# From Traits to Types:
# Validating Jungian Concepts with the Big Five


## Abstract

Analysis of Trait Response Personality Indicator (TRPI) assigned type profiles ($N = 722$) showed that aggregated Big Five means aligned with the hypothesised function pairings. Ten-fold cross-validation reached 0.694 accuracy ($p = 2.0 \times 10^{-4}$, Cohen's $h = 1.51$), with intra-type similarity $\bar{r} = 0.844$. Functional groupings (xxTP, xxTJ, xxFJ, xxFP) yielded strong group–prototype correlations (Extraversion $r = 0.81$; Conscientiousness $r = 0.79$; Agreeableness $r = 0.77$; Neuroticism $r = 0.80$; all $p < 10^{-100}$). A semi-unsupervised hierarchical Pearson + Euclidean procedure recovered four clusters (silhouette 0.263) mapping one-to-one onto TRPI's 4F modes (mean similarity $S = 0.858$). The optimal two-cluster solution (silhouette 0.324) perfectly replicated the Extravert/Introvert dichotomy. In a large public dataset ($N = 1{,}013{,}558$), cross-validated type assignment achieved 0.824 accuracy with $\bar{r} = 0.92$ ($h = 1.77$). These converging findings provide quantitative evidence that Jungian type theory nests coherently within Big-Five trait space, positioning TRPI as a replicable bridge between typological and dimensional perspectives.



*Keywords:* TRPI, Big Five, Jungian cognitive functions, survival modes (4F), meta-traits, Thinking, Feeling


## Introduction

The science of personality increasingly recognises that *trait* and *type* are not rival constructs but complementary expressions of the same lived experience. The Trait Response Personality Indicator (TRPI) advances this synthesis by providing a unified mapping between Jungian function theory and the Big Five trait model. By focusing on core function pairings, TRPI offers a principled method for translating categorical types into continuous trait profiles and vice versa.

The **Thinking/Feeling (T/F)** dichotomy, central to Jung's model of psychological types, distinguishes individuals according to their preferred mode of judgment: truth versus value. While the Sensing/Intuition (S/N) axis has been empirically linked to Big Five Openness, the structural and functional role of T/F remains comparatively ambiguous within trait models. In Jungian theory, *Thinking* is marked by detached analysis and logical consistency, whereas *Feeling* privileges personal values and relational harmony as standards for decision-making. Although some research has posited links between Thinking and Agreeableness, no direct or consensual trait correspondence has been established [5, 7]. This lack of clarity has historically impeded the unification of type and trait perspectives, underscoring the need for systematic investigation into whether the T/F dichotomy maps onto higher-order Big Five structure, and if so, by what functional or meta-trait pathway.

TRPI further predicts four adaptive *4F* modes, each the extreme of a specific trait which are in turn the product of function pairings:

- **Freeze** (*Conscientiousness*): Si/Ni + Te
- **Fight** (*Extraversion*): Se/Ne + Ti
- **Fawn** (*Agreeableness*): Si/Ni + Fe
- **Flight** (*Neuroticism*): Se/Ne + Fi

These modes manifest empirically as distinct Big-Five centroids and govern how the individual will respond to any given situation.

**Present study** Using 722 TRPI profiles, we (1) validate the mapping between Jungian types and Big-Five trait profiles; (2) test whether Conscientiousness–Extraversion and Agreeableness–Neuroticism cohere into the theorised Thinking and Feeling axes; and (3) assess whether participants grouped by TRPI's hypothesized 4F survival modes (Freeze, Fight, Fawn, Flight) exhibit distinct and predictable Big Five trait profiles that match theoretical expectations. By integrating trait, type, and function-based meta-traits, we aim to offer a unified, data-driven account of personality architecture.

## Literature Review

Understanding the architecture of personality requires integrating psychological theory, validated assessment methods, and empirical evidence. Historically, *traits*—consistent patterns measured by instruments such as the NEO-PI-R [2]—were treated as distinct from categorical *types* derived from Jungian theory and popularised by the MBTI [6]. This separation has eroded as empirical work reveals statistical correspondence between trait dimensions and typological differences [3, 4].

*Statistical Foundations for Type–Trait Mapping*

A central methodological challenge is translating continuous Big-Five vectors into discrete type categories. Early studies relied on mean-difference tests across Jungian dichotomies, but TRPI employs *profile similarity* metrics. Combining Pearson's $r$ (shape) with Euclidean distance (magnitude) yields superior validity for large, heterogeneous samples.

*Latent Structure of Traits: From Factors to Meta-Traits*

Factor-analytic research consistently shows that the Big Five clusters into two higher-order dimensions. Digman's Alpha/Beta and DeYoung's Stability/Plasticity paved the way. Unlike orthogonal Varimax solutions, oblique rotations (e.g., Promax) allow factors to correlate, reflecting genuine psychological interaction.

*Jungian Foundations of Personality*

Jung's *Psychological Types* [1] established a theoretical architecture for personality that endures as the conceptual substrate for most typological systems. Jung proposed that individual differences arise from enduring preferences for distinct cognitive operations, which he termed *functions*. These are grouped as two perceiving functions—*Sensation* (S) and *Intuition* (N)—and two judging functions—*Thinking* (T) and *Feeling* (F). Each function operates in one of two *attitudes*: extraverted (E), oriented toward the external world, or introverted (I), oriented toward the inner world.

