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UNDERSTANDING DIMENSIONS AND TYPES OF BORDERLINE PERSONALITY DISORDER THROUGH FACTOR MIXTURE MODELING

A Thesis in

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by

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ABSTRACT

Objective: Borderline personality disorder (BPD) is serious and prevalent and is quite heterogeneous. Identifying subtypes of BPD promises useful diagnostic and treatment implications. Although a series of subtyping studies exist, only two have examined BPD subtypes while taking into account BPD severity. We utilize factor mixture modeling (FMM) to identify discrete BPD subtypes, simultaneously considering symptom severity, in a large nonclinical young adult sample. We also consider how identified subtypes may be reflected in individuals reliably diagnosed with BPD.

Method: Undergraduate students (*N* = 20,010; 63.86% female; mean age=18.75, *SD* = 1.73) and BPD-diagnosed participants (*N* = 66; 97% female; mean age = 29.74, *SD* = 10.94) completed a dimensional version of the McLean Screening Instrument for BPD (MSI-BPD). This was condensed to measure the nine DSM BPD criteria on a True/False scale. We conducted FMM to determine classes of individuals characterized by different responses to the MSI-BPD as well as the composition of underlying BPD severity dimensions.

Results: The nonclinical sample was comprised of three subtypes—Asymptomatic (70%), Impulsive/Externalizing (19%), and Identity Disturbed/Internalizing (11%)—falling along a single continuum of increasing BPD severity. In the BPD sample, a single severity dimension best captured BPD symptomatology and no subtypes were identifiable.

Conclusions: Our results suggest the importance of both dimensional and categorical conceptualizations of BPD, depending on the sample and level of severity in focus. Impulsive/Externalizing and Identity Disturbed/Internalizing classes suggest different treatment targets for subthreshold BPD and potential etiologically relevant profiles for BPD development.

The findings are discussed in terms of their clinical implications regarding diagnosis, treatment, and theoretical conceptualization of BPD.

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There are more things in heaven and earth, Horatio,
Than are dreamt of in your philosophy.

Hamlet Act I, scene v, 166-167

CHAPTER 1

Understanding Dimensions and Types of Borderline Personality Disorder Through Factor Mixture Modeling

Borderline personality disorder (BPD) is a serious, prevalent, and impairing psychiatric disorder that produces significant personal and societal burden. BPD is associated with up to 400 times greater risk for suicide than general population estimates, with roughly 1 in 10 individuals with BPD successfully completing suicide (Brodsky, Groves, Oquendo, Mann, & Stanley, 2006; Paris, 2002). BPD is also associated with high rates of emergency room visits and other forms of costly healthcare service utilization (Bateman & Fonagy, 2003; Frankenburg & Zanarini, 2004). BPD symptoms tend to contribute to significant impairments in social and occupational functioning (Javaras, Zanarini, Hudson, Greenfield, & Gunderson, 2017), even if an individual does not meet full criteria for the disorder (Ellison, Rosenstein, Chelminski, Dalrymple, & Zimmerman, 2015; Gunderson et al., 2011; Zimmerman, Chelminski, Young, Dalrymple, & Martinez, 2012). BPD is also quite common, considered among the most prevalent of the personality disorders (Levy & Johnson, 2016). The literature suggests that 1-5% of the general population (Grant et al., 2008; Trull, Jahng, Tomko, Wood, & Sher, 2010), 10-20% of psychiatric outpatients (Johnson & Levy, 2015; Korzekwa, Dell, Links, Thabane, & Webb, 2008; Zimmerman, Chelminski, & Young, 2008), and 20-40% of psychiatric inpatients (Marinangeli et al., 2000; Ottosson et al., 1998) meet diagnostic criteria for BPD.

Despite a growing body of research on BPD, which has begun to identify developmental trajectories (e.g., Crowell, Beauchaine, & Linehan, 2009), mechanisms of treatment change (e.g., Levy et al., 2006), relevant neurological substrates (e.g., Ruocco, Amirthavasagam, Choi-Kain, & McMain, 2013), and clinical and functional correlates of the disorder (e.g., Morgan, Chelminski, Young, Dalrymple, & Zimmerman, 2013), disagreement remains surrounding the construct of BPD itself and its accuracy as a diagnosis at the individual level. The alternative model of personality disorders introduced during the development of the 5th edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) highlighted the ongoing debate surrounding the utility and accuracy of the BPD diagnostic criteria (Widiger, 2011). Furthermore, the heterogeneity of BPD and how it is displayed among individuals is likewise not well understood (Cooper, Balsis, & Zimmerman, 2010). As the strength of much of the existing BPD research base relies on an understanding of the conceptual boundaries of BPD and who is afflicted with the disorder, consensus on the structure of BPD is vital. Assessing for BPD requires clarity of the conceptual make-up of the disorder, and BPD treatment studies mandate accurate and valid diagnoses in order to isolate BPD maintenance factors and change mechanisms, emphasizing the need to truly understand the BPD construct and those with it. Furthermore, given that there are several empirically supported treatments for BPD, identifying subtypes of BPD may have significant implications for referring patients to ideographically optimal therapies.

There exist two distinct ways in which BPD can be understood. First, an extensive literature has examined the dimensions of the BPD phenomenon. This literature has attempted to answer the question of what “BPD-ness” is in terms of potential subcomponents of the construct (e.g., behavioral or emotional dysregulation). Second, BPD has been explored in terms of the individuals who report symptoms of the disorder. This line of research has attempted to identify subgroups of individuals with BPD features, in the hopes of parsing both clinical and nonclinical samples into various BPD types. However, the conclusions drawn from both of these domains are unclear, in part because these lines of work have largely unfolded independently of one another. The present study attempts to integrate these researches using the largest nonclinical sample to date in order to identify an increased range of subtypes of BPD, while simultaneously taking into account variation along dimensions of the disorder. This study further attempts to validate which of these types of people may seek services for BPD treatment at an outpatient community mental health center.

Dimensions of the BPD Construct

Theoretical foundation. Features of BPD, as generally defined by the DSM (American Psychiatric Association, 2013), hail from several disparate domains of function. BPD presents through affective dysregulation, behavioral dysfunction (e.g., suicidal behavior), cognitive disruption (e.g., dissociation), identity disturbance, and interpersonal difficulties. Theoretical writers have considered several of these aspects of BPD to be at the heart of the disorder. Following Stern (1938) and some other clinical writers' descriptions of borderline personality, Kernberg began a series of detailed descriptions in the 1960s of what he termed borderline personality organization and its treatment (Kernberg, 1967, 1971, 1978, 1985). In part due to the contemporary psychoanalytic focus on internal mental structures, he conceptualized BPD as a disorder of identity. Derived from combined genetic influences and disrupted psychological development, individuals with BPD have fractured identities, comprised of a deficit in coherent mental representations of themselves and others. Specifically, as part of this identity disturbance, those with BPD experience a splitting off of intolerable aspects of themselves, such as feelings of anger or dependence, leading to intense vacillations in object representations and mood states. In Kernberg's theory, then, identity disturbance can be considered the core of the disorder, giving rise to difficulties in affective and interpersonal regulation.

The 1980s saw the introduction of Linehan's behavioral theories of BPD, founded in her clinical experiences with suicidal and parasuicidal women (Linehan, 1986, 1987, 1993a, 1993b). She delineated BPD as a disorder primarily of trait impulsivity and emotional hypersensitivity, which are aggravated by invalidating environments. Linehan described the behavioral features of BPD—namely suicidality and non-suicidal self injury—as being manifestations of this underlying lack of regulatory capacity. Unlike Kernberg's focus on identity disturbance at the heart of BPD, Linehan's theory suggests that impulsivity and affective dysregulation may make up the fundamental domains of the disorder. The leading theories regarding the BPD phenomenon, then, posit different core dimensions of the disorder. Building on the empirical literature outlined below, we seek to test whether BPD is a unitary construct combining the suppositions of Kernberg and Linehan, or if rather identity disturbance and regulatory dysfunction form distinct components of BPD in a multidimensional underlying framework.

The first major cross-disciplinary attempt to codify the clinical observations on BPD into a parsimonious and empirically testable framework was the development of the DSM. Adhering to the medical model, influenced by the taxonometry of Kraepelin, and eschewing etiological theory, the DSM attempted to offer atheoretical symptom-oriented descriptions of the various psychiatric disorders. Although an atheoretical taxonomy was essentially an impossible task (Millon, 1991), one result of this attempt was for BPD to be defined by a broad collection of descriptive symptoms and traits, with none given preeminence. This had the intended benefit of bringing the psychiatric community into mutual conversation regarding the BPD phenomenon, despite often deeply held differences in theoretical opinion. Simultaneously, however, the absence of hypotheses regarding the comparable relevance of, interactions among, and temporal ordering of the listed BPD criteria limited the DSM as a testable framework that could evolve and improve as a diagnostic tool (Blashfield & Livesley, 1991). This sparked a series of studies attempting to identify underlying dimensions among the constellation of BPD symptoms, in the hopes of further contextualizing the DSM criteria and improving upon theories of what BPD really is.

It is worth noting that the DSM is by no means the only conceptual framework that can be used to understand BPD. For instance, the Psychodynamic Diagnostic Manual (PDM; Psychodynamic Task Force, 2006) outlines a range of borderline-level personality disorders, built on the idea of levels of personality functioning written about by Kernberg (1967) and McWilliams (1999), among others. The International Classification of Diseases (ICD; World Health Organization, 1992) also contains a description of “emotionally unstable personality disorder,” largely equivalent to DSM BPD. However, parsing of the DSM definition of BPD provides several theoretical and practical advantages over other systems: 1) Given its intended theory-agnostic bent, the DSM description of BPD phenomenology spans the writings of behavioral and psychoanalytic thinkers alike; 2) the DSM contains item-level descriptions of BPD that are not contained, for instance, in the ICD, making it amenable to statistical modeling at the criterion level; 3) although the ICD and the DSM are the most prevalent diagnostic systems used today, given its clinical focus (American Psychiatric Association, 2013), the DSM provides further clinical utility over the ICD, especially for practitioners at the front line; 4) the bulk of the research on BPD has been conducted through the lens of the DSM, emphasizing the need for clear delineation of this disorder in this framework.

Empirical support. A large body of empirical evidence on dimensions of BPD has accumulated over the past four decades. This research has primarily utilized factor analysis to determine if BPD may be best understood unidimensionally, with each symptom forming a (relatively) equal piece of the larger disorder, or multidimensionally, with a few key symptom clusters (e.g., identity disturbance, behavioral dysregulation) comprising BPD. Of note, we focus here on research that has examined BPD in terms of the individual DSM criteria alone, instead of, for instance, many-item multi-subscale BPD measures, which will necessarily produce increasing numbers of factors and deny comparisons across studies. In 1989, Rosenberger and Miller (1989) conducted one of the first studies to examine the component structure of BPD, attempting to differentiate BPD from its then-counterpart, schizotypal personality disorder. They screened undergraduate students for personality pathology, recruiting a sample of 106 students, with 18 students receiving a diagnosis of BPD. Principal components analysis (PCA) of the eight DSM-III BPD items suggested two BPD components: 1) Interpersonal Disturbance, on which abandonment fears, emptiness, unstable relationships, and identity disturbance loaded strongly, and 2) Instability, comprised mainly of anger, self-harm, impulsivity, and affect instability (**Table 1**). The results of this study aligned relatively well with the conceptualizations of Kernberg and Linehan, with the former identifying identity and relational problems as a core BPD feature, and the latter calling attention to the behavioral dysregulation common among those with the disorder. Importantly, affective instability loaded moderately well with both components (.42 and .51 respectively), echoing the importance placed on affect by both theorists. However, despite screening for high-risk undergraduates, Rosenberger and Miller's sample lacked the representativeness of a clinical population. Furthermore, their study utilized the DSM-III BPD criteria and therefore did not take into account the paranoia/dissociation item introduced with the DSM-IV.

The early 90s saw two subsequent studies of the BPD construct on clinical samples, although both studies also used the DSM-III BPD criteria. Hurt and colleagues (1990) conducted a combination of retrospective chart reviews and semi-structured interviews of 579 individuals with personality disorders. Using single-linkage clustering among the 465 patients with BPD, they identified three item subsets: 1) Identity Disturbance (emptiness, identity disturbance, and fears of being alone), 2) Affect (anger, affect instability, and unstable relationships), and 3) Impulse (self-harm and impulsivity). These clusters largely reflect those identified by Rosenberger and Miller (1989); however, pairing items through single-linkage clustering may not accurately represent the more complex combinations of BPD criteria that might exist in the clinical population, an advantage of factor analytic strategies.

Clarkin, Hull, and Hurt (1993) utilized PCA on dimensionally rated DSM-III-R BPD criteria among a sample of 75 hospitalized women with BPD. The authors found three factors explaining 56% of the variance in BPD items: 1) Disturbed Relatedness, 2) Affect, and 3) Impulsivity. These findings are relatively consistent with previous findings and with both Kernberg and Linehan's theories of BPD. However, the authors noted the feasibility of a four-factor model, explaining an added 14% of the variability in items. In this model, the anger item formed a unique factor and identity disturbance was not uniquely representative of any factor. Two later studies of the DSM-III-R found relatively similar results: Sanislow, Grilo, and McGlashan (2000) identified 1) Disturbed Relatedness, 2) Behavioral Dysregulation, and 3) Affect Dysregulation factors in a sample of 141 inpatients (62 with BPD). In the first analysis of a BPD-diagnosed sample, Whewell, Ryman, Bonanno, and Heather (2000) described behavioral and affective factors (although without a clear disturbed relationships factor) in 288 outpatients with BPD. The authors note that unstable relationships and identity disturbance loaded onto both of these factors, positioning these as core, transdimensional BPD features consistent with Kernberg's theory of BPD. However, the most recent study to use the DSM-III-R criteria, in a sample of 123 inpatient adolescents, identified four distinct components of BPD: depressivity/self-negation, affect dysregulation, interpersonal dysregulation, and impulsivity (Becker, McGlashan, & Grilo, 2006). These results suggest that BPD in adolescence may be more heterogeneous and multifaceted then a more coalesced adult BPD syndrome. However, as this has been the only study to examine dimensions of the BPD criteria among adolescents, this interpretation remains tentative.

