Special Issue: New Approaches Toward Conceptualizing and Assessing Personality
Original Article

Modularity of the Personality Network

Daniel Castro[1,2], Filipa Ferreira[1,2], and Tiago Bento Ferreira[1,2]

[1]Department of Social and Behavioral Sciences, University Institute of Maia (ISMAI), Maia, Portugal
[2]Center of Psychology at University of Porto (CPUP), Portugal

Abstract: The Five Factor Model (FFM) is the most widely used personality model; it proposes a hierarchical structure of personality with personality characteristics, facets, and factors. An increasing number of studies have challenged the FFM and a plethora of factor models with varying numbers of facets and factors have been proposed, leading to uncertainties about the structure of personality. The networked system of interactions between personality characteristics has stimulated promising progresses, however, the methodological developments needed to map the topological structure and functional organization remain scarce. This study aims to explore the hierarchical modular structure of the personality network and the functional role of personality characteristics. A sample of 345,780 individuals (M_{age} = 24.99, SD_{age} = 10.00; 59.18% female) that completed the International Personality Item Pool – NEO-120 in a previous study was reanalyzed. A non-regularized method was used to estimate the personality network and ModuLand was used to characterize its modular structure. Results revealed a modular structure comprising three levels: one level with the 120 personality characteristics, a second level with 35 modules, and a third with 9 modules. Such results suggest that specific personality characteristics and modules have specialized roles in the topological structure of the personality network.

Keywords: FFM, personality network, modular structure, non-regularized methods, ModuLand algorithm

The Five Factor Model (FFM; Digman 1989) is the most influential multidimensional personality model. This model recognizes that personality is hierarchically structured (McCrae & John, 1992) on three levels: factors, facets, and specific personality characteristics. The higher level comprises 5 factors/dimensions defined as Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience (McCrae & Costa, 1997). Subsequently, each of these factors contains subgroups of characteristics identified as facets, which, cover more specific personality characteristics (Mõttus & Allerhand, 2018). Although a substantial number of studies support this model (see John et al., 2008 for a review), there remains no consensus about the structure of personality due to a lack of consistent results pertaining to the different descriptive levels proposed by the FFM. The number of factors has been contested due to the lack of reproducibility across personality inventories, with different studies supporting a variable number of factors ranging from 1 to 12 (e.g., Bäckström, 2007; Digman, 1997; Shedler & Westen, 2004; Wakabayashi, 2014). Furthermore, there is no generally recognized method of deriving facets (McCrae, 2009; Ziegler & Bäckström, 2016), which causes the number of facets to change according to the inventory that is used (Soto & John, 2017). In addition, the number of levels has also been contested and alternative proposals have emerged that attempt to provide more fine-grained views of personality (e.g., DeYoung et al., 2007; Mõttus et al., 2017).

From a psychometric perspective, these discrepancies were attributed to the selection of personality characteristics included in the personality inventories and the choice of factor rotations (Franić et al., 2014), the presence of cross-loadings (McCrae & Costa, 2008), and the misinterpretation of the statistical techniques (usually exploratory factor analysis or principal components analysis), from which the FFM is derived (Borsboom, 2006). Additionally, the personality structures originating from these techniques tend not to adequately fit in a confirmatory context (McCrae et al., 1996). As such, a theoretical interpretation of these results is difficult because the FFM lacks any formal theory (Franić et al., 2014).

In this context, it is significant that recent studies have found personality characteristics to be better predictors in a variety of outcomes than the FFM factors themselves (Mõttus et al., 2017; Seeboth & Mõttus, 2018), suggesting that personality characteristics are more accurate descriptors and might provide better explanations for the personality structure than the factors. This is especially noteworthy in light of the recognition that there exists a lack of clarification in the FFM, of the interactions that emerge between the personality characteristics (Goekoop et al., 2012), and a lack of integration of these interactions in the personality models (Baumert et al., 2017).

In this way, the FFM largely remains descriptive in its nature and so is unable to provide an explanatory theory regarding these interactions (John et al., 2008). In fact, some authors have recently proposed that these interactions between the personality characteristics are responsible for the emergence of the personality structure (Cramer et al., 2012). Altogether, this suggests that the interactions between the personality characteristics are more relevant to the comprehension of the personality structure than acknowledged and implied by previous models. The recently developed network approach for psychology focuses precisely on these interactions (Cramer et al., 2012).

A network is composed of nodes or vertices that are connected by edges or links and can be used to explain various kinds of phenomena such as social, biological, and semantic (Kovács et al., 2010). For psychology, this implies a change in the nature of psychological phenomena from the traditional latent variable perspective to a perspective centred on the interactions between psychological variables. While common factor analytic techniques use these variables to identify an unobserved or latent construct (Wright, 2017), network analysis focuses on the interactions between variables to explain the psychological phenomena without referring to any latent construct beyond the psychological variables in question.

Recently, this approach has been applied to the study of personality (Goekoop et al., 2012), conceptualizing personality as a networked system of interacting personality characteristics (Cramer & Borsboom, 2015; Cramer et al., 2010). In this context, personality characteristics (i.e., items) are viewed as nodes in a network and the interactions (i.e., partial correlations) between them as links. In this perspective, it is through these interactions that the personality structure develops and stabilizes. However, previous studies on the personality network have focused predominantly on establishing the theoretical (Cramer et al., 2012) and methodological (Costantini et al., 2015, 2019; Goekoop et al., 2012) potential of network analysis or on the exploration of specific dimensions of the FFM (Costantini & Perugini, 2016; Christensen et al., 2019). This leaves a large amount of ground uncovered in comparison with the advances made in psychopathological networks. Within the context of psychopathology networks, symptoms are conceptualized as nodes and the interaction between them links (Cramer et al., 2010). Focusing on the interaction between symptoms has facilitated advancements in the nosology and comorbidity of mental disorders (Curtiss & Klemanski, 2016). This has largely been accomplished through the detection of network communities or modules and the identification of bridge symptoms within the network (Bekhuis et al., 2016; McNally et al., 2017).