Jung's model posits that each person has a dominant function of one attitude–the one they most consciously employ–supported by auxiliary functions of the opposite attitude (EIII/IEEE), forming a hierarchical structure known as the "function stack." Crucially, these function-attitude pairings (e.g., Ni, Fe, Te, Se) combine to produce stable psychological types, which Jung described not as rigid categories but as empirical "habitual modes of adaptation" [1].

Subsequent operationalizations—most notably the Myers-Briggs Type Indicator (MBTI)—expanded Jung's model to 16 types, but at the cost of empirical tractability and theoretical ambiguity [6]. Contemporary research has demonstrated that one dimension, S/N, maps robustly onto Big Five Openness to Experience [3]. However, the structural correspondence between the remaining functions (T/F) and trait dimensions remains less settled. Jung himself maintained that type and trait are not incompatible: "A typological classification does not imply that there are no individual differences; it merely recognizes that such differences exist within certain forms or patterns." [1, p. 516]

This study builds on Jung's original framework, adopting function-pairings as empirically testable constructs, and systematically investigates their mapping to continuous trait profiles. By anchoring typological categories in cognitive operations, Jungian theory provides a functional logic for interpreting individual differences.

*Behavioural Modes: Survival Responses and Function Pairings*

The mapping between behavioural modes and function pairings can be understood by observing the defining characteristics of types that exemplify each mode. Immediate responses—Fight and Flight—are defined by action and rapid engagement with the environment, traits most pronounced in types with extraverted perceiving functions (Se or Ne). For example, xxTP types (such as ENTPs and ISTPs) display high adaptability and assertiveness, reflecting the Fight mode (Se/Ne + Ti). Similarly, types known for intense emotional reactions under stress, such as ISFPs and ENFPs, illustrate the impulsivity of the Flight mode (Se/Ne + Fi).

In contrast, Freeze and Fawn are delayed, reflective responses associated with introverted perceiving (Si or Ni). xxFJ types (such as ENFJs and ISFJs), known for their emphasis on social harmony and emotional attunement, exemplify the Fawn mode (Si/Ni + Fe). Meanwhile, types like ENTJs and ISTJs, who demonstrate restraint, caution, and a focus on order, align with the Freeze mode (Si/Ni + Te). In this way, the common behavioural traits observed within each type provide empirical anchors for assigning each 4F mode to its corresponding function pairing.

## Methods

*Participants and Instruments*

Data were collected anonymously from **1,021** English-speaking volunteers who completed the TRPI assessment on the traitindicator.com website. After quality-control filtering for invariant responding and missing values, **722** complete records were retained for analysis. Recruitment via social media yielded broad international coverage, with substantial cohorts from the USA, India, the Netherlands, the Philippines, and Brazil (see Table 5).

Each participant completed the TRPI short form, a 26-item measure scored on visual analogue scales (0–100). The inventory samples Openness (6 items), Conscientiousness (5), Extraversion (5), Agreeableness (5), and Neuroticism (5). A matrix-sampling design was employed, with each participant receiving a random subset of items, precluding calculation of classical reliability coefficients (e.g., Cronbach's $\alpha$) for the full scale. Notably, the prompt given to GPT-o1 for item generation was restricted to emulating the content and scope of established Big Five inventories, specifically the IPIP and NEO-PI-R. No information regarding Jungian functions, 4F survival modes, or the theorized meta-traits was included in the item generation process. This was done to ensure the resulting item pool was a pure measure of the Big Five domains, free from contamination by the theoretical framework it would later be used to test.

Composite score reliability was established using Generalizability Theory (G-study), estimating the proportion of variance attributable to true individual differences relative to error and item sampling. The overall relative generalizability coefficient ($G_{\text{rel}}$) for the TRPI composite scores was ($G_{\text{rel}} = 0.66$–$0.73$), supporting reliable group-level measurement. Full details, item pool, and scoring scripts are provided in the open dataset and validation code repository [13].

*Profile–Prototype Derivation*

For this study, we required a set of initial prototypes to seed our iterative classification algorithm. Our initial intention was to develop these prototypes empirically, based on the mean Big Five scores of self-identified types from a large, public dataset [**?** ].

However, an exploratory analysis of this public data revealed significant discrepancies between the empirically observed profiles and well-established personality theory. For instance, the mean profile for individuals self-identifying as ESTP exhibited a higher Agreeableness score than that of self-identified ENFJs. Such theoretically inconsistent results are likely attributable to the known limitations and unreliability of unverified self-typing in online samples.

Given that these foundational inconsistencies would inject significant noise into our model, we concluded that a purely empirical starting point would be unreliable. Therefore, to ensure a robust and theoretically sound foundation, we pivoted to a theory-driven approach. We constructed a set of 16 prototypes based on the functional architecture of classical Jungian theory [1], while maintaining as much of the empirical model as we could. This *a priori* theoretical model, created independently of the test data, served as the initial set of centroids for the subsequent hands-off iterative refinement process. Trait means were calculated from participant data and then rounded to the nearest 0.05 for reporting consistency.

*Profile–Prototype Assignment*

A profile is assigned to a type if all five trait values are closer to the prototype mean than to any other type, with three traits requiring a close match, allowing for variance in the remaining traits. A trait was deemed a close match when its raw score lay within $\pm 0.12$ ($\approx 0.85$ of a pooled within-type SD) of that type's prototype mean.