The first structural study of the DSM-IV BPD criteria (Blais, Hilsenroth, & Castlebury, 1997)—including the added paranoia/dissociation item—identified a similar three-factor solution as Clarkin and colleagues (1993). The paranoia/dissociation item loaded most strongly on the affect factor, leading the authors to suggest this factor constituted both affective and cognitive dysregulation. Importantly, the three factors identified by Blais and colleagues (1997) were extracted in the same order as previous studies (Clarkin & De Panfilis, 2013; Hurt et al., 1990), suggesting the primary importance of self and other representations in the conceptualization of BPD (Kernberg, 1967). Although this was the first study of the DSM-IV criteria, the authors utilized retrospective chart reviews of 91 outpatients (25 with BPD) rather than data gathered directly from participants, introducing methodological limitations potentially reducing the generalizability of their findings.

As the three-domain model of BPD gained increasing support, Fossati and colleagues (1999) conducted the first confirmatory factor analysis (CFA) study of the DSM-IV BPD items among a sample of 564 mixed clinical inpatients and outpatients (100 with BPD). Assessing BPD criteria via the Structured Clinical Interview for DSM-IV Axis II disorders (SCID-II; First & Gibbon, 2004), the authors tested the three- and four-factor models of Clarkin et al. (1993) and Hurt et al. (1990) alongside the unidimensional model as conceptualized by the DSM. Based on chi-square statistics and model parsimony, Fossati and colleagues argued for a single dimension as best representing the BPD construct. However, their study possessed two major limitations. First, although in a sense a methodological advance, the authors’ use of CFA on the DSM-IV BPD criteria may have been premature. The models they tested were established on only the DSM-III and III-R criteria, which did not include the paranoia/dissociation item, and the authors did not evaluate the three-factor DSM-IV model proposed by Blais et al. (1997). This may have increased the likelihood that a unidimensional model fit the data best in their sample. Second, with large sample sizes (*N* > 200), chi-square tests are subject to trivial differences between observed data and hypothesized factor models (Graham & Connell, 2014). Similar to the importance of reporting effect size metrics to guard against the increased chance of statistical significance in any large sample (Kelley & Preacher, 2012), indices of practical fit in confirmatory factor analysis (e.g., Hu & Bentler, 1999) are vital for understanding meaningful differences between hypothesized factor models. Thus, Fossati and colleagues' selection of a single-factor model as best fitting their data was not validated via comparisons of practical fit indices across models.

In 2002, Sanislow and colleagues attempted a similar analysis as Fossati et al. (1999) but with the addition of indices of practical fit for comparing models. In a large mixed clinical sample (*N* = 668, 240 with BPD), the authors compared a unidimensional model with the repeatedly identified three-dimensional model (disturbed relatedness, behavioral dysregulation, and affect dysregulation). The authors identified both models as fitting the data relatively well in terms of practical fit indices. Although Sanislow and colleagues note that the three-dimensional BPD model provided statistically better fit to the data than the unidimensional model, chi-square difference tests are also subject to spurious significance due to large sample sizes. Graham and Connell (2014) suggest that evaluation of differences in practical fit indices provide a more accurate estimate of meaningful differences between models. Given that the practical fit indices reported by Sanislow et al. differ by less than .01 between models (Graham & Connell, 2014), the unidimensional and multidimensional models are equally likely to represent the BPD construct in their sample. Given its additional parsimony, the single-factor model is likely a better choice to represent the data presented by Sanislow and colleagues, consistent with Fossati et al. (1999). In support of this conceptualization, Johansen, Karterud, Pedersen, Gude, &

Falkum (2004) found nearly identical results using CFA in a sample of 930 patients (252 with BPD) in Norwegian day treatment programs.

In the past decade, researchers have attempted to broaden the methods and samples used to assess the structure of BPD, continuing to find results relatively consistent with one-dimensional and three-dimensional models of the disorder—with some exceptions. Similar to Whewell and colleagues (2000), Benazzi (2006) identified two BPD factors (affective instability and impulsivity) in a sample of 209 outpatients with mood disorders. Of note, both Whewell et al. and Benazzi utilized self-report measures of the BPD criteria (unlike the interview-based assessments primarily used by other studies), potentially contributing to their simpler, two-factor solutions. Becker, Añez, Paris, and Grilo (2010) suggested a single factor best explained the BPD construct among 130 Hispanic outpatients (39 with BPD), providing evidence from the first ethnic minority clinical sample used in the literature. In developing the BPD Severity Index-IV (BPDSI-IV), Giesen-Bloo, Wachters, Schouten, and Arntz (2010) similarly found CFA support for a unidimensional conceptualization of BPD among a mixed clinical and nonclinical sample (N = 242, 108 with BPD). As Giesen-Bloo and colleagues did not assess BPD criteria directly, instead using the nine subscales of the BPDSI-IV to capture the nine BPD criteria, they also suggested a nine-factor model might represent the data well. However, their findings are difficult to compare with the rest of the cited literature, which has assessed BPD criteria on a single-item level.

Andión and colleagues (2011) conducted the first CFA to compare a theoretically driven five-factor model (Oldham, 2006) against models with one and three factors. They found the model with three factors (disturbed relatedness, affect dysregulation, and behavioral dysregulation) fit best among 338 primarily personality disordered outpatients (220 with BPD). Lewis, Caputi, and Grenyer (2012) conducted the first factor analytic study of the DSM-IV criteria among outpatients with BPD (*N* = 95), and they also identified three BPD dimensions among 95 psychiatric outpatients with BPD. However, the content of their factors differed from previous research, perhaps due to their use of oblique factor rotation, rather than the orthogonal factor rotation used by previous research in clinical samples. The authors identified an Affect Dysregulation factor, followed by Rejection Sensitivity (with high loadings of the self-harm, abandonment fears, and emptiness criteria), and Mentalization Failure (with high loadings of the paranoid/dissociation and identity disturbance criteria and a *low* loading of the unstable relationships criterion). These studies generally provide further support for the one- and three-factor models of BPD, although the preference for one model over the other remains unclear.

Even less is clear in terms of the BPD construct in nonclinical samples. Three recent studies have identified one-, three- and four-dimensional models of BPD in young adult samples, in contrast to the early two-dimensional model of Rosenberger and Miller (1989). Taylor and Reeves (2007) sampled a high-risk sample of 82 undergraduates (7 with BPD). They identified disturbed relatedness, affect/low impulsivity, and paranoia/low anger components of BPD. Using the largest sample to date, Selby and Joiner (2009) found four BPD components among 1,140 young adults: 1) Affect Dysregulation, 2) Cognitive Disturbance, 3) Disturbed Relatedness, 4) Behavioral Dysregulation. Given the composition of their sample, they were also able to determine that these factors were consistent across African Americans, Caucasians, and Hispanics. Unfortunately, due to a technical error in the self-report measure used in this study, the identity disturbance item was not included in the authors' analyses, rendering these results questionable. Hawkins and colleagues (2014) conducted the most recent and perhaps most comprehensive examination of the dimensional structure of BPD. Using both psychiatric and community participants (*N* = 281, 86 with BPD), the authors found a unidimensional BPD construct via three assessment modalities (diagnostic interview, retrospective self-report, and momentary assessment) among both BPD and non-BPD individuals separately. Although Hawkins and colleagues' (2014) study is comprehensive and compelling, the heterogeneity of findings among nonclinical samples is striking.

Taken together, the corpus of factor analytic studies among clinical samples suggests interpersonal relations, affect, and behavior may all be distinct domains of functioning compromised by the BPD phenomenon. At the same time, these domains may be able to be considered interrelated subdomains of an overarching single BPD construct (Trull, Distel, & Carpenter, 2011), which may be a more parsimonious and ideal representation of BPD symptomatology. This conceptualization is vaguer among nonclinical samples and BPD-diagnosed samples, as studies have posited one, two, three, and four dimensions of BPD among these samples without much consistency or consensus. However, the most comprehensive multi-method assessment of BPD dimensions (Hawkins et al., 2014) suggests a single factor may well summarize the DSM BPD criteria in the nonclinical population as well.

Subtypes of BPD Individuals

Theoretical foundation. Despite the large body of work on understanding the BPD construct itself, less research has looked at the kinds of individuals themselves who endorse BPD symptoms. Although some BPD researchers cited above have inaccurately claimed that factor analysis allows for the identification of BPD subtypes, the question of whether or not subtypes of individuals with BPD can be reliably identified remains only partially answered. With its polythetic classification system, the DSM (American Psychiatric Association, 2013) allows for 256 different ways to receive a BPD diagnosis. Accordingly, it is feasible that multiple subtypes of BPD might be present among those categorized under its diagnostic label. In order to fully understand the structure and display of BPD, both its dimensions and its potential subtypes must be articulated.

Theoretical writers have proposed clinically relevant subtypes of BPD, usually based on prototypical DSM BPD symptoms, such as anger, that carry the weight of each class. Oldham (2006) outlines five subtypes of BPD drawn from the developmental and clinical literature, along with associated prototypical diagnostic criteria: Affective (affective instability), Impulsive (impulsivity), Aggressive (anger), Dependent (fear of abandonment), and Empty (emptiness). Oldham highlights the use of subtypes for providing foci for treatment (e.g., affective BPD individuals may require more pharmacotherapy than empty individuals). He also emphasizes the importance of identifying BPD subtypes in order to predict individuals' risk for suicide attempts, as certain subtypes (e.g., Impulsive) may be more associated with suicide risk than others. Identifying reliable subtypes may understandably enhance prognostic accuracy and treatment recommendations for groups of individuals. In line with Oldham's argument, it is worth noting that identified subtypes are especially meaningful and clinically relevant if they are associated differentially with useful secondary clinical variables, such as suicide attempts or level of functioning.

Empirical support. Although also an important area of research with a range of potential clinical applications, there are far fewer studies examining BPD subtypes than dimensions of BPD. Some of the research cited above refers to factor analysis as a method to identify subtypes of BPD; yet factor analysis is a construct-centered statistical procedure that is unable to identify individual-level characteristics like subtypes. Instead, several person-centered analyses have been developed for this purpose. Grinker, Werble, and Drye (1968) conducted the first study of subtypes of BPD, utilizing cluster analysis among a sample of 51 inpatients with BPD features. Grinker and colleagues identified four clusters of individuals in terms of 10 components (e.g., negative affect, relationship intimacy, confidence, somatization) (**Table 2**). Two they deemed at the Psychotic Border (35.3% of patients) and at the Neurotic Border (13.7%), recalling the contemporaneous conceptualization of BPD as existing between psychosis and neurosis (Stern, 1938). The third they termed Core Borderline (23.5%) and the last the "Adaptive, Affectless, Defended, "As If" Persons" (27.5) in line with Deutsch's (1945) characterization of borderline patients. Although he and his colleagues did not utilize DSM BPD criteria in their analyses, Grinker's seminal study paved the way for later research on potential subgroups of individuals with BPD.

In 1999, Fossati et al. conducted the first subtyping study with the DSM criteria for BPD. In conjunction with a factor analysis of the DSM-IV BPD criteria (see above), Fossati and colleagues utilized latent class analysis—designed for identifying subtypes of individuals from a group of dichotomous variables, such as BPD symptoms—to examine potential subgroups of 564 mixed clinical participants (100 with BPD) in terms of their BPD criteria endorsement. The authors found three subtypes of BPD: 1) a type comprised of nearly no BPD symptoms (56.0%), 2) a type reflecting a full BPD diagnosis (16.2%), and, perhaps most interestingly, 3) an impulsive/angry subtype of individuals (27.8%). These findings shed light on an important subgroup of clinical individuals characterized by externalizing BPD features who may not meet full criteria for the diagnosis. However, Fossati and colleagues' heterogeneous clinical sample was not equipped to reveal more than one severe type of individuals meeting full criteria for BPD.

Although a series of studies of BPD subtypes has followed that of Fossati et al. (1999)—with somewhat mixed results—the overwhelming majority of these have also not examined subtypes solely among individuals diagnosed with BPD. These studies generally find four classes of individuals characterized in terms of BPD symptoms. Among mixed clinical samples, a highly prevalent "No Symptom" class emerges, capturing those individuals without a BPD diagnosis. However, the remaining classes identified by these studies are varied. Beyond a

Symptom-Free class, Thatcher, Cornelius, and Clark (2005) also identified Moderate (41.3%) and Severe (9.0%) BPD classes, as well as an Impulsive/Angry class (49.7%), further supporting Fossati and colleagues' (1999) discovery of an externalizing subthreshold group of individuals. However, these authors removed participants with no symptoms from their analysis (*N* = 357), leaving 167 patients with at least one BPD symptom among whom these classes were identified. Thus, their results are difficult to compare with other studies. Clifton and Pilkonis (2007) found no content-based subtypes of BPD among 411 mixed clinical participants, identifying only High BPD (41.6%) and Low BPD (58.4%) classes. Their analyses, however, were conducted on DSM-III-R criteria, thus missing the paranoia/dissociation item and reducing generalizability to the current DSM-IV and DSM-5 BPD diagnostic framework. Most recently, Slavin-Stewart (2015) identified Identity/Empty (20%), Abandonment/Suicidality/Dissociation (16%), and Severe BPD (13%) classes among 75 self-harming adolescents, although this study's small sample size, with only 14 individuals with an actual BPD diagnosis, tempers the generalizability of these findings.

Studies of BPD subtypes in nonclinical samples have indicated a spectrum of severity, rather than conceptually distinct groups of individuals identified in mixed clinical samples. One study utilized British epidemiological data to identify subgroups among 8,580 community individuals (16 with BPD), making this the largest sample examined to date (Shevlin, Dorahy, Adamson, & Murphy, 2007). The authors found four classes: None (66.6%), Low (19.2%), Moderate (9.5%), and High (4.6%) in terms of BPD symptomatology. Similarly, in a sample of 382 urban, substance-using men (73 with BPD), Bornovalova, Levy, Gratz, and Lejuez (2010) identified four BPD classes along a spectrum of severity (i.e., No BPD [40.0%], Low [25.3%], Moderate [27.0%], and High [7.7%]). In tandem, these studies suggest that—at least among nonclinical samples—BPD symptoms may be distributed along a latent factor rather than among conceptually distinct BPD subtypes. However, these studies did not evaluate remaining subtypes *after* taking into account this latent severity dimension.