Modules are sets of highly interconnected symptoms and have been used to identify the structure of various mental disorders (e.g., Blanken et al., 2018; Price et al., 2019). This has been achieved either by estimating a network of only one disorder and determining its intrinsic organization (Birkeland & Heir, 2017) or by combining, in the same network, two different but highly comorbid disorders, and establishing which symptoms belong to each disorder (Castro et al., 2018; Jones et al., 2018). This assumes that the symptoms that are more connected with each other correspond to a specific mental disorder or to a specific group of disorder characteristics (Borsboom, 2017). Moreover, by identifying these modules, we can identify the symptoms that connect them. These symptoms are known as bridge symptoms (Jones et al., 2019) and have been proposed to be the mechanisms behind the development of comorbid disorders (Cramer et al., 2010).

In previous psychopathological network studies, bridge symptoms have been divided into two subcategories: symptoms that connect both disorders due to their interactions with other modules in the network (Levinson et al., 2017) and symptoms that connect disorders by belonging to more than one module (Cramer et al., 2010). The identification of these symptoms and modules has been done with two major methods in psychopathological networks. One of these methods was proposed by Jones and colleagues (2019), which uses theory guided defined modules (i.e., the researcher defines the modules) followed by the estimation of a bridge centrality measure for each symptom; this determines the strength of the connections that the symptom has with the other modules. Thus, the higher the bridge centrality of a specific symptom, the more important its role in connecting the modules. However, this method fails to specify the modules based on the network properties and is not able to determine symptoms that belong to both disorders. The other proposed method is the Clique Percolation Method (CPM; Adamcsek et al., 2006; Palla et al., 2005), introduced into the psychopathological networks literature by Blanken and colleagues (2018), which determines the symptoms that belong to both modules; however, the method cannot determine the number of connections of a symptom with the other modules. Translating this into personality networks, modules represent sets of highly interconnected personality characteristics that comprise the personality structure (Goekoop et al., 2012). For example, while in the traditional factor analytic models the extraversion factor occurs due to patterns of covariance in certain items (Wright, 2017), in the network perspective extraversion emerges from the interactions between these items (Cramer et al., 2012). In turn, the characteristics that connect the modules would be bridge characteristics. As with bridge symptoms, these might be characteristics that are responsible for the development of the personality structure.

However, none of the aforementioned algorithms for module and bridge detection are able to determine a hierarchical structure, which is central to the FFM proposal (McCrae & John, 1992). The only approximation to an estimation of a hierarchical structure proposed in the psychological networks studies is the Minimum Spanning Tree (MST) method (Mantegna, 1999). The MST gives us indirect information on hierarchical levels, but it does not produce measures for any of the two types of bridges proposed or for the modules in each hierarchical level. Consequently, none of the methods introduced in psychological networks allow for a complete and detailed exploration of the personality structure.

Therefore, the modular structure of the personality network remains largely unexplored, maintaining current uncertainties about the constitution of personality modules, as well as the mechanisms underlying the interactions between the personality characteristics both within and across the modules. In this context, there exists a need for new methods that can identify the hierarchical structure of personality and both types of bridge characteristics between the various modules in the different hierarchical levels. This paper aims to address these issues by exploring the ModuLand framework (Kovács et al., 2010). ModuLand (Kovács et al., 2010) is an integrated framework for the identification of the hierarchical modular structure of complex networks; it can quantify both types of bridge characteristics and provides information regarding the connections within and across modules for all hierarchical levels. This fine-grained view of personality could provide valuable information about the inner workings and organization of personality, which could, consequently, improve research and clinical practice (Goekoop et al., 2012; Knefel et al., 2016).

Therefore, with this framework we aim to characterize (1) the modular structure of personality; (2) the modular connectivity; and (3) the functional roles of the personality characteristics.

Method

Participants

The open access data from a previous study on the International Personality Item Pool – NEO-120 (IPIP-NEO-120; see Johnson, 2014 for a detailed description) were analyzed. Originally, 690,863 anonymous individuals completed a web-version of the 120 items of the IPIP-NEO-120. The percentage of missing values across the 120 items ranged from 0.1% to 0.7%, and the percentage of mismatch across all pairs of items from 0.13% to 1.37%. The number of missing values did not significantly vary between genders. After removing participants with missing responses, a sample of 345,780 participants (M_{age} = 24.99, SD_{age} = 10.00; 59.18% female) was analyzed.

Measures

International Personality Item Pool – NEO-120 (IPIP-NEO-120)

The IPIP-NEO-120 is a 120-item self-report inventory that measures the five domains of personality and the 30 facets of the FFM. The IPIP-NEO-120 revealed good reliability, with mean αs for facets ranging from .63 to .88, and between .81 and .90 for the dimensions (Johnson, 2014).

Network Estimation and Analysis

The personality network was estimated using a non-regularized method based on multiple regression, implemented in the GGMnonreg package (version 0.1.0; for a detailed description see Williams et al., 2019) for R (version 3.5.1; R Development Core Team, 2018). This method was used since it recently achieved high specificity, as well as a low false positive rate, in comparison with traditional estimation methods (Epskamp et al., 2018). The R package qgraph (version 1.5; Epskamp et al., 2012) was used for the graphical representation of the personality network. The quality of partitions was evaluated through the modularity measure available in igraph package (version 1.2.4.1; Csárdi, 2019) for R (version 3.5.1; R Development Core Team, 2018). Modularity is the number of optimal edges that can be removed to identify communities (Newman, 2006).

Hierarchical Modular Structure

The ModuLand algorithm (Kovács et al., 2010), implemented in Cytoscape 3.5.1. (Shannon et al., 2003), was used to estimate and characterize the hierarchical modular structure of the personality network. This algorithm defines a module as a set of nodes that mutually influence each other. So, in order to estimate the modular structure, ModuLand initially applies the Linkland function to assess the influence zone of each edge in the network. The influence zone is a subgraph of the network that contains the starting edge and all other edges in the network, which has an indirect impact on the starting edge. Subsequently, the community centrality of each edge is estimated by computing the influence zones covered by a given edge. From this, the community centrality of the node is derived (see Kovács et al., 2010 for detailed formulas). Nodes are then expressed in a community centrality landscape, where nodes with higher community centrality (module centres) form hills; overlapping hills are considered overlapping modules. In this way, the number of modules corresponds to the number of hills, that is, the number of nodes with the highest levels of mutual influence (community centrality). According to their positioning in the community centrality landscape, module assignment values for the remaining nodes are estimated.