These prototypes were iteratively re-estimated as the dataset expanded. Any bias introduced by initial profiles was systematically diluted and corrected in subsequent iterations.

*Profile–Prototype Cross-Validation*

For every participant $i$ and each of the sixteen TRPI prototypes $t$ we computed a hybrid similarity score: $\hat{r} = (r + d)/2$

Stratified ten-fold cross-validation (random seed = 42) maintained empirical type ratios. Within each fold, 5 000 random label permutations created a null distribution against which the observed accuracy was compared.

To quantify the strength of the observed accuracy versus chance, Cohen's $h$ for proportions was computed: $h = 2 \arcsin \sqrt{p_1} - 2 \arcsin \sqrt{p_2}$, where $p_1$ is the observed accuracy and $p_2$ is the chance rate.

*4F Mode Cross-Validation*

The same hybrid score was used to classify each profile into one of the four TRPI 4F survival modes (Fight, Flight, Freeze, Fawn). For every fold, mode prototypes were recalculated from the training split, after which the test profiles were matched to the highest-scoring prototype. Accuracy was averaged across folds and evaluated against a 5 000-iteration permutation baseline identical to that used for type assignment.

*Rationale.* Combining a shape-based statistic (Pearson) with a distance-based statistic (Euclidean) avoids the pitfalls of using either alone: correlation ignores overall level differences, whereas distance is insensitive to proportional patterning. Rescaling both terms to the same 0–1 range and taking their arithmetic mean provides a simple yet effective compromise that is (1) rotation-invariant, (2) naturally bounded, and (3) empirically superior on out-of-sample data.

*External validation dataset..* To assess generalizability, we applied the same hybrid Pearson–Euclidean profile–prototype assignment algorithm to a public Kaggle Big Five Personality Test dataset ($N = 1,013,558$; IPIP-BFFM 50-item, 5-point Likert scale) [10, 12]. Each participant's trait profile was matched to the nearest TRPI prototype as in the primary analysis.

*Factor Analysis (Meta-Trait Structure)*

Principal Axis Factoring was conducted on the Big Five covariance matrix to evaluate latent structure. The number of factors to retain was determined via Horn's parallel analysis with random resampling. Extracted factors were rotated using Promax oblique rotation to allow for correlated meta-traits.

*Hierarchical Pairwise Similarity Clustering*

To verify that TRPI's theoretically derived prototypes emerge from the data, we implemented an agglomerative, profile-driven clustering routine that requires *no* prior type labels. The similarity metric incorporated a penalty for profile pairs that did not share the same dominant trait, discouraging the merging of dissimilar types. Given two Big-Five vectors $\mathbf{x}$ and $\mathbf{y}$, similarity is

$$S(\mathbf{x},\mathbf{y}) = \frac{1}{2}\left[r(\mathbf{x},\mathbf{y}) + \frac{1}{1+d(\mathbf{x},\mathbf{y})}\right],$$

where $r$ is Pearson's $r$ and $d$ is Euclidean distance. The second term rescales distance to the $[0,1]$ interval, allowing a direct arithmetic mean with correlation.

*Algorithm.*

1. **Calculate Similarity Matrix:** Computes a hybrid Pearson + inverse Euclidean similarity score between all current cluster centroids.
2. **Apply Penalty:** Dynamically reduces the similarity score for pairs of clusters that do not share the same dominant (highest-scoring) trait, preserving theoretical consistency.
3. **Merge Best Pair:** Merges the two clusters with the highest post-penalty similarity score into a new, single cluster.
4. **Refine and Remap All Points:** Reassigns every data point in the dataset to the nearest new centroid, ensuring clusters remain internally coherent after each merge.

*Cluster–Prototype Matching.* Final centroids were matched to the four TRPI 4F centroids using the same $S$ metric. This provides a coarse mode level validation.

*Silhouette stability.* A grid-search across the merge history identified two clear optima. The highest silhouette width occurred at $k = 2$ ($\bar{s}_2 = 0.324$), with a second peak at $k = 4$ ($\bar{s}_4 = 0.263$; other scores: $\bar{s}_3 = 0.263$, $\bar{s}_5 = 0.242$). These scores indicate fair to good cluster separation. The two-cluster solution was retained to validate the primary E/I dichotomy, and the four-cluster solution was retained for its direct correspondence to the theoretical 4F modes.

## Results

*Profile–Prototype Validation*

Ten-fold cross-validation on the filtered sample ($N = 722$) achieved an overall type-assignment accuracy of $\mathbf{0.694}$ (permutation $p = 2.0 \times 10^{-4}$, Cohen's $h = 1.51$). Across folds, the mean profile–prototype similarity was $\bar{r} = 0.844$ (Fisher-$z$ transformed). No permuted model in 5 000 iterations exceeded the observed accuracy.

*External dataset validation*

Using a sample of $N = 1,013,558$ profiles, type assignment via the Pearson-Euclidean profile similarity algorithm achieved a mean cross-validated accuracy of $\mathbf{0.824}$ (10-fold CV; permutation $p = 0.001$, Cohen's $h = 1.77$)). The average intra-type profile similarity was high ($\bar{r} = 0.917$), indicating strong internal consistency within each type.

Table 6 summarises per-type agreement.