Two studies have utilized BPD-diagnosed samples to identify subtypes of the disorder (Lenzenweger, Clarkin, Yeomans, Kernberg, & Levy, 2008; Ramos, Canta, de Castro, & Leal, 2014). However, both studies examined subtypes in terms of secondary features theoretically relevant to BPD, rather than in the context of the DSM criteria. Using the Millon Adolescent Clinical Inventory (Millon & Davis, 1993), Ramos and colleagues (2014) found both an Internalizing and an Externalizing class among 60 adolescent outpatients with BPD. Using finite mixture modeling in a sample of 90 BPD individuals, Lenzenweger and colleagues (2008) assessed levels of antisociality, paranoia, and aggression based on Kernberg's (1967) theory of borderline personality organization. The authors identified a group with Low responding across all three measures (40.0%), a Paranoid group (27.8%), and an Antisocial/Aggressive group (32.2%). Although both of these studies further establish the likelihood of an externalizing group of BPD individuals, they are limited by the use of secondary measures and no comparison sample of non-BPD individuals. For instance, it is difficult to know if the Internalizing and Externalizing classes of Ramos and colleagues' (2014) study suggest something unique about BPD or if such classes exist in the greater clinical (and nonclinical) populations as well, regardless of an individual's level of BPD pathology. Furthermore, these studies do not address the question of whether or not individuals with BPD fall into specific categories in terms of the DSM BPD criteria themselves, which is important in order to efficiently determine treatment recommendations and prognostic factors from initial clinical assessments.

Despite some discrepancies within this body of research, two common themes arise in terms of BPD subtypes. First, individuals seem to exist on a (perhaps fuzzy) BPD spectrum, especially in nonclinical samples. The majority of individuals (both clinical and nonclinical) appear to present with little to no BPD features, a subset fall into classes of moderate severity, and a relatively distinct few endorse nearly all of the DSM BPD criteria. These findings emphasize the importance of taking into account a latent BPD severity dimension, which may account for quantitatively, but not qualitatively, distinct “subtypes.” Otherwise it is possible that truly distinct subtypes are being masked by severity-based groupings. Second, several studies point to the presence of both dysregulated and identity disturbed classes of individuals with BPD symptoms. Dysregulated individuals are largely characterized in terms of the BPD criteria of anger and impulsivity, although Lenzenweger et al. (2008) and Ramos et al. (2014) both suggest a broader understanding of externalizing behavior, including antisocial acts and aggression. Identity disturbed individuals appear to experience both identity diffusion and emptiness as core BPD features, although, again, these individuals may broadly resemble those encapsulated by Ramos and colleagues’ (2014) internalizing group of BPD adolescents.

Although this body of research has begun to elucidate our understanding of BPD subtypes, further synthesis remains needed. Even more so than in factor analytic research, sample heterogeneity can have a large impact on the results of subtyping studies. For instance, including individuals without a BPD diagnosis in such a study will understandably introduce an asymptomatic subtype, as has been the case in all subtyping studies to date. Furthermore, identifying low-prevalence subtypes (e.g., different classes of severe BPD in a nonclinical sample) requires quite large sample sizes. Finally, no published study to date has explored subtypes of BPD (in terms of the BPD criteria) among a BPD-diagnosed sample, an important consideration if treatment referrals are to be made based on subtypes of the disorder (Oldham, 2006). It is, therefore, important to examine the BPD typology as it truly exists in the broader nonclinical population using a sample adequately powered to find small classes, as well as confirm the presence (or absence) of severe BPD classes in a BPD-only sample.

Integrating BPD Dimensions and Subtypes

The two threads of research outlined above—one attempting to identify dimensions of the BPD construct, the other subgroups of individuals in terms of BPD symptoms—have largely developed in parallel with little interaction (see Fossati et al., 1999, for an exception). Taken independently, previous research suggests that BPD is likely either unidimensional or three-dimensional and that individuals largely fall into asymptomatic, fully symptomatic, or dysregulated or identity disturbed subtypes of the disorder, although research has not yet confirmed the presence or absence of these subtypes among BPD-diagnosed individuals. Furthermore, this corpus provides little insight into how BPD can be best understood in terms of both dimensions and subtypes *simultaneously*. In fact, the current literature points to the importance of considering these methods of analysis together. Multidimensional BPD models posit the question of whether certain individuals meet for BPD via elevations on only one or two dimensions of symptoms. Likewise, the subtyping literature of nonclinical samples suggests that a single BPD factor on which individuals vary may be artifactually generating subtypes that differ only in terms of severity, not conceptual meaning (Lubke & Muthén, 2005). Combining dimensions and subtypes of BPD in a single analysis may reduce unnecessary heterogeneity in previous findings and provide a simpler, more parsimonious understanding of the structure of BPD.

Only recently have statistical techniques reached the psychopathology literature that are able to assess both dimensions and subtypes of a disorder at the same time in a given sample. Such techniques are vital to help resolve the discrepancies produced by prior studies. For instance, factor analyses that do not simultaneously take into account potential BPD subgroups in a population may produce erroneous factors among heterogeneous samples (Lubke & Neale, 2006). Similarly, latent class models designed to identify subtypes of BPD may identify too many population subgroups if heterogeneity in the data is better explained by differences along an underlying continuous factor (Lubke & Neale, 2006). It is also possible that the structure of BPD may vary depending on the group in question. For instance, interpersonal, affective, and behavioral dimensions may exist among severely disturbed individuals (cf. Clarkin et al., 1993), while subclinical individuals may express only a single dimension of BPD symptoms (cf. Fossati et al., 1999). Analyses that simultaneously take into account the latent factor and class composition of BPD, and allow for different factor structures across each class, are therefore vital in order to examine such combinations and resolve inconsistencies produced by past research.

Only two studies to date have utilized a combined trait-based and class-based analysis of BPD (Conway, Hammen, & Brennan, 2012; Hallquist & Pilkonis, 2012). These studies employ factor mixture modeling (FMM; B. O. Muthén & Shedden, 1999), which is able to simultaneously identify the optimal configuration of latent dimensions and classes of BPD. Conway and colleagues (2012) determined that a single-factor latent trait model outperformed both a latent class and factor mixture model in a sample of 700 young adults. These findings suggest that BPD may be best understood as a unidimensional construct, continuously distributed among individuals, without encompassing conceptually distinct subtypes of individuals, similar to several previous studies (Becker et al., 2010; Fossati et al., 1999; Giesen-Bloo et al., 2010; Hawkins et al., 2014). However, Conway and colleagues' (2012) use of FMM was restricted only to models in which the BPD factor structure was maintained strictly invariant across classes (see discussion of measurement invariance below). As noted by Clark and colleagues (2013), this form of model parameterization usually does not adequately reflect true structural heterogeneity between classes. Furthermore, Conway and colleagues sample was not sufficiently powered to detect low-prevalence classes. Collins and Lanza (2013) suggest utilizing samples that are at least 5 times larger than the number of available response patterns in the items being evaluated. Given the 512 different ways of endorsing (or not) the nine BPD criteria, an adequately sized study would require at least 2,560 participants to produce reliable statistical tests of latent class models. Thus, this study was limited in terms of its ability to resolve true BPD subtypes, especially various forms of severe BPD types, in the general population.

Hallquist and Pilkonis (2012) utilized a similar model-comparison approach to their data in a mixed sample of 362 individuals with BPD, another personality disorder, or no personality disorder. The authors first identified a symptomatic (27.6%) and an asymptomatic class of individuals (72.4%)—largely reflecting participants with and without a BPD diagnosis—via a single-factor, two-class FMM model that outperformed both a latent trait and a latent class model. These findings reiterate the importance of capturing dimensions and classes of BPD simultaneously in order to accurately represent the disorder. Hallquist and Pilkonis then evaluated subtypes of the 100 participants in the symptomatic group in terms of a range of several DSM criteria (e.g., Anger) and secondary symptom measures (e.g., aggressiveness as measured by the Inventory of Interpersonal Problems [Horowitz, Rosenberg, Baer, Ureño, & Villaseñor, 1988]), identifying four symptomatic subtypes: Prototypical, Poor Identity/Low Anger, Angry/Mistrustful, and Angry/Aggressive. Although this study provides a useful multistage parsing of a diverse sample, including individuals with and without BPD, the selection procedure with which the authors built their sample presents some concerns in terms of latent class modeling. Sampling strategies that recruit from several distinct populations of individuals, such as the inpatient, outpatient, and community settings utilized by Hallquist and Pilkonis (2012), tend to introduce artifactual latent classes arising from the sampling procedure itself, rather than true person-level differences in the population (Markon & Krueger, 2006), calling into question the generalizability of the initial two-class solution identified in this study. In addition, no study to date has utilized FMM among individuals with BPD in terms of the DSM BPD criteria themselves to confirm the clinical reality of various subtypes identified in the broader population.

The Present Study

There are several lingering questions in the search to understand the BPD nosology. The present study attempts to fill several gaps in the literature by employing factor mixture modeling of BPD symptoms in both the largest nonclinical sample to date and a sample of outpatients with BPD. This study has two interconnected aims. *Aim 1*: We will utilize a sufficiently sized nonclinical sample to approximate a comprehensive range of latent BPD subtypes across the entire spectrum of severity. This approach will allow for the identification of asymptomatic as well as moderately and severely symptomatic subtypes, while taking into account underlying dimensional severity, thus ensuring qualitative differences between the classes (rather than spurious proxies for BPD severity). *Aim 2*: We will then attempt to confirm in a reliably diagnosed BPD sample the presence of any severe classes of BPD individuals identified in the nonclinical sample. This two-step approach will provide the first look at the congruence (or incongruence) of classes between severe nonclinical and treatment-seeking samples.

Hypotheses. We posit four hypotheses in relation to the first study aim. *H1*: We hypothesize, given prior research, that both a single BPD dimension and the three dimensions of disturbed relatedness, affect dysregulation, and behavioral dysregulation will well capture the latent structure of BPD in the nonclinical sample. However, we hypothesize that the three-factor model will not meaningfully improve on the fit of the single-factor model and that the latter will remain the most parsimonious conceptualization of BPD in this sample. *H2*: We hypothesize that, within the nonclinical sample, at least four classes will emerge, the most prevalent being a symptom-free class, followed by several increasingly symptomatic classes and a smaller high severity class. We suggest that that the large size of our sample will allow detection of several classes of moderate-to-high severity identified in some, but not all, previous research, including an impulsive/angry/externalizing class (Fossati et al., 1999; Ramos et al., 2014; Thatcher et al., 2005), an identity disturbed/empty/internalizing class (Ramos et al., 2014; Slavin-Stewart, 2015), and a class defined by fears of abandonment, suicidality, and dissociative experiences (Slavin-Stewart, 2015). *H3*: We hypothesize that a factor mixture model in this sample will reduce the number of identifiable classes significantly, explaining them via a single underlying BPD severity dimension, but that some, if not all, of the three conceptually distinct classes posited in *H2* will be retained. We also hypothesize that strict measurement invariance will not be feasible in the FMM analysis (e.g., Conway et al., 2012) and that the underlying dimensional nature of BPD may vary by class (Clark et al., 2013). *H4*: Finally, comparing the latent factor, latent class, and factor mixture models will show the FMM to outperform both other models, given its ability to simultaneously model the continuous and discrete latent distributions underlying BPD.

We similarly make four hypotheses regarding the optimal models in the BPD-diagnosed sample. In line with the second study aim, we expect to see a translation of severe BPD classes from the nonclinical sample to the outpatient sample and a similar underlying BPD dimensional structure. *H5*: Similar to *H1*, we hypothesize that both one- and three-factor models will capture the data, but that the parsimony of a single dimension will be preferred. *H6*: We first expect to find a class characterized by endorsement of nearly all BPD symptoms, in line with the bulk of past subtyping research. Second, we hypothesize the presence of an identity disturbed/empty/internalizing class of individuals, but potentially no impulsive/angry/externalizing class, given that the former class has exhibited higher levels of severity in previous research than the latter (Fossati et al., 1999; Ramos et al., 2014; Thatcher et al., 2005). Finally, we tentatively hypothesize a class with high levels of paranoia/dissociation, self-injury, and fears of abandonment, which was noted by Slavin-Stewart (2015) as residing high on the severity spectrum. *H7*: Although no previous research directly informs this question, we hypothesize that a FMM model will retain the distinct classes listed in *H6* while adding a single underlying BPD dimension. *H8*: Finally, we hypothesize that model comparisons in the BPD sample will prefer the latent class model, given the restricted range in terms of severity but the heterogeneity in number of ways possible to receive a BPD diagnosis.

CHAPTER 2

Method

Study 1: Nonclinical Sample

Participants. The nonclinical sample included 20,010 undergraduate students from a large rural public mid-Atlantic university who participated in subject pool screening between 2006 and 2016. The sample was predominantly female (63.4%) and ranged in age from 15 to 55 (*M* = 18.76; *SD* = 1.69). Complete BPD symptom data were gathered on 19,833 participants, which constitutes the subset of participants used in the primary analyses below.

Procedure. Data were obtained from participants who completed self-report measures as part of an undergraduate psychology subject pool online screening process from the spring of 2006 to the spring of 2016. Participants received research credit as part of their coursework and no other compensation for completing the screening battery. Participants completed an adapted version of the McLean Screening Instrument for BPD (MSI-BPD; Zanarini et al., 2003), determining presence of self-reported BPD symptoms.

Measures. ***McLean Screening Instrument for BPD***. The version of the MSI-BPD used in the present study is a self-report questionnaire adapted by our laboratory from the original 10-item[1] clinician-rated MSI-BPD developed by Zanarini and colleagues (2003). The adapted measure consisted of 25 items scored on a 0-3 Likert scale anchored by 0 = "False, not at all true" and 3 = "Very true." Four of these items were used as validity items (e.g., "I have answered all of these questions honestly"); data from these items are not analyzed but are used to screen participants with response sets indicative of dishonest, thoughtless, or careless responding. The diagnostic items of the MSI-BPD were adapted from the DSM-5 diagnostic criteria for BPD; examples include "I have chronically felt empty" and "I have engaged in

[1]The stress-related paranoia/dissociation DSM criterion is split into two items on the original MSI-BPD.

impulsive excessive drinking." The adapted MSI-BPD does not yet have published psychometric properties.