In order to create the hierarchical levels, modules from the previous level become meta-nodes and the overlapping values between them the links. Thus, if the first level has five modules, the subsequent level will be a network composed by five nodes and the links between them will be the overlapping values of the modules in the previous level. It is from this network that the next hierarchical level is estimated, repeating the initial procedure. These steps are repeated until the network becomes just one single meta-node.

Moreover, ModuLand allows the characterization of the hierarchical modular structure of the personality network and the functions of the personality characteristics. This framework thereby provides a set of measures that allow a more comprehensive view of the hierarchical modular structure, namely community centrality and effective degree. Community centrality is a measure that displays the extent of the influence each personality characteristic or module possesses. Effective degree corresponds to the effective number of weighted connections of a given characteristic or module. In addition, ModuLand enables the characterization of two types of bridge symptoms through measures of modular bridgeness and modular overlap. Modular bridgeness is a measure of the inter-modularity that corresponds to the effective number of the modules that a personality characteristic is connected to. Similarly, modular overlap is a measure of the trans-modularity of each personality characteristic and corresponds to the effective number of modules that a personality characteristic belongs to.

Network Robustness

The robustness of the personality network was examined according to the procedures of previous studies (e.g., Letina et al., 2019). The initial sample was divided into two random sub-samples by attributing each participant a 50% probability of being assigned to either sub-sample. This procedure was repeated 100 times resulting in 100 pairs of subsamples. For each subsample, the network was estimated according to the procedure described above. The networks corresponding to each pair were compared on several indicators. As presented in Table 1, high reliability was evidenced by all indicators. Procedures and results for robustness under different sample sizes and partitioning are available in the Electronic Supplementary Materials (ESM 1), Figures E21–E28.

Results

Personality Network

Figure 1 depicts the personality network estimated from the 120 personality characteristics included in the IPIP-NEO-120 (Johnson, 2014). Nodes (the circles) represent the 120 personality characteristics of the IPIP-NEO-120 and the edges (the lines connecting the circles) represent the connections apparent between the nodes. The width of the edges between the nodes represents the connection strength. Edges in red represent negative connections, while positive connections are represented in blue. The network is constituted of 4,410 connections (density = .618), of which 2,484 (56.32%) are positive connections and 1,926 (43.67%) are negative. The weights of positive connections range from .005 to .628 (M = 0.031, SD = 0.050); negative connections weigh from .005 to .344 (M = 0.017, SD = 0.016). More network descriptives can be found in Table E2 in ESM 1.

Modular Structure of the Personality Network

The modular structure of the personality network comprised of three levels. The first level corresponded to the 120 personality characteristics (i.e., items), the second level comprised 35 modules, and the third comprised 9 modules. The interactions between the second-level and third-level modules were estimated through the overlap values in the previous level. Figure 2 represents the hierarchical, modular organization of the personality network. The modularity score for the second level was −0.0087, whereas the third level achieved −0.0292.

Level 1: The 120 Personality Characteristics

For the first level, two centrality measures were computed: effective degree and community centrality (ESM 1, Figures E2 and E3). The personality characteristics, “try not to think about the needy” (119), “have difficulty starting tasks” (115), and “remain calm under pressure” (116) showed a higher effective degree. This exposes the strong connections between these personality characteristics, thereby they not only have a high number of connections but also strong connections with the neighboring personality characteristics in the network. Consequently, they may play an important role in the stability of the network.

In terms of community centrality, “am not bothered by difficult social situations” (106), “only feel comfortable with friends” (76), and “have a high opinion of myself” (84) were the characteristics with the highest values. Thus, these characteristics may have a high capacity to reach various

Table 1. Descriptives of the robustness indicators

Robustness indicator	*M* (*SD*)	Minimum–Maximum
Difference in the total number of estimated edges	0.000	.000–.000
Similarity Index	0.871 (0.006)	.856–.885
Proportion of edges that failed to replicate	0.129 (0.006)	.115–.144
Correlation between edges weights	0.992 (0.000)	.992–.993
Correlation between nodes degree	0.982 (0.002)	.977–.986
Correlation between nodes closeness	0.993 (0.001)	.989–.996
Correlation between nodes betweenness	0.984 (0.004)	.973–.990
Correlation between nodes expected influence	0.995 (0.001)	.992–.997
Number of estimated second-level modules on split-halves samples	36 (0.761)	33–37
Number of estimated third-level modules on split-halves samples	10 (3.30)	1–12

other characteristics and could have an important impact on personality development.

Level 2: 35 Modules

In the second level, a network of 35 modules was identified (Figure E19 in ESM 1). This is similar to the 30 facets proposed for the IPIP-NEO-120, with the main differences concerning splits in specific facets; for example, the depression facets "feel comfortable with myself" (101) and "dislike myself" (41) solely form module 15 and the items "often feel blue" (11) and "am often down in the dumps" (71) exclusively form module 25. A detailed description and comparison between the FFM facets and second level modules can be found in ESM 1, Table E1.

Regarding the centrality measures, the personality characteristics that revealed the highest values of modular bridgeness (Figure E9 in ESM 1) were "believe that I'm better than others" (24), "radiate joy" (27), "love to read challenging material" (23), "like to take it easy" (107), and "am afraid to draw attention to myself" (46). These characteristics seem to be positioned between modules, playing a vital role in connecting the different modules of this level. At a facet level, therefore, these seem to be the most important characteristics in the connection of the facets due to their positioning. Moreover, the personality characteristic "am afraid to draw attention to myself" (46) also displayed a high value of modular overlap, along with the "am not bothered by difficult social situations" (106) and "like to take it easy" (107) personality characteristics. So, these characteristics seem to belong to various facets, and this might have important consequences for the development and stabilization of the network. Interestingly, the items "am afraid to draw attention to myself" (46) and "like to take it easy" (107) showed high levels of both modular bridgeness and overlap. In this case, these two characteristics seem to be able to connect the modules due to their positioning in the networks and by belonging to various facets. The dual role of these characteristics might increase their importance in the development and stability of the personality network.