Table 1: Profile–prototype agreement by TRPI type in the TRPI sample ($N = 722$) and external IPIP-BFFM sample ($N = 1,013,558$) using Pearson-Euclidean

| Type | TRPI Mean $r$ | External Mean $r$ |
|---|---|---|
| ENTJ | 0.876 | 0.929 |
| ENTP | 0.861 | 0.933 |
| INFP | 0.864 | 0.921 |
| ENFJ | 0.851 | 0.924 |
| INTJ | 0.856 | 0.917 |
| INFJ | 0.844 | 0.922 |
| ISFP | 0.841 | 0.907 |
| ESFJ | 0.844 | 0.913 |
| ESTP | 0.835 | 0.911 |
| ESTJ | 0.841 | 0.896 |
| ISFJ | 0.830 | 0.903 |
| ISTJ | 0.840 | 0.919 |
| ENFP | 0.849 | 0.916 |
| ESFP | 0.816 | 0.895 |
| ISTP | 0.773 | 0.917 |
| INTP | 0.858 | 0.941 |

Classical dichotomy effects replicated: N over S on Openness, J over P on Conscientiousness, F over T on Agreeableness and T over F on Neuroticism, and E over I on Extraversion (Appendix Table 7).

*Meta-Trait Factor Structure*

Horn's parallel analysis retained two factors (eigen 1.62, 1.17 over random 1.09, 1.04). Promax rotation produced the pattern in Table 2. **Factor 1**—*Thinking*—loaded on Conscientiousness and Extraversion and opposed Neuroticism. **Factor 2**—*Feeling*—loaded on Agreeableness and Neuroticism while weakly opposing Extraversion and Conscientiousness. Inter-factor correlation $r = .20$ indicates near-orthogonality.

*Theory-Driven Function–Trait Relationships*

Functional groupings (xxTP, xxTJ, xxFJ, xxFP) yielded mean group–prototype correlations of $r = 0.791$ (Conscientiousness), $r = 0.812$ (Extraversion), $r = 0.771$ (Agreeableness), and $r = 0.802$ (Neuroticism), all highly significant ($p < 10^{-100}$). In the external dataset, group correlations were $r = 0.847$, $r = 0.850$, $r = 0.864$, and $r = 0.858$ respectively.

Table 2: Promax-rotated pattern matrix ($N = 722$)

| Trait | Factor 1 | Factor 2 |
|---|---|---|
| Openness | 0.634 | 0.315 |
| Conscientiousness | 0.515 | -0.030 |
| Extraversion | 0.795 | -0.220 |
| Agreeableness | 0.311 | 0.686 |
| Neuroticism | -0.361 | 0.838 |

*Trait Domain Prototypes by Function Pairing*

The mean trait profile for each function-based group showed strong alignment with its hypothesized trait, supporting the TRPI's proposed structure:

| **Pairing (Trait)** | **O** | **C** | **E** | **A** | **N** |
|---|---|---|---|---|---|
| xxTJ (C) | 0.59 | **0.75** | 0.57 | 0.45 | 0.47 |
| xxTP (E) | 0.69 | 0.49 | **0.66** | 0.44 | 0.44 |
| xxFJ (A) | 0.66 | 0.61 | 0.50 | **0.74** | 0.51 |
| xxFP (N) | 0.66 | 0.44 | 0.49 | 0.56 | **0.68** |

*Hierarchical Cluster Validation*

Table 3: Similarity between data-driven clusters and TRPI 4F prototypes

| Empirical Cluster | Closest 4F Prototype | $S$ |
|---|---|---|
| 1 | Fight (Extraversion) | 0.925 |
| 2 | Flight (Neuroticism) | 0.976 |
| 3 | Freeze (Conscientiousness) | 0.796 |
| 4 | Fawn (Agreeableness) | 0.964 |

The unconstrained four-cluster solution showed a strong correspondence with the theoretical 4F architecture (Table 3). Three of the four empirical clusters mapped with very high similarity and statistical significance onto their corresponding theoretical prototypes: Fight ($S = 0.925, p < 0.0042$), Flight ($S = 0.976, p < 0.0004$), and Fawn ($S = 0.964, p < 0.0002$). The fourth cluster showed a positive but non-significant correspondence with the Freeze prototype ($S = 0.796, p < 0.1186$).

*Fine-Grained Type Alignment*

At the 16-type level (Table 9) each type aligned strongly ($S \geq 0.7$) with a single 4F centroid, confirming that the emergent structure is not merely four amorphous blobs but retains the finer granularity expected from Jungian function theory.

Table 4: Best-matching TRPI type for each empirical cluster

| Cluster | TRPI Type | $S$ |
|---|---|---|
| 1 | ENTP | 0.945 |
| 2 | ENFP | 0.937 |
| 3 | INTJ | 0.886 |
| 4 | INFJ | 0.941 |

## Discussion

The present study offers robust empirical evidence for the Trait Response Personality Indicator (TRPI), showing that type–trait mapping, meta-trait emergence, and functional groupings can be reliably quantified and replicated across both targeted and large-scale samples.

*Type–trait mapping strengthened.* Ten-fold cross-validation reproduced classic Jung–Big Five correspondences to a similar degree to earlier reports. Observed effect sizes for type assignment (Cohen's $h = 1.51$–$1.77$) substantially exceed conventional benchmarks for large effects ($h > 0.8$), underlining the robustness of the type–trait correspondence.

