Building the Structure of Personality from the Bottom-Up using Hierarchical Exploratory Graph Analysis

Andrew Samo[1,*], Alexander P. Christensen[2,*], Francisco J. Abad[3], Luis Eduardo Garrido[4], Marcos Jiménez[3], Eduardo Garcia-Garzon[5], Hudson Golino[6], and Samuel T. McAbee[1]

[1] Department of Psychology, Bowling Green State University

[2] Department of Psychology and Human Development, Peabody College, Vanderbilt University

[3] Department of Social Psychology and Methodology, Universidad Autónoma de Madrid

[4] School of Psychology, Pontificia Universidad Católica Madre y Maestra

[5] Department of Psychology, Universidad Camilo José Cela

[6] Department of Psychology, University of Virginia

* Authors contributed equally

[This is a preprint of a manuscript under review.

It has not received peer-review feedback yet.

Read with caution!]

Author Note

The first author would like to thank Christopher M. Gallagher for the introduction to EGA.

All project materials are available on the Open Science Framework (OSF): osf.io/hwpa9/

There are no conflicts of interest regarding the authorship or production of this article.

CRediT Roles (ORCiD)

Andrew Samo (0000-0003-2225-184X): Conceptualization, Data Curation, Formal Analysis, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing

Alexander P. Christensen (0000-0002-9798-7037): Data Curation, Formal Analysis, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Francisco J. Abad: Formal Analysis, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing

Luis Eduardo Garrido (0000-0001-8932-6063): Formal Analysis, Methodology, Supervision, Validation, Writing – review & editing

Marcos Jiménez: Methodology, Writing – review & editing

Eduardo Garcia-Garzon (0000-0001-5258-232X): Writing – review & editing

Hudson Golino (0000-0002-1601-1447): Methodology, Software, Supervision, Writing – review & editing

Samuel T. McAbee (0000-0001-9083-1796): Supervision, Writing – review & editing

Abstract

Understanding the structure of personality is fundamental for efforts to describe, predict, and explain it. Many recent calls have suggested that personality should be investigated from the bottom-up, as item-specific variance captures meaningful differences in personality that is often obscured by aggregation. Using a large, open-source 300-item IPIP-NEO dataset (*N* = 149,337), we employed a novel network psychometrics approach to capture personality from the bottom-up. The approach started with identifying sets of locally dependent items using Unique Variable Analysis to remove statistical artifacts that could hinder accurate dimension recovery. This analysis yielded 239 items that were then subjected to a novel, iterative adaptation of Hierarchical Exploratory Graph Analysis to identify the dimensions of personality level-by-level. This method identified 30 first-level dimensions, 6 second-level dimensions, and 2 third-level dimensions. These dimensions were compared against the theoretical assignments of the IPIP-NEO. Although there was considerable overlap, there were many items not assigned to their theoretical facets and several items not assigned within their theoretical trait domains. One strength of our approach was that items and dimensions were allowed to covary freely and these covariances were represented at each level of the trait hierarchy. At each level, we compare our results with the theoretical taxonomy of personality and discuss the promise of our novel approach to understand personality from the bottom-up.

Keywords: personality structure; network analysis; hierarchical; exploratory graph analysis

Building the Structure of Personality from the Bottom-Up using Hierarchical Exploratory Graph Analysis

Personality reflects the typical patterns of thoughts, feelings, and behaviors people have that distinguish them from other people (Allport, 1966; Funder, 2009). Personality traits reliably predict a range of important work and life outcomes, including career attainment and success, marriage and divorce, and health and well-being (Anglim et al., 2020; Barrick & Mount, 1991; Ozer & Benet-Martínez, 2006). These predictions are stable across cultures (McCrae & Terracciano, 2005; Soto, 2019), time (Damian et al., 2019; Roberts & DelVecchio, 2000), and raters (Kim et al., 2019; McAbee & Connelly, 2016).

Traits are typically organized hierarchically based on lexical patterns of covariation (Markon, 2009) and consolidated around the 'Big Few' broad traits – such as the Big Five (Goldberg, 1990; McCrae & John, 1992) or HEXACO (Ashton & Lee, 2007) – despite personality existing beyond the Big Few (see Feher & Vernon, 2021). Above them, there is general consensus of two meta-traits (i.e., stability and plasticity; DeYoung et al., 2007; Digman, 1990), and some have suggested a single, general factor at the top (Musek, 2007). Below the Big Few, reaching a consensus remains a major challenge (Baumert et al., 2017; Block, 2010; Christensen et al., 2019; Condon et al., 2020; Mõttus et al., 2020; Schwaba et al., 2020).

The level below the Big Few varies depending on what inventory is used. Some have proposed personality aspects that are an intermediate level of the personality structure between the Big Few and lower-level facets (DeYoung et al., 2007). For nearly all inventories, the level below traits (and aspects) represents narrower, more specific characteristics called facets. There is wide variation in the number of these facets with some inventories capturing as few as twenty and as many as sixty, demonstrating that there is no clear consensus (Ashton & Lee, 2020; Irwing et al., 2023; Johnson, 2014; McCrae, 2015). Beyond the number of facets, others have suggested that their content remains unclear due to items associating more strongly with other facets (Christensen et al., 2019; Schwaba et al., 2020). Finally, at the lowest level, there appears to be as many personality nuances (e.g., items) as there are stars in the sky (Condon et al., 2020).

The goal of the present paper is to identify the number and content of each level of the trait hierarchy, from items to meta-traits, that is assessed in the International Personality Item Pool NEO (IPIP-NEO) inventory (Kajonius & Johnson, 2019). Using recent developments in network psychometrics, our study aims to address some limitations in previous attempts to establish levels in the trait hierarchy such as local dependence and unconstrained covariation between items and dimensions. This approach has the potential to enhance our understanding of personality structure and may improve subsequent prediction and explanation efforts.

Trait Hierarchies

There is renewed attention to different levels of the trait hierarchy as researchers increasingly reconsider the influence of personality components (Mõttus et al., 2019; Revelle et al., 2021; Stewart et al., 2022) and their roles in dynamic systems (Beck & Jackson, 2021b; Beckmann et al., 2021; Cervone & Little, 2019; Revelle & Wilt, 2021). These distinctions have substantial consequences for any subsequent descriptive, predictive, or explanatory efforts (Blum et al., 2021). Clarifying the trait hierarchy, as captured across people, can lead to more accurate substantive interpretations at each level.

Early investigations into personality's structure examined how item-level trait adjectives grouped together, based on empirical patterns of covariation, as consistently replicable dimensions (i.e., the psycholexical approach; Allport & Odbert, 1936; Cattell, 1943; Goldberg, 1990). After establishing the Big Few, subsequent personality research has largely operated within these frameworks and taxonomies (Block, 1995; John & Srivastava, 1999). Similarly, much of the modern research has reified the Big Few using latent variable methods (Hopwood & Donnellan, 2010; Irwing et al., 2023).

To reassess personality structure, many researchers have argued for more bottom-up approaches to emphasize item-specific variance (Condon et al., 2020; Mõttus et al., 2020). Bottom-up approaches allow covariation to occur freely between items, rather than assigning items to their theoretical facets, aspects, and trait domains, preserving information across hierarchy levels (Markon, 2009). By building from the most basic components of personality (e.g., single items), the taxonomic organization of personality can emerge organically (Condon et al., 2020; Revelle et al., 2021).

Building an Emergent Hierarchy

There are many approaches that can be used to build from the bottom-up (Irwing et al., 2023; Saucier et al., 2023). A natural choice comes from the recently developed field of network psychometrics (Epskamp, 2018). Network models are comprised of nodes (circles) that represent variables (e.g., items) and edges (lines) that represent the relationships (e.g., partial correlations) between nodes. Networks represent relationships between variables without boundaries – there is no clear divide between items that might belong to different theoretical dimensions (e.g., facets, aspects, traits). The theoretical interpretation of this representation, often referred to as the network perspective (Borsboom et al., 2021; Cramer et al., 2010), is that covariation between items arises because thoughts, feelings, and behaviors mutually reinforce one another (Schmittmann et al., 2013).

For personality, each level of its hierarchy can be understood as an emergent feature of the covariation between components at lower levels (Christensen, Golino, et al., 2020; Costantini et al., 2019; Cramer et al., 2012). An example might be that when people talk to other people, they get invited to parties where they talk to new people, and they get invited to more parties (Cramer et al., 2012). Across people, this pattern of behavior tends to co-occur more frequently together than other systems of behaviors (e.g., making the bed, worrying about what to make for dinner, daydreaming about their next hiking trip), representing a meaningful collection of associated behaviors that we refer to as sociability. Sociability, from this perspective, is a summary of more specific behaviors that tend to co-occur across people (Christensen, Golino, et al., 2020; Cramer, 2012).

Moving up the hierarchy, sociability, representing talking to others at parties, might also interact with a collection of associated behaviors that can be summarized by friendliness and another that can be summarized by warmth, which collectively tend to co-occur more frequently than other summaries (e.g., organized, anxiousness, fantasy proneness), resulting in a broad pool of behaviors that we refer to as extraversion. What this description leaves out, however, is that the specific behaviors (items) we might summarize as sociability can and *do* co-occur with other behaviors that may include other summaries within extraversion but also behaviors (e.g., believe other people are good, care about other people’s feelings) and summaries (e.g., trust, empathy) related to agreeableness. The network representation supports these cross-theoretical relationships, allowing them to form without constraint and resulting in emergent summaries that may otherwise be obscured by aggregating items based on theory. The network approach, therefore, embraces the full complexity of personality from the item-level on up.

Exploratory Graph Analysis Framework

The Exploratory Graph Analysis (EGA) framework has emerged as a common approach to evaluate dimension structure in psychology. EGA (Golino & Epskamp, 2017; Golino et al., 2020) applies the graphical least absolute shrinkage and selection operator (GLASSO; Friedman et al., 2008) with extended Bayesian information criterion (EBIC; Chen & Chen, 2008) model selection to obtain a network (commonly referred to as EBICglasso; Epskamp & Fried, 2018). The GLASSO is a regularization method on the (inverse) covariance matrix that shrinks coefficients and reduces some to zero, resulting in a sparse network structure. On this network structure, a community detection algorithm, such as the Walktrap algorithm (Pons & Latapy, 2006), is applied, which identifies *communities* or sets of connected nodes that are consistent with latent factors in factor models (Golino & Epskamp, 2017).

More recently, the Louvain algorithm (Blondel et al., 2008) was identified as a promising alternative to the Walktrap algorithm, demonstrating equivalent performance in simulation studies (Gates et al., 2016; Christensen et al., 2023). A key benefit of the Louvain algorithm is that it identifies communities in iterative passes over the network, resulting in so-called “multi-level” communities such that the first pass identifies many small communities and with each pass larger, broader communities are formed. This feature of the algorithm was leveraged in a recent simulation study to identify hierarchical structures (Jiménez et al., 2023).

Jiménez and colleagues (2023) simulated bifactor data across a variety of conditions and evaluated Kaiser methods (eigenvalue greater-than-one and empirical Kaiser criterion), parallel analysis methods (principal axis factoring and principal component analysis), and EGA with the Louvain algorithm to detect the number of lower (group) and higher (general) order factors. To identify higher order communities, the original Louvain algorithm sums the edges of the nodes that belong to each community to create “latent nodes” representing each community, which are then used in the next pass of the algorithm (Blondel et al., 2008). Jiménez and colleagues (2023) adapted this approach to instead compute exploratory factor analysis scores from the raw data using the number of communities detected after the first pass of the Louvain. This adaptation proved critical. For the lower order factor identification, EGA had the best overall accuracy (0.86) relative to the next most accurate method—parallel analysis with principal component analysis (0.83). For the higher order identification, EGA with factor scores had near perfect accuracy across all conditions (1.00), performing as well as or better than parallel analysis with principal component analysis with factor scores (0.99). Importantly, the factor score adaptation significantly improved the accuracy of the Louvain algorithm over its standard implementation (0.10). This study demonstrates that psychometric networks can be used to accurately identify hierarchical structures.

One benefit of modeling hierarchical structures with networks is that the complexity of the associations between variables are represented at each level of the hierarchy, maintaining a more complete representation of personality from the bottom-up. To our knowledge, there has been one other study that has applied a network approach with hierarchical community detection. Castro, Ferreira, and Ferreira (2020) applied a non-regularized network estimation method to the IPIP-NEO-120, a shortened version of the same scale that our study reanalyzes. To identify a hierarchical structure in the network, they used the ModuLand algorithm (Kovács et al., 2010), which applies a function to assess the proximal space of each edge in the network. Using this proximity function, the algorithm can estimate communities that can have items that overlap (i.e., some items can belong to multiple communities) as well as estimate communities at higher levels. Their results revealed 35 first order communities, which were similar to the theoretical 30 facets, and 9 second order communities with two of the communities comprised of a single Big Five personality trait (openness to experience) and most other communities were mixed with a tendency to reflect more of one trait than the others. These results demonstrate that when a bottom-up approach to personality is applied, the taxonomic structure of personality may not be as definitive as it is often made to be.

Present Research

The present research aims to identify the hierarchical structure of personality from the bottom-up using the hierarchical EGA approach (Jiménez et al., 2023). Building on the original two-level implementation of Jiménez and colleagues (2023), our application involves an iterative implementation of the Louvain algorithm combined with network scores (Golino et al., 2022) to explore more than two levels of personality structure. A key component of our approach involved the detection and mitigation of local dependence violations in the data. Recently, a network psychometrics approach called Unique Variable Analysis (UVA; Christensen, Garrido, Golino, 2023) was developed to identify and remove local dependence violations. UVA was found to perform as well as or better than contemporary approaches for detecting these violations. To our knowledge, taxonomic studies of personality has yet to *statistically* evaluate local dependence violations (cf. Irwing et al., 2023). Local dependence violations can lead to biases in dimension identification (e.g., split dimensions; Castro et al., 2020) and parameter estimation (e.g., loadings; Edwards et al., 2018). These biases can proliferate and compound through each level of the analysis, leading to significant biases in the resulting structure. Identification and mitigation of local dependence was performed before our hierarchical procedure was applied.

