Criteria not Categories: Investigating the Role of Individual Borderline Personality Disorder Criteria and their Association with Well-Being, Past Suicide Attempts, and Comorbidities

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Abstract

Current diagnostic systems rate the presence and severity of disorders by the number of criteria and individual meets. Previous research has shown that criteria do not weigh equally on the severity of a disorder, thus, diagnostic cut-offs and sum-scores obscure information reflected within each criterion. This suggests that disorders are not separate entities but emerge from interactions between criteria. Network models provide a sound theoretical basis to understand the interplay among criteria. We use network analyses to investigate Borderline Personality Disorder (BPD) criteria and examine their relationship to three factors indicative of impairment: (a) well-being, (b) past suicide attempts, and (c) comorbidities. The study aims to identify central criteria, find their strongest connections, and determine the importance of individual criteria by investigating their association to measures of impairment. Data from 518 female participants in the clinical and sub-clinical range was analyzed. Variables were assessed through a structured clinical interview, an intake report, and the Borderline Symptom List. Affective instability, unstable relationships, and suicidal behavior were the most connected criteria in the BPD network. Affective instability and feelings of emptiness were uniquely related to well-being and comorbidities. Additionally, dissociation showed a strong association with comorbidities. Individual criteria both play different roles within BPD and are informative about levels of impairment. Results establish affective instability as a core construct of BPD and highlight the importance of less eminent criteria. Future research should treat criteria as separate entities and investigate causal mechanisms underlying interactions between criteria, and their specific associations with external factors.

Keywords: Network Analysis, Borderline Personality Disorder, Diagnostic Criteria, Well-Being, Past Suicide Attempts, Comorbidities, Dynamic Systems

Criteria not Categories: Investigating the Role of Individual Borderline Personality Disorder Criteria and their Association with Well-Being, Past Suicide Attempts, and Comorbidities

Borderline Personality Disorder (BPD) is a complex and severely disabling mental disorder characterized by a ‘stable instability’ (Gunderson, 2009, p. 2) in patients’ emotion regulation, interpersonal relationships, self-image, and impulse control (Skodol, Gunderson, Pfohl, et al., 2002). It was first classified as a disorder in the third edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association, 1980). Long before this, borderline had been used colloquially as a label for patients that have the tendency to lapse into different mental states (Knight, 1953; Stern, 1938). Initially it was seen as personality organization on the border between psychotic and neurotic (Kernberg, 1967). The term describes something as “being in an intermediate position” (Borderline, n.d.), which captures the difficulties clinicians and researchers experience in determining the diagnostic category of BPD.

The Diagnostic Category of BPD

The broad overlap BPD shows with other syndromes (Paris, 2018) questions, whether it is a diagnosis of its own, or a variant of another Axis I disorder. Critique on its category is often motivated by the aim to simplify BPD into less complex constructs and treat difficult patients for conditions with established interventions (Paris, 2007). However, attempts regarding BPD as form of schizophrenia, treating it with antipsychotics, or viewing it as depression, and prescribing antidepressants does not improve BPD symptoms (Binks et al., 2006). Patients with BPD suffer from mood swings, but in contrast to bipolar-patients, do not respond to mood stabilizers (Paris, 2005). Similar to Post-Traumatic Stress Disorder (PTSD), patients with BPD often report trauma, however this is not a prerequisite for the disorder (Sanislow et al., 2005).

BPD thus demands a separate category, but remains one that shows high rates of comorbidity (McGlashan et al., 2000).

According to the DSM-IV, a BPD diagnosis requires a minimum of five out of the following nine criteria: Frantic efforts to avoid abandonment, a pattern of unstable relationships, identity disturbance, impulsivity, suicidal behavior, affective instability, emptiness, difficulty controlling anger, and paranoid ideation or dissociation (American Psychiatric Association, 2000). The estimated lifetime prevalence of BPD is 5.9% in the general population (Grant et al., 2008). However, these prevalence rates have shown to be dependent on the type of diagnostic interview being conducted (Zimmerman, Rothschild, & Chelminski, 2005). Research on personality disorders (PD) aims to identify abnormalities in personality functioning. Ongoing efforts to draw a line between normal and abnormal functioning have demonstrated how difficult it is to determine a sensible number of criteria that function as a threshold for definite discrimination (Widiger, 2003). The change in prevalence rates of PDs across each edition of the DSM indicates the arbitrary nature of cut-off scores (Skodol, Gunderson, Pfohl, et al., 2002).

Dimension(s) of BPD

The polythetic format of the diagnostic manual results in 151 different ways of meeting the requirements of BPD, demonstrating substantial heterogeneity within this disorder (Skodol, Gunderson, Pfohl, et al., 2002). A large body of research has shown how multifaceted BPD is in its presentation of various affective, cognitive, and behavioral components. Latent class analyses have been applied to find homogeneous subgroups of BPD based on criteria and external factors. Various studies have identified varied numbers of classes depending on the covariates included in the models. Different group taxonomies have been proposed – in which paranoid, aggressive, and impulsive features (Lenzenweger, Clarkin, Yeomans, Kernberg, & Levy, 2008), or the degree of emotion dysregulation (Rufino, Ellis, Clapp, Pearte, & Fowler, 2017) discriminate classes. Most solutions retrieve a class, including more cases of BPD, followed by intermediate classes, and a non-BPD class (Bornovalova, Levy, Gratz, & Lejuez, 2010; Shevlin, Dorahy, Adamson, & Murphy, 2007). Generally, findings have shown classes that are parsed in terms of illness severity rather than by qualitative indicators, comparable to latent class analyses in other fields of psychopathology (van Loo, de Jonge, Romeijn, Kessler, & Schoevers, 2012). In other words, latent class analyses are likely cutting into a continuum, rather than identifying qualitatively different classes. This underlines the consensus that BPD is not dichotomous (Trull, Widiger, & Guthrie, 1990), but of dimensional structure, where people lie on a spectrum ranging from less to more severe types of the disorder (Shevlin et al., 2007). Empirical evidence establishes the range between personality trait and personality disorder (Skodol & Bender, 2009), but does not agree on a meaningful score for diagnostic practice to decide where one becomes the other. To better understand the dimensional structure of BPD we must take people into account who meet the diagnostic criteria, as well as those that fall below the cut-off (Conway, Hammen, & Brennan, 2012). Research should not only focus on clinical cases, but also include subjects in the sub-clinical range, who endorse individual criteria, and investigate informative value of these.

Sum-Scores

Categorizations in the DSM treat disorders as isolated constructs made up of common characteristics, representative of an underlying syndrome (Borsboom, 2008). BPD criteria are ordered by how prototypical they are for the diagnosis (Leichsenring, Liebing, Kruse, New, & Leweke, 2011). Since each criterion is assumed to have the same weight they can be summed. However, the practice of sum-scores aggravates the problem of heterogeneity that researchers face, as two patients with the same score may be very different. For example, the number of BPD criteria does not provide information about specific comorbid Axis I disorders or the levels of psychosocial functioning of a patient (Asnaani, Chelminski, Young, & Zimmerman, 2007).

It has been shown that important information lies within the individual criteria that make up disorders and that the practice of sum-scores discards a lot of crucial information (Fried & Nesse, 2015a). Individual PD criteria do not weigh equally, and combinations of criteria at the sub-threshold level of diagnoses can lead to more personality impairment than those at the diagnostic level (Cooper, Balsis, & Zimmerman, 2010). For BPD it has been found that some criteria are more useful in differentiating severe classes; abandonment fear and self-harm have been proposed as informative criteria for severity (Bornovalova et al., 2010). Therefore, it is important to assess which criteria that are indicative of severity to understand how they contribute to the manifestation of the disorder and impairment of the individual (Krueger & Piasecki, 2002). In general, diagnostic sum-scores only provide limited insight, which highlights the question whether all criteria add equally to a diagnosis or if there are core criteria that are more essential to a disorder (Oldham, 2005). Furthermore, individual criteria may have differential relationships to specific adverse outcomes. A study on suicide in BPD patients has shown that not a global BPD score, but the criterion of impulsivity specifically was the only variable significantly related to a higher number of suicide attempts (Brodsky, Malone, Ellis, Dulit, & Mann, 1997). This major clinical insight has wide implications, and, if replicated, would allow making more precise predictions about suicide attempts than the diagnostic status, or the sum of criteria of BPD.

Relations among BPD criteria

Factor analytic studies have aimed to define the relationships among BPD criteria and to find broader categories of similar criteria. For example three factors, organized as interpersonal and identity problems, affect disturbance and self-harm, and impulsivity (Clarkin, Hull, & Hurt, 1993) have been identified (Sanislow et al., 2002). This differs from clinical approaches; for instance, Lieb et al. (2004) group the nine criteria into four sectors of psychopathology: affective, cognitive, behavioral, and interpersonal, where self-harm and impulsivity are categorized together as behavioral criteria and a separate cognitive category is highlighted. Other studies base analyses on the Five-Factor Model (Costa & McCrae, 1992), showing that BPD criteria align with the five personality facets (Trull & Brown, 2012). These studies suggest that BPD is multidimensional rather than represented by one latent construct, however consensus on number and definition of underlying factors is lacking.

