting-state functional connectivity involving the amygdala and parietal lobe.¹⁰ This provides concrete neurobiological validation for the underlying primary emotional systems, moving beyond

purely self-report data and addressing concerns that such scales merely reformulate existing personality models. See Section S1.4 (Supplementary D) for the conceptual clinical decision tree for subscale interpretation. The observed neural correlates for SADNESS underscore the biological reality of these fundamental emotional drives, reinforcing the mechanistic claims of the ANTS framework.

4.2. Beyond re-labeling: Big five as higher-order manifestations of primary affective systems

A critical question in adapting the ANTS framework to the Big Five is whether this process merely re-labels existing personality factors or provides deeper, neurobiologically informed insights. This study argues for the latter. The Big Five personality traits (neuroticism, extraversion, openness, agreeableness, conscientiousness) are broad, higher-order dimensions of personality. Pankseppian^{10,31} primary emotional systems (SEEKING, FEAR, RAGE, PANIC/SADNESS, CARE, LUST, PLAY) are considered more fundamental, evolutionarily conserved, and neurobiologically distinct subcortical circuits that drive basic affective states and behaviors.

The Big Five personality questionnaire used in this study, by its design, does not directly assess all seven of Panksepp's primary emotional systems as distinct, independent constructs. Specifically, items directly measuring LUST, CARE, and PLAY are less explicitly represented within the standard 50-item Big Five inventory. Therefore, these systems were not expected to emerge as separate factors in our five-factor solution, which is inherently constrained by the Big Five item pool.

However, the study's contribution lies in the conceptual mapping and interpretation of the empirically derived Big Five factors through the lens of Panksepp's framework. This approach posits that these primary emotional systems are the bottom-up drivers of the Big Five traits. For instance, high neuroticism is not just a label for emotional instability; within the ANTS framework, it is interpreted as reflecting heightened activity in the FEAR, RAGE, and PANIC/SADNESS circuits. Similarly, extraversion and openness are seen as manifestations of a robust SEEKING and PLAY system.

This interpretation is supported by existing research using the ANPS, a self-report measure specifically designed to assess Panksepp's primary emotional systems. Studies have consistently demonstrated robust associations between ANPS subscales and Big Five traits.^{17,18,27,30} Furthermore, as detailed in our Results section, external fMRI evidence³² provides direct neurobiological corroboration for primary emotions like SADNESS, demonstrating their association with distinct patterns

of resting-state functional connectivity involving the amygdala and parietal lobe. This reinforces the notion that these primary emotions are not arbitrary constructs but have distinct biological realities.

Therefore, this adaptation is not a simple re-labeling. Instead, it offers a mechanistic interpretation of well-established personality traits by linking them to their proposed neurobiological roots. This approach allows clinicians to move beyond merely describing a patient's personality profile to inferring the underlying neuroaffective dynamics that contribute to their psychological presentation, thereby informing more targeted interventions. The current Big Five dataset, while robust for personality validation, serves as a valuable proxy for exploring these conceptual links, highlighting the need for a dedicated ANTS scale that directly measures all primary emotional systems for a more comprehensive neuroaffective profile. The finished survey and preliminary scoring are provided in Section S1.1 (Supplementary A), with the instrument items, as listed in Table S1. Table S2 contains subscale scoring and conceptual clinical interpretation guidance. To further assist, Section S1.2 (Supplementary B) contains conceptual neural circuit correspondences, with Table S3 giving conceptual neural circuit correspondences across items in the scale.

4.3. Reliability and inter-factor relationships

The reliability findings presented in Table 3 and the inter-factor correlations shown in Table 4 should be interpreted within the five-factor Big Five validation model reported in the present study. Taken together, these results support the view that the factors are distinguishable yet not wholly independent, which is consistent with hierarchical models of personality in which broad traits may share some variance.

4.4. Theoretical and clinical implications

This study's adaptation of the ANTS framework to a large, real-world Big Five dataset offers significant theoretical and potential clinical implications. Theoretically, it reinforces the transdiagnostic utility of a neuroaffective approach to understanding psychological distress. By demonstrating how broad personality traits, which are transdiagnostic dimensions, can be conceptually mapped to underlying primary emotional systems, this work supports the ANTS's goal of moving beyond descriptive diagnostic categories toward more mechanistic formulations of psychopathology. This aligns with the National Institute of Mental Health's RDoC initiative, which emphasizes functional domains over surface-level symptoms.¹⁰ The findings underscore Panksepp's^{10,33} model that primary emotions serve as evolutionary foundations for both personality and psychopathology.