Method

Participants

We used archival personality data from Johnson's IPIP-NEO repository (e.g., Kajonius & Johnson, 2019). The IPIP-NEO has been identified as an ideal starting place for bottom-up efforts (Castro et al., 2020; Condon et al., 2020). The IPIP-NEO 300 item dataset has 307,313 cases and is available on their OSF (https://osf.io/tbmh5). All items were kept in their original coding, which was coded in the direction of the theoretical facet (e.g., *Seldom get mad* was recoded such that 1 = 5, 2 = 4, 4 = 2, and 5 = 1). The dataset was subset to include respondents based in the United States of America (U.S.) between 19 to 69 years old for a working sample of N = 149,337. The constraint on the region and age range was intended to mitigate common sources of noninvariance such as age and culture (but see Beck et al., 2023, Olaru et al., 2019, and Syed, 2021 for limitations that may exist beyond our constraint).

Statistical Analysis

Missingness

Although the rate of missing data was small (0.4%), there were 183,923 total missing observations due to the large sample. Missing data were imputed by taking the rounded mean of each variable (e.g., 3.56 = 4; 2.21 = 2), as is appropriate when the missing data rate is minor (i.e., < 1 – 2%; Widaman, 2006).[1]

Network Estimation

All networks were estimated with the EBICglasso (Epskamp & Fried, 2018; Foygel & Drton, 2010). The EBICglasso estimates a Gaussian Graphical Model (GGM; Lauritzen, 1996), where nodes represent variables and edges represent partial correlations between two variables conditioned on all other variables. For the UVA and the first level, polychoric correlations were computed between the ordinal item scores; for the second and third levels, Pearson's correlations were computed between the continuous network scores.

Unique Variable Analysis

With the complete dataset, UVA was used to identify and remove local dependence in the data (e.g., Forbes, 2023). UVA detects local dependencies in the data by estimating a network and quantifying the similarity between nodes with the weighted topological overlap and retains nodes based on their similarity to other nodes (see Christensen et al., 2023). The UVA weighted topological overlap (wTO) threshold was set to 0.20.

To select which variables to retain and remove from redundant pairs (two items) or sets (three or more items), an automated, heuristic procedure was used (Christensen et al., 2023). For redundant pairs, the item that had the lowest maximum wTO with all other variables was retained. The rationale for this heuristic is that the variable with the lower wTO to all other items will possess more unique information. For redundant sets, the item that has the highest mean wTO to all other variables within the set is retained and all other variables are removed. The rationale for this heuristic is that the variable with information most common across items in the redundant set will retain the largest proportion of common variation in the set.

Exploratory Graph Analysis

Community detection. The Louvain community detection algorithm with consensus clustering was applied at each level. The Louvain algorithm is an iterative procedure that starts with each node as a community. The algorithm then proceeds over each node in order, merging nodes into existing communities that maximize modularity (i.e., a statistic that quantifies the extent to which within-community connections are greater than between-community

[1] See the Supplementary Information for a breakdown of the frequency of missing observations.

connections; Newman, 2006). Once all nodes have been passed over once, the procedure concludes its first pass. The standard implementation constructs a new network by summing the edges between the nodes in each community (Blondel et al., 2008). Our implementation, however, followed Jiménez and colleagues' (2023) approach by computing network scores based on the first pass of communities. These network scores were then used to estimate the next level in the hierarchy. One limitation of the Louvain algorithm is that the algorithm merges communities node-by-node. This limitation means that the order in which the nodes are submitted to the algorithm can result in different solutions. It is common practice to shuffle the node order when applying the algorithm. Because of this shuffling, the algorithm is stochastic.

Consensus clustering. The community consensus approach aims to mitigate the stochastic nature related to the node order in the Louvain algorithm, providing more stable solutions (Lancichinetti & Fortunato, 2012). This approach applies a community detection algorithm (i.e., Louvain) *N* times to the same network. The standard approach is to cluster nodes based on how frequently they co-occur in their community memberships across applications. A threshold of 0.30 is usually applied to set co-occurrences less than 30% to zero before iteratively applying the algorithm again for *N* iterations. Our approach deviated from this method and instead applied the Louvain algorithm N = 100,000 times once and used the most common solution. To arrive at a more stable, reproducible solution, we applied the community consensus method with 100,000 iterations 100 times (replicates) and used the most common solution across these 100 replicates. This procedure mirrors the Bootstrap EGA procedure that has been used to identify the generalizability of empirical EGA results (Christensen & Golino, 2021).

Comparison to theory. To compare the current, empirically derived network solutions to the existing, theoretical IPIP-NEO structure, the first and second level solutions were evaluated. For the first level, the proportion of items in each theoretical dimension that were identified together in an empirical dimension was computed. For instance, if 8 of 10 items of Neuroticism's Anxiety facet were identified as belonging to one empirical dimension, then the proportion would be 0.80. For the second level, each empirical dimension was "mapped" to a theoretical dimension based on the overall proportion of items that were represented in the theoretical dimension (see Figure 2).

Procedure

Statistical Analysis

Our data analysis procedure started with UVA, which was iteratively applied until there were no remaining local dependencies. Over three passes, UVA identified 46 local dependencies, reducing the 300-item IPIP to 249 items.[2] Next, the first level structure was estimated by applying EGA with the first pass of the Louvain algorithm using consensus clustering with 100,000 iterations for 100 repetitions (Lancichinetti & Fortunato, 2012). In this first application, there were 10 two-node communities, which are considered problematic in terms of establishing a dimension in psychometrics (DeVellis, 2017). Only one variable from each of these communities were retained resulting in a final total of 239 items.

To estimate the next level, network scores were computed by matrix multiplying each variable's assigned community's network loading by the data resulting in a weighted sum score for each community (Christensen & Golino, 2021; Golino et al., 2022). Based on these network scores, EGA was applied using the same approach as the first level: the first pass of the Louvain algorithm using consensus clustering with 100,000 iterations 100 repetitions. This procedure was repeated at each new level.

Dimension Interpretation

To interpret and label the network dimensions at each level several of the authors met to interpret the dimension content and label the dimensions accordingly. The authors aimed to keep the dimension interpretations in line with the existing theoretical IPIP structure; opting to keep the theoretical IPIP labels for dimensions with mostly theoretically aligned content and considering new labels for dimensions with new content orientations. At the same time, GPT-4, a foundational language model (OpenAI, 2023), was used to augment the human decision-making process (i.e., Brynjolfsson, 2023) by providing detailed prompting and item-based descriptions of the communities to the language model (see the Supplementary Information for prompts and full GPT-4 output). The authors met again to compare the sets of human and GPT-4 labels in order to finalize the dimension interpretation and labelling.

Openness & Transparency

All code, output, supplemental tables, and a link to the Johnson IPIP-NEO repository are available on the project OSF (osf.io/hwpa9/). Analyses were conducted in R (version 4.3.1; R Core Team, 2023) using *EGAnet* (version 2.0.0; Golino & Christensen, 2023).

Results

Level 1: Facets

Based on the most common community solutions identified by the consensus clustering, there were two solutions that were most frequently identified. The two solutions were identical, except that one dimension either remained as a single dimension (second most common solution with 19 out of 100 repetitions;) or it was split into two dimensions (most common

[2] Variables that were retained and removed are presented in the Supplemental Information

solution with 34 out of 100 repetitions;). To select between these two solutions, we computed the Total Entropy Fit Index (TEFI; Golino et al., 2021), where lower values are better, which suggested that the second most common solution (single dimension; TEFI = -605.710) had a better fit than the most common solution (split dimension; TEFI = -594.72).

This final first level solution of EGA identified 30 communities (Figure 1). A summary of each of the empirically-derived dimensions are provided below with brief descriptions that were informed by their item content (full descriptions provided by GPT-4 are provided in the Supplemental Information; OpenAI, 2023). The theoretical dimensions that are most represented in the dimensions are listed along with the number of items from the theoretical facet (in parentheses). As a reminder for the interpretation of the empirical dimensions, all items were originally recoded in the direction of their theoretical facet. Polychoric correlations between items are presented in the Supplemental Information.

Dimension 1: Anxiety (17 items)

There were 17 items in total that represented mainly a mix of Anxiety (8 of 10 items) and Vulnerability (7 of 8 items). When considering a label for this dimension, much of the item content are clearly related to anxiety including the Vulnerability items (e.g., *Remain calm under pressure* [reversed], *Panic easily*, *Become overwhelmed by events*). Indeed, the theoretical definition of Vulnerability is highly consistent with anxiety: “vulnerability to stress…easily rattled, panicked, and unable to deal with stress” (p. 86, Piedmont, 1998). The label “Anxiety” is therefore apt, and the theoretical facet Vulnerability appears to potentially be mislabeled, as the content of this dimension may reflect sensitivity to negative stimuli. The top three items loading (in parentheses) on this dimension were *Panic easily* (0.28), *Worry about things* (0.27), and *Get stressed out easily* (0.27).

Dimension 2: Gregariousness (24 items)

The second dimension had the most items, twenty-four, and represented a heterogeneous mixture of several theoretical facets but was largely comprised of Friendliness (8 of 10 items) and Gregariousness (8 of 8 items) as well as half of Neuroticism’s Self-consciousness (5 of 10 items), relating to interacting with others or being the center of attention. This dimension equally merged the Friendliness and Gregariousness facets. Much like the theoretical Anxiety and Vulnerability facets, the Friendliness and Gregariousness facets appear to be closely aligned where they represent a single dimension rather than two distinct dimensions. People high in Gregariousness are characterized as “having many friends and seeking social contact” and those low as “tend to be loners who do not seek—or who even actively avoid—social stimulation” (p. 86, Piedmont, 1998). This definition aligns with the item descriptions of the Friendliness items such as *Make friends easily*, *Feel comfortable around people*, and *Avoid contacts with others*. Given the consistency of this dimension with the theoretical definition, the Gregariousness label was retained. The top three items loading (in parentheses) on this dimension were *Feel comfortable around people* (0.30), *Talk to a lot of different people at parties* (0.24), and *Love large parties* (0.23).

Dimension 3: Trust (6 items)

The third dimension was comprised of 6 items with most of them representing the Trust facet (4 of 4 items) with single items from Altruism (1 of 10 items) and Cooperation (1 of 9 items). Because this dimension fully captured the theoretical Trust items, and optimism toward others, “Trust” was used as the label. The top three items loading (in parentheses) on this dimension were *Trust others* (0.36), *Believe in human goodness* (0.36), and *Suspect hidden motives in others* (0.31).

Dimension 4: Diligence (9 items)

Nine items comprised the fourth dimension with Self-efficacy (4 of 10 items) being the dominate theoretical facet. The other five items in the dimension came from the other five theoretical facets of Conscientiousness. This dimension was characterized by a competence at completing tasks and was labeled “Diligence.” The top three items loading (in parentheses) on this dimension were *Handle tasks smoothly* (0.36), *Complete tasks successfully* (0.32), and *Know how to get things done* (0.24).

Dimension 5: Anger (9 items)

All nine, except for one (Agreeableness’s Cooperation), items were from the theoretical Anger facet (8 of 9 items) and made up the fifth dimension, making “Anger” an appropriate label. There were 9 items in both the empirical and theoretical Anger dimensions, leading to a mostly replicated dimension. The top three items loading (in parentheses) on this dimension were *Get angry easily* (0.40), *Seldom get mad* (0.35), and *Rarely get irritated* (0.34).

Dimension 6: Conformity (4 items)

The sixth dimension had 4 items which were equally divided by the Conscientiousness’s Dutifulness (2 of 9 items) and Agreeableness’s Morality (2 of 9 items) facets. This dimension related to conforming to the rules (e.g., *Try to follow the rules*, *Know how to get around the rules*) and did not capture the majority of the representation of either theoretical facet. The label “Conformity” most aptly described the item content of this dimension. The top three items loading (in parentheses) on this dimension were *Break the rules* (0.47), *Try to follow the rules* (0.39), and *Know how to get around the rules* (0.27).

Dimension 7: Orderliness (6 items)

All six, except for one (Self-discipline), items were from the theoretical Orderliness facet (5 of 6 items), largely replicating Orderliness and retaining the label. The top three items loading (in parentheses) on this dimension were *Like to tidy up* (0.57), *Like order* (0.30), and *Leave my belongings around* (0.30).

Dimension 8: Dominance (15 items)

The eighth dimension included 15 items and represented a mixture of several different theoretical facets, mostly comprised of Agreeableness's Cooperation (6 of 9 items) and Extraversion's Assertiveness (3 of 5 items). The Cooperation items were mostly items that would be negatively (reverse) coded in the theoretical facet such as *Love a good fight* and *Insult people*, capturing quarrelsome or antagonistic content, but would actually be positively coded items in this empirical dimension. Assertiveness items included *Take charge* and *Seek to influence others*. These behaviors were all related to social dominance and therefore the label "Dominance" was selected. The top three items loading (in parentheses) on this dimension were *Can't stand confrontations* (0.30), *Am able to stand up for myself* (0.25), and *Put people under pressure* (0.24).

Dimension 9: Emotionality (7 items)

All seven, except for one (Neuroticism's Vulnerability), items for the ninth dimension were from the theoretical Emotionality facet (6 of 8 items). This dimension largely captured emotionally intensity and therefore the label remained "Emotionality." The top three items loading (in parentheses) on this dimension were *Seldom get emotional* (0.40), *Am not easily affected by my emotions* (0.39), and *Experience my emotions intensely* (0.34).