Overall, the heterogeneity and complexity of the disorder seems inconsistent with the idea that one underlying cause gives rise to all the BPD criteria (Fried, 2017b). Thus, it has been suggested to investigate the associations of individual criteria (Fried & Nesse, 2015b) with an alternative framework that determines how their interactions explain their observed co-occurrence (Borsboom, 2008). This network approach embraces a perspective on mental disorders, where they are not treated as discrete entities but as a system consisting of different elements that show a systematic pattern of connecting with each other (Borsboom & Cramer, 2013). It emphasizes the role of diagnostically defined criteria for the course and outcome of a disease (Armour, Fried, & Olff, 2017), and deals with the shortcomings of sum-scores and diagnostic thresholds by studying the relations among criteria (Fried, 2017a).

Network analysis has become one of the most popular methods of investigation in the field of psychometrics (Borsboom, 2017), breaking free from the search of latent constructs, and zooming-in on interactive processes instead (Fried & Cramer, 2017). Defining psychopathology as a dynamical system of factors interacting with each other allows researchers to study the interplay between criteria that make up disorders. Recent work has shown preliminary insights into the connections of symptoms arising within disorders, especially PTSD (see Armour et al., 2017 for a review), psychosis (e.g. Isvoranu et al., 2017; van Rooijen et al., 2017) and depression (e.g. Cramer et al., 2016; Fried, Epskamp, Nesse, Tuerlinckx, & Borsboom, 2016; Santos, Fried, Asafu-Adjei, & Jeanne Ruiz, 2017), as well as explaining comorbidity between disorders (e.g. Beard et al., 2016; Cramer, Waldorp, Van Der Maas, & Borsboom, 2010; Jones, Mair, Riemann, Mugno, & McNally, 2018). Research focusing on these lower-level interactions has demonstrated that symptoms are not simply the result of a disorder but in themselves the driving force behind it (McNally et al., 2015). In depression, for example, insomnia may give rise to fatigue, which in turn causes concentration difficulties, inducing feelings of worthlessness which eventually increases depressed mood (Guloksuz, Pries, & van Os, 2017).

An earlier limitation of this framework was that most research only focused on psychological factors, namely symptoms (Fried & Cramer, 2017). However, it has been proposed that, to increase understanding of disorders, internal elements as well as variables from the external field should be regarded as relevant factors (Borsboom, 2017). This means to look beyond symptoms and expand networks, including information about social factors, or functional and occupational impairment as candidates for etiology and maintenance of a disorder (Jones, Heeren, & McNally, 2017). We want to follow the call to extend the symptom-level approach and take variables outside of the diagnostic category into account in our investigation. We consider impairment as an important aspect to address here. Three representative indicators of this in BPD may be well-being, suicide attempts, and Axis I comorbidities.

Impairment in Borderline Personality Disorder

BPD impacts well-being greatly, since patients are impaired in daily functioning, areas of work, social relationships, and leisure (Skodol, Gunderson, McGlashan, et al., 2002). Suicide is the major cause of death in patients with BPD and completed suicides are more common than in the general population: About 10% of BPD patients complete suicide (Paris, 2002), and about half of the patients show multiple suicidal behaviors throughout their lifetime (Pompili, Girardi, Ruberto, & Tatarelli, 2005). As noted previously, a high overlap of BPD with other clinical syndromes is evident. Comorbidities also influence the level of impairment from the disorder, affecting general psychopathology, resulting in a poorer course and outcome of each disorder, and increased psychosocial impairment (Clark, Nuzum, & Ro, 2018).

Aim of the current study

This study investigates the relations among the nine diagnostic criteria of BPD and their associations with impairment. Statistical models based on network psychometrics provide the framework to visualize conditional dependence relations in multivariate data (Epskamp, Maris, Waldorp, & Borsboom, 2018). With this, we aim to uncover important relationships between criteria, assess their centrality, and determine each criterion's informative value regarding impairment.

First, we expected that criteria would show different associations with each other and form a network where certain criteria will have more connections to other criteria.

Second, the number and strength of connections a criterion draws with others indicates its' centrality. Previous research on the relevance of individual BPD criteria has found affective instability and identity disturbances to be particularly pertinent to the disorder (Farmer & Chapman, 2002). Recent network analysis identified affective instability, identity, and effort to avoid abandonment as most central criteria in the BPD network (Richetin, Preti, Costantini, & De Panfilis, 2017). We expected similar results from our investigation, possibly replicating this finding in a different sample, and therefore hypothesized those three criteria to be the most central.

Third, considering criteria are not created equal (Cooper et al., 2010) we hypothesized individual BPD criteria would vary in their associations to indicators of impairment. The relation to well-being, past suicide attempts, and number of comorbidities may differ from one criterion to another. Previous research has shown that impulsivity is significantly related to suicidality (Brodsky et al., 1997). We expected that the two criteria impulsivity and suicidal behavior would be connected to past suicide attempts. The relations of criteria to past suicide attempts may be different from their relations to well-being or comorbidities. For the latter two, the investigation remained purely data-driven and exploratory, since we found no previous studies that have examined the differential impact of individual BPD diagnostic criteria on these outcomes.

Until now, network analyses have only modeled BPD features (Southward & Cheavens, 2018) or assessed criteria on the trait-level, using self-report symptom checklists (Richetin et al., 2017). These studies relied on samples mainly drawn from students with the inclusion of a small number of clinical cases. In this study, we applied the network approach to a larger sample of subjects in the clinical and sub-clinical range of BPD, recognizing the dimensional nature of the disorder. We examined data of diagnostic criteria, obtained from clinical assessment, rather than self-reported BPD traits. To our knowledge, there has not been any research applying this method to large-scale clinical data and simultaneously examining variables related to impairment. Our study embraces the complexity of BPD and aims to contribute to a perspective of mental disorders, where we rely less on diagnostic sum-scores and categorical cut-off values but consider the importance of individual criteria.

Method

Sample

Participants. The data used for this study was gathered from various studies conducted by the Department for Psychosomatic Medicine and Psychotherapy, Central Institute of Mental health (CIMH) in Mannheim, Germany. Participants were recruited from multiple sites through existing databases within the Clinical Research Unit 256 (Schmahl et al., 2014). Studies were compiled into a large-scale dataset, from which we selected our sample. The total sample comprised 1400 female subjects and included patients as well as healthy controls. As our study focused on individuals in the clinical and sub-clinical range of BPD, we only included cases exhibiting any one out of nine BPD diagnostic criteria in their lifetime. We selected 518 participants who scored at least one criterion as 'definite' or 'probable' on the lifetime measure of BPD. Participants who scored all criteria as 'negative' or 'available/unclear' were excluded.

Assessments. Each participant was interviewed by a trained psychologist and underwent a standardized diagnostic procedure to determine all psychiatric diagnoses. The Structured Clinical Interview for DSM-IV (SCID-I; First et al., 1997) and the International Personality Disorder Examination (IPDE; Loranger, 1999) were used for diagnosis.

International Personality Disorder Examination. The IPDE is a semi-structured interview procedure that assesses all PDs. It is the most commonly used tool to determine personality disorders and shows high external validity with familial, biological, treatment and prognostic correlates (Zimmerman et al., 2005). The whole BPD section of the IPDE was administered by trained clinicians to assess the nine BPD criteria according to the DSM-IV: Efforts to avoid abandonment, unstable interpersonal relationships, identity disturbance, impulsivity, recurrent suicidal behavior, affective instability, feelings of emptiness, difficulty controlling anger, and paranoid ideation or dissociation. The criteria are rated as 'negative', 'probable', 'definite', not 'available/unclear'. We derived three categories from this, scoring criteria on a 3-point ordinal rating scale as 'negative' (0), 'probable' (1), or 'definite' (2). Criteria that were rated as not available or unclear were coded as missing. Inter-rater reliability kappa for BPD was .77.

Visual Analog Scale for Global Well-Being. The Borderline Symptom List (BSL; Bohus et al., 2001) is a self-report assessment that quantitatively assesses subjective impairment of borderline patients. It is a standardized instrument to quantify borderline-specific symptomatology based on the DSM-IV diagnostic criteria of BPD. The BSL includes a visual analog scale for global well-being, which explicitly assesses well-being of the subject on a scale ranging from 0 ('very bad') to 100 ('very good'). This was used to assess well-being on a continuous level.