From a clinical perspective, while this study did not directly validate a specific 17-item ANTS scale or its specific treatment allocation algorithms, it provides a conceptual bridge. It is important to emphasize that the present analysis, while offering a rigorous psychometric validation of a conceptual framework, does not provide empirical evidence of the ANTS model's clinical impact. At this stage, the application of the ANTS framework to treatment planning remains theoretical. No conclusions can yet be drawn about its influence on clinical formulation accuracy, treatment selection efficacy, or outcome prediction. Furthermore, the extrapolation of these findings to therapeutic contexts assumes that clinicians can interpret neuroaffective profiles reliably and that such profiles translate into measurable improvements in care delivery, claims which remain untested. Thus, all statements concerning clinical applicability must be interpreted as hypothesis-generating rather than evidentiary. This limitation is non-trivial, and future studies will require explicit examination of whether ANTS outputs can be feasibly integrated into decision-making workflows across diverse clinical settings. Clinicians often use personality assessments to understand a patient's enduring patterns of thought, feeling, and behavior. Interpreting these Big Five traits through an affective neuroscience lens, as proposed by the ANTS framework, could offer deeper insights into potential underlying neurobiological dysregulations. For example, a patient scoring high on neuroticism might be inferred to have an overactive FEAR or PANIC system, suggesting that interventions targeting threat processing (e.g., exposure therapy) or emotion regulation (e.g., DBT) might be particularly beneficial. Conversely, low extraversion and openness might suggest SEEKING hypoactivity, pointing toward activation-focused approaches like behavioral activation. This neuroaffective interpretation could enhance the precision and rationale for psychotherapy allocation, moving toward a more personalized medicine approach. The ANTS framework, as conceptually outlined in Section S1.3 (Supplementary C), has demonstrated a significant improvement in theoretical treatment-target alignment (38.2% over random allocation and 22.7% over DSM-based modality assignments), suggesting the promise of this framework.

4.5. Interpreting neuroaffective profiles for therapeutic interventions

The conceptual mapping of Big Five traits to Panksepp's primary emotional systems within the ANTS framework provides a powerful lens for guiding therapeutic interventions. By inferring which core affective systems are dysregulated, clinicians can select modalities with established efficacy in modulating those specific neural circuits.

4.5.1. Elevated neuroticism (inferred high FEAR, RAGE, PANIC/SADNESS)

For FEAR, individuals with heightened system activity, characterized by excessive threat detection and hypervigilance, would benefit significantly from exposure-based cognitive behavioral therapy. This modality directly targets the amygdala and associated threat circuits, promoting inhibitory learning and habituation to feared stimuli.³⁴ Eye movement desensitization and reprocessing is also highly relevant for trauma-related fear, aiming to reprocess distressing memories and reduce amygdala hyperresponsivity.³⁵ Autonomic regulation techniques, such as heart rate variability (HRV) biofeedback, can help individuals gain control over physiological arousal linked to the FEAR system.³⁶

For RAGE, individuals exhibiting heightened activity in this system may present with irritability and reactive aggression, which suggests dysregulation in medial amygdala, periaqueductal gray, and hypothalamic circuits. DBT is particularly effective here, emphasizing distress tolerance, emotion regulation, and impulse control skills to manage intense anger and reduce impulsive outbursts.³⁷ Somatic therapies^{38,39} and affect labeling can also help individuals process and regulate intense anger responses.

For PANIC/SADNESS, elevated activity, often linked to separation distress and abandonment, indicates dysregulation in the anterior cingulate cortex and periaqueductal gray. Compassion-focused therapy⁴⁰ can be particularly useful in addressing self-criticism and promoting self-soothing, thereby fostering a sense of safety and emotional connectedness. Attachment-based therapies⁴¹ are crucial for exploring and repairing insecure attachment patterns that fuel panic and grief responses. For trauma-related panic, narrative exposure therapy⁴² can help integrate traumatic memories and reduce their emotional impact.

4.5.2. Low extraversion/low openness (inferred low SEEKING, low PLAY)

For SEEKING, individuals with blunted activity in this system may exhibit symptoms such as anhedonia, amotivation, and disengagement, which are commonly associated with hypodopaminergic states in the mesolimbic pathway.⁴³ In such cases, behavioral activation⁴⁴ serves as a primary intervention by encouraging engagement in rewarding activities, thereby reactivating the SEEKING system and improving overall mood. In addition, ACT⁴⁵ can be beneficial in helping individuals clarify values and commit to actions that align with those values, even in the presence of low motivation. Motivational interviewing⁴⁶ can help resolve ambivalence and strengthen commitment to change.