Dimension 10: Variety-seeking (9 items)

The tenth dimension replicated (8 of 9 items) the majority of the original theoretical facet Adventurousness. This dimension largely replicated a data-driven dimension called "Variety-seeking" that was identified when analyzing multiple Openness to Experience inventories (including NEO-PI-3; Christensen et al., 2019) and therefore this label was used. The top three items loading (in parentheses) on this dimension were *Don't like the idea of change* (0.45), *Prefer to stick with things that I know* (0.31), and *Am a creature of habit* (0.27).

Dimension 11: Contentment (5 items)

The eleventh dimension had 5 items centered around low activity, easy-going, and laid-back items that were most in the theoretical facet of Activity Level (3 of 6 items). All items except for *Am easy to satisfy* (Cooperation) were items that would be negatively (reverse) coded in their theoretical dimensions. This dimension was labeled "Contentment." The top three items loading (in parentheses) on this dimension were *Let things proceed at their own* (0.34), *Like to take my time* (0.28), and *Am relaxed most of the time* (0.27).

Dimension 12: Determination (8 items)

The twelfth dimension had 8 items that were another mixture of different Conscientious-related facets with Achievement-striving (3 of 8 items) having the most items while all other items were single items from various facets. This dimension could be characterized by a motivation to have goals, direction, and carry out plans, earning the label “Determination.” The top three items loading (in parentheses) on this dimension were *Carry out my plans* (0.42), *Turn plans into actions* (0.27), and *Stick to my chosen path* (0.25).

Dimension 13: Excitement-seeking (5 items)

Five items comprised the thirteenth dimension with Excitement-seeking (3 of 10 items) comprising the majority of the items in the dimension. All items in this dimension were a desire to seek out stimulation such as *Am always on the go*, *Seek adventure*, and *Love action*. This dimension did not truly align with the theoretical facet since the rest of the Excitement-seeking items comprise another empirical dimension; however, this dimension had high activity content that was more related to general excitement-seeking than the other empirical dimension (i.e., Dimension 30: Recklessness), which tended toward more extreme forms of excitement-seeking. For this reason, this dimension retained the label of “Excitement-seeking.” The top three items loading (in parentheses) on this dimension were *Seek adventure* (0.46), *Love action* (0.40), and *Love excitement* (0.36).

Dimension 14: Intellect (14 items)

The fourteenth dimension comprised 14 items mostly related to self-assessment of problem-solving ability and intellectual interests. The theoretical Intellect facet (7 of 8 items) represented half of the items in the dimension, with items from all theoretical domains, except Extraversion, having cognitively loaded content (e.g., Neuroticism’ *Stumble over my words* and Agreeableness’ *Know the answer to many questions*). The top three items loading (in parentheses) on this dimension were *Have difficulty understanding abstract ideas* (0.38), *Have a rich vocabulary* (0.30), and *Know the answers to many questions* (-0.28).

Dimension 15: Modesty (7 items)

Seven items comprised the fifteenth dimension, composed of (not) seeking attention, with five items coming from the theoretical Modesty facet (5 of 8 items). The theoretical dimension, Modesty, was mostly captured in this dimension so the label was retained. The top three items loading (in parentheses) on this dimension were *Don’t like to draw attention to myself* (-0.43), *Make myself the center of attention* (0.39), and *Dislike being the center of attention* (0.29).

Dimension 16: Cheerfulness (10 items)

All ten, except for one, items of the sixteenth dimension belonged to the theoretical Cheerfulness facet (9 of 9 items). Because this dimension completely replicated the theoretical Cheerfulness facet with one item, *Cheer people up*, in the theoretical Friendliness facet, it retained the label “Cheerfulness.” The top three items loading (in parentheses) on this dimension were *Laugh aloud* (0.34), *Seldom joke around* (0.31), and *Amuse my friends* (0.27).

Dimension 17: Liberalism (7 items)

Similarly, the seventeenth dimension had all seven, except for one, items belong to the theoretical Liberalism facet (6 of 6 items). The other item belonged to Agreeableness’s Sympathy facet, *Believe in eye for an eye*. Because this dimension completely replicated the theoretical Liberalism facet, the label was retained. The top three items loading (in parentheses) on this dimension were *Tend to vote for liberal political candidates* (0.42), *Believe that criminals should receive help rather than punishment* (0.36), and *Believe laws should be strictly enforced* (0.29).

Dimension 18: Melophile (3 items)

Three items related to enjoyment of music (*Like music*, *Do not like concerts*, *Dislike loud music*) were identified as the eighteenth dimension, earning the label “musicophilia.” This narrow dimension was given the label “Melophile” to describe an affinity for music. The top three items loading (in parentheses) on this dimension were *Like music* (0.41), *Dislike loud music* (0.38), and *Do not like concerts* (0.35).

Dimension 19: Empathy (16 items)

The nineteenth dimension had 16 items that were largely from the theoretical Altruism (7 of 10 items) and Sympathy (6 of 8 items). These items, along with the others, were all related to caring about others, being interested in others, and showing concern for people less fortunate. All items were consistent with the label “Empathy.” The top three items loading (in parentheses) on this dimension were *Am concerned about others* (0.37), *Am indifferent to the feelings of others* (0.29), and *Am not really interested in others* (0.29).

Dimension 20: Work Ethic (5 items)

All five items in the twentieth dimension represented working hard in the theoretical Achievement-striving facet (5 of 9), resulting in a fully homogeneous dimension that was labelled “Work Ethic.” This dimension was characterized by the intensity of goal pursuit. The top three items loading (in parentheses) on this dimension were *Do just enough work to get by* (0.40), *Do more than what’s expected of me* (0.36), and *Put little time and effort into my work* (0.34).

Dimension 21: Impulsivity (9 items)

The 9 items of the twenty-first dimension largely represented the theoretical facet of Cautiousness (7 of 9 items). The other two items, *Don't know why I do some of the things I do* and *Don't see the consequences of things*, were from the theoretical facets Immoderation and Self-efficacy. Across the items, the label of "Impulsivity" best captured the acting first and thinking later behaviors. The top three items loading (in parentheses) on this dimension were *Act without thinking* (0.49), *Jump into things without thinking* (0.44), and *Rush into things* (0.37).

Dimension 22: Aesthetic Appreciation (6 items)

The twenty-second dimension represented the 6 items of the theoretical Artistic Interests facet (6 of 8) that were not related to music. Although this dimension mostly replicated the theoretical dimension, the refined content focused on aesthetics more broadly than art (i.e., nature) and most aligned with previous evidence of "Aesthetic Appreciation" (Christensen et al., 2019). The top three items loading (in parentheses) on this dimension were *Do not like poetry* (0.38), *Enjoy the beauty of nature* (0.36), and *Love flowers* (0.30).

Dimension 23: Morality (8 items)

The eight items of the twenty-third dimension were a combination of the theoretical Morality (5 of 8 items) and Dutifulness (3 of 9 items) facets. These items were largely related to manipulative and conniving tendencies like *Use flattery to get ahead*, *Obstruct others' plans*, and *Cheat to get ahead*. Because the items are scored in the direction of the theoretical dimensions of Morality and Dutifulness, the label of "Morality," as the opposite of manipulativeness was selected. This dimension mostly replicated the theoretical Morality facet and therefore the label was retained. The top three items loading (in parentheses) on this dimension were *Take advantage of others* (0.43), *Use others for my own ends* (0.36), and *Get others to do my duties* (0.24).

Dimension 24: Moodiness (3 items)

The twenty-fourth dimension had three items that related to "Moodiness" (theoretical facet and loadings in parentheses): *Have frequent mood swings* (Depression; 0.37), *Am often in a bad mood* (Anger; 0.37), *Seldom feel blue* (Depression; 0.20).

Dimension 25: Self-esteem (3 items)

All three items of the twenty-fifth dimension were related to "Self-esteem" (theoretical facet and loadings in parentheses): *Have a low opinion of myself* (Depression; 0.48), *Feel comfortable with myself* (Depression; 0.38), and *Think highly of myself* (Modesty; 0.36).

Dimension 26: Introspection (6 items)

The twenty-sixth dimension had 6 items that were mainly from the theoretical

Imagination facet (4 of 4 items). The other two items were related to thinking deeply (theoretical dimensions in parentheses): *Enjoying examining myself and my life* (Emotionality) and *Enjoy thinking about things* (Intellect). Although the theoretical Imagination facet was fully represented, the content was a combination of self-reflection, imagination, and introspection. The overall theme seemed best captured by the label “Introspection” and is consistent with previous theoretical work on Openness to Experience (Connelly et al., 2014). The top three items loading (in parentheses) on this dimension were *Enjoy thinking about things* (0.41), *Spend time reflecting on things* (0.40), and *Seldom get lost in thought* (0.27).

Dimension 27: Integrity (3 items)

Three items of the theoretical Dutifulness facet (3 of 9 items) comprised the twenty-seventh dimension: *Tell the truth*, *Listen to my conscience*, and *Break my promises*. “Integrity” was used as the label for this dimension given to the content relating to being straightforward and keeping one’s word (opposite of breaking promises). The top three items loading (in parentheses) on this dimension were *Tell the truth* (0.44), *Break my promises* (0.27), and *Listen to my conscience* (0.20).

Dimension 28: Immoderation (6 items)

The twenty-eighth dimension was comprised of 6 items all from the theoretical Immoderation facet (6 of 7 items). This dimension mostly replicated the theoretical dimension of “Immoderation” and therefore retained the label. The top three items loading (in parentheses) on this dimension were *Rarely overindulge* (0.51), *Am able to control my cravings* (0.41), and *Easily resist temptations* (0.29).

Dimension 29: Self-discipline (4 items)

The four items of the twenty-ninth dimension all belonged to the theoretical Self-discipline facet (4 of 7 items) and related to motivational activation and associated difficulties of getting to work. Because all items were mostly represented by “Self-discipline”, this dimension retained the label. The top three items loading (in parentheses) on this dimension were *Find it difficult to get down to work* (0.50), *Need a push to get started* (0.30), and *Get to work at once* (0.26).

Dimension 30: Recklessness (5 items)

The final dimension was comprised of 5 items from the theoretical Excitement-seeking dimension (5 of 10), which all corresponded to excitement-seeking in a perilous way (e.g., *Seek danger*, *Enjoy being reckless*, *Act wild and crazy*). Although this dimension was comprised of Excitement-seeking items only, a more apt label was “Recklessness” as the excitement sought in these items were on the more extreme end. The top three items loading (in parentheses) on this dimension were *Seek danger* (0.43), *Enjoy being reckless* (0.36), and *Would never go hang gliding or bungee jumping* (0.27).

Summary

Overall, the 30 dimensions first order dimensions identified by EGA analysis aligned moderately well with the IPIP-NEO's proposed 30 facets (Kajonius & Johnson, 2019; Figure 2). The major differences were either the result of similar content across different IPIP-NEO facets being combined into a comprehensive, broader facet or unique content being subset into more nuanced, specific facets. One takeaway was that only five theoretical facets (i.e., Gregariousness, Trust, Cheerfulness, Liberalism, Imagination) remained completely intact across the empirical dimensions. There were many facets that had the majority of their items (often missing a single item) in the empirical dimensions (i.e., Anger, Orderliness, Adventurousness, Intellect, Inmoderation). This result suggests that while the theoretical facets usually represent consistent content, there are some idiosyncratic item(s) that may better fit with other dimensions.

Level 2: Trait Domains

The second level of EGA identified 6 communities (Figure 3). A summary of each of the empirically-derived dimensions are provided below with the first order dimensions that were assigned to them. Pearson correlations between dimensions are presented in the Supplemental Information on the OSF.

Dimension 1: Neuroticism (65 items)

The first dimension (loadings in parentheses) was comprised of Anger (0.49), Anxiety (0.41), Moodiness (0.41), Emotionality (0.25), Trust (-0.20), Contentment (0.17), Self-esteem (0.16), and Dominance (-0.09) first-level dimensions. This dimension had the majority of items in the theoretical dimension of Neuroticism (34 of 50 items) followed by Agreeableness (18 of 48 items), Extraversion (7 of 48 items), and Openness to Experience (6 of 43 items). Overall, the dimension reflected a susceptibility towards negative affectivity and irritability versus emotional stability and regulation. Note that some theoretical Neuroticism facets are more represented in other dimensions (i.e., Self-consciousness in Sociability, and Immoderation in Sensation-Seeking; Figure 2).

Dimension 2: Sociability (41 items)

The second dimension (loadings in parentheses) was composed of Gregariousness (0.53), Modesty (-0.34), and Cheerfulness (0.27) first-level dimensions. This dimension had the majority of items in the theoretical dimension of Extraversion (29 of 48 items) followed equally by Agreeableness (6 of 48 items) and Neuroticism (6 of 50 items). Overall, the dimension reflected a tendency for engagement with versus withdrawal from the social world. Note that some theoretical Extraversion facets were more represented in other dimensions (i.e., Assertiveness and Activity-level in Neuroticism, and Excitement-seeking in Sensation-seeking; Figure 2).

Dimension 3: Conscientiousness (32 items)

The third dimension was comprised of the Self-discipline (0.45), Diligence (0.44), Determination (0.38), Work Ethic (0.35), and Orderliness (0.23) first-level dimensions. This dimension, relative to all other empirical dimensions, most closely mirrored a theoretical trait domain: Conscientiousness (30 of 50 items). There were a couple items from Neuroticism (1 of 50 items) and Extraversion (1 of 48 items). Overall, the dimension reflected an orientation towards achievement, organization, and goal pursuit as opposed to procrastination, disorganization, and goal disengagement. Note that some theoretical Conscientiousness facets are more represented in other dimensions (i.e., Dutifulness in Moral Integrity and Cautiousness in Sensation-seeking; Figure 2).

Dimension 4: Moral Integrity (31 items)

The fourth dimension (loadings in parentheses) was composed of Morality (0.48), Integrity (0.32), Conformity (0.27), and Empathy (0.23) first-level dimensions, which overlapped most with Agreeableness (21 of 48 items) followed by Conscientiousness (8 of 50 items), Extraversion (1 of 48 items), and Openness to Experience (1 of 43 items). Overall, the dimension reflected a tendency for honesty and ethical behavior versus dishonesty and manipulativeness. Note that some theoretical Agreeableness facets are more represented in other dimensions (i.e., Trust and Cooperation in Neuroticism, and Modesty in Sociability).