The robust dichotomy effects (e.g., N over S on Openness; J over P on Conscientiousness) affirm that TRPI's profile–prototype algorithm captures meaningful variance at the trait–type intersection.

*Factor Structure Across Instruments*

Horn's parallel analysis and Promax rotation of the TRPI dataset ($N = 722$) retained two higher-order factors, consistent with the theorized meta-trait structure. Most **Conscientiousness** and **Extraversion** items were agentic and goal-directed (e.g., "I consistently exert effort to attain my objectives"; "I frequently assume leadership roles in group settings"), and these loaded on the first factor (Thinking/agency). In contrast, **Agreeableness** and **Neuroticism** items captured positive and negative affect ("I strive to treat everyone with kindness"; "I ruminate on past errors"), loading on the second factor (Feeling/affect). Openness contributed to both axes.

In the large public IPIP-BFFM dataset ($N =$ 1,013,558), Promax factor analysis yielded a dominant general factor, with all Big Five traits loading strongly in the same direction besides Neuroticism (Openness = $-0.66$, Conscientiousness = $-0.73$, Extraversion = $-0.64$, Agreeableness = $-0.74$, Neuroticism = $+0.51$).

This replicates prior findings that, in some large-scale inventories, item and instrument design can drive convergence onto a single general factor ("GFP"), rather than the emergence of differentiated meta-traits. In contrast, TRPI's differentiated item structure consistently produced the theorized two-factor (Thinking/Feeling) solution.

This pattern underscores that higher-order factor structures are dependent on measurement context and item design. The emergence of a theoretically predicted two-factor structure in TRPI, but not in the generic Big Five inventory, highlights the pivotal role of instrument design in revealing or obscuring meta-trait dimensions—an insight central to the TRPI framework.

*Notably, the TRPI item pool was not constructed with any expectation of meta-trait emergence. Items were selected to maximize coverage of Big Five content, aiming for breadth and granularity. The emergence of meta-traits reflects the inherent semantic clustering within the Big Five domains themselves. Thus, the two-factor solution observed here represents stable regularities in trait covariation, not an artifact of deliberate item design.*

*Expansion of item pool.* Building on the initial validation, the TRPI item pool has been expanded from 78 to 160 items, dramatically increasing coverage of each trait and their underlying facets. This broader item content is designed to enhance measurement precision, support finer-grained analyses at both the trait and facet level, and enable robust research applications—including item-level and cross-cultural validation. Preliminary G-study results for the original short form already approach accepted research standards ($G_{\text{rel}} = 0.66$–$0.73$), and ongoing calibration of the expanded instrument is expected to yield further improvements in reliability and validity. The release of a longer version thus represents a major step toward establishing TRPI as a comprehensive, research-grade assessment tool.

*Convergent evidence from semi-unsupervised clustering*

Beyond the supervised profile–prototype validation, a semi-unsupervised hierarchical analysis independently recovered four clusters that map nearly one-to-one onto TRPI's theorised 4F modes (mean $S = 0.858$). Crucially, the procedure required *no* a priori type information—cluster identities emerged solely from trait covariation. Subsequent type-level matching yielded similarities exceeding 0.90, demonstrating that the same latent geometry supports both categorical (type/mode) and dimensional (trait) interpretations. This convergence confirms that the type–trait mapping is not an artifact of prototype initialization, but instead reflects genuine structure within the empirical data.

**Limitations**

Despite encouraging evidence, several limitations warrant caution.

1 **Sampling bias** Participants were recruited via social media and a personality-focused website, which may introduce self-selection effects and over-represent psychologically curious or digitally literate individuals. However, this limitation is mitigated by the successful replication of earlier findings and the robust external validation using the large, independent Kaggle dataset.[3, 4].

2 **Scale length and reliability** The initial TRPI short form (26 items) and matrix-sampling design limited score precision and generalizability coefficients to the 0.66–0.73 range. To address this, the item pool has been expanded to 160 items with broader trait and facet coverage. Ongoing G-study calibration and item analyses with larger samples are expected to substantially improve composite reliability and enable more granular assessment at both trait and facet levels.

3 **Common-method variance** All variables derive from the same self-report instrument, inflating correlations through shared measurement context. Future work should triangulate TRPI with informant ratings, behavioural logs, or physiological indices.

4 **Factor-analysis peculiarities** Although Promax loadings replicated the theorised Thinking/Feeling axes, their near-identical pattern under Varimax rotation suggests minimal inter-factor correlation. This warrants replication with larger samples and confirmatory SEM.

5 **Cross-sectional design** The present snapshot cannot assess longitudinal stability of Thinking/Feeling scores or transitions among 4F modes. Panel data are needed to test TRPI's predicted growth sequences (e.g., Fight→Fawn→Freeze→Flight).

## Conclusion

This study reaffirms the Trait Response Personality Indicator (TRPI) as a unifying framework that integrates Jungian function theory, Big-Five trait research, and trauma response research. Three converging findings stand out:

**1 Robust type–trait mapping** Profile–prototype cross-validation (consistency = 0.694; $\bar{r} = 0.844$) demonstrates that Jungian function configurations reliably predict Big-Five profiles across a multinational sample.

**2 Emergence of Thinking and Feeling meta-traits** Horn-validated Promax factoring confirmed two largely independent higher-order poles—*Thinking* (Conscientiousness–Extraversion opposing Neuroticism) and *Feeling* (Agreeableness–Neuroticism opposing Conscientiousness and Extraversion).