In order to best reflect the nine DSM criteria, as well as to maintain consistency across some semesters in which various formats of the MSI were administered, MSI-BPD data in the present analyses were condensed to a binary scale. Responses of 0 or 1 were coded as "1" (or "False") and responses of 2 or 3 were coded as "2" (or "True"). Similar items derived from the same DSM BPD criterion (e.g., "I have often felt that I had no idea who I am" and "I have often felt that I have no identity") were then combined such that any response of 2 ("True") in any of the original variables generated a score of 2 in the combined variable; the result was nine items, coded 1 ("False") or 2 ("True"), each representing one of the nine DSM BPD criteria. We considered reducing the items in the adapted version of the MSI-BPD via factor analysis (i.e., allowing same-criterion items to load on BPD criterion factors and producing factor scores for each criterion for each individual). However, given the way the adapted form was constructed, we were concerned about the conservative nature of this preliminary analysis. For instance, the fear of abandonment criterion was split into 6 items in the adapted form. Theoretically, we would argue that significant fears of abandonment in even one of these domains would suggest the presence of this BPD symptom. Using a common factor approach to reduce these 6 items to an "averaged" score would reduce the severity of this BPD criterion in individuals who experience significant abandonment fears in a single domain compared to those who experience slight abandonment fears across multiple domains.

Data analytic plan. As highlighted in the literature review, there have been two general ways researchers have attempted to understand the display of BPD features. One may be described as "construct-centered" and the other as "person-centered." Construct-centered approaches, such as factor analysis, attempt to determine the number of latent components that comprise the theoretical construct of BPD. These techniques focus on BPD in isolation: When types of individuals play a role in such analyses, researchers are attempting to determine whether or not the BPD construct can be defined in the same way (and with the same components) across different (observed) groups of people (e.g., racial groups). Person-specific techniques, on the other hand, such as latent class analysis, address BPD heterogeneity by asking if individuals with the disorder tend to display it in different ways. For instance, one person may be considered to be “internalizing,” showing high levels of emptiness, and another “externalizing,” reporting high levels of impulsivity, even though both can be considered to have BPD according to their number of symptoms and level of functioning.

Construct-centered analyses. In order to determine the optimal dimensional structure of BPD in our sample, we first conducted exploratory factor analysis (EFA) on the MSI-BPD items. Due to the binary nature of the data and the potential for measurement error implicit in psychological measures, we utilized the tetrachoric correlation matrix as input matrix and weighted least squares with mean and variance adjustment (WLSMV) estimation. Using WLSMV estimation addresses some of the issues intrinsic to the principal axis factoring and principal components analysis utilized in previous studies (de Winter & Dodou, 2012). For comparison with past research, we report results using both oblique (Promax) and orthogonal (Varimax) rotation and note any discrepancies between the two. Given that previous research has identified solutions with 1, 2, 3, and 4 dimensions, we examined models with up to 5 factors to evaluate all possible models. As parallel analysis is not recommended with dichotomous indicators (Wirth & Edwards, 2007), a combination of scree plot examination, detection of eigenvalues ≥ 1.0, and substantive interpretation of factor loadings and correlations was used in order to identify the optimal number of factors to represent the data.

Given the large sample size, we aimed to increase model reliability by performing the above EFA on only half of the sample (randomly selected). We then confirmed the optimal factor structure using CFA in the second half of the sample and report the goodness-of-fit of this model. We evaluate the model fit using a combination of the chi-square statistic and three indices of practical fit: the Root Mean Squared Error of Approximation (RMSEA), the Comparative Fit Index (CFI), and the Tucker-Lewis Index (TLI). Indices of practical fit were compared against accepted fit thresholds (RMSEA < .05-.06; CFI > .95-.96; TLI > .95; (Bentler & Bonett, 1980; Browne & Cudeck, 1992; Graham & Connell, 2014; Hu & Bentler, 1999; West, Taylor, & Wu, 2012).

Finally, we reran the analysis using maximum likelihood estimation in order to produce the Bayesian Information Criterion (BIC) and adjusted BIC for comparison with the latent class and factor mixture models outlined below. Rather than using the frequentist approach of comparing models via likelihood ratio tests, we prefer information criteria, which estimate the divergence between a hypothesized model and the “true” distribution of the data and have been shown through simulation studies to provide better comparisons of latent variable models (Markon & Krueger, 2006). Furthermore, Monte Carlo simulation data from Nylund, Asparouhov, and Muthén (2007) suggest that the BIC and adjusted BIC may be best suited to selection of the true mixture model in large samples, rather than likelihood ratio statistics such as the Vuong-Lo-Mendell-Rubin and adjusted Lo-Mendell-Rubin likelihood ratio tests (LRT; Lo, Mendell, & Rubin, 2001), or the bootstrapped LRT (BLRT; McLachlan, 1987; Nylund et al., 2007). Also, we do not interpret the common Akaike Information Criterion (AIC) as models with increasing numbers of latent classes are incorrectly preferred by the AIC (Celeux & Soromenho, 1996; Lin & Dayton, 1997; Soromenho, 1994)

After selecting the most appropriate model to reflect the data, we tested for measurement invariance between genders as a supplementary analysis. Given differences in genders in the prevalence of BPD (American Psychiatric Association, 2013), internalizing and externalizing symptom clusters (Kramer, Krueger, & Hicks, 2008), and in subtypes of BPD (Bornovalova et al., 2010; Ramos et al., 2014), it is possible that the BPD factor structure (as assessed by the MSI-BPD) may differ by gender. In order to test this possibility, we first tested the previously confirmed model separately within each gender. We then tested two models in which 1) factor loadings were allowed to freely vary between genders, and 2) factor loadings were constrained to be equal between genders. A lack of change in model fit between models suggests we may assume similar BPD factor structures in men and women.

Person-centered analyses. After providing an updated factor structure to help clarify the mixed results produced by prior research, we also examined the latent class structure of the nonclinical sample. Latent class analysis (LCA), a form of finite mixture modeling designed for dichotomous indicators, is a person-centered approach based upon the assumption that a latent, or unobservable, construct comprised of several qualitatively different classes produces variation in measures of manifest, or directly observable, categorically measured variables called indicators. LCA provides researchers the ability to categorize individuals into these underlying classes based on variability in the individuals' responses to items measuring the indicators relevant to the construct of interest. LCA can be highly useful for identifying distinct subgroups of individuals that comprise a larger amorphous category.

Koehler and Larntz (1980; Koehler, 1986; Larntz, 1978) have shown that designs that have sample sizes smaller than five times the number of possible response patterns made available by a set of items (i.e., the number of cells included in an LCA contingency table) produce a biased estimate of the likelihood-ratio statistic used in LCA for hypothesis testing. Although comparing the fit of models of different classes is still possible (e.g., using information criteria such as the AIC and BIC), a reliable estimate of the accuracy of the selected class model is difficult in small samples (Collins & Lanza, 2013). Given the nine possible symptom criteria relevant for BPD, there are 512 different potential response patterns to a Yes/No response to each of these items, suggesting that an adequately sized study would require at least 2,560 participants to produce reliable statistical tests of latent class models. Besides ours, only one published study has employed LCA of BPD criteria with a sample of this size (Shevlin et al., 2007).

As in the FA, we first split the data in half and examined the latent class structure in this portion of the data and attempted to replicate the class structure in the second half of the data. We then report the latent class structure of the overall sample. We conducted models with 1,000 random starts to determine that maximum likelihood estimates are estimates of general, and not local, maxima for all identified models. We selected the optimal model by examining the adjusted BIC, which has been shown to outperform the BIC and other information criteria and likelihood ratio tests in LCA with large sample sizes (Nylund et al., 2007), as well as through substantive evaluation of the models.

Factor mixture models. Although the construct-centered and person-centered techniques address different questions regarding the makeup of BPD, there is clearly overlap in the two frameworks of analysis. If two subgroups of individuals exist in a dataset, for instance an internalizing and an externalizing group, then the correlation between internalizing and externalizing BPD criteria across the entire sample will be reduced by this between-group heterogeneity. In this way, the presence of BPD subtypes may reduce the strength of certain items' factor loadings on a general BPD factor and suggest multidimensional solutions may better characterize the data if latent classes are not taken into account. Likewise, two groups of individuals with different types of BPD may sometimes be better characterized by different factor structures among the BPD items, rather than a single undifferentiated factor structure that is the same for both groups. For instance, individuals characterized by an Identity Disturbed subtype of BPD may not differentiate among interpersonal and intrapersonal forms of dysregulation due to poor self-other boundaries, while classes with better identity functioning may generate two distinct inter and intrapersonal factors. These examples emphasize the importance of addressing the BPD item factor structure and identifying subtypes of BPD individuals in the same analysis.

Only recently have statistical techniques been used that marry construct- and person-centered methods for understanding BPD (Conway et al., 2012; Hallquist & Pilkonis, 2012). These studies have utilized factor mixture modeling (B. O. Muthén & Shedden, 1999) to simultaneously model latent factors and latent classes via the same indicators. FMM combines factor analysis with latent class analysis by allowing for an underlying latent categorical variable (i.e., on which latent classes are located) and any number of unique latent continuous variables (i.e., latent factors) within each latent class that is identified. In effect, both factor analysis and LCA are forms of FMM: factor analysis can be considered a version of FMM in which there are no latent classes (Hallquist & Wright, 2014), and LCA can be considered FMM in which there are no factors (or factors with zero variance; Lubke & Muthén, 2007). Because of its ability to simultaneously extract latent factors and classes, FMM also provides advantages over other limitations of factor analysis and LCA. For instance, FMM allows for indicators that are nonindependent (i.e., items are correlated even after controlling for class membership), which LCA cannot (Lubke & Muthén, 2005). This advantage is potentially necessary in understanding the intercorrelated items of BPD.

When fitting FMM models, various forms of parameterization must be taken into account. Clark (2010) describes five different forms of measurement invariance (MI) that should be tested in order to find the model that best fits the data at hand. FMM-1 (strict MI) allows for classes to differ only on factor means, constraining factor variances and covariances, item thresholds (i.e., the cutoff point on the latent factor at which the binary response shifts from 0 to 1), and factor loadings to be equal across classes. FMM-2 (strong MI) allows for factor means and variances/covariances to vary across classes, but still constrains item thresholds and factor loadings to equality. FMM-3 (weak MI) allows for item thresholds to be freely estimated, while constraining factor variances/covariances across classes and fixing factor means at zero. Similar to FMM-3, FMM-4 (weak MI) further allows the factor covariance matrix to differ by class. Finally, FMM-5 (weak MI) allows factor loadings, thresholds, and covariance matrix to differ by class, leaving only factor means fixed (at zero). FMM-1 (strict MI) and FMM-2 (strong MI) are conceptually ideal for cross-class comparisons in terms of the latent factor(s), as the general factor structure is defined identically between classes. However, these forms of MI often do not represent real data well due to their restrictiveness (Clark et al., 2013).

An alternative option, partial MI, is available, which strikes a balance between the weak MI of FMM-3 through 5 and the strong MI of FMM-2 (Clark, 2010; Clark et al., 2013). Partial MI consists of freeing certain item thresholds, but not others, allowing for partial identicalness in the factor structure across classes. To test for partial MI, a series of models are run in which all item thresholds are freed but one. For each run, difference tests between classes for the freed items are evaluated and items which accumulate many significant difference tests after all consecutive runs are allowed to vary in the final model (Clark, 2010; see Hallquist & Pilkonis, 2012, for an example). Models with at least partial MI are acceptable for cautious comparative interpretation (Byrne, Shavelson, & Muthén, 1989; Hallquist & Wright, 2014). Models with weak MI suggest that distinct subpopulations, each with their own factor structure, exist in the sample

In order to identify the best overall FMM model to conceptualize BPD in our sample, we follow the steps outlined by Clark and colleagues (2013; Clark, 2010). First, we decided the upper bounds in terms of latent factors and classes to be tested among the FMM models via the best fitting factor analytic and LCA models as described above. For instance, if a three-factor model and a three-class LCA model best fit the data, we will test FMM models up to three factors and three classes (i.e., a 1-factor, 1-class model; a 1-factor, 2-class model, and so on up to a 3-factor, 3-class model). More complex FMM models are considered unnecessary, as factor analyses and LCA models tend to identify too many—rather than too few—factors and classes compared to FMM models (Lubke & Neale, 2006). Second, we evaluated each model up until the end point determined by the best factor analysis and best LCA model. For each model, we evaluated the five forms of FMM parameterization described above, as well as partial MI as necessary. We then compared models using the BIC, which has been shown to outperform the sample size adjusted BIC and BLRT in FMM with large sample sizes (Henson, Reise, & Kim, 2007; Lubke & Neale, 2006; Nylund et al., 2007). The optimal FMM model, taking into account both fit criteria and interpretability, was then selected. It is possible that the added complexity of

FMM will not add enough useful information to be worthwhile over a more parsimonious latent trait or latent class model. Thus, finally, we compared the fit of the best factor analysis, LCA, and FMM models identified using the fit criteria identified above and select the optimal model for interpretation. All analyses described above were conducted in M*plus* version 7.4 (L. K. Muthén & Muthén, 2015).

Study 2: BPD Sample

Participants. Sixty-six participants comprised the BPD-diagnosed sample. Participants were 29.74 years of age on average (*SD* = 10.94), making them roughly a decade older than the nonclinical sample. The majority of participants were female (97%) and Caucasian (74.2%). Participants were diagnosed with a range of Axis I comorbidities (not included here) as well as Axis II comorbidities (**Table 3**). All participants were diagnosed with BPD.