Dimension 5: Openness to Experience (42 items)

The fifth dimension (loadings in parentheses) was comprised of Intellect (0.38), Introspection (0.38), Aesthetic Appreciation (0.28), Variety-seeking (0.27), and Liberalism (0.22) first-level dimensions. This dimension had the second highest overlap with a theoretical trait domain, Openness to Experience (33 of 38 items). The other domains included Conscientiousness (4 of 50 items), Agreeableness (3 of 48 items), and Neuroticism (2 of 50 items). Overall, the dimension reflected an orientation toward new experiences, aesthetics, and cognitive complexity versus being closed, conventional, and cognitively rigid. Note that some theoretical Openness facets are more represented in other dimensions (i.e., Emotionality in Neuroticism).

Dimension 6: Sensation-seeking (28 items)

The sixth dimension (loadings in parentheses) represented a novel dimension relative to the theoretical Big Five, comprised of Recklessness (0.47), Excitement-seeking (0.36), Impulsivity (-0.34), Melophile (0.15), and Immoderation (0.15) first-level dimensions. In terms of overlap, this dimension was evenly represented across Extraversion (10 of 48 items), Conscientiousness (8 of 50 items), Neuroticism (7 of 50 items), and Openness to Experience (3 of 43 items). Overall, the dimension reflected a tendency toward action, stimulation, risk-taking and thrill-seeking versus being deliberate, thoughtful, and cautious.

Summary

Although the 6 communities might initially appear to support the existing five and six factor models (i.e., HEXACO; Ashton et al., 2007; 2020), closer inspection reveals several notable departures from the content space of previously established taxonomies (Figure 2). Starting first with the most similar, Conscientiousness was most similar to the Conscientiousness content in the IPIP-NEO. Only two items, *Can manage many things at the same time* (Extraversion) and *Feel that my life lacks direction* (Neuroticism), were included from other theoretical trait domains, with both items capturing content related to having and managing goals.

The Openness to Experience dimension was also quite similar to the Openness to Experience content in the IPIP-NEO, diverging mostly due to the empirical Liberalism and Intellect inclusion of theoretical Agreeableness (e.g., *Believe in an eye for an eye*) and Conscientiousness (e.g., *Don't understand things*) items, respectively. Sociability largely represented the theoretical Extraversion domain but included items from theoretical Agreeableness related to Modesty (e.g., *Don't like to be the center of attention*) and theoretical Neuroticism related to Self-consciousness (e.g., *Find it difficult to approach others*) domains. These items may reflect meaningful overlap between these dimensions such that they may have different pathways — finding it difficult to approach others because a person is shy or because they are depressed.

The Moral Integrity and Neuroticism dimensions had a majority of items from their respective theoretical dimensions, Agreeableness and Neuroticism, respectively, but were also considerably more heterogeneous than the other empirically-derived dimensions. Both dimensions had notable secondary content from the theoretical domains of Conscientiousness and Agreeableness, respectively. The biggest departure from the theoretical domains was the emergence of a sixth dimension, Sensation-seeking, composed of an even mixture of Extraversion, Conscientiousness, and Neuroticism domains with a dash of Openness to Experience. This novel domain represented a tendency toward pursuing new experiences, acting on impulses, and disregarding consequences. Another notable departure from the theoretical structure was the dissolution of the IPIP-NEO's Agreeableness dimension. The Agreeableness content was spread across the six empirical second-level domains but was largely captured by the Sociability and Moral Integrity dimensions.

Figure 4 depicts the Pearson's zero-order correlations (left) and EBICglasso partial correlations (right) between the second level dimensions with black boxes drawn around the dimensions that comprise the two third level dimensions (discussed next). Conscientiousness and Moral Integrity as well as Sociability and Sensation-seeking had the largest zero-order (r = 0.43 and r = 0.41, respectively) and partial correlations (r_p = 0.31 and r_p = 0.39, respectively). There were several moderate correlations between Neuroticism and other dimensions Sociability (r = -0.33), Conscientiousness (r = -0.33), and Moral Integrity (r = -0.28). The partial correlations of Neuroticism with Conscientiousness (r_p = -0.16) and Moral Integrity (r_p = -0.13) were diminished relative to their zero-order counterparts suggesting that weaker unique relationships after accounting for other dimensions.

Openness to Experience, in general, had the smallest zero-order correlations with all other dimensions with a moderate correlation with Sociability (r = 0.25). This correlation, however, is roughly consistent with the meta-trait Plasticity, which represents a tendency for exploration with Openness to Experience and Extraversion domains, respectively (DeYoung, 2002). For our novel dimension of Sensation-seeking, the strongest zero-order (r = 0.41) and partial correlation (r_p = 0.39) with Sociability, demonstrating a related but separate distinction from a dimension reflecting more traditional conceptualizations of Extraversion. Like Neuroticism, the partial correlations were diminished considerably, relative to their zero-order counterpart, for the Conscientiousness (r = -0.21 and r = -0.39, respectively) and Moral Integrity (r = -0.10 and r = -0.30, respectively) dimensions.

Level 3: Meta-traits

The third level of EGA identified 2 communities (Figure 5), which had a negligible correlation (r = 0.08). A summary of each of the empirically-derived dimensions are provided below with the second order dimensions that were assigned to them. At the highest level, most researchers have generally found two meta-traits. One common set of meta-traits are Plasticity (a tendency for exploratory involving the domains of Openness to Experience and Extraversion) and Stability (a tendency for preservation involving the domains of Conscientiousness, Agreeableness, and Neuroticism; DeYoung, 2006; DeYoung et al., 2002; 2008; Digman, 1997). Another common set come from the cross-lexical literature, finding two meta-traits, Dynamism and Social Self-regulation, across cultures (Saucier et al., 2014). These meta-traits are characterized by a tendency for agency and "getting ahead" involving the domains of

Extraversion, Openness, and Conscientiousness's Industriousness and a tendency for communion and "getting along" involving the domains of Agreeableness, Honesty-Humility, Emotional Stability (opposite of Neuroticism), and Conscientiousness's Orderliness.

Dimension 1: Dynamism (176 items)

The first dimension (loadings in parentheses) encompassed the Sociability (0.58), Sensation-seeking (0.31), Openness to Experience (0.24), and Neuroticism (-0.19) second-level dimensions. This dimension most broadly covered theoretical domains of Extraversion (46 of 48 items), Neuroticism (49 of 50 items), and Openness to Experience (42 of 43 items), linking most closely to the Plasticity meta-trait (88 of 91 items) and Dynamism (128 of 132 items). Though this dimension captured the majority of Plasticity and Dynamism, there was greater similarity to Dynamism, representing behaviors related to navigating social situations and engaging with risky but potentially rewarding activities (Saucier et al., 2014).

Dimension 2: Social Self-regulation (63 items)

The second dimension (loadings in parentheses) was nearly one-third the size of the first dimension, encompassing Conscientiousness (0.39) and Moral Integrity (0.39). This dimension mostly included theoretical domains of Conscientiousness (38 of 50 items) and Agreeableness (21 of 48 items). This dimension was more closely related to the Social Self-regulation (59 of 107 items) meta-trait relative to the Stability meta-trait (60 of 148 items). The item content of this dimension was represented by adherence to rules and norms, respecting others and authority, and keeping promises (Saucier et al., 2014), so this label was used.

Summary

Overall, the two empirical meta-traits were more closely aligned in terms of content with Dynamism and Social Self-regulation than Plasticity and Stability. This alignment led to the decision to retain these labels. Further support for these labels were found when looking deeper at the zero-order and partial correlation in Figure 4. Neuroticism and Conscientiousness were both related to second-level dimensions in both empirical meta-traits with the former favoring Dynamism and the latter favoring Social Self-regulation, consistent with the pattern of correlations that Saucier and colleagues' (2014) identified with their meta-traits and the NEO-PI-R's Big Five.

Discussion

The present research aimed to evaluate the taxonomic structure of personality, as measured by the IPIP-NEO-300 inventory, using a bottom-up network psychometrics approach. Our study re-analyzed a large, U.S.-based dataset (*N* > 150,000) from the open-source Johnson IPIP-NEO repository (https://osf.io/tbmh5/; Kajonius & Johnson, 2019) using novel network psychometrics approaches that included a quantitative assessment of local dependence (UVA; Christensen et al., 2023) and an iterative, hierarchical EGA method (Golino, Shi, et al., 2020; Jiménez et al., 2022) to implement a bottom-up, taxonomic approach (Christensen, Golino, et al., 2020; Condon et al., 2020). From the initial 300-item pool, the items were reduced to 239 after handling local dependencies. The first level identified 30 communities that formed 6 second level communities, which grouped into 2 third level communities. Tentative labels for each community were generated based on overlap with theoretical precedent, current empirical item content, and natural language processing via a large language model (GPT-4; OpenAI, 2023). The final result is a hierarchy that captures the full complexity of personality (Figure 6).

This research offers important contributions to psychometric modeling and substantive research on personality. For psychometric modeling, a robust framework to analyze psychological phenomena from the bottom-up is presented (Condon et al., 2020). This framework starts by assessing the item pool for redundancies that may be due to similar item phrasing (Leising et al., 2020; Rosenbusch et al., 2020). Once redundancies are assessed, the item pool can be submitted to an iterative process based on network psychometrics to construct a bottom-up, data-driven hierarchical structure. The iterative hierarchical EGA (Jiménez et al., 2023) approach applied in this study represents a generalized approach to assess psychological constructs beyond two levels. This approach contrasts with more traditional applications that often assume that items represent their theoretical facet unequivocally (e.g., Irwing et al., 2023).

This methodological approach revealed a novel hierarchical personality structure that included both similarities and departures from existing frameworks. The substantive implications start with the methodological differences: items were allowed to freely associate and form dimensions that often departed from their theoretical facets. Relative to existing theory, some items formed larger, broad dimensions involving multiple theoretical facets (e.g., Anxiety and Dominance); other items formed refined, narrow dimensions involving fewer items from a single facet (e.g., Moodiness and Aesthetic Appreciation). Some items replicated their theoretical facet (e.g., Trust and Anger); other items formed a facet distinct from theory (e.g., Work Ethic and Recklessness). Overall, the first level results demonstrate that the common practice of aggregating items into their theoretical facets may obscure item-specific variance that could fit better elsewhere (Condon et al., 2020).

Although most of these placements resulted in an item being placed in another facet of its theoretical trait, there were several instances where a few items from different traits were assigned to the same dimension. The most extreme example is the first-level empirical dimension that represented (social) dominance. This 16-item dimension mainly included items from Agreeableness's (9 items) Cooperation (6 items), Sympathy (1 item), Morality (1 item), and Altruism (1 item) facets. The dimension also included items from Extraversion's Assertiveness (3 items) and Activity-level (1 item) facets as well as Neuroticism's Self-consciousness (2 items) facet. The identification of these cross-facet and cross-domain assignments can substantively inform researchers why certain facets and domains tend to be correlated, and why outcomes related to these dimensions are multiply related to different facets and traits (Mõttus, 2016).

There were also several interesting reorganizations of facet-level content within their higher-order domains. One example is for the facets within the second-level Conscientiousness dimension. Theoretical work has proposed that the motivational mechanisms of Conscientiousness are related to goal-pursuit systems (DeYoung, 2015; Jayawickreme et al., 2019). The content of the refined first level facets of Conscientiousness appear to relate to the motivational characteristics of activation, direction, intensity, and persistence (Kanfer et al., 2017) as Self-Discipline, Determination, Work Ethic, and Diligence, respectively. Similarly, the Contentment, Excitement-Seeking, and Recklessness facets reorganized Extraversion content, with these refinements perhaps indicating that Excitement-Seeking and Recklessness are not simply stronger patterns of Contentment and Excitement-Seeking, respectively, but separate systems altogether. These content refinements have interesting implications for the motivational mechanisms of personality systems.

At the second level, there were six dimensions that had small-to-moderate correlations and ranged from a dimension near-identical to theory (Conscientiousness) to a relatively novel dimension not often, if at all, identified in Big Five and HEXACO models (Sensation-seeking). Most second-level dimensions had content that represented the majority of one theoretical trait domain suggesting that despite the spread of items across theoretical facets at the first level much of the theoretical trait domains remained intact. This result is not necessarily surprising given that most of the diversity at the first level was items switching between theoretical facets within the same theoretical trait domain.

To our surprise, the empirical Openness to Experience largely corresponded to its theoretical domain. Openness to Experience has generally been considered the most heterogeneous and hardest to pin down domain yet its content appears to hang together relatively well (Christensen et al., 2019; Connelly et al., 2014). On the other side, the theoretical Agreeableness domain was not recovered as its theoretical content was mainly split across two empirical dimensions: Neuroticism and Moral Integrity. The item content associated with the dissolution of Agreeableness appears to correspond to the theoretical aspects found in the Big Five Aspects Scale (DeYoung et al., 2007): Politeness and Compassion, respectively. Although Agreeableness is consistently recovered across personality taxonomies, its conceptualization and operationalization frequently changes across inventories (Thielmann et al., 2023), so another change with its disappearance was relatively novel but not entirely surprising.

The most novel finding at this level was a sixth dimension that was labelled Sensation-seeking. This dimension was equally comprised of three theoretical domains (and three items from Openness to Experience) and largely specific facets from those domains (facets in parentheses): Conscientiousness (Cautiousness), Extraversion (Excitement-seeking), and Neuroticism (Immoderation). The item content represented themes related to risk-taking (e.g., *Seek danger*) and impulsivity in both actions (e.g., *Rush into things*) and habits (e.g., *Go on binges*), broadly capturing tendencies towards novel, varied, and intense sensations and experiences potentially involving risk. Although this content is traditionally considered to be outside of the Big Five or HEXACO models (i.e., Figner & Weber, 2011 and Frey et al., 2017; but see Highhouse et al., 2022), much of it is consistent with Surgency in temperament (e.g., impulsivity, high activity, intense pleasure, low inhibitory control; Rothbart et al., 2001). Therefore, the appearance of Sensation-seeking as a trait domain is relatively novel but not necessarily unexpected (Irwing et al., 2023).