Past Suicide Attempts. A semi-structured intake interview was used to assess past suicidal behavior. Participants were asked if they had ever attempted suicide, and if so, how many suicide attempts had occurred. We determined total past suicide attempts for participants and placed them into categories based on this number ('one', 'one', 'two', 'three', 'four and more'). Categories reflect ranks of increasing severity and were treated at an ordinal measurement level.

Comorbidities. The SCID was used to determine all disorders, formally known as Axis I disorders, for each participant, providing information on the number of comorbidities the participant exhibits. Interviews were conducted by trained clinicians who identified all current and lifetime Axis I disorders for each subject. We summed the number of Axis I diagnoses and placed participants into categories based on the number of comorbidities they exhibited (‘none’, ‘one’, ‘two’, ‘three’, ‘four and more’). The score marks increase of impairment severity by number of comorbidities and is operationalized on an ordinal scale in the present paper.

Data Analysis

We formally preregistered the study before inspecting the data and conducting analyses. The registration can be found in the OSF Registries (https://osf.io/d4p7h/), all code and supplementary materials are available online.

Network Estimation. We estimated a total of four network structures in two levels of complexity. The baseline model (N1) comprised the nine BPD diagnostic criteria. Three further models additionally included one of the indicators of impairment: (N2) - well-being, (N3) - past suicide attempts, and (N4) - comorbidities. Within each network, all criteria and indicators of impairment are presented as nodes. Nodes are connected by edges if they show associations with each other. Since the data is cross-sectional, the edges are undirected.

The pairwise associations between the variables in the network were estimated based on a Gaussian Graphical Model (GGM; Epskamp, Waldorp, Mõttus, & Borsboom, 2018; Lauritzen, 1996). Associations between variables are connections that remain after controlling for all other variables and represent partial correlation coefficients (Epskamp, Rhemtulla, & Borsboom, 2017). We used the *estimateNetwork* function from the *bootnet* package in R to compute the matrix with the weighed partial correlation coefficients, encoding the strength of association between two variables in each network (Epskamp & Fried, 2019). Since the main variables – BPD criteria – were measured on an ordinal scale, a GGM is the most appropriate model.

Criteria were treated as ordered-categorical, so we computed Spearman correlations to determine the covariance matrix. As expected, past suicide attempts and comorbidities were both positively skewed, more observations were found in the lower categories. Both variables only had 5 categories so we could not perform the recommended non-paranormal transformation. Since edges in the network were unknown and many parameters had to be estimated from the data, the chance of drawing false-positive edges was increased (Epskamp, Kruis, & Marsman, 2017). To avoid spurious relations, we applied a tuning parameter, regularizing the partial correlation coefficients with the least absolute shrinkage and selection operator (LASSO) (Tibshirani, 1996). This limited the sum of absolute parameter values by shrinking all edge-weights towards zero and setting small edge-weights to exactly zero, generating a sparse network structure (Epskamp & Fried, 2018). The GGM estimation method *EBICglasso* uses a graphical LASSO, which selects the optimal tuning parameter lambda (λ) by minimizing the Extended Bayesian Information Criterion (EBIC). The hyperparameter gamma (γ) controls the extent to which the EBIC favors the more parsimonious solution; we used the default of $\gamma = .5$. For dense networks it has been shown that the *EBICglasso* can have low specificity and retrieve edges that are not true edges (Williams & Rast, 2018). To enforce high specificity we applied a threshold, which was computed by reducing the false positive rate. Edge-weights below the threshold in the returned final model and the EBIC computations of all considered models were set to zero (Epskamp, 2018).

Network Visualization.

Four separate networks were plotted with the R-package *qgraph* (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). We used the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991) to place nodes with stronger and/or more connections in the center and averaged the layout across N1-N4. Positive associations are presented as blue edges, negative associations are red. The amount of variance in a node explained by nodes it is connected to is presented by a ring around it (Haslbeck & Fried, 2017).

Network Inference.

Centrality. N1 explored the role of individual criteria in the overall network. Based on the derived network structure we calculated the centrality index *Expected Influence* (EI) for each node obtaining the degree to which a criterion is interconnected. We quantified each nodes' position in the network by summing the positive and negative edge-weights between a criterion and its neighbors (Robinaugh, Millner, & McNally, 2016). This can be interpreted as the relative importance of a criterion compared to others in the network.

Predictability. For N1-N4 we computed a measure of *node predictability* to look at the extent to which a variable is determined by the variables it connects to (Haslbeck & Waldorp, 2018). Predictability explains the proportion of variance for each node that is explained by its neighbors (Haslbeck & Fried, 2017). It is an absolute measure of the amount of variance a variable shares with connecting variables and can be interpreted as R^2. The metric is represented as a value ranging from zero to 100% of explained variance. We estimated the shared variance of each node with all of its neighbors using the R package *mgm* and transferred the estimates to our networks using the method applied in Fried et al. (2018). Unlike EI, which is a relative metric, predictability it is an absolute metric of interrelatedness (McNally, 2016).

Network Accuracy and Stability. To evaluate the robustness of each network, we assessed the accuracy of the edge-weights and the stability of the EI values using non-parametric bootstrapping routines implemented the R-package *bootnet* (Epskamp & Fried, 2019).

Accuracy. Accuracy of the edges was assessed by computing the bootstrapped sampling distributions for each edge-weight, based on 2000 bootstrap samples drawn with replacement. We display the 95% Confidence Intervals (CIs) of the bootstrapped sampling distribution around the edge-weights. The widths of CIs give an indication of the accuracy of edge-weights and enable us to compare them to each other, but do not test whether edges are different from zero (Epskamp, Borsboom, & Fried, 2017).

Stability. To investigate the stability of the centrality estimates in N1 we re-calculated EI values from subsets of the data. In a stable network the order of EI values in sample-subsets will correlate highly with the order in the full data. We applied a case-dropping subset bootstrap and estimated bootstrapped EI values in the sub-samples, using 2000 bootstraps each. From this we determined the *correlation stability coefficient* (CS-coefficient), which represents the maximum percentage of cases that can be dropped so that with 95% certainty the correlation between the order of EI values in the original networks and those based on sub-samples will be at least.7 (Epskamp, Borsboom, et al., 2017).

Difference Tests. Specific centrality indices and edge-weights can be compared using the *bootstrapped difference test.* We tested whether some connections were stronger than others and whether criteria statistically differed in the degree to which they were interconnected. The *edge-weight bootstrapped difference test* compared edge-weights within each network to each other and the *centrality bootstrapped difference test* determined whether the centrality of a certain node differs from the centrality of other nodes (i.e. whether the EI value of node A is meaningfully higher than that of node B) (Epskamp, Borsboom, et al., 2017). The same method is used for both tests: First, we obtained non-parametric bootstrap values for the edge-weights and EI values in each network. Then we took the difference between the bootstrap values of one edge-weight or EI and another edge-weight or EI and constructed bootstrapped CIs around these difference scores (Epskamp, Borsboom, et al., 2017). Differences were tested under the Null Hypotheses that the estimates do not differ. For edge-weights or EIs that significantly differ from each other the bootstrapped CIs will not include zero. Note that this test does currently not control for multiple testing, and needs to be interpreted with care.

Results

Sample Characteristics

The sample consisted of 518 women with a mean age of 29.18 (*SD* = 8.65, *range* = 15-52) and various levels of education (44% completed the highest level of high school education, 27% medium level, 6% lower level, 4% had other types of education, 1% without education, for remaining subjects information as missing). Sixty-five percent of participants were diagnosed with BPD, 32% received a negative diagnosis, for 2% diagnosis was probable, and for the remaining 1% no decision was made. Therefore, our sample comprised a substantive proportion of sub-clinical cases, endorsing at least BPD criterion without meeting the diagnostic criteria. Other Axis I diagnoses are presented in Table 1. The rate of past suicide attempts ranged from 0-26, the distribution was highly skewed (*M* = 1.17, *SD* = 2.26), 59.9% of participants had no attempts at all.

Table 1.

Prevalence of Axis I Disorders in the Sample.