Procedure. Participants were recruited through a community mental health center via brochures distributed by therapists conducting initial diagnostic intakes. During intake at the clinic, clients are assessed with the Anxiety Disorders Interview Schedule (Brown, Barlow, & DiNardo, 1994) to identify anxiety, mood, and other formerly Axis I disorders, and the International Personality Disorder Examination (IPDE; Loranger, Janca, & Sartorius, 1997) to determine the presence of personality disorders. Clients who were indicated to have significant features of BPD were then recruited into one of three studies. Clients who met criteria for a psychotic spectrum disorder, any developmental disorder (e.g., Autism spectrum disorder), or who were intellectually disabled were excluded, given the specific requirements of the procedures involved in the primary studies for which the participants were recruited. To confirm the presence of BPD, eligible participants were assessed with the IPDE by research staff specifically trained in the identification of personality disorders. Participant diagnoses were also confirmed (or modified) via expert consensus meetings in which the Longitudinal, Expert, All Data (LEAD) standard was employed (Spitzer, 1983), which has been shown to improve personality disorder diagnoses (Pilkonis, Heape, Ruddy, & Serrao, 1991). Reliably diagnosed participants completed a battery of questionnaires as part of the specific protocol of each study, including the adapted version of the MSI-BPD.

Measures. Participants in the BPD sample completed the MSI-BPD (see **Study 1** for description). Data was also collected in terms of participants' endorsement of personality disorder symptoms as assessed via the IPDE.

Data analytic plan. The analytic procedures described in **Study 1** were repeated in the BPD sample, with three alterations. 1) As part of the CFA, differences in the factor structure of the BPD symptoms were not tested between genders because the majority of participants in the BPD sample were female. 2) In selection of the optimal mixture models and when comparing across models, the corrected AIC is reported as a useful information criterion in small samples (Burnham & Anderson, 2002; Sugiura, 1978). We also prefer the BLRT over the BIC or adjusted BIC in selecting the appropriate number of latent classes, as the BLRT outperforms information criteria in small samples (Nylund et al., 2007). 3) IPDE variables (comorbid PD diagnosis, PD dimensional score) were utilized as validity measures to further identify associations with identified BPD dimensions and clinically relevant differences among latent classes.

CHAPTER 3

Results

Study 1: Nonclinical Sample

Interitem correlations among the MSI-BPD items are reported in **Table 4**. In general, items were correlated between .2 and .4, which is consistent with previous research (e.g., Becker et al., 2010; Hawkins et al., 2014; Johansen et al., 2004; Sanislow et al., 2000; Taylor & Reeves, 2007). Of note, emptiness and identity disturbance produced the highest correlation (r = .53), followed by anger and affective instability (r = .50). The smallest correlation was between suicidality/self-harm and relationship chaos (r = .15). All correlations were significant at p < .001. Women endorsed fear of abandonment, relationship chaos, impulsivity, suicidality/self-harm, affective instability, and paranoia/dissociation more often than men (**Table 5**). Although there were several significant relationships between time (i.e., semester of assessment) and BPD criterion endorsement (relationship chaos, identity disturbance, impulsivity, suicidality/self-harm, anger, and paranoia/dissociation), none of these correlations were greater than .10 in magnitude, suggesting the significance of the associations between these items and time may be driven by the large number of observations. Participant age was not associated with any BPD criterion except impulsivity (r = .05, p < .001).

Factor analysis. As outlined above, the sample was split in half at random and an EFA was performed on the first half of the sample (n = 9,925). The results of the EFA suggested that a single-factor solution best represented the data. This determination was made based on several considerations. 1) Only the first factor had an eigenvalue exceeding 1; 2) visual examination of the scree plot suggested leveling off in the eigenvalues beginning at factor 2 (**Figure 1**); 3) 60.61% of the variance was explained by the first factor; 4) Promax rotation suggested high interfactor correlations with multifactor solutions (roughly .70); 5) neither Varimax nor Promax solutions of more than one factor approximated simple structure (e.g., several items loaded between .3 and .6 on both factor of the 2-factor Promax rotated solution) or produced single-indicator factors (e.g., the 3-factor solution suggested only abandonment loaded highly on the third factor).

Subsequently, we evaluated the fit of the single-factor model in the second half of the data (n = 9,908). A CFA allowing all items to load on a single BPD dimension showed good fit to the data ($\chi^2(27) = 743.09$, $p < .001$; CFI = .98, TLI = .97, RMSEA = .05). Although the χ^2 test was significant, suggesting poor model fit, the significance of χ^2 tests (like other test statistics) is dependent on the number of observations (Graham & Connell, 2014); therefore, given our large sample, we elected to focus on indices of practical fit to assess the quality of the model. Given the fit of this model, we then estimated a single factor CFA model using the entire sample, which also showed good fit to the data ($\chi^2(27) = 1{,}653.10$, $p < .001$; CFI = .98, TLI = .97, RMSEA = 06). We confirmed via CFA of 2- and 3-factor models suggested from the EFA that model fit marginally improved (roughly .01-.02 points on practical fit indices) but high interfactor correlations (~.85) again argued for the preferability of the 1-factor model. Standardized factor loadings for the final model varied from .56 (relationship chaos) to .84 (emptiness), with all loadings being significant, suggesting the presence of a relatively cohesive BPD factor. Information criteria for the 1-, 2-, and 3-factor CFAs (produced via ML, rather than WLSMV, estimation) are presented in **Table 6**. The unitary factor structure was invariant by gender, such that constraining factor loadings to be equivalent for men and women reduced the fit of the model by a negligible amount ($RMSEA_\Delta = .004$, $CFI_\Delta = .001$, $TLI_\Delta = .004$).

Latent class analysis. We evaluated the fit of latent class models with 2-9 classes in the first half of the sample. Examination of the AIC, BIC, and several log-likelihood-based test statistics suggested that a 6-class model might best represent the data. We then attempted to confirm this latent class structure in the second subset of the data. However, a model with only 5 classes appeared to provide optimal fit in this case. We then conducted an LCA with the entire sample and detected 7 latent classes (**Table 6**). The 7-class model was able to detect two severe subtypes, one with less self-injury and interpersonal difficulties than the other, which were apparently combined in the 6-class model, and a moderate impulsive/angry class undetected in the 5-class model. Given that class solutions in LCA are highly affected by sample size (more so than FA), requiring large samples to resolve low-prevalence classes, it is likely that, despite our large sample, splitting the data in half (reducing the number of observations to around 9,500) did not allow for the identification of the two severe subtypes detected in the total sample. For this reason, we elected to interpret only the full sample results. Interestingly, given that our split datasets were still larger than any previous subtyping study (e.g., Shevlin et al., 2007), it is likely that prior LCAs have been unable to effectively detect low-prevalence, similar classes such as the two severe subtypes in our analyses. **Table 7** presents the prevalence of membership in each of the seven latent classes (Asymptomatic, Mild, Angry, Moderate Internalizing, Moderate Dysregulated, Severe With Interpersonal Functioning, and Severe Without Interpersonal Functioning) across the entire sample, as well as the probability that individuals in a given class will endorse a given BPD criterion item.

Factor mixture modeling. Given that FA suggested an optimal 1-factor solution and LCA suggested 7 classes best represented the data, we tested FMMs with a single factor and from 2 to 7 classes. In that our split-half comparisons of the LCA models suggested that the reduction in sample size disallowed the identification of reliable classes in the overall sample, all FMM analyses were conducted on the entire sample to avoid similar limitations. The BIC pointed to the 1-factor, 3-class model as the optimal representation of the data (**Table 6**). Specifically, the FMM-3 parameterization, in which item thresholds are freed across classes while factor variance and loadings are equal across classes, provided the best fit among the models. Given that the FMM-3 parameterization does not assume strong MI, we tested for the presence of partial MI in the item thresholds. Results suggested that item thresholds for all 9 MSI-BPD items varied significantly across classes, denying the feasibility of partial MI in this sample. Thus, the 1-factor, 3-class FMM-3 model was selected as the final FMM model.

Comparing models. Table 6 shows information criteria and relevant statistics for each of the optimal FA, LCA, and FMM models. Comparisons of these indices suggest that the 1-factor, 3-class FMM-3 model outperforms both the best CFA model (1 factor) and LCA model (7 classes). The BIC and BIC_{adj} of the FMM model was the lowest among all three.

Exploring the optimal model. Table 8 indicates the class prevalences and the marginal and conditional response probability for the BPD items across the three classes in the FMM-3 model. Given the patterns of item endorsement, the first class, including 70% of the sample, was labeled Asymptomatic due to the low probability of endorsing any BPD symptoms. The second class, comprising 19% of the sample, we labeled the Impulsive – Moderate Risk class, due to unique elevations in impulsivity and relationship conflict. The third class, 11% of the sample, endorsed high rates of identity disturbance and emptiness, which we labeled the Identity Disturbed – High Risk class. The Impulsive and Identity Disturbed classes were not differentiated in terms of the affective lability, anger, or suicidality/self-harm items. On average, the Identity Disturbed class had a higher chance of endorsing BPD symptoms, followed closely by the Impulsive class, with the Asymptomatic class scoring lowest, as expected (**Table 9**). **Table 10** shows the shifts in individuals' membership from the 7 classes in the 7-class LCA to the 3 classes in the 1-factor, 3-class FMM. In general, it appears that the Asymptomatic and Angry LCA classes were subsumed by the Asymptomatic FMM class, the Mild and Moderate Dysregulated LCA classes were subsumed by the Impulsive FMM class, and the Moderate Internalizing and the majority of the two Severe classes were subsumed by the Identity Disturbed FMM class, although the Severe With Interpersonal Functioning LCA class was more heterogeneously distributed across the FMM classes.

Table 8 also shows the shared factor loadings and class-specific item thresholds for the MSI-BPD items as they relate to the underlying FMM-3 factor. Anger, affective lability, and emptiness appeared to load highest (.82-.86), and relationship chaos only loaded moderately on the factor (.46), suggesting variance in this item was not well captured by the underlying factor. As expected, item thresholds were highest for the least severe Asymptomatic class (0.95-4.72), and were generally similar in the Identity Disturbed and Impulsive classes, except for a large discrepancy in the identity disturbance and emptiness items. It is worth noting that the FMM-3 parameterization, in which item thresholds are allowed to vary by class, suggests that the underlying factor is defined differently in each class and that comparisons between classes in terms of the latent factor (e.g., "BPD-ness") should be made with caution.

Study 2: **BPD Sample**

The MSI-BPD items were generally moderately intercorrelated, although the relationship chaos item was strikingly uncorrelated with any of the other MSI-BPD items (**Table 11**). Participant age was not associated with any BPD criterion.

Factor analysis. Due to the small number of BPD participants in this study, we were only able to test 1- and 2-factor EFA models (i.e., the 3-factor model did not converge). Both models appeared feasible as representations of the data. The first and second factor had eigenvalues greater than 1, although there was a considerable plateauing of the scree plot between these factors (**Figure 2**). Alone, the first factor explained 54% of the variance, while the second factor increased the variance explained to 68%. Promax rotation suggested a strong correlation between the two factors (.59) but generated two relatively distinct factors, the first characterized by fear of abandonment (.88), suicidality/self harm (.68), and emptiness (.79), and the second characterized by paranoia/dissociation (1.00), impulsivity (.78), identity disturbance (.70), and anger (.81). Therefore, we evaluated the fit of both models using CFA. For the two factor model, we required items with the higher loading on a given factor in the EFA to load only with that factor and we estimated the correlation between the two factors. Fear of abandonment, suicidality/self-harm, emptiness, and relationship chaos loaded on Factor 1, and paranoia/dissociation, impulsivity, identity disturbance, anger, and affective lability loaded on Factor 2.

The fit of the models is presented in **Table 12**. The 2-factor model slightly outperformed the 1-factor model, in terms of statistical fit (χ^2_{dif} (1): 4.02, $p < .045$), practical fit, and based on information criteria. However, in comparing the information criteria, the 2-factor model showed declines of only 1-5 points in comparison to the 1-factor model. Specifically, the AIC_c, which is more appropriate for small samples than the AIC, differed only by 1.92 between the models. AIC changes of this magnitude suggest near identicalness of the two models (Burnham & Anderson, 2002). This, in conjunction with the high factor correlation in the 2-factor CFA model (.79), which was higher than the majority of item loadings themselves, suggested that the more parsimonious 1-factor model was the optimal model to represent the data. The factor structure of this model is shown in **Table 13**.

Latent class analysis. We examined the fit of LCA models with 2-5 classes (**Table 12**). The 2-class model provided the optimal fit to the data, showing significant improvement over the 1- and 3-class models in terms of likelihood ratio statistics and outperforming all other models in terms of AIC_c and BIC. **Table 14** presents the prevalence of membership in the two latent classes and the probability that individuals in a given class will endorse a given BPD criterion item. According to the patterns of conditional item response probabilities, we labeled the classes Mild (30.3%) and Severe (69.7%) BPD.

Factor mixture modeling. Given that FA suggested an optimal 1-factor solution and LCA suggested a 2-class model, we tested an FMM model with 1 factor and 2 classes. Results showed the 1-factor, 2-class FMM-1 model best represented the data (**Table 12**), in which classes only varied in terms of their mean level on a factor that was identically defined across the classes. Given this parameterization, this model was statistically equivalent to the 2-class LCA, which produced Mild and Severe classes of individuals (see **Table 14**).

Comparing models. Table 12 shows information criteria and relevant statistics for each of the optimal FA, LCA, and FMM models. Comparisons of these indices suggest that the 1-factor model best captured the variance in the MSI-BPD items in this sample. This model generated the lowest AIC_c and BIC of all of the presented models.

Exploring the optimal model. Table 13 shows the factor loadings for the single-factor model. Interestingly, paranoia/dissociation loaded highest on the factor (.90), followed by anger (.85), and emptiness (.84). As in the nonclinical sample, relationship chaos loaded most weakly on the factor (.28). Probability of endorsement of each BPD criterion across the entire sample is also shown in **Table 13**.

Model validation. In separate models, we regressed the latent factor on the IPDE variables. Neither of the covariate analyses produced significant results, likely as the analyses were underpowered. Examination of the strength of the standardized regression coefficients suggested the BPD factor did not appear to be related to presence of a comorbid PD (β = .08), although there was a stronger relationship between the factor and the overall IPDE dimensional PD score (β = .22).