At the third level, two dimensions emerged that appeared to resemble other conceptualizations of meta-traits (DeYoung, 2006; DeYoung et al., 2002, 2008; Digman, 1997; Saucier et al., 2014). These two dimensions were compared with Plasticity and Stability, finding Plasticity mostly intact while also subsuming some of Stability (due to Neuroticism and Sensation-seeking). A key finding was that the correlation between the two meta-traits was negligible (r = 0.08), providing empirical evidence against the idea of a single, general factor of personality (Musek, 2007). This correlation is congruent with DeYoung's (2006) multi-method, multi-informant analysis of Plasticity and Stability.

Although these two dimensions were compared with Plasticity and Stability, they better resembled the cross-lexical Big Two, which often emerges from trait taxonomies in the psycholexical tradition that can be identified in different languages and cultures (Saucier et al., 2014). Social Regulation and Dynamism comprise the Big Two and were used to describe our two empirical dimensions. The theoretical Social Regulation is thought to reflect a tendency towards communion, morality, warmth, interpersonal care, and "using norms as standards for regulating one's own behavior" (i.e., adhering to rules, behaving properly, respecting others and authority, and keeping promises; Saucier et al., 2014, p. 11). This description generally aligns with the Moral Integrity second level dimension. Our dimension differs in that Conscientiousness content is not between the theoretical Social Regulation and Dynamism dimensions and instead rounds out the rest of the third-level dimension.

The theoretical Dynamism, in contrast, is thought to reflect a tendency towards agency, competence, interpersonal dominance, and behavioral activation (i.e., dealing with social situations, skills for social situations, whether one feels comfortable or shy, and engaging with risky but potentially rewarding social situations). This description largely aligns with the Sociability and Sensation-seeking second level dimensions. The addition of the empirical Openness to Experience to this dimension suggests that there may be broader contributions toward Plasticity, reflecting general flexibility in thought, emotions, and behavior (DeYoung, 2006; DeYoung et al., 2002, 2008; Digman, 1997).

Strengths and Limitations

There are a few strengths of this work that warrant consideration for future evaluations of the personality taxonomy. First, the evaluation of the relations between items without constraint on their placement into dimensions highlighted many inconsistencies in the theoretical placement of items. The takeaway is that researchers should take greater care when developing and validating scales. Most scale development efforts derive items within a specific facet of a specific trait, and they are often validated within the silo of the trait domain. Our results demonstrate that such a narrow view during development can lead to content overlap outside of the intended domain's facets or domain itself (e.g., the item, *Like to be the center of attention,* theoretically assigned to Agreeableness but was empirically aligned with Extraversion or the near identical items *Am afraid to draw attention to myself* versus *Don't like to draw attention to myself* from Extraversion and Neuroticism). These artifacts may emerge as cross-loadings in traditionally messy personality data (Marsh et al., 2010).

Second, this study is the first, to our knowledge, to use a robust statistical approach to detect and handle local dependence in an item pool. Local dependence can arise for many reasons and most often appears in personality inventories due to common measurement practices aiming to capture a specific facet. An unintended consequence, however, is that facets often reflect varying levels of local dependence which can substantially affect dimension recovery efforts (Christensen et al., 2023). Third, our approach leverages network psychometric methods that allow for each level to be represented as covarying within and between designated dimensions. This representation captures the full complexity of the relationships within each level of the hierarchy.

Although a major strength of this approach is its accuracy and robustness for building up to higher levels of personality structure, there is value in the richness of lower-level personality information (Mõttus et al., 2019; Stewart et al., 2022). Considering that psychometric networks excel at modeling the complexity of personality information, a natural question is why (or when) we should use higher-order network dimensions? Beyond enhancing our understanding, there are at least two practical reasons. First, scientist-practitioners often work within practical modeling considerations: when they are unable to measure 300 personality nuances due to power, identification, or other resource constraints they benefit from higher-order structures that help summarize lower-level information (Mõttus et al., 2020). Second, between-person taxonomies largely inform most applied prediction efforts (e.g., Bleidorn & Hopwood, 2019). It may often be theoretically relevant to use higher-order dimensions when other constructs or outcomes of interest are equally broad, like work performance or life satisfaction (i.e., predictor-criterion alignment; Jenkins & Griffith, 2004; Tett & Christiansen, 2007).

There are also a few limitations. First, although a novel advance, the iterative implementation of hierarchical EGA has not been thoroughly vetted. One simulation demonstrated that hierarchical EGA is accurate at identifying two-level, bifactor structures (Jiménez et al., 2022), with empirical work demonstrating its utility to identify hierarchical structures in health behaviors (Golino, Thiyagarajan, et al., 2020) and aesthetic experiences (Christensen et al., 2022). The current work, however, is an initial demonstration of the effectiveness of hierarchical EGA for modeling complex structures. Future work should continue using iterative hierarchical EGA across multiple levels to investigate the structure of other complex constructs, such as work attitudes (e.g., Judge et al., 2017) or well-being (e.g., Tay et al., 2023).

Second, our results are based on a single personality inventory, risking results that have a mono-operation bias (Gallagher et al., 2020). The IPIP-NEO is a comprehensive, open-access inventory based on the widely used the NEO-PI-R (Costa & McCrae, 2008) and IPIP (Goldberg et al., 2006). Although the IPIP-NEO is broad measure, future work should also investigate other inventories in combination to ensure a comprehensive consensus on the structure identified in this study (including Big Few alternatives; Feher & Vernon, 2021). Aside from the inventory, our data were restricted to a single country (U.S.), which limits the generalizability of the results; however, it’s important to note that very large samples are required for these analyses, which are usually difficult to obtain from many countries. Future work should continue contributing to open-source personality data so that researchers and practitioners have access to large, representative datasets that comprehensively sample the content space of personality so that researchers with a variety of perspectives and methodological approaches can continue exploring the structure of personality.

Conclusion

The taxonomic structure of personality is often the foundation on which subsequent prediction and explanatory models of personality are built. Although most contemporary theories of personality start with the Big Five and work down, more recent calls have emphasized the need for more bottom-up, exploratory approaches to capture item-specific variance that is often neglected in theoretical-driven approaches (e.g., Condon et al., 2020). Previously, the main constraint on such analyses has been the limited availability of validated statistical methods to evaluate complex, hierarchical structures in this manner. Open-source data and methodological innovations, however, have paved the way for personality to start putting the pieces together from the bottom-up. This study demonstrates a promising statistical framework, using UVA and iterative hierarchical EGA, to capture the full complexity of personality, building from the bottom-up.

REFERENCES

Allport, G. W. (1966). Traits revisited. *American Psychologist*, 21(1), 1. https://doi.org/10.1037/h0023295

Anglim, J., Horwood, S., Smillie, L., Marrero, R., & Wood, J. (2020). Predicting psychological and subjective well-being from personality: A meta-analysis. *Psychological Bulletin*, 146. https://doi.org/10.1037/bul0000226

Ashton, M. C., & Lee, K. (2007). Empirical, Theoretical, and Practical Advantages of the HEXACO Model of Personality Structure. *Personality and Social Psychology Review*, 11(2), 150–166. https://doi.org/10.1177/1088868306294907

Ashton, M. C., Lee, K., & De Vries, R. E. (2014). The HEXACO Honesty-Humility, Agreeableness, and Emotionality factors: A review of research and theory. *Personality and Social Psychology Review*, 18(2), 139–152. https://doi.org/10.1177/1088868314523838

Ashton, M. C., & Lee, K. (2020). Objections to the HEXACO model of personality structure—and why those objections fail. *European Journal of Personality*, 34(4), 492–510. https://doi.org/10.1002/per.2242

Barabási, A.-L. (2012). The network takeover. *Nature Physics*, 8(1), 14–16. https://doi.org/10.1038/nphys2188

Barrick, M. R., & Mount, M. K. (1991). The Big Five personality dimensions and job performance: A meta-analysis. *Personnel Psychology*, 44(1), 1–26. https://doi.org/10.1111/j.1744-6570.1991.tb00688.x

Baumert, A., Schmitt, M., Perugini, M., Johnson, W., Blum, G., Borkenau, P., Costantini, G., Denissen, J. J. A., Fleeson, W., Grafton, B., Jayawickreme, E., Kurzius, E., MacLeod, C., Miller, L. C., Read, S. J., Roberts, B., Robinson, M. D., Wood, D., & Wrzus, C. (2017). Integrating Personality Structure, Personality Process, and Personality Development. *European Journal of Personality*, 31(5), 503–528.

https://doi.org/10.1002/per.2115

Beck, E. D., & Jackson, J. J. (2020a). Idiographic Traits: A Return to Allportian Approaches to Personality. Current Directions in Psychological Science, *29*(3), 301–308. https://doi.org/10.1177/0963721420915860

Beck, E. D., & Jackson, J. J. (2020b). Consistency and change in idiographic personality: A longitudinal ESM network study. *Journal of Personality and Social Psychology*, 118(5), 1080–1100. https://doi.org/10.1037/pspp0000249

Beck, E. D., & Jackson, J. J. (2021a). Network Approaches to Representing and Understanding Personality Dynamics. In D. Wood, S. J. Read, P. D. Harms, & A. Slaughter (Eds.), Measuring and Modeling Persons and Situations (pp. 465–497). Academic Press.

Beck, E. D., & Jackson, J. J. (2021b). Within-Person Variability. n J. F. Rauthmann (Ed.), *The handbook of personality dynamics and processes* (pp. 75–100). Elsevier Academic Press. https://doi.org/10.1016/B978-0-12-813995-0.00004-2

Beck, E. D., Condon, D., & Jackson, J. (2023). Interindividual age differences in personality structure. *European Journal of Personality, 37*(3), 257-275. https://doi.org/10.1177/08902070221084862

Beckmann, N., Birney, D. P., Minbashian, A., & Beckmann, J. F. (2021). Personality dynamics at work: The effects of form, time, and context of variability. *European Journal of Personality*, 35(4), 421–449. https://doi.org/10.1177/08902070211017341

Biderman, M. D., McAbee, S. T., Hendy, N. T., & Chen, Z. J. (2019). Validity of evaluative factors from Big Five and HEXACO questionnaires. *Journal of Research in Personality*, 80, 84–96. https://doi.org/10.1016/j.jrp.2019.04.010

Bleidorn, W., & Hopwood, C. J. (2019). Using machine learning to advance personality assessment and theory. *Personality and Social Psychology Review*, 23, 190–203. https://doi.org/10.1177/1088868318772990

Block, J. (2010). The Five-Factor framing of personality and beyond: Some ruminations.

Psychological Inquiry, 21(1), 2–25. https://doi.org/10.1080/10478401003596626

Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10), P10008. https://doi/org/10.1088/1742-5468/2008/10/P10008

Blum, G. S., Baumert, A., & Schmitt, M. (2021). Personality processes—From description to explanation. In J. F. Rauthmann (Ed.), The Handbook of Personality Dynamics and Processes (pp. 33–55). Academic Press.

Borsboom, D., Mellenbergh, G. J., & van Heerden, J. (2003). The theoretical status of latent variables. *Psychological Review*, 110(2), 203–219. https://doi.org/10.1037/0033-295X.110.2.203

Borsboom, D. (2006). The attack of the psychometricians. *Psychometrika*, 71(3), 425. https://doi.org/10.1007/s11336-006-1447-6

Borsboom, D., & Cramer, A. O. J. (2013). Network Analysis: An Integrative Approach to the Structure of Psychopathology. *Annual Review of Clinical Psychology*, 9(1), 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608

Borsboom, D., Deserno, M. K., Rhemtulla, M., Epskamp, S., Fried, E. I., McNally, R. J., Robinaugh, D. J., Perugini, M., Dalege, J., Costantini, G., Isvoranu, A.-M., Wysocki, A. C., van Borkulo, C. D., van Bork, R., & Waldorp, L. J. (2021). Network analysis of multivariate data in psychological science. *Nature Reviews Methods Primers*, 1(1), 58. https://doi.org/10.1038/s43586-021-00055-w

Bringmann, L. F., & Eronen, M. I. (2018). Don't blame the model: Reconsidering the network approach to psychopathology. *Psychological Review*, 125, 606–615. https://doi.org/10.1037/rev0000108

Cattell, R. B., & Tsujioka, B. (1964). The importance of factor-trueness and validity, versus homogeneity and orthogonality, in test scales. *Educational and Psychological Measurement*, 1, 3-30. https://doi.org/10.1177/001316446402400101

Castro, D., Ferreira, F., & Ferreira, T. B. (2021). Modularity of the personality network. *European Journal of Psychological Assessment*, 36(6), 998. https://doi.org/10.1027/1015-5759/a000613

Cervone, D., & Little, B. R. (2019). Personality architecture and dynamics: The new agenda and what's new about it. *Personality and Individual Differences*, 136, 12–23. https://doi.org/10.1016/j.paid.2017.07.001

Christensen, A. P., Cardillo, E., & Chatterjee, A. (2022). What kind of impacts can artwork have on viewers? Establishing a taxonomy for aesthetic cognitivism. *British Journal of Psychology* (London, England: 1953), 10.1111/bjop.12623. Advance online publication. https://doi.org/10.1111/bjop.12623

Christensen, A. P., Cotter, K. N., & Silvia, P. J. (2019). Reopening Openness to Experience: A Network Analysis of Four Openness to Experience Inventories. *Journal of Personality Assessment*, 101(6), 574–588. https://doi.org/10.1080/00223891.2018.1467428