	N	*Percent*		*N*	*Percent*
Bipolar II	1	0.2	**OCD**	20	4.0
Major Depression	98	19.5	**PTSD**	144	28.6
Dysthymia	62	12.3	**GAD**	16	3.2
Depression NOS	5	1.0	**Anxiety Disorder NOS**	1	0.2
Mood Disorder (Medical)	3	0.6	**Somatization Disorder**	3	0.6
Alcohol Dependence	1	0.2	**Pain Disorder**	8	1.6
Cannabis Dependence	1	0.2	**Somatoform Disorder NOS**	11	2.2
Opioid Dependence	1	0.2	**Hypochondriasis**	1	0.2
Nicotine Dependence	62	12.3	**Body Dysmorphic Disorder**	5	1.0
Panic Disorder	45	8.9	**Anorexia**	8	1.6
Agoraphobia	17	3.4	**Bulimia**	55	10.9
Social Anxiety Disorder	113	23.5	**Binge Eating**	39	7.8
Specific Phobia	69	13.7	**Adjustment Disorder**	4	0.8
			Other Axis I	5	1.0

Network Inference

Associations Between BPD Criteria. Figure 1 shows the network structure of the nine DSM-IV BPD criteria (N1). The connections between criteria are edges that remain after controlling for all other associations in the network. The final model only retained edge-weights above the threshold of 0.073. All of the edge-weights or partial correlation coefficients were positive. In the network, 21 of 36 potential edges were estimated to be above zero, with a mean weight of 0.16. Edge-weights ranged from a minimum of 0.10 (IDE-DIS) and to a maximum of 0.26 (AFF-SUI) (Fig 2.). This is a surprisingly homogeneous distribution.

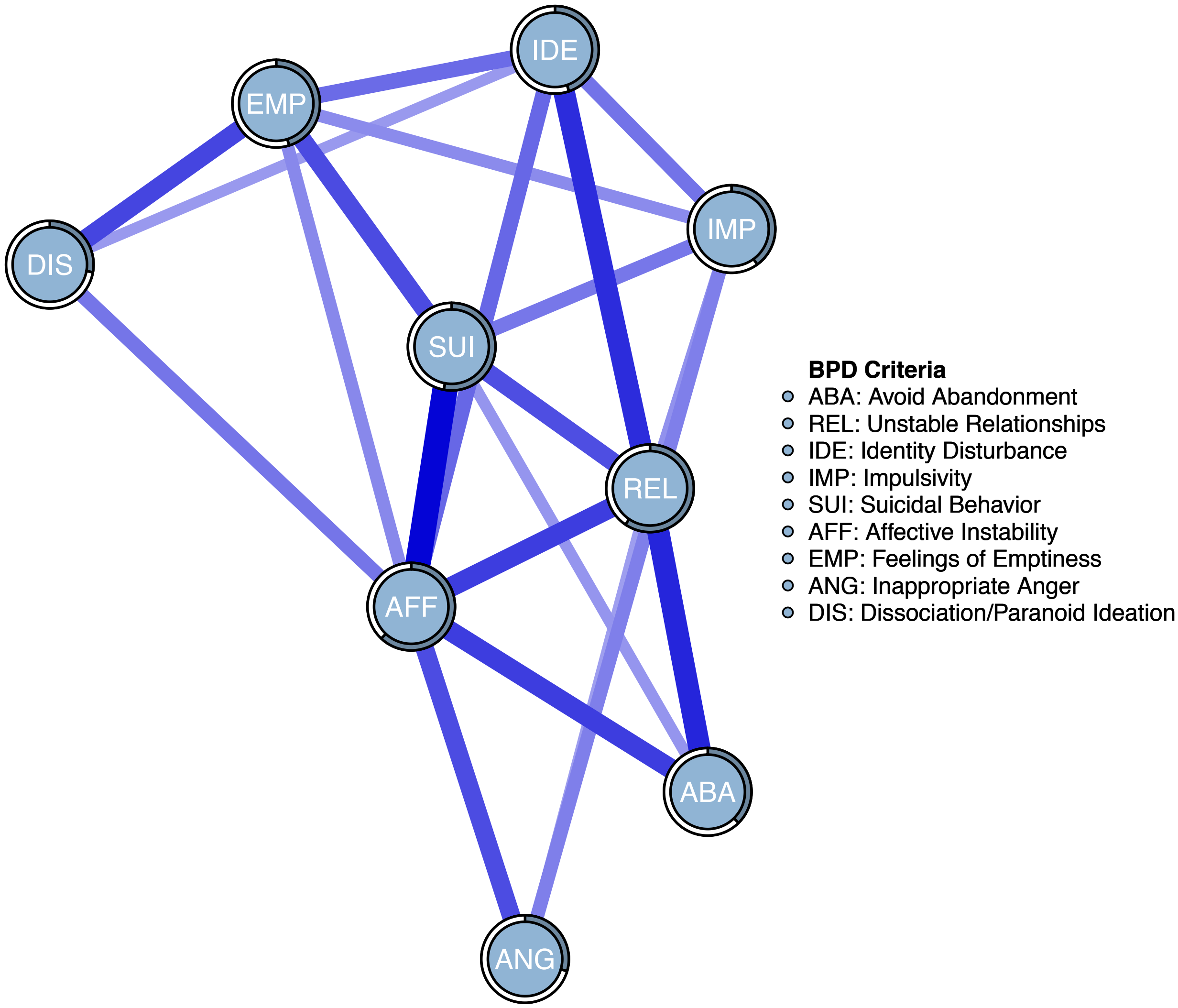

Figure 1. Regularized partial correlation network of BPD criteria (N1). Connections between criteria represent positive conditional dependence relationships. Of note, the *edge-weight bootstrapped difference test* yielded that edges are not statistically different from each other, thus the strength of edge-weights should be interpreted with care. Only the edge AFF-SUI significantly differs from other edges.

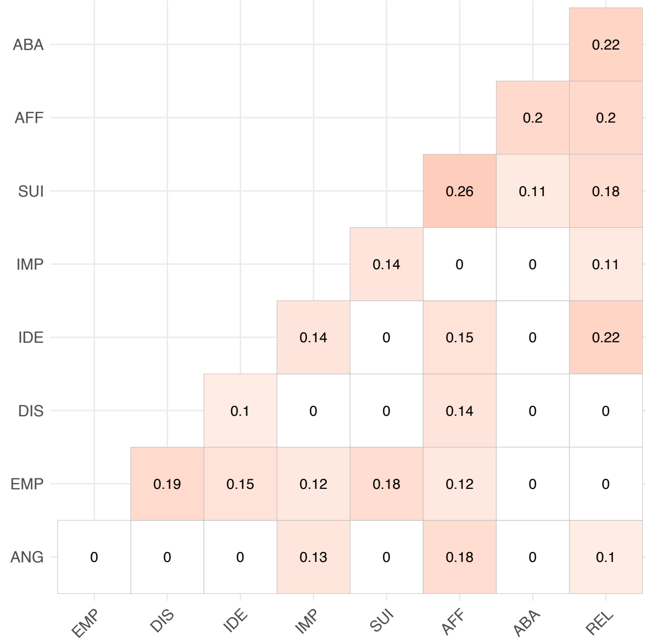

Figure 2. Edge-weights in N1.

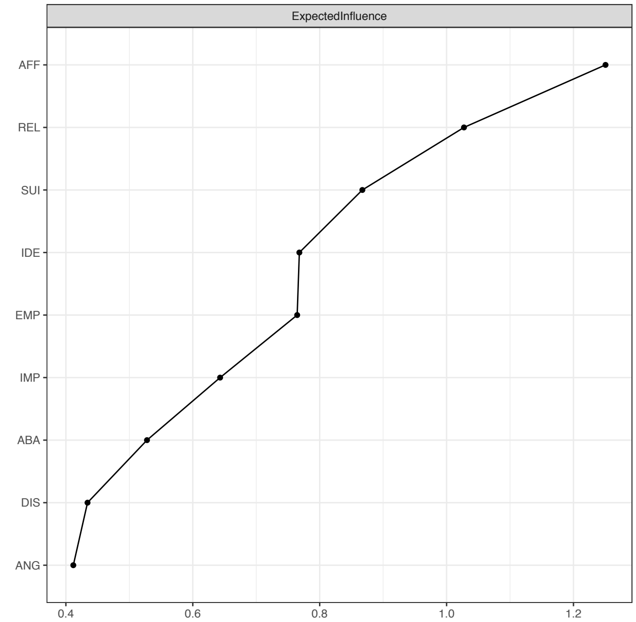

Figure 3. Expected influence in N1 (raw scores).

Centrality. We determined the EI of each criterion to assess its centrality (Figure 3 and Table 2). The three nodes with the highest centrality index were affective instability (*EI* = 1.25), unstable relationships (*EI* = 1.03) and suicidal behavior (*EI* =0.87). Affective instability drew most connections to other criteria, whereas the two criteria with the lowest EI – dissociation (*EI* = 0.43) and inappropriate anger (*EI* = 0.41) – had fewer connections.

A higher variance in a node may affect its ability to connect with other nodes and different variances of criteria could impact differences in centrality. In general we found little differential variability, as standard deviations were similar for all criteria (Table 2). To test whether nodes with more variance had higher centrality indices the correlation between criterion EI and criterion standard deviation was calculated (*r* = -.50), implying that nodes with higher EI had lower standard deviations, and that EI results are thus not merely a result of node variability.

Table 2.

Means, Standard Deviations, Expected Influence and Predictability of Criteria.