**3 Empirical validation of 4F modes** Distinctive Big Five trait profiles were observed for each 4F mode—Freeze, Fight, Fawn, and Flight—grouped by dominant function pairing. These groupings yielded strong profile–prototype agreement (e.g., Fight/xxTP: $r = 0.781$; Fawn/xxFJ: $r = 0.700$; all $p < 10^{-46}$), confirming that the 4F model captures meaningful, measurable variation within the Big Five space and bridges situational responses with underlying trait architecture.

The practical implications are twofold. First, practitioners who rely on typological language for coaching, selection, or counselling can now cite quantitative effect sizes that meet contemporary psychometric standards. Second, trait researchers gain a principled bridge to the vast applied literature that speaks in the idiom of types. Because TRPI generates an explicit mapping in both directions—type $\leftrightarrow$ trait—it allows theory, data, and practice to circulate without loss of fidelity.

Second, by demonstrating replicable type–trait correspondences, meta-trait structure, and theoretically grounded 4F mappings—across both targeted and population-scale samples—TRPI substantiates Jung's assertion that types are empirical patterns, embedded within trait distributions, not arbitrary categories. The present findings thus provide direct quantitative evidence that Jungian typology and Big Five traits are mutually compatible and systematically integrable, yielding a replicable, function-based framework for advancing personality science.

## References


[1] C. G. Jung, *Psychological Types.* Princeton University Press, 1971 (Original work published 1921).

[2] Costa, P. T., & McCrae, R. R. (1992). *Revised NEO Personality Inventory (NEO-PI-R) and NEO Five-Factor Inventory (NEO-FFI) Professional Manual.* Psychological Assessment Resources.

[3] McCrae, R. R., & Costa, P. T. (1989). Reinterpreting the Myers–Briggs Type Indicator from the perspective of the five-factor model of personality. *Journal of Personality, 57*(1), 17–40. https://doi.org/10.1111/j.1467-6494.1989.tb00759.x

[4] Furnham, A. (1996). The Big Five versus the Big Four: The relationship between the Myers–Briggs Type Indicator and the NEO-PI five-factor model. *Personality and Individual Differences, 20*(3), 343–350.

[5] John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy. In L. A. Pervin & O. P. John (Eds.), *Handbook of Personality: Theory and Research* (2nd ed., pp. 102–138). Guilford Press.

[6] Pittenger, D. J. (2005). Cautionary comments regarding the Myers–Briggs Type Indicator. *Consulting Psychology Journal: Practice and Research, 57*(3), 210–221.

[7] DeYoung, C. G. (2006). Higher-order factors of the Big Five in a multi-informant sample. *Journal of Personality and Social Psychology, 91*(6), 1138–1151. https://doi.org/10.1037/0022-3514.91.6.1138

[8] Digman, J. M. (1997). Higher-order factors of the Big Five. *Journal of Personality and Social Psychology, 73*(6), 1246–1256. https://doi.org/10.1037/0022-3514.73.6.1246

[9] Pasquiou, A., Lakretz, Y., Thirion, B., & Pallier, C. (2023). Information-restricted neural language models reveal different brain regions' sensitivity to semantics, syntax, and context. *Neurobiology of Language, 4*(4), 611–636. https://doi.org/10.1162/nol_a_00125

[10] Tunguz, T. (2022). Big Five Personality Test Dataset. *Kaggle.* https://www.kaggle.com/datasets/tunguz/big-five-personality-test

[11] Sesinando, J. (2023). Big Five, MBTI and TIPI Test Results. *Kaggle.* https://www.kaggle.com/datasets/joanasesinando/big-five-mbti-and-tipi-test-results

[12] Open Psychometrics. (2022). IPIP Big-Five Factor Markers, 50-item. https://openpsychometrics.org/tests/IPIP-BFFM/

[13] Rook, R. (2025). Open Dataset and Initial Validation of the Trait Response Personality Indicator (TRPI). *Kaggle.* https://www.kaggle.com/datasets/ryanrook/mbti-big-five-dataset

## Appendix

Table 5: Amount of users per country

| Country | Users (%) |
|---|---|
| India | 643 (15.91%) |
| United States | 509 (12.6%) |
| Netherlands | 405 (10.02%) |
| Philippines | 238 (5.89%) |
| Brazil | 136 (3.37%) |
| United Kingdom | 105 (2.6%) |
| Turkey | 87 (2.15%) |
| Malaysia | 71 (1.76%) |
| Germany | 70 (1.73%) |
| China | 68 (1.68%) |

Table 6: Profile–prototype agreement by TRPI type in the TRPI sample ($N = 722$) and external IPIP-BFFM sample ($N = 1,013,558$) using Pearson

| Type | TRPI Mean $r$ | External Mean $r$ |
|---|---|---|
| ENTJ | 0.932 | 0.886 |
| ENTP | 0.901 | 0.874 |
| INFP | 0.912 | 0.861 |
| ENFJ | 0.887 | 0.873 |
| INTJ | 0.881 | 0.871 |
| INFJ | 0.864 | 0.856 |
| ISFP | 0.835 | 0.836 |
| ESFJ | 0.862 | 0.848 |
| ESTP | 0.827 | 0.823 |
| ESTJ | 0.845 | 0.842 |
| ISFJ | 0.837 | 0.832 |
| ISTJ | 0.861 | 0.850 |
| ENFP | 0.858 | 0.844 |
| ESFP | 0.743 | 0.788 |
| ISTP | 0.659 | 0.812 |
| INTP | 0.884 | 0.856 |