Concerning the modules, Figure E13 in ESM 1 shows the modular overlap and bridgeness for each module in this hierarchical level. Modules 31, 22, and 2 tend to group the personality characteristics with higher overlap. It can also be seen that modules 6, 27, 22, and 18 tend to cluster the characteristics with higher bridgeness. Regarding community centrality (Figure E6 in ESM 1), modules 14, 10, and 34 exhibited the higher values. In addition, module 14 also showed the higher values of effective degree, followed by modules 18 and 28 (Figure E10 in ESM 1). In contrast, module 31 had the lowest values of effective degree and community centrality measures. These results point to a certain level of specialization of the modules, with some modules being more closely related with trans-modular processes (i.e., grouping high overlapping characteristics) or to an intermodular role (i.e., grouping high bridgeness characteristics).

Level 3: 9 Modules

In the third hierarchical level, a 9-module network (ESM 1, Figure E20) was derived from the second level (ESM 1, Figure E19). In comparison with the FFM factors, only modules 8 and 4 were composed by personality characteristics of the same FFM factor, Openness to Experience. The remaining modules were all composed of personality characteristics from different factors. For example, module 1 had personality characteristics corresponding to all the FFM factors. Despite this, each module consistently demonstrated more personality characteristics of a given factor. For example, module 1, while possessing personality characteristics from each factor, has a higher number of personality characteristics from Neuroticism (see ESM 1, Table E1 for a detailed description of all the modules).

Regarding the centrality measures, the personality characteristics (ESM 1, Figure E4) "go on binges" (21), "easily resist temptations" (81), and "am able to control my cravings" (111) showed the highest values of modular bridgeness. This means that, when looking at the personality characteristics that connect these 9 modules, these characteristics are those that are positioned between them.