Christensen, A. P., Garrido, L. E., & Golino, H. (2020a). Unique variable analysis: A novel approach for detecting redundant variables in multivariate data. [Preprint] https://osf.io/preprints/psyarxiv/4kra2

Christensen, A. P., Garrido, L. E., & Golino, H. (2020b). Comparing community detection algorithms in psychological data: A Monte Carlo simulation [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/hz89e

Christensen, A. P., Garrido, L. E., & Golino, H. (2023). Unique variable analysis: A network psychometrics method to detect local dependence. Multivariate Behavioral Research, 1–18. https://doi.org/10.1080/00273171.2023.2194606

Christensen, A. P., & Golino, H. (2021a). On the equivalency of factor and network loadings. *Behavior Research Methods*, 53(4), 1563–1580. https://doi.org/10.3758/s13428-020-01500-6

Christensen, A. P., & Golino, H. (2021b). Estimating the stability of psychological dimensions via bootstrap exploratory graph analysis: A Monte Carlo simulation and tutorial. *Psych*, 3(3), Article 3. https://doi.org/10.3390/psych3030032

Christensen, A. P., Golino, H., & Silvia, P. J. (2020). A psychometric network perspective on the validity and validation of personality trait questionnaires. *European Journal of Personality*, 34(6), 1095–1108. https://doi.org/10.1002/per.2265

Christensen, A. P., Kenett, Y. N., Aste, T., Silvia, P. J., & Kwapil, T. R. (2018). Network structure of the Wisconsin Schizotypy Scales–Short Forms: Examining psychometric network filtering approaches. *Behavior Research Methods*, 50(6), 2531–2550. https://doi.org/10.3758/s13428-018-1032-9

Chen, J., & Chen, Z. (2008). Extended Bayesian information criteria for model selection with large model spaces. *Biometrika*, 95, 759–771. https://doi.org/10.1093/biomet/asn034

Condon, D. M., Wood, D., Mõttus, R., Booth, T., Costantini, G., Greiff, S., Johnson, W., Lukaszewski, A., Murray, A., Revelle, W., Wright, A. G. C., Ziegler, M., & Zimmermann, J. (2020). Bottom up construction of a personality taxonomy. *European Journal of Psychological Assessment*, 36(6), 923. https://doi.org/10.1027/1015-5759/a000626

Connelly, B. S., Ones, D. S., & Chernyshenko, O. S. (2014). Introducing the special section on openness to experience: Review of openness taxonomies, measurement, and nomological net. *Journal of Personality Assessment, 96*(1), 1-16. https://doi.org/10.1080/00223891.2013.830620

Costa Jr, P. T., & McCrae, R. R. (1992). Four ways five factors are basic. *Personality and individual differences*, 13(6), 653-665. https://doi.org/10.1016/0191-8869(92)90236-I

Costa, P. T., & McCrae, R. R. (2008). The Revised NEO Personality Inventory (NEO-PI-R). In The sage handbook of personality theory and assessment: Volume 2—Personality measurement and testing (pp. 179–198). SAGE Publications Ltd. https://doi.org/10.4135/9781849200479.n9

Costantini, G., Epskamp, S., Borsboom, D., Perugini, M., Mõttus, R., Waldorp, L. J., & Cramer,

A. O. J. (2015). State of the aRt personality research: A tutorial on network analysis of personality data in R. *Journal of Research in Personality*, 54, 13–29. https://doi.org/10.1016/j.jrp.2014.07.003

Costantini, G., Richetin, J., Preti, E., Casini, E., Epskamp, S., & Perugini, M. (2019). Stability and variability of personality networks. A tutorial on recent developments in network psychometrics. *Personality and Individual Differences*, 136, 68–78. https://doi.org/10.1016/j.paid.2017.06.011

Cramer, A. O. J., van der Sluis, S., Noordhof, A., Wichers, M., Geschwind, N., Aggen, S. H., Kendler, K. S., & Borsboom, D. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality*, 26(4), 414–431. https://doi.org/10.1002/per.1866

Cramer, A. O. J., Waldorp, L. J., van der Maas, H. L. J., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences*, 33(2–3), 137–150. https://doi.org/10.1017/S0140525X09991567

Damian, R. I., Spengler, M., Sutu, A., & Roberts, B. W. (2019). Sixteen Going on Sixty-Six: A Longitudinal Study of Personality Stability and Change Across 50 Years. Journal of *Personality and Social Psychology*, 117(3), 674–695. https://doi.org/10.1037/pspp0000210

DeVellis, R. F. (2017). Scale development: Theory and applications (4th ed.). Thousand Oaks, CA: SAGE Publications.

DeYoung, C. G., Grazioplene, R. G., & Peterson, J. B. (2012). From madness to genius: The Openness/Intellect trait domain as a paradoxical simplex. *Journal of Research in Personality*, 46, 63-78. https://doi.org/10.1016/j.jrp.2011.12.003

DeYoung, C. G., Peterson, J. B., & Higgins, D. M. (2002). Higher-order factors of the Big Five predict conformity: Are there neuroses of health? *Personality and Individual Differences*, 33(4), 533–552. https://doi.org/10.1016/S0191-8869(01)00171-4

DeYoung, C. G., Quilty, L. C., & Peterson, J. B. (2007). Between facets and domains: 10 aspects of the Big Five. *Journal of Personality and Social Psychology*, 93(5), 880–896. https://doi.org/10.1037/0022-3514.93.5.880

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

DeYoung, C. G. (2015). Cybernetic Big Five theory. *Journal of Research in Personality*, 56, 33–58. https://doi.org/10.1016/j.jrp.2014.07.004

Digman, J. M. (1990). Personality Structure: Emergence of the Five-Factor Model. *Annual Review of Psychology*, 41(1), 417–440. https://doi.org/10.1146/annurev.ps.41.020190.002221

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

Edwards, M. C., Houts, C. R., & Cai, L. (2018). A diagnostic procedure to detect departures from local independence in item response theory models. *Psychological Methods, 23*(1), 138-149. https://doi.org/10.1037/met0000121

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, 50(1), 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., & Fried, E. I. (2018). A Tutorial on Regularized Partial Correlation Networks. Psychological Methods, 23(4), 617–634. https://doi.org/10.1037/met0000167

Eysenck, H. J. (1992). Four ways five factors are not basic. *Personality and individual differences*, 13(6), 667-673. https://doi.org/10.1016/0191-8869(92)90237-J

Feher, A., & Vernon, P. A. (2021). Looking beyond the Big Five: A selective review of alternatives to the Big Five model of personality. *Personality and Individual Differences*, 169, 110002. https://doi.org/10.1016/j.paid.2020.110002

Figner, B., & Weber, E. U. (2011). Who takes risks when and why? Determinants of risk taking. *Current Directions in Psychological Science*, 20(4), 211-216. https://doi.org/10.1177/0963721411415790

Fokkema, M., Iliescu, D., Greiff, S., & Ziegler, M. (2022). Machine learning and prediction in psychological assessment: Some promises and pitfalls. *European Journal of Psychological Assessment*, 38, 165–175. https://doi.org/10.1027/1015-5759/a000714

Forbes, M. K. (2023). Improving hierarchical models of individual differences: An extension of Goldberg's bass-ackward method. *Psychological Methods*. Advance online publication. https://doi.org/10.1037/met0000546

Foygel, R., & Drton, M. (2010). Extended Bayesian information criteria for Gaussian graphical models. In J. D. Lafferty, C. K. I. Williams, J. Shawe-Taylor, R. S. Zemel, & A. Culotta (Eds.), *Advances in neural information processing systems* (pp. 604–612). Retrieved from https://papers.nips.cc/paper/4087-extended-bayesian-information-criteria-for-gaussian-graphical-models

Frey, R., Pedroni, A., Mata, R., Rieskamp, J., & Hertwig, R. (2017). Risk preference shares the psychometric structure of major psychological traits. *Science advances*, 3(10), 10.1126/sciadv.1701381

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, 9(3), 432–441. https://doi.org/10.1093/biostatistics/kxm045

Funder, D. C. (2009). Persons, behaviors and situations: An agenda for personality psychology in the postwar era. *Journal of Research in Personality*, 43(2), 120–126. https://doi.org/10.1016/j.jrp.2008.12.041

Gallagher, C. M., Samo, A., Shea, M. A., & Mcabee, S. T. (2020). Distinguishing between instruments and constructs in Big Six research. *European Journal of Personality*, 34(4), 526-527.

Goldberg, L. R. (1990). An alternative "description of personality": The Big-Five factor structure.

Journal of Personality and Social Psychology, 59, 1216–1229. https://doi.org/10.1037/0022-3514.59.6.1216

Goldberg, L. R. (2006). Doing it all Bass-Ackwards: The development of hierarchical factor structures from the top down. *Journal of Research in Personality*, 40(4), 347–358. https://doi.org/10.1016/j.jrp.2006.01.001

Goldberg, L. R., Johnson, J. A., Eber, H. W., Hogan, R., Ashton, M. C., Cloninger, C. R., & Gough, H. G. (2006). The international personality item pool and the future of public-domain personality measures. *Journal of Research in Personality*, 40(1), 84–96. https://doi.org/10.1016/j.jrp.2005.08.007

Golino, H., Christensen, A. P., & Garrido, L. E. (2022). Exploratory Graph Analysis in context. https://doi.org/10.31234/osf.io/pfzkh

Golino, H., Christensen, A. P., Moulder, R., Kim, S., & Boker, S. M. (2022). Modeling latent topics in social media using dynamic exploratory graph analysis: The case of the right-wing and left-wing trolls in the 2016 US elections. *Psychometrika*, 87(1), 156–187. https://doi.org/10.1007/s11336-021-09820-y

Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PloS One*, 12(6), e0174035.

Golino, H., Moulder, R., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Nesselroade, J., Sadana, R., Thiyagarajan, J. A., & Boker, S. M. (2021). Entropy Fit Indices: New Fit Measures for Assessing the Structure and Dimensionality of Multiple Latent Variables. *Multivariate Behavioral Research*, 56(6), 874–902. https://doi.org/10.1080/00273171.2020.1779642

Golino, H., Shi, D., Christensen, A. P., Garrido, L. E., Nieto, M. D., Sadana, R., Thiyagarajan, J. A., & Martinez-Molina, A. (2020a). Investigating the performance of exploratory graph analysis and traditional techniques to identify the number of latent factors: A simulation and tutorial. *Psychological Methods*, 25, 292–320. https://doi.org/10.1037/met0000255

Golino, H., Thiyagarajan, J. A., Sadana, R., Teles, M., Christensen, A. P., & Boker, S. M. (2020b). Investigating the broad domains of intrinsic capacity, functional ability and environment: An exploratory graph analysis approach for improving analytical methodologies for measuring healthy aging. [Preprint] https://osf.io/preprints/psyarxiv/hj5mc

Herrmann, A., & Pfister, H.-R. (2013). Simple measures and complex structures: Is it worth employing a more complex model of personality in Big Five inventories? *Journal of Research in Personality*, 47(5), 599–608. https://doi.org/10.1016/j.jrp.2013.05.004

Hickman, L., Bosch, N., Ng, V., Saef, R., Tay, L., & Woo, S. E. (2022). Automated video interview personality assessments: Reliability, validity, and generalizability investigations. *Journal of Applied Psychology*, 107, 1323–1351. https://doi.org/10.1037/apl0000695

Highhouse, S., Wang, Y., & Zhang, D. C. (2022). Is risk propensity unique from the big five factors of personality? a meta-analytic investigation. *Journal of Research in Personality*, 98, 104206. https://doi.org/10.1016/j.jrp.2022.104206

Hopwood, C. J., & Donnellan, M. B. (2010). How should the internal structure of personality inventories be evaluated? *Personality and Social Psychology Review*, 14(3), 332–346. https://doi.org/10.1177/1088868310361240

Jayawickreme, E., Zachry, C. E., & Fleeson, W. (2019). Whole Trait Theory: An integrative approach to examining personality structure and process. Personality and Individual Differences, 136, 2–11. https://doi.org/10.1016/j.paid.2018.06.045

Jenkins, M., & Griffith, R. (2004). Using Personality Constructs to Predict Performance: Narrow or Broad Bandwidth. *Journal of Business and Psychology*, 19(2), 255–269. https://doi.org/10.1007/s10869-004-0551-9

Jiménez, M., Abad, F. J., Garcia-Garzon, E., Golino, H., Christensen, A. P., & Garrido, L. E. (2022). Dimensionality assessment in generalized bi-factor structures: A network psychometrics approach [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/2ujdk

Johnson, J. A. (2014). Measuring thirty facets of the Five Factor Model with a 120-item public domain inventory: Development of the IPIP-NEO-120. *Journal of Research in Personality*, 51, 78–89. https://doi.org/10.1016/j.jrp.2014.05.003

Judge, T. A., Weiss, H. M., Kammeyer-Mueller, J. D., & Hulin, C. L. (2017). Job attitudes, job satisfaction, and job affect: A century of continuity and of change. *Journal of Applied Psychology*, 102(3), 356. https://doi.org/10.1037/apl0000181

Kanfer, R., Frese, M., & Johnson, R. E. (2017). Motivation related to work: A century of progress. *Journal of Applied Psychology, 102*(3), 338–355. https://doi.org/10.1037/apl0000133

Kajonius, P. J., & Johnson, J. A. (2019). Assessing the Structure of the Five Factor Model of Personality (IPIP-NEO-120) in the Public Domain. *Europe's Journal of Psychology*, 15(2), 260–275. https://doi.org/10.5964/ejop.v15i2.1671

Kanfer, R., Frese, M., & Johnson, R. E. (2017). Motivation related to work: A century of progress. *Journal of Applied Psychology*, 102(3), 338. https://doi.org/10.1037/apl0000133

Kim, H., Di Domenico, S. I., & Connelly, B. S. (2019). Self–Other agreement in personality reports: A meta-analytic comparison of self- and informant-report means. *Psychological Science*, 30(1), 129–138. https://doi.org/10.1177/0956797618810000

Kovács, I., Palotai, R., Szalay, M., & Csermely, P. (2010). Community landscapes: an integrative approach to determine overlapping network module hierarchy, identify key nodes and predict network dynamics. *PLoS ONE*, *5*(9), e12528. https://doi.org/10.1371/journal.pone.0012528

Lancichinetti, A., & Fortunato, S. (2012). Consensus clustering in complex networks. *Scientific Reports*, 2(1), 1–7. https://doi.org/10.1038/srep00336

Leising, D., Burger, J., Zimmermann, J., Ba €ckstr€ om, M., Oltmanns, J., & Connelly, B. (2020).