	Mean	*SD*	*EI*	R^2
ABA	1.00	.91	.53	.38
REL	1.31	.87	1.03	.60
IDE	1.08	.90	.77	.45
IMP	1.04	.87	.64	.40
SUI	1.27	.91	.87	.53
AFF	1.55	.74	1.25	.62
EMP	1.14	.89	.76	.45
ANG	1.10	.85	.41	.30
DIS	1.12	.86	.43	.28

Predictability. The mean predictability of nodes in N1 was 44.3%, which means that on average, 44.3% of variance in each criterion was explained by criteria it was connected to. The most central nodes were also the ones with the highest predictability: affective instability shared 62.0% of variance with its neighbors, unstable relationships 59.5%, and suicidal behavior 52.9% (Table 2). Similar predictabilities show that these nodes share a large amount of variance between each other. As expected, predictability and EI values were highly correlated (r = .98).

Associations Between BPD Criteria and Impairment. We estimated the associations of BPD criteria with well-being, past suicide attempts, and comorbidities; the resulting networks are shown in Figure 4. Relevant relationships between BPD criteria and impairment emerged only in N2 and N4. The threshold for N2 was above 0.096, for N3 above 0.070, and for N4 above 0.087. Edges in the networks present unique relationships between specific BPD criteria and the indicator of impairment that remain after controlling for other criteria. Adding the indicators of impairment to N1 had little impact on the associations between BPD criteria (see Appendix A). Their predictability remained stable and there was only one difference in edge-weights from N1 to N2 and N4, namely that the edge between identity disturbances and dissociation disappeared.

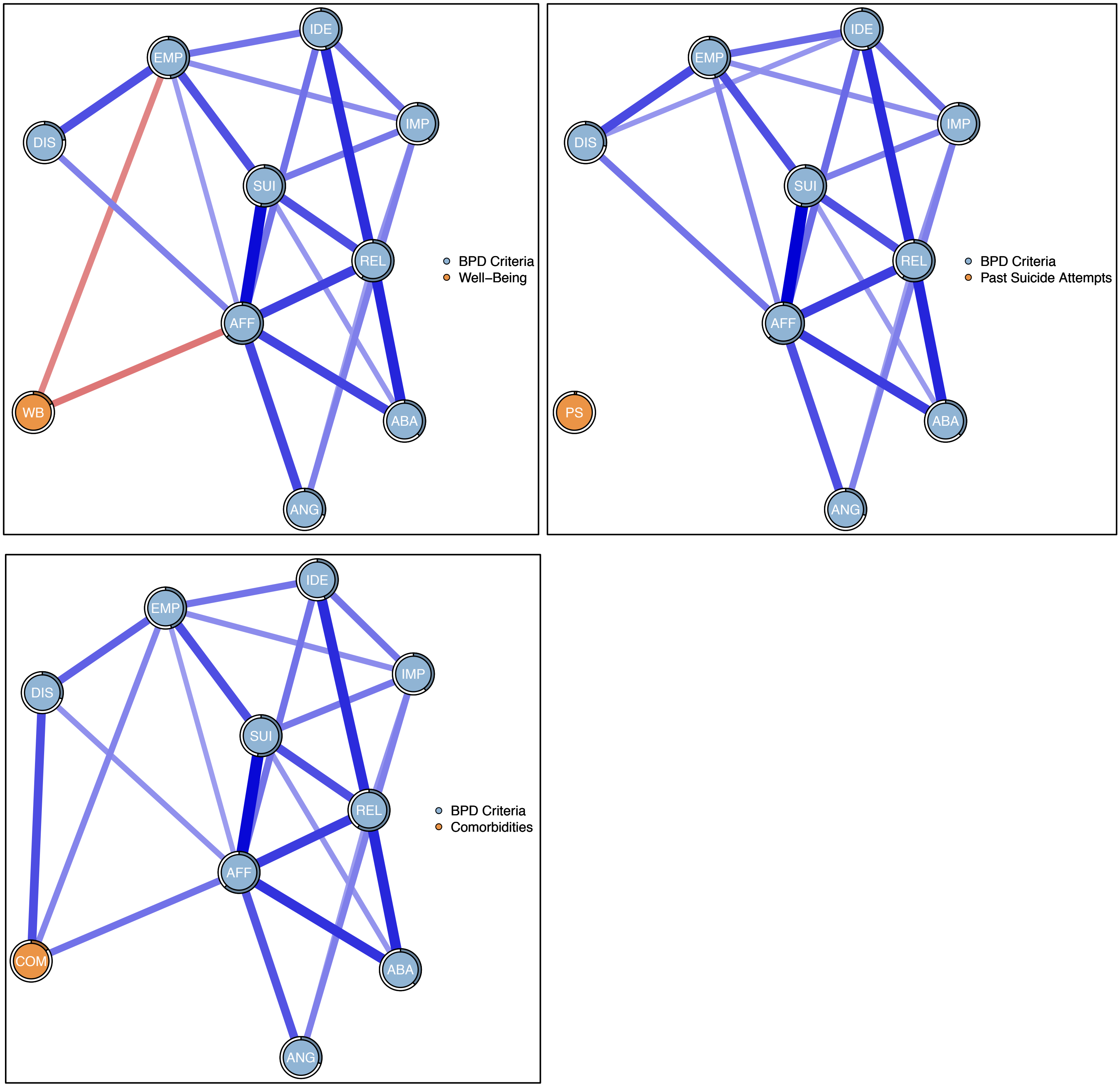

Figure 4. Regularized partial correlation networks of well-being (N2), past suicide attempts (N3) and comorbidities (N4).

Well-Being. Well-being showed negative associations with two BPD criteria, namely affective instability (-0.14) and feelings of emptiness (-.013). The predictability values report that 18.1% of variance in well-being can be explained by affective instability and feelings of emptiness.

Past Suicide Attempts. We found no associations between past suicide attempts and individual BPD criteria.

Comorbidities. In N4 we found three positive associations between BPD criteria and the number of Axis I disorders. Similar to well-being, comorbidities were related to affective instability (0.15) and feelings of emptiness (0.13). Additionally, a connection to dissociation (0.18) emerged. The predictability is slightly lower than that of well-being, the three BPD criteria explain 17.1% of the variance found in number of comorbidities.

Network Accuracy and Stability Accuracy. The edge-weight accuracy plots present the edge-weights, the average edge-weights obtained from the bootstrap samples and their CIs. The bootstrapped CIs for edge-weights between BPD criteria were large in all four networks (Fig. 5 and 6). In N2, the bootstrapped CIs for edge-weights between well-being and the two BPD criteria were larger than the CIs of edge-weights between criteria (Fig. 5). The same holds for bootstrapped CIs of edge-weights that were estimated in N4, where even the strong edge between dissociation and comorbidities has a wide CI (Fig. 6). Edges between past suicide attempts and comorbidities were all set to zero (Fig 6). Overall, the strength of the edges should be interpreted with care. Of note is that most CIs overlap, which indicates that edge-weights are likely not very different from one-another and the order of the edges by strength in the plots needs to be interpreted with caution. This observation is consistent across all four networks that were estimated.

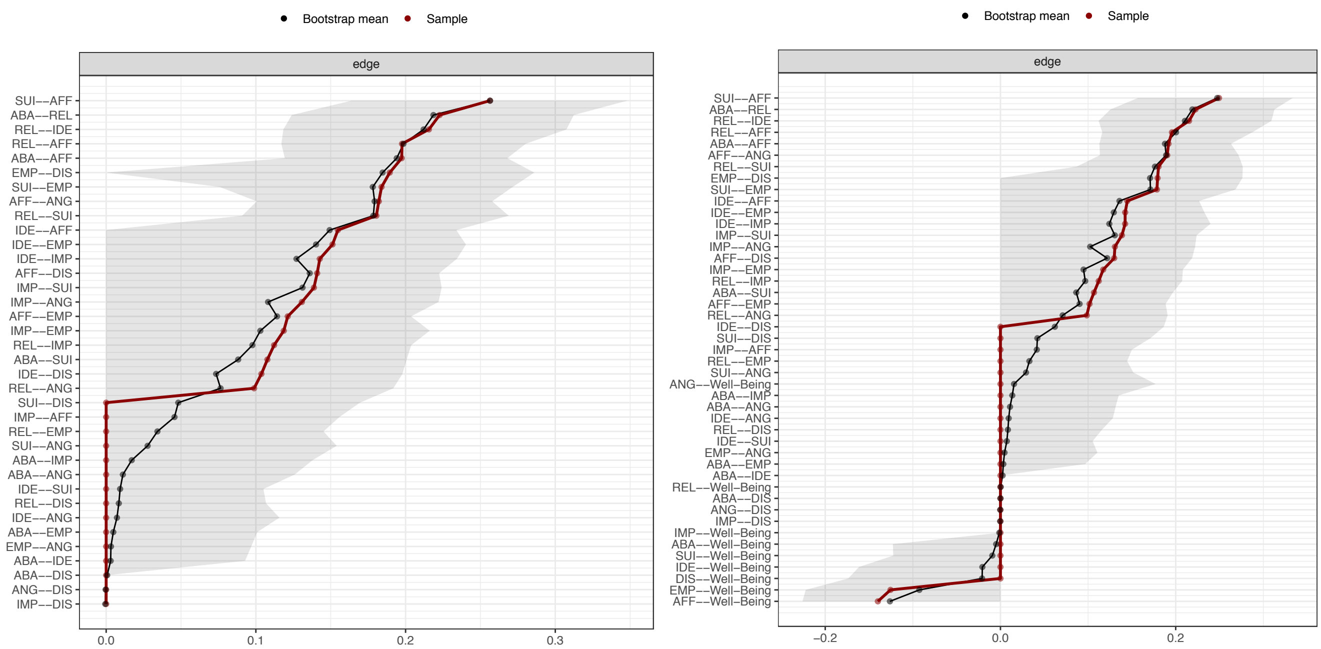

Figure 5. Bootstrapped CIs of edge-weights in N1 and N2.