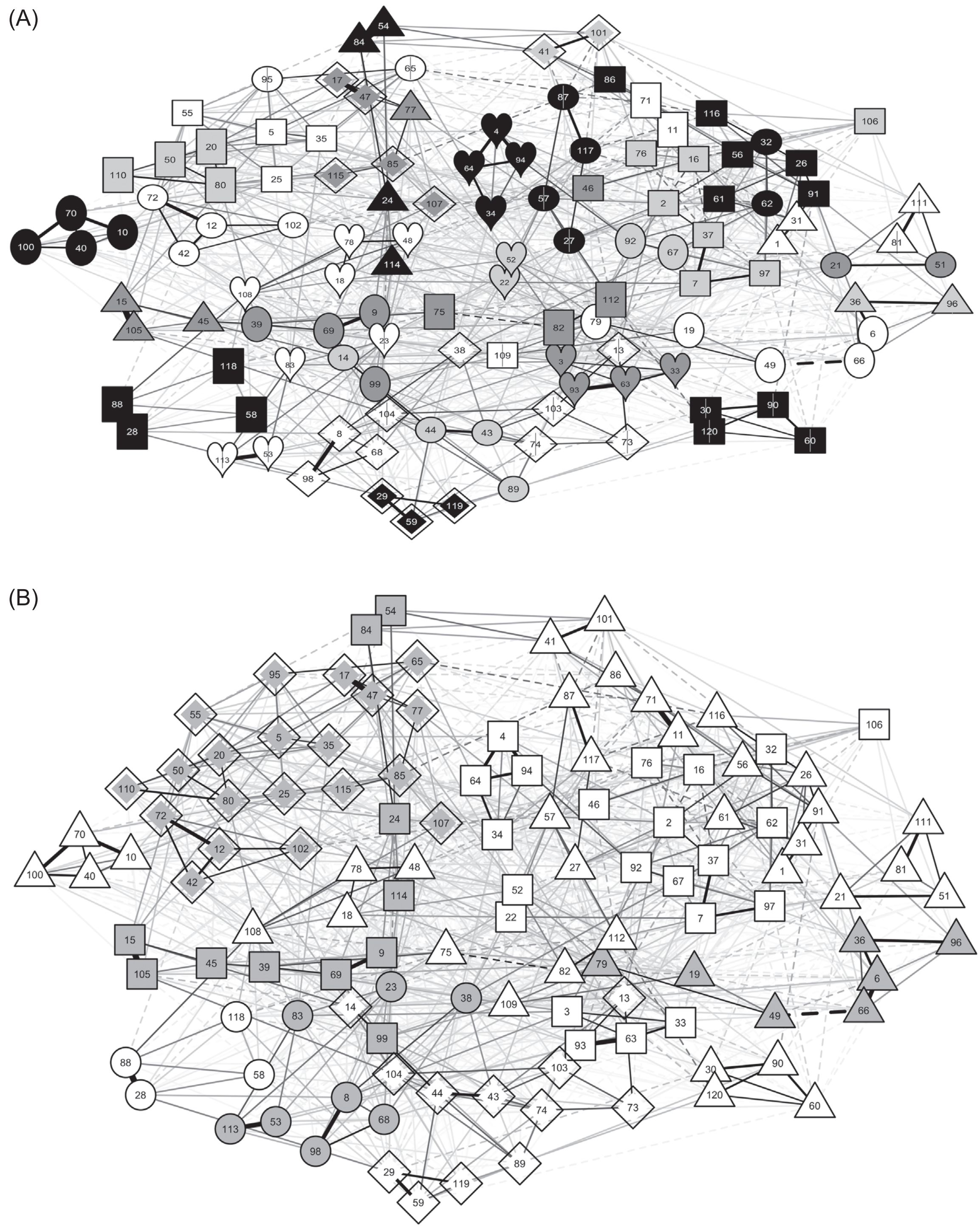

Figure 1. Graphical representation of the first level network. Nodes represent the 120 items in the IPIP-NEO-120. (A) Projection of the second level modules in the first level network. (B) Projection of the third level modules in the first level network. In panel (A), each polygon represents the second level modules to which the nodes are most assigned to. Nodes assigned to module 1 are represented by white triangles, nodes assigned to module 2 are represented by white squares, nodes assigned to module 3 are represented by white diamonds, nodes assigned to module 4 are represented by white circles, nodes assigned to module 5 are represented by gray triangles, nodes assigned to module 6 are represented by gray squares, nodes assigned to module 7 are represented by gray diamonds, nodes assigned to module 8 are represented by gray circles, nodes assigned to module 9 are represented by black triangles, nodes assigned to module 10 are represented by black squares, nodes assigned to module 11 are represented by black diamonds, nodes assigned to module 12 are represented by black circles, nodes assigned to module 13 are represented by light gray triangles, nodes assigned to module 14 are represented by light gray squares, nodes assigned to module 15 are represented by light gray diamonds, nodes assigned to module 16 are represented by light gray circles, nodes assigned to module 17 are represented by white hearts, nodes assigned to module 18 are represented by light gray hearts, nodes assigned to module 19 are represented

Figure 1. (continued) by gray hearts, nodes assigned to module 20 are represented by black hearts, nodes assigned to module 21 are represented by white ellipses, nodes assigned to module 22 are represented by light gray ellipses, nodes assigned to module 23 are represented by gray ellipses, nodes assigned to module 24 are represented by black ellipses, nodes assigned to module 25 are represented by white rectangles, nodes assigned to module 26 are represented by light gray rectangles, nodes assigned to module 27 are represented by gray rectangles, nodes assigned to module 28 are represented by black rectangles, nodes assigned to module 29 are represented by white circles with a black bar, nodes assigned to module 30 are represented by white diamonds with a black bar, nodes assigned to module 31 are represented by white squares with a black bar, nodes assigned to module 32 are represented by white triangles with a black bar, nodes assigned to module 33 are represented by white hearts with a black bar, nodes assigned to module 34 are represented by black circles with a white bar and nodes assigned to module 35 are represented by black squares with a white bar. In panel (B), each polygon represents the third level modules to which the nodes are most assigned to. Nodes assigned to module 1 are represented by white triangles, nodes assigned in module 2 are represented by white squares, nodes assigned to module 3 are represented by white diamonds, nodes assigned to module 4 are represented by gray triangles, nodes assigned to module 6 are represented by gray squares, nodes assigned to module 7 are represented by gray diamonds and the nodes assigned to module 8 are represented by gray circles. In both panels, the edges between the nodes represent the interaction between the nodes and the width of the edge represents the interaction strength. Only edges with weights superior to .3 are represented in the figure. Non-thresholded figures are available in ESM 1.

Consequently, these characteristics provide access to the different modules and might help develop high order ones, which, in turn, might provide access to the development of the specific second level modules (facets). The personality characteristics “easily resist temptations” (81), “rarely overindulge” (51), and “am able to control my cravings” (111) exhibited the highest values of modular overlap. These characteristics belong to more than one of the 9 modules in this level, meaning that these characteristics also connect the modules and due to their overlap might also contribute to their stability. Regarding the modules in this level, ESM 1, Figure E14 shows the modular bridgeness and overlap; clearly, modules 4, 6, and 8 tend to group the personality characteristics with the highest overlap. It can also be observed that the bridgeness values of the personality characteristics were broadly similar across the 9 modules, with modules 4 and 8 tending to group personality characteristics with slightly higher values of this measure. Across these 9 modules, the higher values of community centrality were on modules 1 and 2 (ESM 1, Figure E7), with modules 5, 3, and 8 revealing the highest values of effective degree (ESM 1, Figure E12). Despite this, none of these modules simultaneously had high values in both effective degree and community centrality measures. This could indicate that modules 1 and 2 are more associated with the development of the other modules and that modules 5, 3, and 8 are more associated with the stability of the high order level of the personality structure. The second level modules with the highest assignment values in the third level are illustrated in ESM 1, Table E1. Interestingly, none of the second level modules had the highest assignment value on module 0.

Discussion

We aimed to contribute to the clarification of the personality structure by proposing a hierarchical model and outlining the distinct functions for the different personality characteristics through network analysis and ModuLand framework. ModuLand allowed for the estimation and characterization of the hierarchical modular structure of the personality network rooted on the theoretical grounds that have been proposed for psychological networks (Borsboom, 2017; Borsboom, Cramer, & Kalis, 2019). Although other cluster and hierarchy detection methods have been proposed in psychological networks, such as the Exploratory Graph Analysis (EGA; Golino & Epskamp, 2017) and the Minimal Spanning Tree (MST; Letina et al., 2019). There are several theoretical proposals that have been made in psychopathological and personality networks that are not embodied in these methods, i.e., bridge and overlap personality characteristics (Cramer et al., 2012; Jones et al., 2019). Moreover, the structure of personality is assumed to encompass 3 hierarchical levels (McCrae & John, 1992) and none of the cluster detection methods introduced in psychopathological and personality networks can estimate more than one hierarchical level. For example, in EGA the clustering method only allows for the estimation of one hierarchical level. Moreover, in EGA clusters are determined via the walktrap algorithm, which assumes that there are no overlapping features in the network (Golino & Epskamp, 2017). Even in other clustering methods introduced in psychological networks where the overlapping features can be estimated, for example, Clique Percolation Method (Blanken et al., 2018), the hierarchical structure is limited to one level, which in personality research would be the equivalent to the facets level. In turn, in ModuLand the modules from one level become nodes in the next hierarchical level and their overlapping values in the previous level become the edges between the modules. This allows for the estimation of a hierarchical structure with various levels, resulting in a hierarchical structure grounded in the overlapping features of the network.