Why do items correlate with one another? A conceptual analysis with relevance for general factors and network models. PsyArXiv, https://doi.org/10.31234/osf.io/7c895

Loevinger, J. (1957). Objective tests as instruments of psychological theory. *Psychological Reports*, 3, 635–694. https://doi.org/10.2466/PR0.3.7.635-694

Markon, K. E. (2009). Hierarchies in the Structure of Personality Traits. *Social and Personality Psychology Compass*, 3(5), 812–826. https://doi.org/10.1111/j.1751-9004.2009.00213.x

Marsh, H. W., Lüdtke, O., Muthén, B., Asparouhov, T., Morin, A. J. S., Trautwein, U., & Nagengast, B. (2010). A new look at the big five factor structure through exploratory structural equation modeling. *Psychological Assessment*, 22(3), 471–491. https://doi.org/10.1037/a0019227

McAbee, S. T., & Connelly, B. S. (2016). A multi-rater framework for studying personality: The trait-reputation-identity model. *Psychological Review*, 123(5), 569–591. https://doi.org/10.1037/rev0000035

McCrae, R. R. (2015). A more nuanced view of reliability: Specificity in the trait hierarchy. *Personality and Social Psychology Review*, 19(2), 97–112. https://doi.org/10.1177/1088868314541857

McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and ts applications. *Journal of Personality*, 60(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McCrae, R. R., & Terracciano, A. (2005). Universal features of personality traits from the observer's perspective: Data From 50 cultures. *Journal of Personality and Social Psychology*, 88(3), 547. https://doi.org/10.1037/0022-3514.88.3.547

Molenaar, P. C. M. (2010). Latent variable models are network models. *Behavioral and Brain Sciences*, 33(2–3), 166–166. https://doi.org/10.1017/S0140525X10000798

Mõttus, R. (2016). Towards more rigorous personality trait–outcome research. *European Journal of Personality, 30*(4), 292–303. https://doi.org/10.1002/per.2041

Mõttus, R., Kandler, C., Bleidorn, W., Riemann, R., & McCrae, R. R. (2017). Personality traits below facets: The consensual validity, longitudinal stability, heritability, and utility of personality nuances. *Journal of Personality and Social Psychology*, 112(3), 474–490. https://doi.org/10.1037/pspp0000100

Mõttus, R., Sinick, J., Terracciano, A., Hřebíčková, M., Kandler, C., Ando, J., Mortensen, E. L., Colodro-Conde, L., & Jang, K. L. (2019). Personality characteristics below facets: A replication and meta-analysis of cross-rater agreement, rank-order stability, heritability, and utility of personality nuances. *Journal of Personality and Social Psychology*, 117, e35–e50. https://doi.org/10.1037/pspp0000202

Mõttus, R., Wood, D., Condon, D. M., Back, M., Baumert, A., Costantini, G., Epskamp, S., Greiff, S., Johnson, W., Lukaszewski, A., Murray, A. L., Revelle, W., Wright, A. G. C., Yarkoni, T., Ziegler, M., & Zimmermann, J. (2020). Descriptive, predictive and explanatory personality research: Different goals, different approaches, but a shared need to move beyond the Big Few traits [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/hvk5p

Musek, J. (2007). A general factor of personality: Evidence for the Big One in the five-factor model. *Journal of Research in Personality*, 41(6), 1213–1233. https://doi.org/10.1016/j.jrp.2007.02.003

Newman, M. E. J. (2006). Finding community structure in networks using the eigenvectors of matrices. *Physical Review E*, 74(3), 036104. https://doi.org/10.1103/PhysRevE.74.036104

Olaru, G., Schroeders, U., Wilhelm, O., & Ostendorf, F. (2019). ‘Grandpa, do you like roller coasters?’: Identifying age–appropriate personality indicators. *European Journal of Personality, 33*(3), 264-278. https://doi.org/10.1002/per.2185

Ozer, D. J., & Benet-Martínez, V. (2006). Personality and the prediction of consequential outcomes. *Annual Review of Psychology*, 57(1), 401–421.

https://doi.org/10.1146/annurev.psych.57.102904.190127

Piedmont, R. L. (1998). *The revised NEO Personality Inventory: Clinical and research applications*. New York, NY: Springer Science+Business Media.

Revelle, W., Dworak, E. M., & Condon, D. M. (2021). Exploring the persome: The power of the item in understanding personality structure. Personality and Individual Differences, 169, 109905. https://doi.org/10.1016/j.paid.2020.109905

Revelle, W., & Wilt, J. (2021). The History of Dynamic Approaches to Personality. In J. F. Rauthmann (Ed.), The Handbook of Personality Dynamics and Processes (pp. 4–24). Academic Press.

Roberts, B. W., & DelVecchio, W. F. (2000). The rank-order consistency of personality traits from childhood to old age: A quantitative review of longitudinal studies. Psychological Bulletin, 126(1), 3–25. https://doi.org/10.1037/0033-2909.126.1.3

Rosenbusch, H., Wanders, F., & Pit, I. L. (2020). The Semantic Scale Network: An online tool to detect semantic overlap of psychological scales and prevent scale redundancies. Psychological Methods, 25(3), 380–392. https://doi.org/10.1037/met0000244

Saucier, G. (1992). Benchmarks: Integrating affective and interpersonal circles with the Big-Five personality factors. Journal of Personality and Social Psychology, 62(6), 1025.

Saucier, G., Thalmayer, A. G., Payne, D. L., Carlson, R., Sanogo, L., Ole-Kotikash, L., Church, A. T., Katigbak, M. S., Somer, O., Szarota, P., Szirmák, Z., & Zhou, X. (2014). A basic bivariate structure of personality attributes evident across nine languages. Journal of Personality, 82(1), 1–14. https://doi.org/10.1111/jopy.12028

Saucier, G., Iurino, K., & Thalmayer, A. G. (2020). Comparing predictive validity in a community sample: High–dimensionality and traditional domain–and–facet structures of personality variation. *European Journal of Personality*, 34(6), 1120-1137. https://doi.org/10.1002/per.2235

Schmittmann, V. D., Cramer, A. O. J., Waldorp, L. J., Epskamp, S., Kievit, R. A., & Borsboom,

D. (2013). Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas in Psychology*, 31(1), 43–53. https://doi.org/10.1016/j.newideapsych.2011.02.007

Schwaba, T., Rhemtulla, M., Hopwood, C. J., & Bleidorn, W. (2020). A facet atlas: Visualizing networks that describe the blends, cores, and peripheries of personality structure. *PLOS ONE*, 15(7), e0236893. https://doi.org/10.1371/journal.pone.0236893

Soto, C. J. (2019). How replicable are links between personality traits and consequential life outcomes? The Life Outcomes of Personality Replication Project. *Psychological Science*, 30(5), 711–727. https://doi.org/10.1177/0956797619831612

Stewart, R. D., Mõttus, R., Seeboth, A., Soto, C. J., & Johnson, W. (2022). The finer details? The predictability of life outcomes from Big Five domains, facets, and nuances. *Journal of Personality*, 90(2), 167–182. https://doi.org/10.1111/jopy.12660

Syed, M. (2021). Where are race, ethnicity, and culture in personality research. *PsyArXiv. https://doi.org/10.31234/osf.io/m57ph*

Tay, L., Batz-Barbarich, C., Yang, L. Q., & Wiese, C. W. (2023). Well-Being: The ultimate criterion for organizational sciences. *Journal of Business and Psychology*, *38*(6), 1141-1157. https://doi.org/10.1007/s10869-023-09908-5

Tett, R. P., & Christiansen, N. D. (2007). Personality tests at the crossroads: A response to Morgeson, Campion, Dipboye, Hollenbeck, Murphy, and Schmitt (2007). *Personnel Psychology*, 60(4), 967–993. https://doi.org/10.1111/j.1744-6570.2007.00098.x

Thielmann, I., Moshagen, M., Hilbig, B., & Zettler, I. (2022). On the comparability of basic personality models: Meta-analytic correspondence, scope, and orthogonality of the Big Five and HEXACO dimensions. *European Journal of Personality*, *36*(6), 870-900. doi:10.1177/08902070211026793

Tippins, N., Oswald, F., & McPhail, S. M. (2021). Scientific, legal, and ethical concerns about AI-based personnel selection tools: A call to action. *Personnel Assessment and Decisions*, 7(2). https://doi.org/10.25035/pad.2021.02.001

van Bork, R., Rhemtulla, M., Waldorp, L. J., Kruis, J., Rezvanifar, S., & Borsboom, D. (2021). Latent Variable Models and Networks: Statistical Equivalence and Testability. *Multivariate Behavioral Research*, 56(2), 175–198. https://doi.org/10.1080/00273171.2019.1672515

Widaman, K. F. (2006). Best practices in quantitative methods for developmentalists: III. Missing data: What to do with or without them. *Monographs of the Society for Research in Child Development*, 71, 42-64. https://doi.org/10.1111/j.1540-5834.2006.00404.x

Figure 1. Level 1 EGA network plot

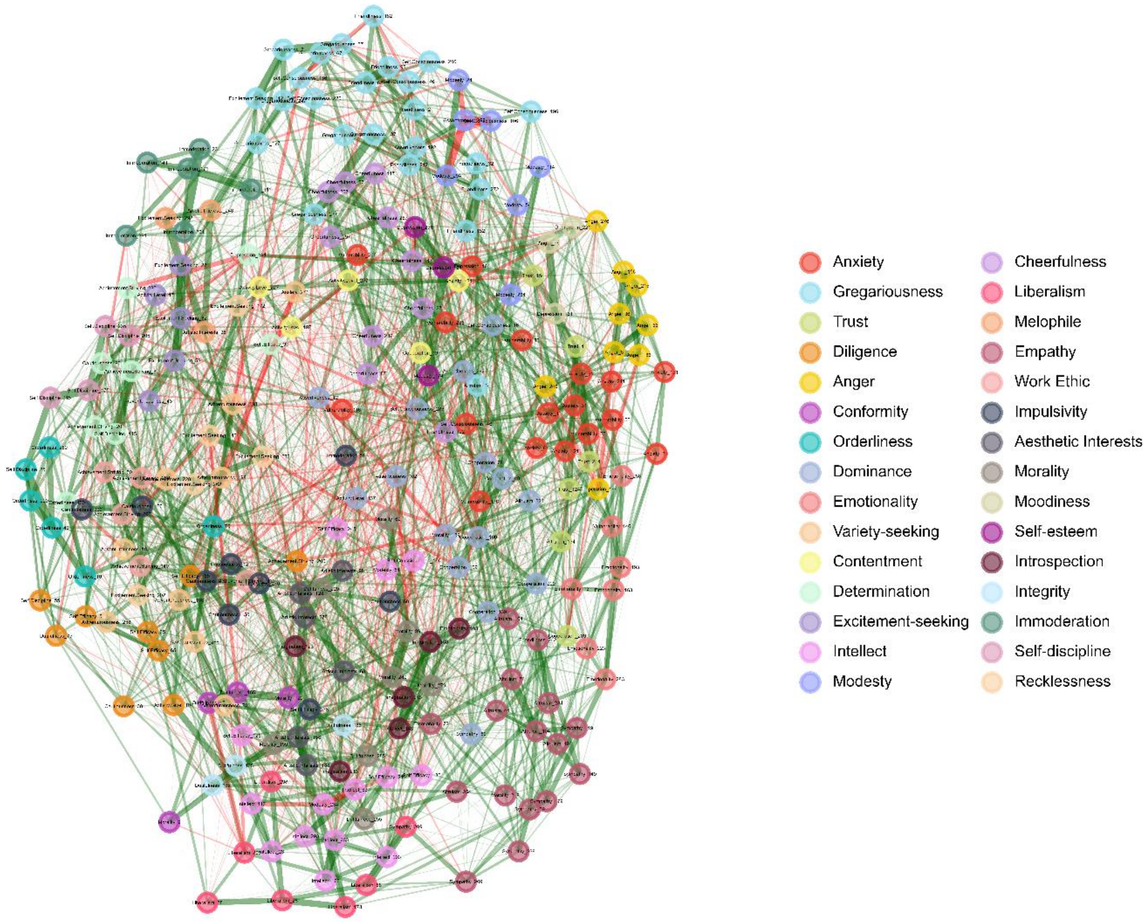
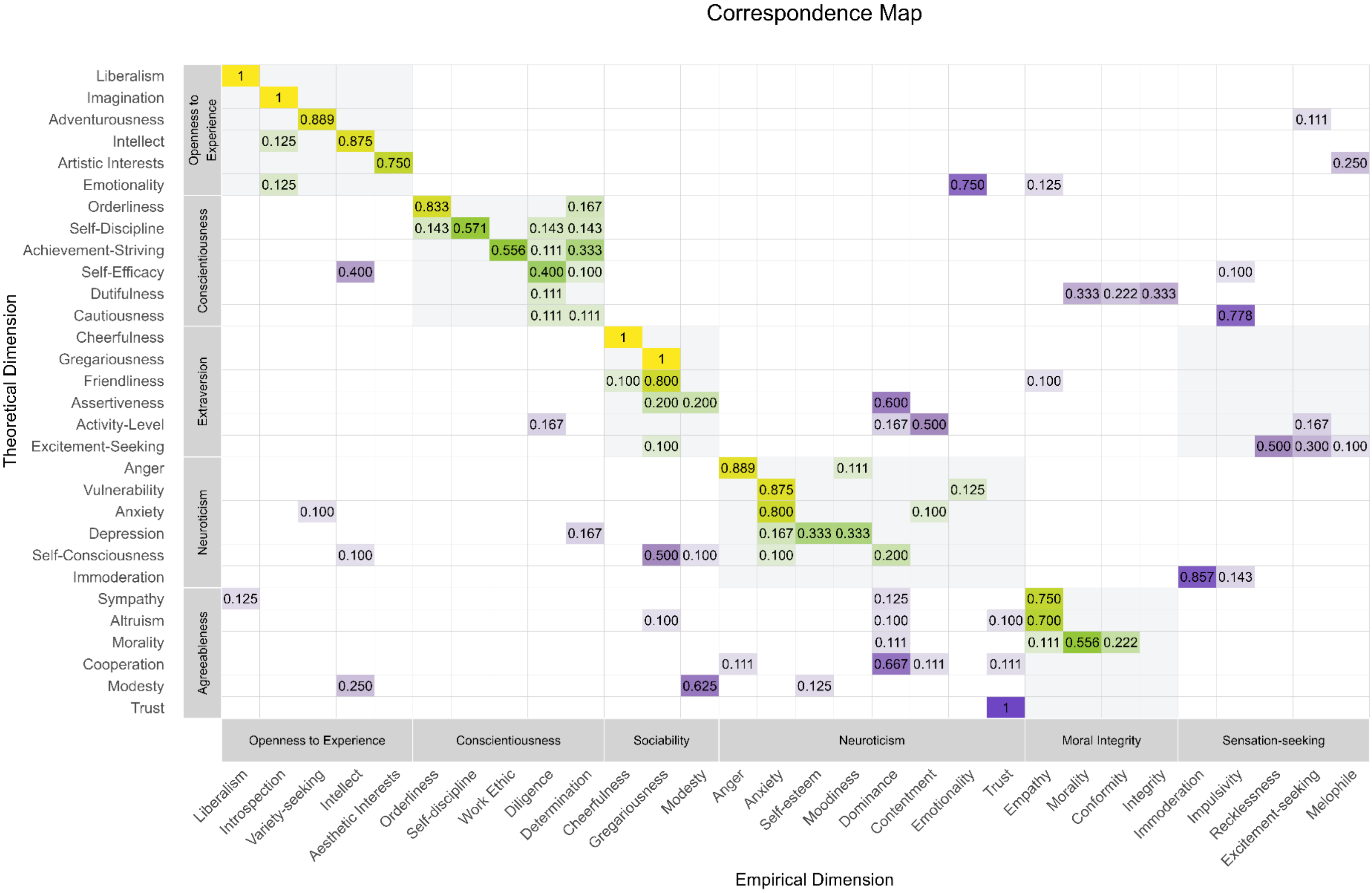