CHAPTER 4

Discussion

Our study provides an examination of the latent structure and typology of BPD with the largest nonclinical sample to date and the first diagnosed BPD sample using factor mixture modeling. Specifically, we examined for the variety of possible subtypes and dimensions of BPD in the nonclinical population (*Aim 1*) and evaluated which severe classes would also be represented among the BPD-diagnosed sample (*Aim 2*). In line with hypotheses *H3* and *H4*, results from the nonclinical sample suggested that three subgroups of individuals exist in terms of the types of BPD symptoms they endorse: an Asymptomatic group, an Impulsive – Moderate Risk group, endorsing impulsivity and relational conflict, and an Identity Disturbed – High Risk group, characterized by identity disturbance and emptiness. These groups tend to fall along a single dimension of BPD severity, although individuals in each group define BPD in slightly different ways. For instance, Asymptomatic individuals appear to require much higher BPD severity in order to endorse fears of abandonment in relation to other BPD symptoms compared to the other groups.

In contrast to *H8*, the BPD sample fell along a single severity dimension with no clearly identifiable subgroups of individuals. This BPD dimension appeared to potentially be related to PD dimensional scores, but not comorbid PD diagnosis. However, these relationships were not statistically significant likely due to the small size of the sample, so these associations may be unreliable.

Enhancing the Literature

These findings build on the foundation of the BPD dimensions and subtyping literature and help to resolve some of the discrepancies present in this body of research. They also build on and contextualize the factor mixture modeling results of Conway et al. (2012) and Hallquist and Pilkonis (2012). Conway and colleagues chose a single BPD dimension as best representing their data, arguing for the consideration of BPD as a continuous construct without qualitative differences between individuals in terms of their BPD presentation. However, Conway et al. only examined strict measurement invariance in their FMM analyses, allowing only factor means to vary across classes (FMM-1). Although a growing body of evidence argues for a dimensional consideration of personality disorders (see Levy & Johnson, 2016, for a review; Trull & Durrett, 2005; Widiger & Costa, 2012), factor mixture results from analyses of other psychiatric conditions (e.g., Clark, 2010) suggest it is reasonable to evaluate whether the definition of the BPD construct (i.e., its factor structure) might differ depending on an individual's symptom severity or presentation (i.e., latent class). Thus, our testing of various forms of measurement invariance in the FMM models seems merited and is an advance over the more restricted analytic plan of Conway and colleagues. In fact, neglecting to test for various forms of MI across latent classes may lead to erroneous assumptions about the pure dimensionality of psychiatric disorders. Indeed, our results suggest that, were only strict MI examined, a latent variable model would also have best represented BPD symptoms in our nonclinical sample; yet, it is more likely that a BPD dimension populated by three types of individuals (healthy, impulsive, and identity disturbed), each with slightly varying definitions of the BPD construct, better captures the BPD phenomenon in the nonclinical population. Our larger sample size also increases the likelihood that we have captured all meaningful classes of individuals in terms of BPD symptoms in the nonclinical population.

Hallquist & Pilkonis (2012) identified several clinically validated subtypes of high BPD-symptom individuals based on Kernberg's theory of BPD. Our findings further corroborate

Hallquist and Pilkonis's suggestion that the BPD "diagnostic criteria tell us how persons with BPD are similar but provide little information about how they may differ" (Hallquist & Pilkonis, 2012, p. 229). In that a single latent dimension of BPD adequately captured variation in these symptoms among our BPD-only sample, we concur that subtypes among BPD individuals may not be identifiable in terms of the DSM BPD criteria themselves. These findings add to a body of literature suggesting that individuals with BPD may be homogeneous in terms of diagnostic criteria, despite the DSM allowing for 256 ways in which to receive a diagnosis. As Hallquist and Pilkonis show, secondary clinical correlates (e.g., aggressiveness) may be more useful for identifying specific clinically relevant types of individuals with a BPD diagnosis.

Although the two symptomatic classes of individuals identified in the nonclinical sample generally do not meet criteria for BPD, individuals in these classes may be at increased risk for problems in functioning or psychological distress. Recent evidence, building on a body of previous work on the functioning impairment associated with "remitting" BPD (Gunderson et al., 2011), has suggested that even a single BPD criterion may increase ones risk for suicidality, hospitalizations, and problems with psychosocial functioning (Ellison et al., 2015; Zimmerman et al., 2012). Our findings suggest that even beyond single BPD items, specific *patterns* of BPD items may occur in individuals among "normal" samples, and future research will need to determine to what extent these patterns are associated with functioning interference or other problems.

Contextualizing Theory

As BPD severity increases, as in the BPD-diagnosed sample, heterogeneity decreases and we understandably see a drop-off of latent subtypes. Specifically, BPD-ness, as assessed via the self-report measure MSI-BPD, was distributed relatively homogeneously throughout the BPD sample along a single BPD severity dimension. This finding argues against the theorizing of writers like Oldham (2006) who suggest that individuals with BPD may be categorized into subtypes based on their principal presenting symptoms (e.g., Empty subtype). This finding also elucidates the points made by (Cooper et al., 2010) and others regarding the number of ways one may meet the DSM diagnostic threshold for BPD (i.e., 256): Although there may be many ways to be diagnosed with BPD, these ways do not appear to cluster into distinctive *types* of BPD. Rather, individuals with BPD may endorse different amounts of BPD severity in a relatively homogeneous way. Although the BPD sample in the present study was small (N = 66), such that true subtypes of individuals with BPD may have been overlooked, the two-class (Mild and Severe) LCA similarly suggests that even identifiable subtypes may be better understood along a severity dimension, rather than as qualitatively distinct subgroups.

Although we expected to find similar subtypes of BPD in the BPD-diagnosed sample as the severe subtypes extracted from the nonclinical sample (in this case, an Identity Disturbed subtype and potentially an Impulsive subtype), the individuals comprising the BPD sample actually resembled more the severe subtype(s) identified in the LCA but that were explained via an underlying BPD severity dimension in the FMM. It is possible that individuals with a BPD diagnosis do not represent a qualitatively distinct group of individuals in comparison with the nonclinical population but are simply those at the highest ends of the BPD severity distribution, in line with a body of research suggesting the utility of a dimensional conceptualization of personality pathology (Trull & Durrett, 2005; Widiger & Costa, 2012; see Johnson, Ashe, & Wilson, 2016, for an empirical example). However, clearly an entirely dimensional view of BPD does not fully explain the preference for a three-class FMM over a single-factor FA in the nonclinical sample. Given that the BPD-diagnosed sample reflected a combination of the

Impulsive and Identity Disturbed nonclinical subtypes (and that only mild and severe forms of BPD were identified in the less preferred two-class model) we tentatively suggest the possibility that impulsivity and identity disturbance may form distinct, but equifinal, developmental trajectories of BPD (Zanarini & Frankenburg, 1997). As our nonclinical sample was assessed during emerging adulthood, and the BPD cohort was roughly 10 years older, it may be that symptomatic BPD subtypes in the nonclinical sample reflect distinct pathways to BPD which eventually merge into a similar constellation of multiple elevated BPD features in treatment-seeking individuals.

It is also possible that these identified subthreshold subtypes point to distinct groups of individuals who will not go on to develop BPD. They may rather simply reflect types of individuals in the broader population characterized by externalizing (Impulsive) or internalizing (Identity Disturbed) problems, consistent with general theories of psychopathology (Caspi et al., 2014). In that BPD consists of a confluence of internalizing and externalizing features (Zanarini et al., 1998; 2004), it is reasonable to assume that individuals without BPD will be more likely to respond to one domain of symptoms (i.e., externalizing or internalizing) than the other. However, the more severe Identity Disturbed individuals also displayed moderate levels of externalizing features, suggesting that internalizing symptoms may not exist in isolation and that identity disturbance and emptiness may be especially characteristic of a subthreshold BPD phenomenology.

Determining which symptomatic young adults will experienced increased BPD symptomatology and which will not will be an important goal for future research (Bornovalova, Hicks, Iacono, & McGue, 2009). Our findings highlight the possibility that those who develop BPD may have either a distinct pattern of impulsive or of identity disturbance problems in young adulthood. Interestingly, as both Kernberg and Linehan take developmental approaches to their conceptualizations of BPD, describing the combination of genetic and environmental insults that confer early risk for the disorder, their divergent theories may prove even more perspicacious in terms of understanding pre-treatment BPD subtypes, rather than differences among a seemingly homogeneous clinical sample. Although the literature is sparse, several preventative treatment studies have begun to focus on presyndromal BPD, employing cognitive, behavioral, psychoanalytic, and systemic approaches (Chanen & McCutcheon, 2013). Adaptations of Kernberg's transference-focused psychotherapy (Clarkin, Yeomans, & Kernberg, 2005) and Linehan's dialectical behavior therapy (Linehan, 1993a) may likewise prove especially appropriate for preventative work, given the overlap between Identity Disturbed and Impulsive subtypes of subsyndromal BPD and these authors' theoretical frameworks.

Improving Assessment

The identification of an Impulsive subtype and a more severe Identity Disturbed subtype is strikingly similar to the categorizations subsumed under emotionally unstable personality disorder in the ICD-10 (World Health Organization, 1992). The ICD-10 outlines an "impulsive" type as presenting primarily with impulsivity and affective lability, and a "borderline" type as additionally displaying identity disturbance, emptiness, chaotic relationships, and suicidality/self-injury. Although several features of these types do not align entirely with the subtypes identified in our sample (e.g., the classes displayed similar levels of self-injurious behavior), our findings generally corroborate the typology outlined by the ICD. This suggests that the DSM BPD criteria may also be useful for identifying the two subtypes of emotionally unstable PD outlined in the ICD-10, which may aid comparisons between diagnostic systems.

Importantly, none of the optimal FA or FMM models in either sample consisted of more than one latent dimension of BPD. It is possible that the cohesion of the MSI-BPD items is driven in part by a goal of the 3rd and 4th editions of the DSM being to increase the internal consistency of psychiatric diagnostic criteria sets (Spitzer, Endicott, & Gibbon, 1979). Nevertheless, the DSM BPD criteria were also derived in part via expert consensus, clinical observation, and from a range of theoretical underpinnings (e.g., Gunderson & Singer, 1975). Thus, our findings, like many previously, mark the unidimensionality not only of a relatively internally consistent diagnostic system, but also of disparate theoreticians' views of the BPD construct. These results suggest that BPD may be best understood, at least as defined by the DSM criteria, as residing along a single dimension. Simultaneously, however, the definition of the BPD construct appeared to differ depending on the subtype of BPD being considered. The relative "difficulty" of endorsement of various items changed across classes, indicating that what it means to be borderline might depend on the symptom complex an individual displays.

Our study, like those of Conway et al. (2012) and Hallquist and Pilkonis (2012), emphasizes the importance of using factor mixture modeling in order to simultaneously understand the latent dimensions and subtypes of psychological disorders. For instance, we were able to identify seven distinct BPD symptom classes in the nonclinical sample, but these were reduced to only three after taking into account the latent BPD severity dimension. We argue that studies that only evaluate the dimensional structure of the BPD construct may miss important subpopulations in the data and research on latent classes may identify spurious classes that are better understood via differences in disorder severity. Factor mixture modeling may help to resolve the diagnostic heterogeneity of other personality disorders and psychiatric disorders (e.g., attention-deficit/hyperactivity disorder, Clark, 2010).

Informing Practice

Our study has several clinical implications. Counter to our goals of identifying unique subtypes of BPD-diagnosed individuals that might inform referrals of certain individuals to certain treatments, our results suggest that those who may respond to certain treatments and not others cannot be easily differentiated via patterns of features endemic to BPD itself, but rather by secondary clinical correlates (Hallquist & Pilkonis, 2012). This finding is important, as it suggests that the "heterogeneity" in BPD (i.e., individuals with BPD may only share one feature of the disorder) may not be true heterogeneity and that individuals with BPD may be more alike than different in terms of the types of BPD features they endorse. This finding reiterates the importance of BPD treatment studies to include a range of secondary clinical measures in order to find individual differences that might moderate treatment efficacy. Supplementary assessment packages beyond the common practice of evaluation of BPD symptoms themselves may eventually be designed to help identify which BPD patients may do best in which treatment.

Although subtypes were not identified in the BPD-diagnosed sample, clinically relevant and distinct subtypes did emerge in the nonclinical sample. This finding may call for an expansion of the diagnostic framework currently used for BPD in order to include these subthreshold subpopulations and proffer therapeutic resources to these individuals who may experience psychosocial challenges. The DSM-5 AMPD (American Psychiatric Association, 2013) may allow for the assessment and detection of such individuals, as it desegregates personality-related symptom severity from personality pathology type, which are combined in the DSM-IV via the requirement of 5 of 9 BPD-specific criteria for a diagnosis. The ICD will also consider subthreshold personality pathology to be clinically meaningful (Chanen &

McCutcheon, 2013; Levy & Johnson, 2016), marking a shift towards a broadly defined view of psychiatric problems.

Limitations and Future Directions

The implications of the present study are limited in several ways. First, although we examined the latent structure of BPD in the largest nonclinical sample to date, analyses of the BPD sample and correlates of BPD severity were likely underpowered due to the small sample size. Future research should examine subtypes of diagnosed BPD in a larger sample of individuals who meet diagnostic criteria for the disorder. However, the optimal LCA in this sample identified two classes differing in severity, not type, suggesting that larger samples may not easily identify distinct subtypes of diagnosed BPD. Second, the sample was predominantly female, suggesting that the factor structure and number of identified classes may be more representative of women than men. However, given that BPD is predominantly diagnosed in women compared to men (American Psychiatric Association, 2013), these findings may be representative of those generally diagnosed with BPD. Further, the factor structure, at least in the factor analytic model, did not differ by gender.

Third, the current study utilized a self-report measure of BPD symptoms, potentially limiting the generalizability of the findings. Although the BPD sample was diagnosed via a structured interview, future research should examine the combined latent factor and class composition of BPD in terms of criteria assessed via structured interview in both large nonclinical and clinical samples. Use of the MSI-BPD may also inflate estimates of BPD severity in our analyses. We recommend making interpretations of diagnostic criterion cutoffs at 6 or 7 items, rather than 5, when using the MSI-BPD (McLaughlin, Medved, Scala, & Levy, 2013; Zanarini et al., 2003). Fourth, the measure we utilized was an adapted version of the 10-

item MSI-BPD (Zanarini et al., 2003) without tested psychometric properties. Future research should retain the original 10-item scale or should confirm the optimal way to bin items in the adapted measure for maximal representation of DSM BPD criteria.