Thus, to study the personality structure from a network perspective, from the proposed network theory of mental disorders and in the previous theoretical approaches in personality, methods like ModuLand allow for an integrative framework. With this in mind, we have opted for ModuLand in order to determine a personality structure that

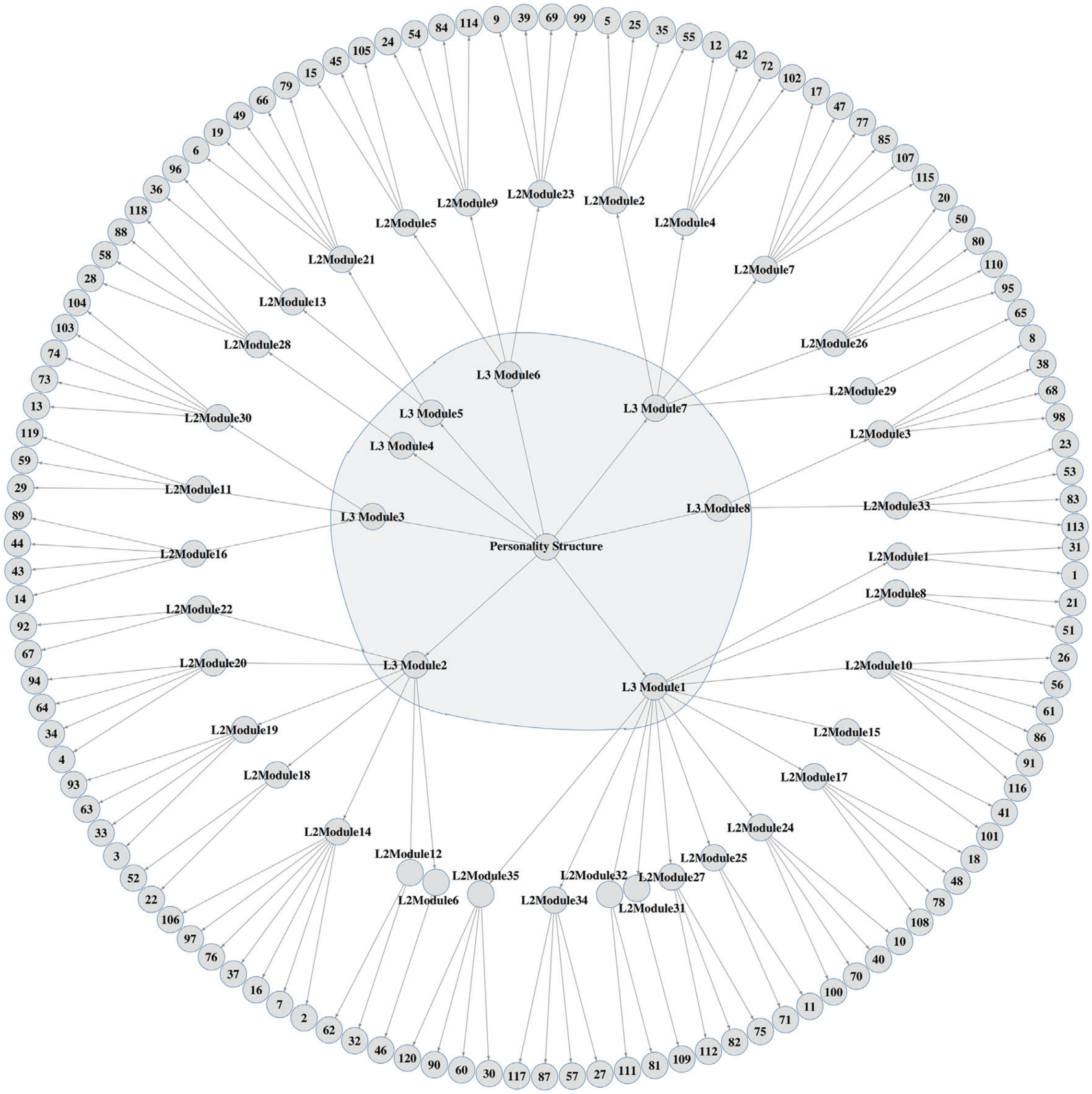

Figure 2. Hierarchical structure of personality. The outer ring represents the first hierarchical level with its 120 personality characteristics (numbers 1–120). The subsequent ring represents the 35 modules of the second hierarchical level (L2Module1–L2Module35). The third hierarchical level is represented by the central ring. The area surrounding the second level modules (L2) corresponds to the L3 Module 0. This representation of L3 Module 0 was implemented as none of the L2 modules were primarily assigned to this module.

could accommodate these theoretical perspectives and provide an increased detail in its characterization. ModuLand allows for a fine-grained characterization of each characteristic and module that might shed some light in the mechanisms at play in the development and maintenance of the personality structure.

In the present paper, we propose that centrality measures might represent different roles for modules and for personality characteristics (see Results section); however, none of these roles have been evaluated and are solely derivations from the other fields of network science. Future research should focus on examining the centrality measures and their possible roles in the development and stability of the personality structure. We envision two ways of examining the proposed roles for the personality characteristics. First, as typically done in network science, simulated contagion might give us a first glimpse into the personality characteristics that are more prone to disseminate information across the network and, consequently, play an important role in the development of personality. We suggest characteristics with high bridgeness or overlap as an initial hypothesis. Second, we suggest that some characteristics might act as stabilizers and might be harder to change. In order to test this hypothesis, we suggest the deactivation of these characteristics and the analysis of the impact that this deactivation has on the network structure (for a detailed discussion on the role of centrality measures see the supplementary discussion in ESM 1).

However, the results of this study should be interpreted carefully and considering some limitations. Cross-sectional data might not be suited to directly examine the hypothesis pertaining to the functions of the personality characteristics and modules. Additionally, the use of a set of items from a specific inventory (IPIP-NEO-120) might have constrained the correlational structure of the personality characteristics and the modular structure of the personality network. Moreover, although we have used the most up-to-date methods for psychological networks estimation, our network still has a high number of small edges that might have driven the modular structure found. As can be seen in the Table 1 and Figure E28 in ESM 1, the modular structure of the split halves samples in the second level has a mean of 36 modules and the second level has a mean of 10 modules. And, although the network shows high robustness at this sample size (see Figures E25–E27 in ESM 1), the mean number of modules found was different for each hierarchical level from those obtained with the full sample. The large number of small edges might have driven these small differences in module detection between the full sample and the split halves. Moreover, to estimate the hierarchical structure with ModuLand algorithm, the negative edges cannot be considered. While this might be an important limitation of the method used, a clear theoretical interpretation of these edges has not been put forward. These limitations call for caution on the interpretation of the results and more studies regarding the robustness of ModuLand algorithm in psychological networks are required. Consequently, future studies should, firstly, try to replicate these results, then to specifically test the hypothesis suggested for the different centrality measures. Furthermore, this is the first time that the ModuLand algorithm has been applied to the study of the personality structure and its replicability across other samples and direct comparison with other module detection algorithms remains to be seen.