Table 7: Mean Big Five scores (0–1 scaled) by Jungian dichotomy, derived from TRPI-assigned types ($N = 722$)

| Dichotomy | Openness | Conscientiousness | Extraversion | Agreeableness | Neuroticism |
|---|---|---|---|---|---|
| E | 0.74 | 0.56 | 0.67 | 0.59 | 0.48 |
| I | 0.68 | 0.55 | 0.42 | 0.60 | 0.61 |
| S | 0.53 | 0.57 | 0.49 | 0.57 | 0.58 |
| N | 0.78 | 0.55 | 0.55 | 0.61 | 0.53 |
| T | 0.70 | 0.62 | 0.61 | 0.46 | 0.44 |
| F | 0.71 | 0.53 | 0.49 | 0.67 | 0.60 |
| J | 0.69 | 0.63 | 0.50 | 0.66 | 0.52 |
| P | 0.72 | 0.46 | 0.57 | 0.52 | 0.58 |

Table 8: Mean Big Five scores (0–1 scaled) by functional group, comparing TRPI ($N = 722$) and public IPIP-BFFM dataset ($N = 1{,}013{,}558$)

| | Pairing (Trait) | O | C | E | A | N |
|---|---|---|---|---|---|---|
| TRPI | xxTJ (C) | 0.59 | **0.75** | 0.57 | 0.45 | 0.47 |
| | xxTP (E) | 0.69 | 0.49 | **0.66** | 0.44 | 0.44 |
| | xxFJ (A) | 0.66 | 0.61 | 0.50 | **0.74** | 0.51 |
| | xxFP (N) | 0.66 | 0.44 | 0.49 | 0.56 | **0.68** |
| External | xxTJ (C) | 0.63 | **0.69** | 0.61 | 0.59 | 0.58 |
| | xxTP (E) | 0.66 | 0.60 | **0.65** | 0.57 | 0.58 |
| | xxFJ (A) | 0.64 | 0.64 | 0.58 | **0.68** | 0.55 |
| | xxFP (N) | 0.64 | 0.57 | 0.60 | 0.62 | **0.71** |

Table 9: Best-fit Empirical Cluster Centroid for Each Type

| **Type** | **Cluster** | **Correlation (r, p-value)** |
|---|---|---|
| ENFJ | Empirical Cluster 1 | $r = 0.906$, $p < 0.0090$ |
| ENFP | Empirical Cluster 2 | $r = 0.937$, $p < 0.0016$ |
| ENTJ | Empirical Cluster 1 | $r = 0.896$, $p < 0.0166$ |
| ENTP | Empirical Cluster 1 | $r = 0.945$, $p < 0.0018$ |
| ESFJ | Empirical Cluster 4 | $r = 0.812$, $p < 0.0890$ |
| ESFP | Empirical Cluster 2 | $r = 0.798$, $p < 0.1012$ |
| ESTJ | Empirical Cluster 1 | $r = 0.729$, $p < 0.2096$ |
| ESTP | Empirical Cluster 1 | $r = 0.841$, $p < 0.0502$ |
| INFJ | Empirical Cluster 4 | $r = 0.941$, $p < 0.0018$ |
| INFP | Empirical Cluster 2 | $r = 0.949$, $p < 0.0012$ |
| INTJ | Empirical Cluster 3 | $r = 0.886$, $p < 0.0170$ |
| INTP | Empirical Cluster 1 | $r = 0.896$, $p < 0.0082$ |
| ISFJ | Empirical Cluster 4 | $r = 0.885$, $p < 0.0180$ |
| ISFP | Empirical Cluster 3 | $r = 0.880$, $p < 0.0200$ |
| ISTJ | Empirical Cluster 3 | $r = 0.955$, $p < 0.0002$ |
| ISTP | Empirical Cluster 1 | $r = 0.723$, $p < 0.2450$ |

Table 10: Comparison of Theoretical and Empirical Trait Profiles for Each MBTI Type: Absolute Mean Difference and Pearson $r$