Fifth, BPD dimensions and subtypes of individuals must be validated with secondary functioning and symptom measures, in order to determine their clinical utility (e.g., Hallquist & Pilkonis, 2012). Although we examined the relations between general personality pathology and the BPD factor identified in the BPD sample, much more extensive validation of identified latent factors and classes in both clinical and nonclinical samples is needed. Finally, although data for the nonclinical sample were collected over several years, our analyses were cross-sectional in nature, significantly limiting any claims regarding the developmental progression of BPD types. Further research should examine the stability of the BPD construct and its subtypes over time. This research should also attempt to confirm or negate our suppositions that the nonclinical Impulsive and Identity Disturbed BPD subtypes may evidence equifinal developmental trajectories of later-diagnosable BPD.

Conclusions

We suggest that BPD is a unidimensional construct that may take on impulsive or identity disturbed types in the general population. Individuals who seek treatment and are diagnosed with BPD may derive from more distinct subtypes of the disorder, eventually displaying an increasing range of BPD symptoms. Future literature surrounding the use of the AMPD and the upcoming ICD-11 will be critical to determine whether or not these classification systems will be able to identify various putative BPD subsyndromal subtypes. Capturing the range of individuals with functional impairments associated with their BPD symptoms is an important step toward providing optimal clinical care and preventing development of pathological symptoms.

Furthermore, identifying different subthreshold subtypes of disorders such as BPD may have important clinical significance in terms of treatment referral for those in distress. Future research utilizing factor mixture modeling should explore and validate potential subtypes of BPD and their progression over time, in order to further delineate ideographic treatment targets and the temporal progression of the disabling condition of BPD.

APPENDIX A

FIGURES

Figure 1. *Scree Plot of Eigenvalues From Exploratory Factor Analysis – Nonclinical Sample (*N *= 19,833)*

Figure 2. *Scree Plot of Eigenvalues From Exploratory Factor Analysis – BPD Sample (*N *= 66)*

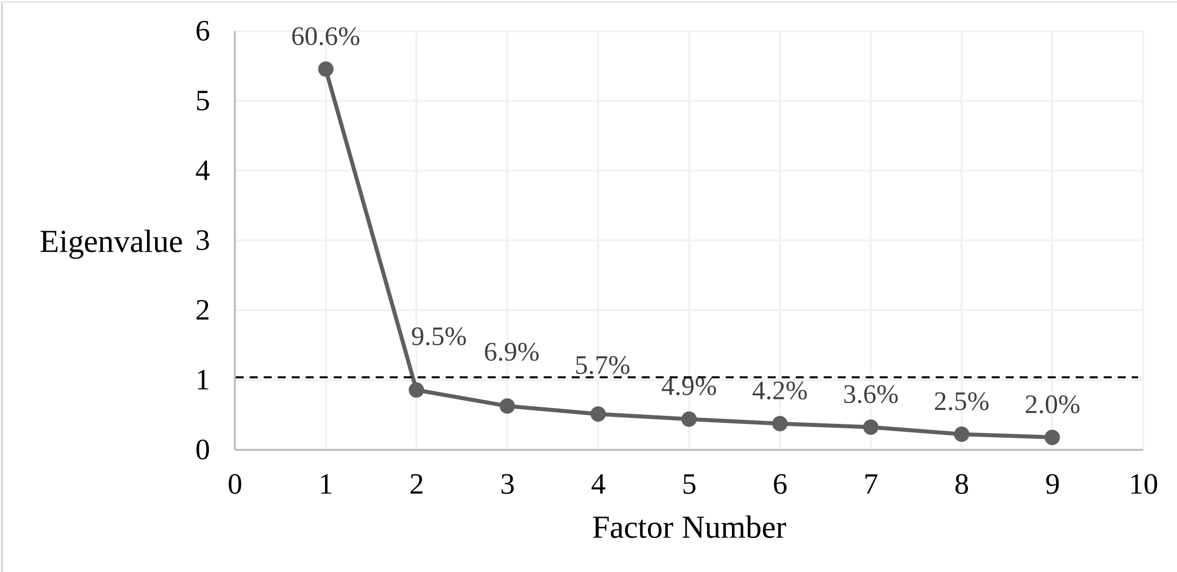

Figure 1. Scree plot of eigenvalues from exploratory factor analysis – nonclinical sample (N = 19,833). Values above the solid line reflect unique variance explained by each factor. The horizontal dashed line indicates a cutoff of eigenvalue = 1.

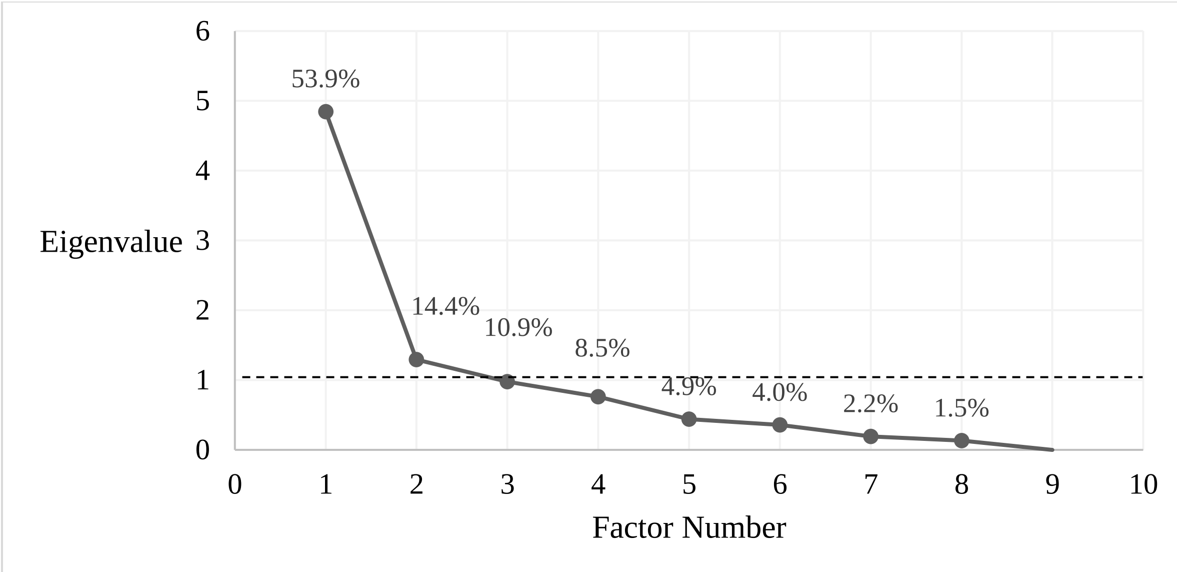

Figure 2. Scree plot of eigenvalues from exploratory factor analysis – BPD sample (N = 66). Values above the solid line reflect unique variance explained by each factor. The horizontal dashed line indicates a cutoff of eigenvalue = 1.

APPENDIX B

TABLES

Table 1. *BPD Dimension Studies: Samples, Analyses, and Results*

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Table 1

BPD Dimension Studies: Samples, Analyses, and Results

Year	Author(s)	*N*	% BPD	Sample	DSM Version	Measure	Statistical Technique	Rotation	# of Dimensions	Dimension Labels*	Variance Explained (%)
1989	Rosenberger & Miller	106	17.0	Undergraduates screened for personality pathology	DSM-III	SIDP & DIB	PCA	Varimax	2	1. Interpersonal Disturbance 2. Instability	55.5
1990	Hurt et al.	465	100.0	Outpatients and inpatients with BPD	DSM-III	Chart review & semi-structured interviews	Single-linkage clustering	N/A	3	1. Identity Disturbance 2. Affect 3. Impulse	N/A
1993	Clarkin et al.	75	100.0	Inpatients with BPD (women only)	DSM-III-R	SCID-II$_3$	PCA	Varimax	3	1. Disturbed Relatedness 2. Affect 3. Impulsivity	56.0
1997	Blais et al.	91	27.5	University-based outpatients	DSM-IV	Retrospective chart review	PCA	Varimax	3	1. Disturbed Relatedness 2. Affect/Cognitive Dysregulation 3. Behavioral Dysregulation	56.0
1999	Fossati et al.	564	17.7	Outpatients and inpatients	DSM-IV	SCID-II$_4$	Weighted-least-squares CFA	N/A	1	N/A	N/A
2000	Sanislow et al.	141	44.0	Inpatients	DSM-III-R	PDE + LEAD	PCA; EFA	Varimax	3	1. Disturbed Relatedness 2. Behavioral Dysregulation 3. Affect Dysregulation	57.2

2000	Whewell et al.	288	100.0	Outpatients with BPD	DSM-III-R	STCPD	PCA	Varimax	2	1. Behavioral Dysregulation 2. Affect Dysregulation	39.8
2002	Sanislow et al.	668	35.9	Outpatients and inpatients oversampled for personality disorders	DSM-IV	DIPD-IV	CFA	N/A	3	1. Disturbed Relatedness 2. Affect Dysregulation 3. Behavioral Dysregulation	N/A
2004	Johansen et al.	930	27.1	Patients in 18-week day treatment programs	DSM-IV	SCID-II_4 + LEAD and clinical observation	PCA; CFA	Varimax	PCA: 1; CFA: 1 & 3	1. Disturbed Relatedness 2. Behavioral Dysregulation 3. Affect Dysregulation	Unknown
2006	Becker et al.	123	52.8	Inpatient adolescents	DSM-III-R	PDE + LEAD	PCA	Varimax	4	1. Depressivity/Self-Negation 2. Affect Dysregulation 3. Disturbed Relatedness 4. Impulsivity	67.0
2006	Benazzi	209	Unknown	Outpatients with mood disorders	DSM-IV	SCID-II-PQ	PCA	Varimax	2	1. Affective Instability 2. Impulsivity	43.1
2007	Taylor & Reeves	82	8.5	Undergraduates screened for personality pathology	DSM-IV	SID-P IV & SCID-II_4	PCA	Promax	3	1. Disturbed Relatedness 2. Affect/Low Impulsivity 3. Paranoia/Low Anger	65.4
2009	Selby & Joiner	1140	Unknown	Community sample of young adults	DSM-IV	IPDE-SQ	PCA	Varimax, Oblimin	4	1. Cognitive Disturbance 2. Affective Dysregulation	~70.0

										3. Disturbed Relatedness 4. Behavioral Dysregulation	
2010	Becker et al.	130	30.0	Hispanic outpatients with alcohol and substance use disorders	DSM-IV	S-DIPD-IV + LEAD	EFA	Unknown	1	N/A	53.0
2010	Giesen-Bloo et al.	242	44.6	Mixed clinical (outpatient and inpatient, most with BPD) and nonclinical (community) sample	DSM-IV	BPDSI-IV	CFA	N/A	1	N/A	N/A
2011	Andion et al.	338	65.1	Outpatients referred for BPD treatment	DSM-IV	SCID-II$_4$ & DIB-R	CFA	N/A	3	1. Disturbed Relatedness 2. Affect Dysregulation 3. Behavioral Dysregulation	N/A
2012	Lewis et al.	95	100.0	Outpatients with BPD	DSM-IV	SCID-II$_4$	EFA	Oblimin	3	1. Affect Dysregulation 2. Mentalization Failure 3. Rejection Sensitivity	57.8
2014	Hawkins et al.	281	30.6	Outpatients screened for BPD symptoms and community members	DSM-IV	SIDP	EFA	Unknown	1	N/A	N/A

Note. BPD = borderline personality disorder; DSM = Diagnostic and Statistical Manual of Mental Disorders; SIDP = Structured Interview for the DSM-III Personality Disorders (Pfohl, Stangl, & Zimmerman, 1984); DIB = Diagnostic Interview for Borderlines (Gunderson, Kolb, & Austin, 1981); PCA = principal components analysis; EFA = exploratory factor analysis (with principal axis factoring); SCID-II_3 = Structured Clinical Interview for DSM-III-R Axis II Disorders (Williams et al., 1992); SCID-II_4 = Structured Clinical Interview for DSM-IV Axis II Disorders (First & Gibbon, 2004); CFA = confirmatory factor analysis; LEAD = Longitudinal, Expert, All Data (Spitzer, 1983); PDE = Personality Disorder Examination (Loranger, Susman, Oldham, & Russakoff, 1988); STCPD = Screening Test for Comorbid Personality Disorder (Dowson, 1992); DIPD-IV = Diagnostic Interview for DSM-IV Personality Disorders (Zanarini, Frankenburg, Sickel, & Yong, 1996); SCID-II-PQ = SCID-II_4 Personality Questionnaire (First, Gibbon, Spitzer, Williams, & Benjamin, 1997); IPDE-SQ = International Personality Disorder Examination—Screening Questionnaire (Loranger et al., 1994); S-DIPD-IV = Spanish-Language Version of the DIPD-IV (Grilo, Añez, & McGlashan, 2003); BPDSI-IV = BPD Severity Index-IV (Giesen-Bloo et al., 2010); DIB-R = Revised DIB (Zanarini, Gunderson, Frankenburg, & Chauncey, 1989).

*Factors are ordered in terms of most variance explained.