For PLAY, individuals with reduced activity in this system may present with emotional restriction, self-criticism, and a lack of joy or spontaneity, which are hallmarks of diminished engagement with play-based activities. In these cases, creative expression therapies⁴⁷ can foster spontaneity and emotional release. Furthermore, interpersonal group therapy formats can provide a safe space for re-learning social play and building authentic interpersonal connections.

4.5.3. High conscientiousness (potentially high executive function, but also rigidity)

Whilst conscientiousness is not directly mapped to a primary emotion, its association with executive functions (prefrontal cortex, anterior cingulate cortex) suggests that interventions focusing on cognitive control and flexibility could be relevant. For instance, if high conscientiousness manifests as rigid perfectionism or excessive self-control, ACT⁴⁵ can help foster psychological flexibility, allowing individuals to adapt to changing circumstances rather than adhering rigidly to rules.

4.5.4. High agreeableness (potentially high CARE, low RAGE)

For CARE, individuals with high agreeableness, linked to heightened activity in the CARE system, may exhibit patterns of over-functioning or enmeshment in relationships, potentially placing the needs of others consistently above their own. In such cases, compassion-focused therapy⁴⁰ can help individuals cultivate a balance between self-compassion and compassion for others, thereby preventing emotional burnout and fostering healthier boundaries. In addition, relational group therapy can provide a structured context in which to practice more balanced reciprocal interpersonal dynamics.

This neuroaffective interpretation provides a mechanistic rationale for treatment selection, moving beyond a trial-and-error approach and offering a more precise, evidence-informed pathway to therapeutic intervention.

4.6. Limitations

Despite its strengths, this study has several important limitations. First, while the ANTS framework and its underlying primary emotional systems are supported by robust meta-analytic and direct neuroimaging evidence (as discussed in the Results section), the current study's adaptation to the Big Five dataset does not include new individual-level neuroimaging or physiological recordings. Therefore, direct empirical validation of the specific Big Five factor-to-neural circuit mappings derived in this study remains an area for future research.

Furthermore, the study relies on reverse inference when linking psychological constructs to neural circuits, which inherently carries limitations.⁴⁸ While supported by meta-analytic neuroimaging data, direct empirical confirmation via concurrently acquired neural or physiological biomarkers (e.g., fMRI, event-related potential, HRV) was not included in this study.

This study, like the conceptual ANTS framework, does not include clinical outcome data or real-world treatment allocation efficacy. The demonstrated improvement in theoretical treatment-target alignment within the ANTS framework was based on conceptual alignment, not on actual patient outcomes.

Finally, while the dataset is large and publicly available, its generalizability to diverse clinical populations (e.g., specific diagnostic groups, different cultural backgrounds) needs further empirical confirmation. The Big Five items, by their nature, do not directly measure all seven of Panksepp's primary emotional systems (e.g., LUST, CARE, PLAY are not explicitly covered by the Big Five items used here), which limits the comprehensiveness of the neuroaffective profile derived in this adaptation.

More critically, it must be explicitly acknowledged that the Big Five Personality Inventory, while psychometrically robust, does not provide direct operational coverage of all seven of Panksepp's primary emotional systems. Specifically, LUST, CARE, and PLAY, each central to prosocial behavior, reproductive motivation, and affective resonance, are not directly captured in the 50-item inventory used herein. Whilst indirect associations (e.g., between agreeableness and CARE, or between extraversion and PLAY) have been proposed,^{17,18} these remain inferential and lack item-level specificity. As such, any derived neuroaffective profiles from this dataset necessarily omit critical systems central to interpersonal affiliation and motivational salience.⁴⁹ This structural limitation constrains the comprehensiveness of the inferred affective phenotype and must temper interpretations of the framework's holistic neurobiological mapping.

Currently, no data are available on whether ANTS output directly alters clinical formulation, improves treatment selection accuracy, or integrates seamlessly into standard clinical workflows. Structured usability studies will be essential to determine whether clinicians without specialist neuroscience training can efficiently interpret ANTS outputs and how integration into electronic health record systems might affect feasibility. Such studies should be explicitly designed to evaluate two key translational dimensions: (i) the capacity of non-specialist clinicians to interpret ANTS-derived profiles without additional neurobiological training, and (ii) the

operational feasibility of embedding ANTS within real-world electronic health records and triage workflows. This may involve simulated clinical vignettes with and without ANTS guidance, randomized assessments of clinician confidence or formulation accuracy, and evaluations of inter-rater agreement in interpreting ANTS outputs. Furthermore, cluster-randomized implementation trials could assess whether ANTS-informed treatment allocation improves therapeutic engagement, alliance formation, or longitudinal symptom reduction. The current findings offer a methodological and theoretical springboard for these studies, but their execution will be essential for validating the model's clinical utility beyond psychometric coherence. These practical domains necessitate structured feasibility assessment before widespread adoption, and pilot feasibility trials are a crucial immediate next step.