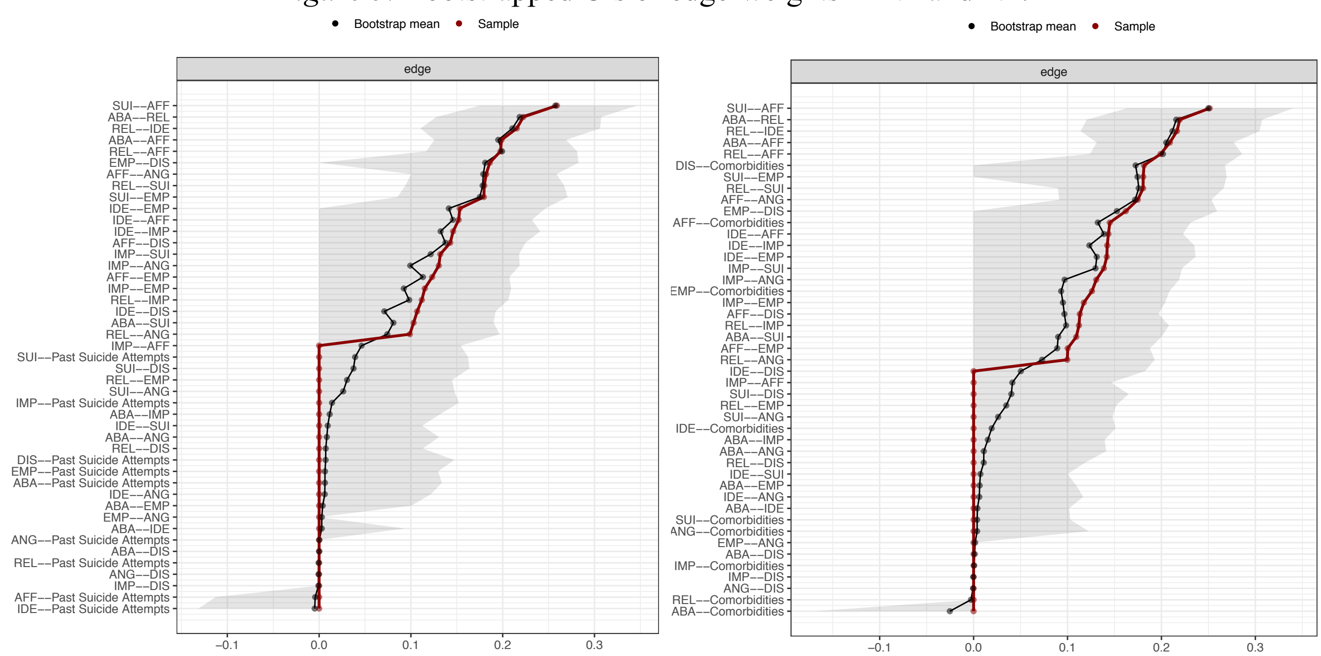

Figure 6. Bootstrapped CIs of edge-weights in N3 and N4.

Stability. The centrality stability test yielded a CS-coefficient of .66, which means that, if 66% of the cases were dropped, the correlation between the order of resulting EI values with the original order of EI values would still be at least .7. This coefficient should not be below .25 and ideally above .5 (Epskamp, Borsboom, et al., 2017), as it is the case here. Figure 7 shows how stable estimated EI values are.

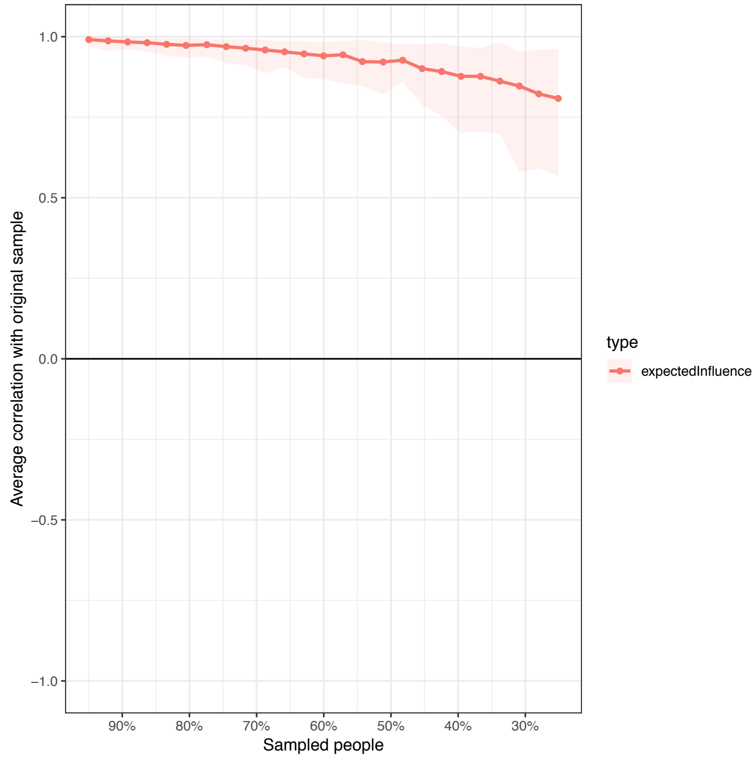

Figure 7. Average correlation between EI values of original and case dropped networks (N1).

Difference Tests

Edge-weight Bootstrapped Difference Tests. Overlapping CIs in the accuracy plots indicated that the order of the edge-weights should be interpreted cautiously; therefore we tested statistical differences between edge-weights. The edge-weight bootstrapped difference tests show that most edge-weights did not differ. In N1 one edge (SUI-AFF) was statistically different from seven other edges (Fig. 8). For N2 we found that edges from BPD criteria to well-being were different from edges among criteria (Fig 9.). This is the case because the edge-weights between criteria are positive, whilst the association between criteria and well-being is negative. The difference between the two edges well-being - affective instability, and well-being - emptiness was not significant. Edges for N1 and N3 were identical, so the difference test yields the same result as for N1 (Fig 8.).

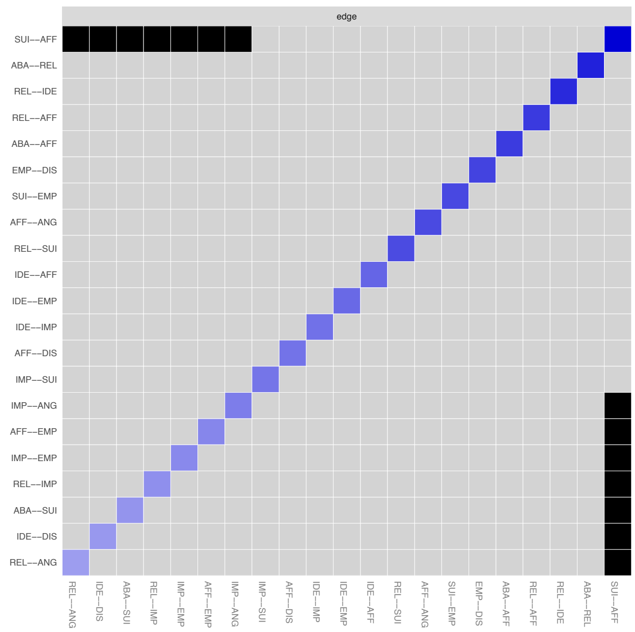

Figure 8. Edge-weight bootstrapped difference test N1 and N3.