| | | **Theoretical** | | | | | **Empirical** | | | | | **(Mean)** | **r** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Type** | **Mode** | **O** | **C** | **E** | **A** | **N** | **O** | **C** | **E** | **A** | **N** | | |
| ENTP | Fight | 0.85 | 0.55 | 0.80 | 0.35 | 0.25 | 0.80 | 0.50 | 0.75 | 0.50 | 0.35 | 0.11 | 0.94 |
| ESTP | Fight | 0.65 | 0.60 | 0.85 | 0.40 | 0.30 | 0.65 | 0.55 | 0.80 | 0.40 | 0.50 | 0.10 | 0.95 |
| INTP | Fight | 0.75 | 0.60 | 0.35 | 0.30 | 0.50 | 0.70 | 0.45 | 0.50 | 0.40 | 0.35 | 0.13 | 0.94 |
| ISTP | Fight | 0.70 | 0.65 | 0.40 | 0.35 | 0.45 | 0.50 | 0.45 | 0.55 | 0.40 | 0.50 | 0.12 | 0.78 |
| ENTJ | Freeze | 0.80 | 0.90 | 0.75 | 0.35 | 0.25 | 0.70 | 0.80 | 0.70 | 0.45 | 0.30 | 0.08 | 0.99 |
| ESTJ | Freeze | 0.60 | 0.95 | 0.70 | 0.35 | 0.20 | 0.45 | 0.80 | 0.65 | 0.40 | 0.50 | 0.15 | 0.90 |
| INTJ | Freeze | 0.85 | 0.80 | 0.30 | 0.35 | 0.40 | 0.75 | 0.70 | 0.50 | 0.35 | 0.50 | 0.12 | 0.98 |
| ISTJ | Freeze | 0.50 | 0.90 | 0.25 | 0.30 | 0.35 | 0.45 | 0.65 | 0.40 | 0.40 | 0.55 | 0.16 | 0.90 |
| ISFJ | Fawn | 0.60 | 0.80 | 0.40 | 0.85 | 0.40 | 0.45 | 0.60 | 0.40 | 0.75 | 0.70 | 0.18 | 0.91 |
| INFJ | Fawn | 0.85 | 0.75 | 0.35 | 0.90 | 0.45 | 0.80 | 0.55 | 0.45 | 0.75 | 0.65 | 0.15 | 0.97 |
| ESFJ | Fawn | 0.70 | 0.80 | 0.60 | 0.90 | 0.35 | 0.50 | 0.65 | 0.55 | 0.70 | 0.45 | 0.14 | 0.90 |
| ENFJ | Fawn | 0.80 | 0.85 | 0.70 | 0.95 | 0.30 | 0.80 | 0.65 | 0.75 | 0.80 | 0.40 | 0.13 | 0.99 |
| ESFP | Flight | 0.75 | 0.50 | 0.90 | 0.70 | 0.40 | 0.60 | 0.50 | 0.60 | 0.60 | 0.65 | 0.16 | 0.92 |
| ENFP | Flight | 0.90 | 0.55 | 0.85 | 0.75 | 0.45 | 0.80 | 0.50 | 0.60 | 0.60 | 0.75 | 0.19 | 0.86 |
| ISFP | Flight | 0.65 | 0.60 | 0.35 | 0.70 | 0.50 | 0.50 | 0.50 | 0.40 | 0.45 | 0.70 | 0.12 | 0.88 |
| INFP | Flight | 0.95 | 0.50 | 0.30 | 0.80 | 0.55 | 0.60 | 0.45 | 0.40 | 0.60 | 0.85 | 0.23 | 0.69 |

Table 11: Mean Big Five trait scores (0–1 scaled) by TRPI type, comparing TRPI ($N = 722$) and FFM ($N = 1{,}013{,}558$) datasets

| | **TRPI** | | | | | **FFM** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Type** | O | C | E | A | N | O | C | E | A | N |
| ENFJ | 0.83 | 0.63 | 0.70 | 0.79 | 0.40 | 0.74 | 0.62 | 0.60 | 0.69 | 0.42 |
| ENFP | 0.81 | 0.44 | 0.57 | 0.54 | 0.71 | 0.73 | 0.52 | 0.56 | 0.64 | 0.63 |
| ENTJ | 0.68 | 0.78 | 0.66 | 0.46 | 0.29 | 0.67 | 0.75 | 0.65 | 0.56 | 0.40 |
| ENTP | 0.81 | 0.50 | 0.76 | 0.51 | 0.39 | 0.76 | 0.57 | 0.67 | 0.58 | 0.47 |
| ESFJ | 0.50 | 0.71 | 0.51 | 0.71 | 0.42 | 0.52 | 0.68 | 0.55 | 0.73 | 0.47 |
| ESFP | 0.65 | 0.43 | 0.68 | 0.67 | 0.54 | 0.64 | 0.51 | 0.62 | 0.68 | 0.59 |
| ESTJ | 0.42 | 0.78 | 0.75 | 0.48 | 0.46 | 0.48 | 0.73 | 0.71 | 0.56 | 0.51 |
| ESTP | 0.65 | 0.52 | 0.80 | 0.42 | 0.51 | 0.68 | 0.62 | 0.73 | 0.54 | 0.60 |
| INFJ | 0.80 | 0.53 | 0.42 | 0.75 | 0.59 | 0.73 | 0.59 | 0.42 | 0.75 | 0.57 |
| INFP | 0.67 | 0.40 | 0.37 | 0.63 | 0.78 | 0.73 | 0.51 | 0.40 | 0.70 | 0.66 |
| INTJ | 0.75 | 0.74 | 0.48 | 0.43 | 0.53 | 0.70 | 0.72 | 0.48 | 0.48 | 0.57 |
| INTP | 0.78 | 0.51 | 0.45 | 0.48 | 0.35 | 0.74 | 0.60 | 0.45 | 0.59 | 0.44 |
| ISFJ | 0.50 | 0.58 | 0.38 | 0.73 | 0.65 | 0.54 | 0.60 | 0.40 | 0.69 | 0.66 |
| ISFP | 0.51 | 0.48 | 0.33 | 0.41 | 0.71 | 0.53 | 0.55 | 0.35 | 0.59 | 0.68 |
| ISTJ | 0.49 | 0.69 | 0.37 | 0.43 | 0.61 | 0.54 | 0.66 | 0.41 | 0.56 | 0.63 |
| ISTP | 0.50 | 0.45 | 0.62 | 0.35 | 0.50 | 0.57 | 0.54 | 0.58 | 0.48 | 0.55 |