In terms of generalizability, several sample-specific limitations must be emphasized. The OpenPsychometrics.org dataset comprises self-selected participants, disproportionately drawn from English-speaking and digitally literate populations, with potential overrepresentation of younger, Western-educated adults. These demographic features introduce non-trivial cultural and developmental biases, especially when mapping constructs like agreeableness or openness to neuroaffective functions that may manifest differently across sociocultural contexts.⁵⁰ The dataset further excludes clinical samples, thereby limiting extrapolation to populations with psychiatric disorders, trauma histories, or neurodevelopmental conditions where affective circuitry may be significantly dysregulated,⁵¹ although this is in line to assess affective activation in functional neurology. Multi-site clinical replications with demographically stratified samples are therefore necessary to confirm the structural invariance and clinical sensitivity of the adapted ANTS framework.

4.7. Future directions

The findings of this study highlight several critical directions for future research. The most important next step is the direct psychometric validation of a dedicated ANTS scale on diverse clinical and non-clinical populations. This should involve rigorous EFA and CFA to confirm its proposed factor structure and psychometric properties.

Longitudinal studies are essential to assess the temporal stability of ANTS subscales and their sensitivity to therapeutic change. This would involve repeated administration of the ANTS across treatment windows to determine whether changes in subscale scores correspond with known neural plasticity induced by specific therapeutic modalities.

Building on the external neurobiological evidence presented, a critical next step is to conduct direct fMRI and other biomarker studies specifically with a dedicated ANTS scale, to empirically confirm its hypothesized neural mappings at the individual subject level.

To enhance the comprehensiveness and clinical utility of the ANTS, continued development should focus on the inclusion and validation of items for positive affective systems, such as CARE, LUST, and PLAY. Their incorporation would allow for a more holistic assessment of resilience factors and positive affective states, relevant to therapeutic approaches focused on relational healing, empathy development, or post-traumatic flourishing.

Finally, rigorous clinical utility trials are necessary to evaluate whether ANTS outputs directly alter clinical formulation, improve treatment selection accuracy, and integrate seamlessly into routine clinical workflows. This includes structured usability studies to assess interpretability by clinicians without specialist neuroscience training and the feasibility of integration into electronic health record systems. Multi-group CFA should also be employed to evaluate measurement invariance across diverse demographic and cultural subgroups to ensure broad generalizability.

5. Conclusion

The ANTS framework, as adapted and conceptually validated in this study, represents a novel synthesis of affective neuroscience theory, empirical psychometric evidence, and clinical relevance. By demonstrating a robust mapping between higher-order personality traits and underlying primary affective systems, this work provides a foundation for a mechanistically informed approach to understanding psychological distress. The empirical analyses, conducted on a large, publicly available dataset, confirm the psychometric soundness of this adapted framework.

This study offers a compelling conceptual bridge for clinicians to move beyond descriptive diagnostic categories toward inferring neuroaffective dysregulations, thereby enhancing the precision and rationale for psychotherapy allocation. While this study provides foundational psychometric evidence for the framework's adaptation, future research is crucial to directly validate a dedicated ANTS scale, assess its clinical utility, and confirm its longitudinal responsiveness in real-world therapeutic settings.

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Conflict of interest

The author declares no conflict of interest.

Author contributions

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Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

The raw data for this study are publicly available from the OpenPsychometrics.org repository (http://openpsychometrics.org/_rawdata/BIG5.zip). The R script detailing all data preparation and analysis steps is provided within this manuscript (Section S1.6 [Supplementary F]). For full transparency and replicability, the cleaned and processed dataset (BIG5_cleaned_for_analysis.csv) used for the analyses is deposited in a public, open-access repository, the Open Science Framework, at DOI 10.17605/OSF.IO/5SBGC under the “Datasets” component. In addition, the conceptual ANTS item pool, scoring instructions, and all tabulated neural evidence are provided in Sections 1.1 (Supplementary A) and 1.2 (Supplementary B). All fMRI data referenced for external neurobiological corroboration are publicly available via Neurosynth, NeuroQuery, BrainMap, or the specified OpenNeuro repositories.

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