In N4, the edges from feelings of emptiness to comorbidities differed from one BPD edge (SUI-AFF), whereas edges from affective instability and dissociation to comorbidities were equal to edges among BPD criteria (Fig. 9). The edge-weight between suicidal behavior and affective instability still differed in N2 and N4; the edge between these criteria is significantly stronger than other edges, even after adjusting for comorbidities and well-being.

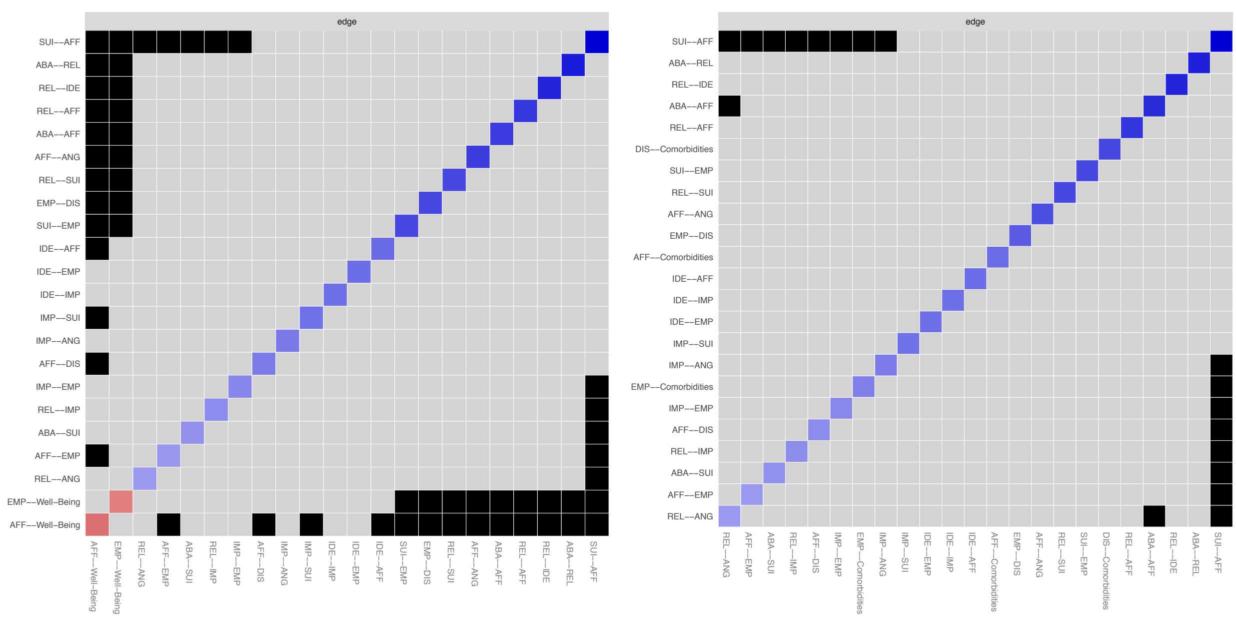

Figure 9. Edge-weight bootstrapped difference tests for N2 and N4.

Centrality Bootstrapped Difference Test. The stability of the EI values is also explained by statistical differences in node interconnectedness we found in the centrality bootstrapped difference test (Fig. 10). Affective instability significantly differed from all other criteria except unstable relationships; unstable relationships and suicidal behavior differed from the criteria that were less central, so did identity disturbance and feelings of emptiness. Nodes are meaningfully different from one-another in their overall connectedness.

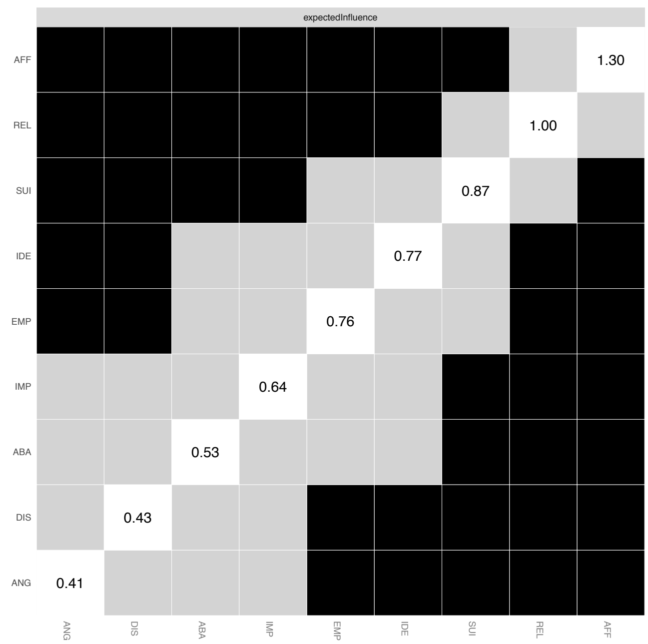

Figure 10. Centrality bootstrapped difference test of EI Values in N1

Discussion

This study investigated how the diagnostic criteria of BPD are related to one-another and how they interact with different indicators of impairment using a cross-sectional cohort design. We performed between-subject network analyses in a sample of females that exhibit BPD in the clinical and sub-clinical range. The networks provide insight into how the variables of interest could be structured within this population. Here we will address the differences in connectivity of criteria and further interpret the relationship between criteria and impairment.

Role of Individual BPD Criteria

An analysis on the differences in associations between criteria revealed the most connected criteria. The network only included positive relationships and overall the strength of associations was high. The majority of edge-weights were similar to each other, indicating that the underlying model could well be a homogeneous structure where most variables are roughly equally connected. Every criterion related to at least three others, showing that the nine diagnostic criteria present a coherent syndrome. Nonetheless, about 40% of possible edges were missing, with some criteria explaining more variance in the network and accounting for the relationships between unconnected criteria. The two criteria suicidal behavior and identity disturbance, for example, were not connected, because remaining criteria account for this relationship.

We found statistical differences between the centrality indices of the criteria, which gives perspective to the notion that criteria are not interchangeable. The most connected criteria were affective instability, unstable relationships, and suicidal behavior. Affective instability shared the highest amount of variance with all other criteria, connecting to every criterion but impulsivity. It can be seen as central to the structure of BPD-psychopathology. This observation is consistent with the biosocial theory of BPD, which states that the disorder is most strongly driven by emotion regulation difficulties (Linehan, 1993). Linehan explains the etiology of BPD by placing individual factors of temperament and biological vulnerabilities in the context of the environment. Emotional instability is shaped and maintained by invalidating relationships; likewise, it is strongly tied to maladaptive coping strategies and poor impulse control. However, impulsivity and affective instability might not directly be related because suicidal behavior, which connects to both of these criteria, controls for this correlation. The association between suicidal behavior and affective instability was the strongest edge-weight, and the only one that statistically differed from other edge-weights in the network. There is a strong direct interaction between the two criteria that cannot be explained by other criteria. Although we cannot disentangle the cause-effect relationship, this association can be interpreted in the light of previous research, hypothesizing that self-harm behavior in BPD patients is a maladaptive emotion regulation strategy (Carpenter & Trull, 2013).

Demonstrating the relevance of social-environmental factors in the biosocial model (Gratz & Tull, 2010), unstable relationships were identified as the second most connected criterion. Emotion regulation underlies the emergence of interpersonal problems (Herr, Rosenthal, Geiger, & Erikson, 2013) and rapid mood changes can be either the source of conflict or be elicited by interpersonal difficulties (Bagge et al., 2004). Looking at the link from unstable relationships to affective instability, and suicidal behavior, the latter two could reciprocally reinforce each other, and jointly influence relationships. Unstable relationships may, in turn, magnify unregulated emotions and maladaptive behaviors (Crowell, Beauchaine, & Linehan, 2009). This vicious cycle ultimately exacerbates BPD in its development and course.

As expected, the three most central criteria are also the ones with the highest amount of variance explained. Assuming that a network is the data-generating model we interpret the shared variance among the most connected nodes as being due to the effect they have on each other. This is in line with Gross' theory (2002) of emotion regulation, which focuses on the interaction between affective processes, demands from the social environment and behaviors. Emotions are highly dependent on situations and a mismatch between the two requires behavioral as well as affective responses – some might be adaptive some not. Rather than getting lost in the chicken-and-egg debate, our model and Gross theory encourage research to focus on the viciously cycling interaction among all of these factors instead (Schmahl et al., 2014).

Importance of Individual BPD Criteria on Indicators of Impairment

The second aim of this study was to uncover the unique associations between BPD criteria and impairment. We found three criteria to be especially important in this regard: Affective instability and feelings of emptiness were both connected to well-being and comorbidities, while dissociation was uniquely associated with comorbidities. The specific associations these criteria have with well-being and comorbidities support the notion that individual criteria have varying implications for the impairment of individuals

As evident from the network of BPD criteria, affective instability can be interpreted as a core aspect underlying the pathology of BPD, central to the interaction between criteria. In patients' daily lives, affective instability is observed as the extreme reactivity to external events and interactions with others (Carpenter & Trull, 2013). It universally influences a persons' state and well-being, as it is directly linked to impairment (Skodol et al., 2005), and specifically accounts for decreased social functioning (Herr et al., 2013).