Despite these limitations, the analysis of the hierarchical modular structure of the personality network is promising as it overcomes a number of the limitations observed in previous studies and promotes a modular perspective of the personality network (see also Goekoop et al., 2012), encompassing the inter-modularity and trans-modularity of the personality characteristics. Besides, our proposed framework can accommodate all the previous theoretical contributions made in the personality field and network theory for psychological phenomena, adding detail to the characterization of the personality structure.

Electronic Supplementary Materials

The electronic supplementary material is available with the online version of the article at https://doi.org/10.1027/1015-5759/a000613

ESM 1. Comparison between the Five-Factor Model and the ModuLand structure. Global properties of the network. Centrality estimates. Correlation between modules profiles. Graphical representation of the network. Robustness and stability of the network.

References

Adamcsek, B., Palla, G., Farkas, J., Derényi, I., & Vicsek, T. (2006). CFinder: Locating cliques and overlapping modules in biological networks. *Bioinformatics, 22*, 1021–1023. https://doi.org/10.1093/bioinformatics/btl039

Bäckström, M. (2007). Higher-order factors in a five-factor personality inventory and its relation to social desirability. *European Journal of Psychological Assessment, 23*(2), 63–70. https://doi.org/10.1027/1015-5759.23.2.63

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

Bekhuis, E., Schoevers, R., Van Borkulo, D., Rosmalen, M., & Boschloo, L. (2016). The network structure of major depressive disorder generalized anxiety disorder and somatic symptomatology. *Psychological Medicine, 46*(14), 2989–2998. https://doi.org/10.1017/S0033291716001550

Birkeland, S., & Heir, T. (2017). Making connections: exploring the centrality of posttraumatic stress symptoms and covariates after terrorist attack. *European Journal of Psychotraumatology, 8*, 1333387. https://doi.org/10.1080/20008198.2017.1333387

Blanken, T. F., Deserno, M. K., Dalege, J., Borsboom, D., Blanken, P., Kerkhof, G. A., & Cramer, A. (2018). The role of stabilizing and communicating symptoms given overlapping communities in psychopathology networks. *Scientific Reports, 8*, Article 5854. https://doi.org/10.1038/s41598-018-24224-2

Borsboom, D. (2006). The attack of psychometricians. *Psychometrika, 71*(3), 425–440. https://doi.org/10.1007/s11336-006-1447-6

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry, 16*(1), 5–13. https://doi.org/10.1002/wps.20375

Castro, D., Ferreira, F., Mendes, A., & Ferreira, T. (2018). Bridges between bipolar and borderline personality disorders: Clarifying comorbidity through the analysis of the complex network of connections between symptoms. *The Psychologist Practice and Research Journal*, *1*(1).

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

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., & Perugini, M. (2016). The network of conscientiousness. *Journal of Research in Personality, 65*, 68–88. https://doi.org/10.1016/j.jrp.2016.10.003

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., & Borsboom, D. (2015). Problems attack problems: A network perspective on mental disorders. In R. Scott & S. Kosslyn (Eds.), *Emerging trends in the social and behavioral sciences* (pp. 1–15). Wiley. https://doi.org/10.1002/9781118900772.etrds0264

Cramer, A., Sluis, S., Noordhof, A., Wichers, M., Geschwind, N., Aggen, S., Kendler, K., & 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, 431*, 414–431. https://doi.org/10.1002/per.1866

Cramer, A., Waldorp, L., Maas, H., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Science, 33*, 137–193. https://doi.org/10.1017/S0140525X09991567

Csárdi, G. (2019). *Network analysis and visualization*. (R package version 1.2.4.1). https://cran.r-project.org/web/packages/igraph/igraph.pdf

Curtiss, J., & Klemanski, D. H. (2016). Taxonicity and network structure of generalized anxiety disorder and major depressive disorder: An admixture analysis and complex network analysis. *Journal of Affective Disorders, 199*, 99–105. https://doi.org/10.1016/j.jad.2016.04.007

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

Digman, J. M. (1989). Five robust trait dimensions: Development, stability, and utility. *Journal of Personality, 57*(2), 195–214. https://doi.org/10.1111/j.1467-6494.1989.tb00480.x

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

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., Cramer, A. O., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualizations of relationships in psychometric data. *Journal of Statistical Software, 48*(4), 1–18. https://doi.org/10.18637/jss.v048.i04

Franić, S., Borsboom, D., Dolan, C. V., & Boomsma, D. I. (2014). The Big Five personality traits: Psychological entities or statistical constructs? *Behavior Genetics, 44*(6), 591–604. https://doi.org/10.1007/s10519-013-9625-7

Goekoop, R., Goekoop, J. G., & Scholte, H. S. (2012). The network structure of human personality according to the NEO-PI-R: Matching network community structure to factor structure. *PLoS One, 7*(12), e51558. https://doi.org/10.1371/journal.pone.0051558

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. https://doi.org/10.1371/journal.pone.0174035

John, O. P., Naumann, L., & Soto, J. (2008). Paradigm shift to the integrative Big Five trait taxonomy: History, measurement and conceptual issues. In O. John, W. Robin, & L. Pervin (Eds.), *Handbook of personality: Theory and research* (pp. 114–158). Guildford Press.