Figure 2. Correspondence Map of the Theoretical and Empirical First Level Dimensions



Note. Theoretical first level dimensions are on the y-axis with their theoretical second level labels; empirical first level dimensions are on the x-axis with their theoretical second level labels. The values represent the proportion of items in the theoretical first level dimension that is represented in each empirical first level dimension. The color represents whether the empirical first level dimension is consistent (yellow) or inconsistent (purple) with the theoretical first level dimension based on the second level dimensions (grey boxes).

Figure 3. Level 2 EGA network plot

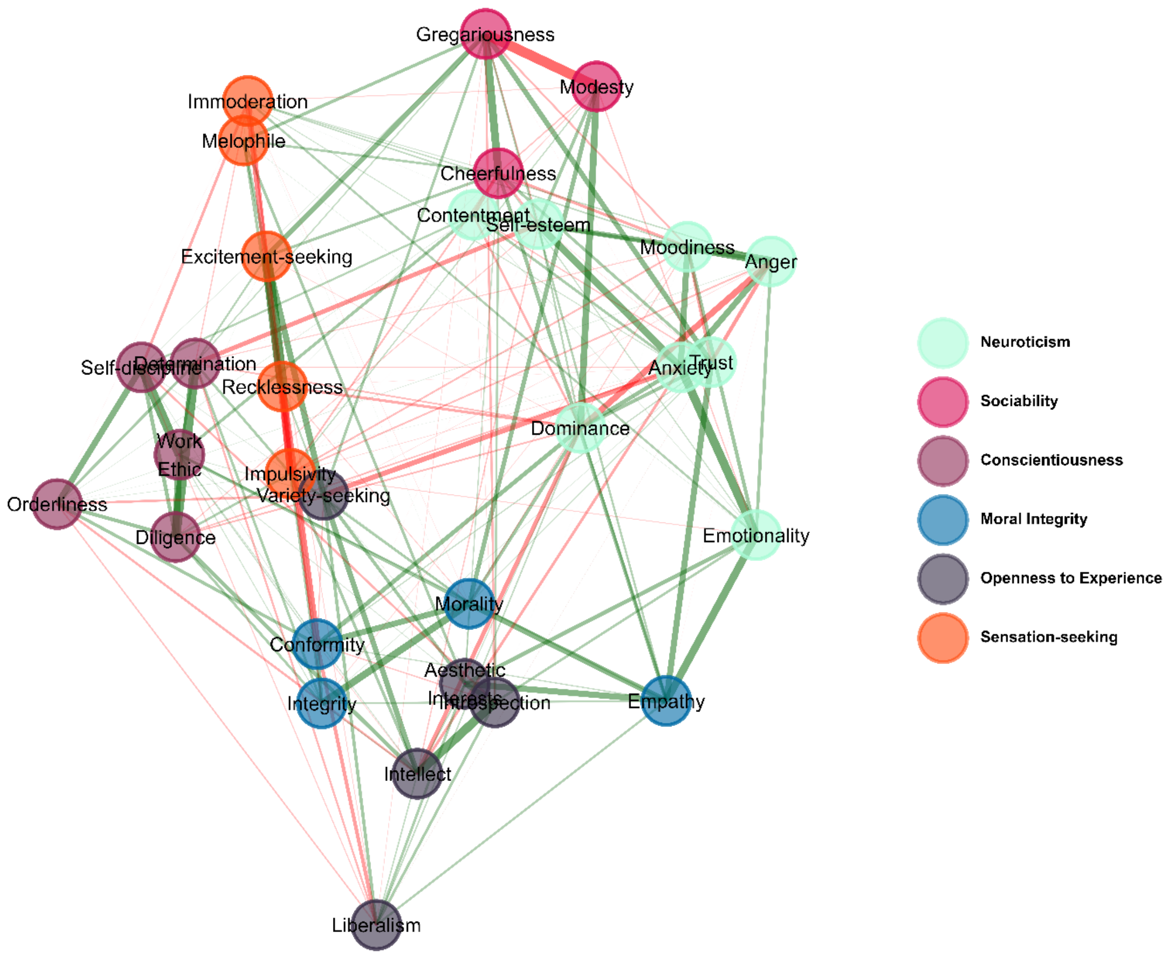


Figure 4. Pearson's and EBICglasso partial correlations between the level 2 EGA dimensions

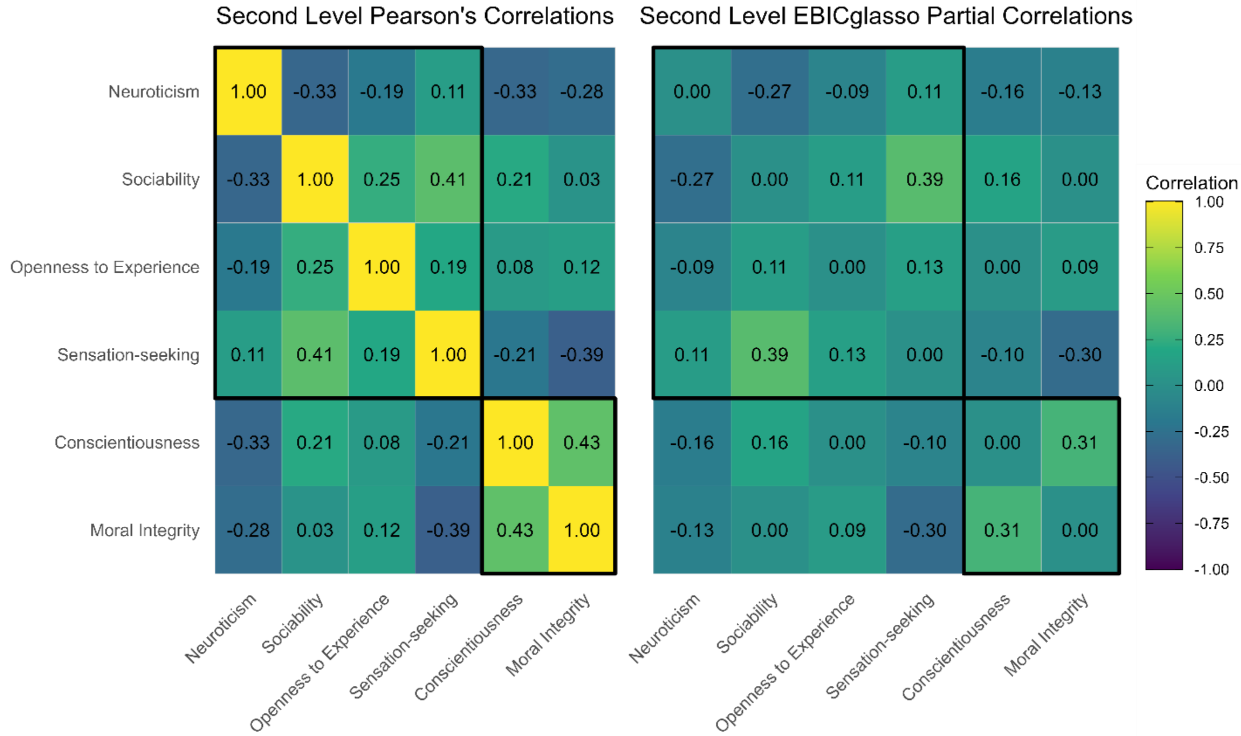


Figure 5. Level 3 EGA network plot

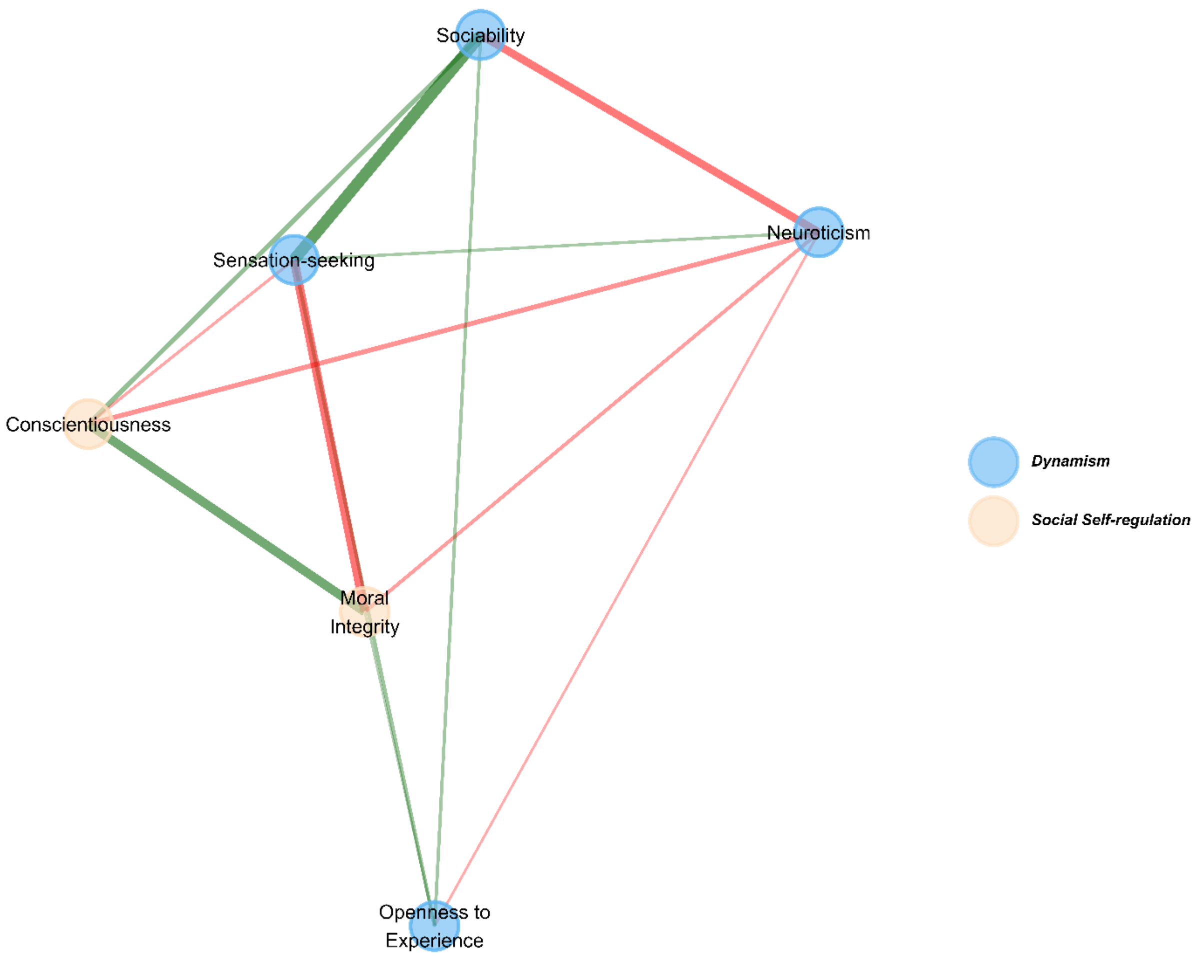


Figure 6. Full hierarchical EGA network plot