Furthermore, affective instability is related to a higher number of Axis I disorders. From a network perspective, comorbidity is conceptualized as the interplay between individual criteria of multiple disorders (Cramer, Waldorp, van der Maas, & Borsboom, 2010). Symptoms included in several diagnostic categories can be seen as bridge symptoms connecting disorders with each other (Fried et al., 2017). Our findings indicate that affective instability is not only central to BPD, but that it is related to an increased number of comorbidities. The association with other mental disorders suggests that affective instability may not be very specific for BPD. This is supported by previous studies investigating the role of affective instability in Post-Traumatic

Stress Disorder (PTSD) and Bulimia Nervosa, where subjects displayed a similar pattern of variability in affect as patients with BPD (Ebner-Priemer et al., 2015). Although this criterion is not defined in any other diagnoses it might be a connector between BPD and specific symptoms of other disorders, explaining their co-occurrence.

As much as affective instability presents itself as core aspect of BPD one should not neglect the importance of less eminent criteria. Feelings of emptiness are a critical component of the burden experienced by patients with BPD (Elsner, Broadbear, & Rao, 2018). We found that emptiness is associated with less well-being and more comorbidities. Previous research has shown that patients meeting only this criterion have worse psychosocial impairment than those endorsing anger, impulsivity, or affective instability (Ellison, Rosenstein, Chelminski, Dalrymple, & Zimmerman, 2016). Our results suggest that the presence of feelings of emptiness require special attention when addressing patients' well-being. Loneliness, one aspect of emptiness (Klonsky, 2008), has been linked to decreased well-being caused by a lack of interpersonal interactions (Liebke et al., 2017). Therefore, research is needed to determine whether targeting emptiness will improve well-being, or whether well-being can be fostered with enhanced interpersonal skills in order to decrease emptiness.

Furthermore, emptiness might be related to comorbidities and cause impairment, due to its strong relationship with feelings of depression. Since emptiness and loneliness are characteristic of 'borderline depression' most investigations focus on their role in depression, (Westen et al., 2011). Although these factors discriminate BPD-specific depression from other types of depression (Gunderson, 2001), emptiness may be a bridge-criterion between BPD and mood disorders.

Even though clinicians do not regard dissociation as important to BPD as other criteria (Kim & Ahn, 2002), its significance becomes evident from the strong association it has with comorbidities. Dissociation is suggested to be a trans-diagnostic criterion. Similar rates of dissociation have been found in patients with BPD and PTSD and it seems to be prevailing in nearly all mental disorders (Lyssenko et al., 2018). It is linked to alterations in affective-cognitive functioning (Krause-Utz, Frost, Winter, & Elzinga, 2017), such as impaired working memory (Krause-Utz et al., 2018), and emotion processing (Winter et al., 2015). This may have negative effects on treatment and lead to a higher burden of illness, as BPD and PTSD patients are less likely to benefit from therapy if dissociation is high (Kleindienst et al., 2016). PTSD was the most common comorbid disorder in our sample diagnosed in 28.6% of participants, which we presume had a profound effect on the link between dissociation and comorbidities. Individuals endorsing this criterion might need a different treatment approach, first reducing dissociation in order to aid therapeutic recovery from BPD and other Axis I disorders.

In sum, it is apparent that each criterion is important to consider in its own right. We found that specific criteria are related to well-being and to comorbidities, supporting the claim that individual BPD criteria may be indicative of impairment severity on their own (Clark et al., 2018). Especially the unique associations that emerged between criteria with lower centrality indices and impairment propose that a criterion-specific approach is warranted when assessing patients. This way optimal interventions for each patient’s individual symptomology can be provided. Ultimately, the relevance of affective instability is underlined by its positive association to the number of Axis I disorders and its negative association to well-being.

Limitations

Firstly, the data was drawn from a selective sample, where participants had been recruited for BPD or as healthy controls, which limits the generalizability of the findings. There was no clinical control group to test how specific our findings are to BPD. Since the sample only consisted of female subjects the extension of our findings to male and mixed populations needs to be investigated. In this regard, it has been shown that affective instability is more common in women and anger more common in men (Tadić et al., 2009). Second, our analysis was based on cross-sectional data so we cannot draw inferences about the direction of associations, but interpret them in light of empirical and theoretical knowledge. Since our models yield no causal explanation of the interactions, the question remains whether reducing one central criterion would lead to a decrease in other criteria. Likewise, there might be different possibilities regarding the directional relationship between criteria and impairment. The cross-sectional design of this study cannot determine whether targeting specific criteria will decrease other criteria or if increasing well-being and treating comorbidities can improve BPD. These are important points to keep in mind when considering the treatment implications. Third, we did not account for situational factors such as social signals and threat cues that emotion regulation is dependent on (Herpertz, Schneider, Schmahl, & Bertsch, 2018). A host of research established that emotions are extremely dynamic and fluctuations differ per person and across situations (Kuppens & Verduyn, 2017). It is thus important to take this variability into account and assess affective instability and its association with other criteria using high-frequency data collection methods such as ecological momentary assessment (Shiffman, Stone, & Hufford, 2008). This will reveal not only the heightened affective variability in patients over time and context (Ebner-Priemer et al., 2015) but also inform us about the putative causal direction in which affective instability connects to other criteria (Bringmann, Vissers, Wichers, Geschwind, & Kuppens, 2013). Fourth, our study did not find associations between criteria and past suicide attempts. While the threshold method ensures specificity in dense network, it also increases the rate of false negatives for small effects (Epskamp, 2018). The variable was highly skewed, which decreased the probability that it would connect to other nodes. Findings should therefore be interpreted with caution. First studies have shown that network analyses are a valuable tool in assessing suicidal symptoms and their direct association with suicidal behavior (de Beurs, van Borkulo, & O'Connor, 2017). We hope these attempts will further extend into research on BPD, since an alarming proportion of 40.7% participants in our sample had at least one suicide attempt and Cluster-B personality disorders are robust predictors of suicide (May, Klonsky, & Klein, 2012). Finally, comorbidities were measured as count variable, since more comorbidities indicate greater impairment. We did not control for different types of Axis I disorders because modeling them as individual nodes would have created insufficient statistical power. Future investigations should look at BPD criteria that connect strongly to criteria of other disorders and identify critical connecting-points.

Clinical and Research Implications

The goal of this study was to complement diagnostic level research by contributing to the understanding of which criteria are most central to BPD and aid the endeavors of determining targets in treatment and prevention of the disorder. We obtained results that show overlap with network models of BPD features and advance the ongoing effort of replicating networks across samples. Our study focused on criteria assessed by a diagnostic interview and included a large range of clinical cases, as well as, individuals in the sub-clinical range. Further, we managed to extend the psychopathological network of BPD and investigate indicators of impairment as plausible factors associated with the severity of the disorder.

We applied a data-driven approach to aid the generation of more specific hypotheses that will structure clinical and methodological research at the criterion level. Identifying strongly connected criteria sheds light on psychopathological mechanisms. This knowledge provides a basis to determine cause-effect relationships that can be addressed in criterion-tailored interventions. For a better understanding of the mechanisms behind disorder course and change, it is thus crucial to investigate the interdependence of affective instability, unstable relationships, and suicidal or self-harming behavior. Additionally, our findings offer indications on criteria that might be critical connectors to other disorders, which need to be addressed in order to better understand comorbidities.

Ultimately, it is important to keep in mind that some criteria, even the ones less connected to other criteria, can indicate more impairment severity than others. Therefore, it is necessary that especially those criteria associated with impairment are given special attention in the diagnosis and treatment of BPD, so that diagnosed patients, as well as, individuals that fall below the diagnostic cut-off receive the support they need.

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Appendix A

Influence of Indicators of Impairment on Network Structure of BPD Criteria

We assessed the impact of indicators of impairment on the associations among the nine BPD criteria. The network of the BPD criteria was compared to the structure of connections between BPD criteria in the impairment networks. First we dropped the indicator of impairment from the adjacency matrix in the impairment network so only connections among BPD criteria remained controlling for the indicators of impairment. For each N2-N4 we compared these adjacency matrices to the full network of N1. The correlation of the criterion structure between N1 and N2 was $r = .98$, for N1 and N3 it was $r = .9991$, for N1 and N4 it was $r = .98$. The network between criteria stays robust when adding the indicators of impairment as covariates. The edge between identity disturbance and dissociation was missing in N2 and N4, which is likely due to the loss of power in detecting edges when adding nodes.