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

Jones, P., Ma, R., & McNally, R. (2019). Bridge centrality: A network approach to understanding comorbidity. *Multivariate Behavioral Research*, 1–15. https://doi.org/10.1080/00273171.2019.1614898

Jones, P., Mair, P., Riemann, B. C., Mugno, B. L., & McNally, R. J. (2018). A network perspective on comorbid depression in adolescents with obsessive-compulsive disorder. *Journal of Anxiety Disorders, 53*, 1–8. https://doi.org/10.1016/j.janxdis.2017.09.008

Knefel, M., Tran, S., & Lueger-Schuster, B. (2016). The association of posttraumatic stress disorder, complex posttraumatic stress disorder, and borderline personality disorder from a network analytical perspective. *Journal of Anxiety Disorders, 43*, 70–78. https://doi.org/10.1016/j.janxdis.2016.09.002

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), Article e12528. https://doi.org/10.1371/journal.pone.0012528

Letina, S., Blanken, T., Deserno, M., & Borsboom, D. (2019). Expanding network analysis tools in psychological networks: Minimal spanning trees, participation coefficients, and motif analysis applied to a network of 26 psychological attributes. *Complexity, 2019*, Article 9424605. https://doi.org/10.1155/2019/9424605

Levinson, C. A., Zerwas, S., Calebs, B., Kordy, H., Hofmeier, S., Collaborative, V., & Bulik, C. M. (2017). The core symptoms of bulimia nervosa, anxiety, and depression: A network analysis. *Journal of Abnormal Psychology, 126*(3), 340–354. https://doi.org/10.1037/abn0000254

Mantegna, R. (1999). Hierarchical structure of financial markets. *The European Physical Journal, 11*, 193–197. https://doi.org/10.1007/s100510050929

McCrae, R. (2009). The Five-Factor Model of personality traits: Consensus and controversy. In P. Corr & G. Matthews (Eds.), *The Cambridge handbook of personality psychology* (pp. 148–161). Cambridge University Press.

McCrae, R. R., & Costa, P. T. (1997). Personality Trait Structure as a Human Universal. *American Psychologist*. https://doi.org/10.1037/0003-066X.52.5.509

McCrae, R., & Costa, P. (2008). The five factor theory of personality. In O. John, W. Robin, & L. Pervin (Eds.), *Handbook of psychotherapy theory and research* (pp. 139–153). Guilford Press.

McCrae, R., & John, O. (1992). An introduction to the five-factor model and its applications. *Journal of Personality, 60*(2), 175–275. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

McCrae, R., Zonderman, A., Costa, P., Bond, M., & Paunonen, S. (1996). Evaluating replicability of factors in the revised NEO Personality Inventory: Confirmatory factor analysis versus prosecutes rotation. *Journal of Personality and Social Psychology, 70*(3), 552–566. https://doi.org/10.1037/0022-3514.70.3.552

McNally, R. J., Mair, P., Mugno, B. L., & Riemann, B. C. (2017). Co-morbid obsessive-compulsive disorder and depression: A Bayesian network approach. *Psychological Medicine, 47*(7), 1204–1214. https://doi.org/10.1017/S0033291716003287

Mõttus, R., & Allerhand, M. H. (2018). Why do traits come together? The underlying trait and network approaches. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *The SAGE handbook of personality and individual differences: The science of personality and individual differences* (pp. 130–151). Sage Reference. https://doi.org/10.4135/9781526451163.n6

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

Newman, M. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America, 103*(23), 8577–8582. https://doi.org/10.1073/pnas.0601602103

Palla, G., Derényi, I., Farkas, I., & Vicsek, T. (2005). Uncovering the overlapping community structure of complex networks in nature and society. *Nature, 435*(7043), 814–818. https://doi.org/10.1038/nature03607

Price, M., Legrand, A., Brier, Z., & Hébert-Dufresne, L. (2019). The symptoms at the center: Examining the comorbidity of post-traumatic stress disorder, generalized anxiety disorder, and depression with network analysis. *Journal of Psychiatric Research, 109*, 52–58. https://doi.org/10.1016/j.jpsychires.2018.11.016

R Development Core Team. (2018). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Seeboth, A., & Mõttus, R. (2018). Successful explanations start with accurate descriptions: Questionnaire items as personality markers for more accurate predictions. *European Journal of Personality, 32*(3), 186–201. https://doi.org/10.1002/per.2147

Shannon, P., Markiel, A., Ozier, Owen., Baliga, N. S., Wang, J. T., Ramage, D., Amin, N., Schwikowski, B., & Ideker, T. (2003). Cytoscape: A software environment for integrated models of biomolecular interaction networks. *Genome Research, 13*(11), 2498–2504. https://doi.org/10.1101/gr.1239303.metabolite

Shedler, J., & Westen, D. (2004). Dimensions of personality pathology: An alternative to the five-factor model. *American Journal of Psychiatry, 161*(10), 1743–1754. https://doi.org/10.1176/ajp.161.10.1743

Soto, C. J., & John, O. P. (2017). The next Big Five Inventory (BFI-2): Developing and the next Big Five Inventory (BFI-2): Developing and assessing a hierarchical model with 15 facets to enhance bandwidth, fidelity, and predictive power. *Journal of Personality and Social Psychology, 13*(1), 117–143. https://doi.org/10.1037/pspp0000096

Wakabayashi, A. (2014). A sixth personality domain that is independent of the Big Five domains: The psychometric properties of the HEXACO Personality Inventory in a Japanese sample. *Japanese Psychological Research, 56*(3), 211–223. https://doi.org/10.1111/jpr.12045

Williams, D. R., Rhemtulla, M., Wysocki, A., & Rast, P. (2019). On non-regularized estimation of psychological networks. *Multivariate Behavioral Research, 54*(5), 719–750. https://doi.org/10.1080/00273171.2019.1575716

Wright, A. G. C. (2017). The current state and future of factor analysis in personality disorder research. *Personality Disorders: Theory, Research, and Treatment, 8*(1), 14–25. https://doi.org/10.1037/per0000216

Ziegler, M., & Bäckström, M. (2016). 50 facets of a trait–50 ways to mess up? *European Journal of Psychological Assessment, 32*(2), 105–110. https://doi.org/10.1027/1015-5759/a000372

History
Received April 24, 2019
Revision received July 13, 2020
Accepted July 17, 2020
Published online January 19, 2021
EJPA Section / Category Personality

Daniel Castro
Department of Social and Behavioral Sciences
University Institute of Maia
Avenida Carlos Oliveira Campos – Castêlo da Maia
4475-690 Maia
Portugal
dcastro@ismai.pt