Table 2

BPD Subtype Studies: Samples, Analyses, and Results

Year	Author(s)	*N*	% BPD	Sample	DSM Version	Measure	Statistical Technique	# of Classes	Class Labels & Prevalence (%)
1968	Grinker et al.*	51	Unknown	Inpatients	N/A	Observer ratings	Cluster analysis	4	1. Psychotic Border (35.3) 2. Core Borderline (23.5) 3. Adaptive, Affectless, Defended (27.5) 4. Neurotic Border (13.7)
1999	Fossati et al.	564	17.7	Outpatients and inpatients	DSM-IV	SCID-II	LCA	3	1. Present (16.2) 2. Impulsive/Angry (27.8) 3. Absent (56.0)
2005	Thatcher et al.	167	Unknown	Adolescent mixed clinical sample (i.e., inpatient, outpatient, residential, & juvenile justice programs) with at least 1 BPD symptom	DSM-IV	SCID-II	LCA	3	1. Severe (9.0) 2. Moderate (41.3) 3. Impulsive/Angry (49.7)
2007	Shevlin et al.	8,580	0.19	British epidemiological sample	DSM-IV	SCID-II	LCA	4	1. High (4.6) 2. Moderate (9.5) 3. Low (19.2) 4. None (66.6)
2007	Clifton & Pilkonis	411	24.6	Mixed clinical (inpatient and outpatient) & nonclinical (university)	DSM-III-R	PDE or SIDP-R, + LEAD	LCA	2	1. High (41.6) 2. Low (58.4)
2008	Lenzenweger et al.*	90	100.0	Pre-treatment BPD-diagnosed individuals	N/A	IPDE & IPO: antisociality,	Finite mixture modeling	3	1. Antisocial/Aggressive (32.2) 2. Paranoid (27.8) 3. Low (40.0)

						paranoia, and aggression			
2010	Bornovalova et al.	382	19.1	Inpatient substance users	DSM-IV	SCID-II	LCA	4	1. High (7.7 2. Moderate (27.0) 3. Low Intermediate (25.3) 4. Baseline (40.0)
2014	Ramos et al.*	60	100.0	Adolescent outpatients with BPD	N/A	MACI personality scales	LCA	2	1. Externalizing (46.7) 2. Internalizing (53.3)
2015	Slavin-Stewart	75	18.7	Adolescent female outpatients	DSM-IV	BPQ	LCA	4	1. Severe (13.3) 2. Identity Disturbed/Empty (21.3) 3. Abandonment/Suicidality/Dissociation (16) 4. Low (49.3)

Note. BPD = borderline personality disorder; DSM = Diagnostic and Statistical Manual of Mental Disorders; SCID-II4 = Structured Clinical Interview for DSM-IV Axis II Disorders (First & Gibbon, 2004); LCA = latent class analysis; PDE = Personality Disorder Examination (Loranger et al., 1987); SIDP-R = Structured Interview for DSM-III-R Personality (Pfohl, Blum, Zimmerman, & Stangl, 1989); LEAD = Longitudinal, Expert, All Data (Spitzer, 1983); IPDE = International Personality Disorder Examination (Loranger, 1999); MACI = Millon Adolescent Clinical Inventory (Millon & Davis, 1993); BPQ = Borderline Personality Questionnaire (Poreh et al., 2006).

*Did not use DSM BPD criteria for subtyping analysis.

Table 3

*Comorbid Personality Disorder Diagnoses for the BPD Sample (*N *= 66)*

	n	%
Current Axis II Diagnoses		
Any PD	26	38.8
Cluster A	**3**	**4.5**
Paranoid	3	4.5
Schizoid	0	0.0
Schizotypal	0	0.0
Cluster B	**9**	**13.4**
Antisocial	3	4.5
Histrionic	5	7.5
Narcissistic	3	4.5
Cluster C	**11**	**16.4**
Avoidant	11	16.4
Dependent	0	0.0
Obsessive-Compulsive	1	1.5
PD NOS	11	16.4
	M	*SD*
# of Axis II diagnoses	0.40	0.75
# of IPDE Criteria Met	8	5.71
IPDE Dimensional Score	27.65	13.76

Note. Data derived from IPDE assessment. Results do not include IPDE data related to BPD (e.g., BPD diagnoses not included in Cluster B total. BPD = borderline personality disorder; IPDE=International Personality Disorder Examination.

Table 4

*Correlations Among the MSI-BPD Items – Nonclinical Sample (*N *= 19,829)*

	Fear of abandonment	Relationship chaos	Identity disturbance	Impulsivity	Suicidality/ self-harm	Affective instability	Emptiness	Anger
MSI-BPD								
Fear of abandonment								
Relationship chaos	.27							
Identity disturbance	.34	.17						
Impulsivity	.33	.23	.26					
Suicidality/self-harm	.28	.15	.29	.26				
Affective instability	.36	.26	.33	.42	.27			
Emptiness	.36	.18	.53	.26	.31	.36		
Anger	.31	.26	.30	.39	.25	.50	.31	
Paranoia/dissociation	.34	.25	.35	.34	.26	.38	.36	.42

Note. Correlations among MSI-BPD items are tetrachoric correlations. Number of observations vary by correlation, depending on available data; sample size reported is highest number of valid observations for a bivariate correlation. All correlations significant at $p < .001$. MSI-BPD = McLean Screening Instrument for Borderline Personality Disorder.

Table 5

*Probability of MSI-BPD Item Endorsement by Gender – Nonclinical Sample (*N*=19,868)*

MSI-BPD Item	Percent item endorsement			
	Men *n* = 7,181 (36.1%)	Women *n* = 12,687 (63.9%)	*Z*	*p*
Fear of abandonment	12.6	17.8	9.64	<.001
Relationship chaos	12.3	14.1	3.60	<.001
Identity disturbance	11.7	12.2	0.90	.37
Impulsivity	29.5	31.0	2.21	.03
Suicidality/self-harm	5.7	8.0	6.09	<.001
Affective instability	13.8	23.4	16.18	<.001
Emptiness	10.0	10.8	1.60	.11
Anger	22.6	22.6	0.13	.90
Paranoia/dissociation	23.9	26.8	4.42	<.001
Mean	1.41	1.65		

Note. Mann-Whitney *U* test used to compare probability of item endorsement between genders. *t*-tests conducted after correction for unequal variances between genders. MSI-BPD = McLean Screening Instrument for Borderline Personality Disorder.

Table 6

Factor Analytic, Latent Class, and Factor Mixture Model Results – Nonclinical Sample

*(*N*=19,833)*

Model	Log-Likelihood	Parameters	BIC	BIC_{adj}
Factor analysis				
One-factor	**-65,292**	**18**	**130,763**	**130,706**
Two-factor	-64,976	19	130,140	130,080
Three-factor	-64,904	21	130,015	129,948
Latent class analysis				
One class	-79,499	9	159,088	159,059
Two classes	-66,361	19	132,910	132,850
Three classes	-65,293	29	130,873	130,781
Four classes	-64,844	39	130,074	129,950
Five classes	-64,713	49	129,911	129,755
Six classes	-64,639	59	129,861	129,674
Seven classes	**-64,597**	**69**	**129,877**	**129,658**
Eight classes	-64,570	79	129,921	129,670
Nine classes	-64,545	89	129,971	129,688
Factor mixture analysis				
One-factor, two-class				
FMM-1	-66,361	19	132,910	132,850
FMM-2	-65,255	21	130,718	130,651
FMM-3	-64,728	28	129,732	129,643
FMM-4	-64,711	29	129,776	129,617
FMM-5	-64,704	37	129,773	129,656
One-factor, three-class				
FMM-1	-65,319	21	130,845	130,788
FMM-2	-65,253	24	130,744	130,668

FMM-3	**-64,629**	**38**	**129,633**	**129,512**
FMM-4	-64,624	40	129,643	129,516
FMM-5	-64,592	56	129,739	129,561
One-factor, four-class				
FMM-1	-65,259	23	130,747	130,673
FMM-2†	-65,144	27	130,556	130,470
FMM-3	-64,589	48	129,654	129,501
FMM-4	-64,581	51	129,667	129,505
FMM-5†	-64,540	75	129,822	129,584
One-factor, five-class				
FMM-1	-65,252	25	130,752	130,673
FMM-2†	-65,011	30	130,319	130,223
FMM-3	-64,554	58	129,683	129,499
FMM-4†	-64,548	62	129,709	129,512
FMM-5†	-64,528	94	129,986	129,687
One-factor, six-class				
FMM-1	-65,252	27	130,771	130,686
FMM-2	-65,169	33	130,664	130,559
FMM-3	-64,528	68	129,729	129,512
FMM-4†	-64,524	73	129,770	129,538
FMM-5†	-64,454	113	130,026	129,667
One-factor, seven-class				
FMM-1	-65,252	29	130,791	130,699
FMM-2†	-65,127	36	130,610	130,496
FMM-3†	*Model estimation did not terminate normally*			
FMM-4†	*Model estimation did not terminate normally*			
FMM-5	-64,477	132	130,261	129,841

Note. Factor analysis model derived via maximum likelihood estimation. Latent class and factor mixture models run with 600 random starts and 120 final stage iterations to ensure identification of global, not local, maxima in the likelihood function. Optimal factor analytic, latent class, and factor mixture model presented in **bold** font. Although 2- and 3-factor factor analytic models revealed meaningfully lower information criteria than the 1-factor model, factors among these models were highly correlated (~.85), suggesting the preferability of the 1-factor model. Optimal latent class model selected based on lowest BIC_{adj} (Nylund et al., 2007). Optimal factor mixture model selected based on lowest BIC (Nylund et al., 2007). BIC = Bayesian Information Criterion; BIC_{adj} = sample-size adjusted BIC (n* = (n +2) / 24); FMM = factor mixture model. †Lowest log-likelihood not replicated, suggesting identification of local, rather than global, maximum.

Table 7

*Probability of Class Membership and Indicator Responses in a Seven-Latent-Class Model of MSI-BPD Items – Nonclinical Sample (*N *= 19,833)*

		Latent Class						
		1	2	3	4	5	6	7
Assigned Class Label	Marginal Probabilities	Asymptomatic	Mild	Angry	Moderate Internalizing	Moderate Dysregulated	Severe w/ Interpersonal Functioning	Severe w/o Interpersonal Functioning
Class Prevalence	--	64% (12,787)	10% (1,939)	9% (1,719)	5% (952)	5% (967)	3% (680)	4% (789)
Conditional probability of a "True" response								
Fear of abandonment	.16	*.02*	.24	.10	**.39**	**.55**	**.46**	**.87**
Relationship chaos	.13	*.04*	.20	.18	.17	**.47**	.21	**.58**
Identity disturbance	.12	*.01*	.06	.07	**.65**	.13	**.66**	**.82**
Impulsivity	.31	*.09*	.53	.50	.38	**.86**	**.72**	**.94**
Suicidality/self-harm	.07	*.005*	.08	.05	**.16**	**.20**	**.24**	**.57**
Affective instability	.20	*.02*	.24	.36	.15	**.79**	**.94**	**.86**
Paranoia/dissociation	.26	*.06*	.32	.43	**.61**	**.69**	**.75**	**.93**
Anger	.23	*.03*	*.00*	**1.00**	.24	**.82**	**.78**	**.88**
Emptiness	.11	*.005*	*.03*	*.03*	**.58**	.07	**.77**	**.82**

Note. Probabilities of class membership represent the proportion of the overall sample with most likely class membership in each mutually exclusive latent class. Marginal probabilities represent the overall item endorsement across the classes. Conditional item response probabilities suggest that likelihood that individuals in a given class (as indicated by the column label) will endorse a given item (as indicated by the row label). Item response probabilities at least twice the marginal probability are indicated in **bold, red** font and half the marginal probability in *italic, green* font for interpretability. MSI-BPD = McLean Screening Instrument for Borderline Personality Disorder.

Table 8

*Probability of Class Membership, Indicator Responses, and Factor Structure of a One-Factor, Three-Class Factor Mixture Model of BPD Criteria – Nonclinical Sample (*N *= 19,833)*

		Latent Class						
		1	2	3				
Assigned Class Label	Marginal Probabilities	Asymptomatic	Impulsive	Identity Disturbed		Asymptomatic	Impulsive	Identity Disturbed
Class Prevalence	--	70% (13,881)	19% (3,720)	11% (2,232)	Standardized Factor Loadings	Unstandardized Item Thresholds		
Conditional probability of a "True" response								
Fear of abandonment	.16	*.00*	**.56**	**.48**	.59	11.08	0.88	.58
Relationship chaos	.13	*.04*	**.39**	.25	.46	3.21	1.27	1.72
Identity disturbance	.12	*.01*	.09	**.83**	.73	5.14	3.38	-0.21
Impulsivity	.30	*.15*	**.72**	.56	.65	2.26	-0.04	0.47
Suicidality/self-harm	.07	*.00*	**.22**	**.26**	.59	5.15	2.56	1.81
Affective instability	.19	*.08*	**.47**	**.46**	.82	4.13	1.36	1.46
Paranoia/dissociation	.26	*.12*	**.53**	**.64**	.67	2.67	0.83	-0.10
Anger	.23	.15	.40	.40	.86	3.60	1.61	1.90
Emptiness	.10	*.01*	.07	**.75**	.82	6.59	4.37	0.05

Note. Probabilities of class membership represent the proportion of the overall sample with most likely class membership in each mutually exclusive latent class. Marginal probabilities represent the overall item endorsement across the classes. Conditional item response probabilities suggest that likelihood that individuals in a given class (as indicated by the column label) will endorse a given item (as indicated by the row label). Item response probabilities twice the marginal probability are indicated in **bold, red** font and half the marginal probability in *italic, green* font for interpretability. BPD = borderline personality disorder.

Table 9

*Severity of Three FMM-Derived Latent Classes in Terms of MSI-BPD Item Endorsement – Nonclinical Sample (*N *= 19,833)*

Factor Mixture Model Class	Class Size (% of sample)	Average # MSI-BPD Items Endorsed (SD)	Average Probability of Item Endorsement	*n* With MSI-BPD Items > 6 (% class/% sample)	*n* With MSI-BPD Items > 7 (% class/% sample)
Asymptomatic	13,881 (70.0%)	0.58 (1.00)	.06	0 (0.0%/0.0%)	0 (0.0%/0.0%)
Impulsive	3,720 (18.8%)	3.46 (1.77)	.38	600 (16.0%/3.0%)	222 (5.97%/1.1%)
Identity Disturbed	2,232 (11.3%)	4.64 (2.37)	.51	850 (38.2%/4.3%)	597 (26.8%/3.0%)

Note. Class size represents the proportion of the overall sample with most likely class membership in each mutually exclusive latent class. Average probability of item endorsement is the average across conditional probabilities of a “True” response to all 9 MSI-BPD items. All classes differ significantly ($p < .001$) in terms of average number of MSI-BPD items endorsed. MSI-BPD cutoffs balance sensitivity and specificity in terms of predicting actual BPD diagnosis; derived from McLaughlin et al. (2013) (>6) and Zanarini et al. (2003) (>7). FMM = factor mixture modeling; MSI-BPD = McLean Screening Instrument for Borderline Personality Disorder.

Table 10

*Class Membership Shift From LCA Classes to FMM Classes – Nonclinical Sample (*N *= 19,833)*

		Factor Mixture Model Classes		
Latent Class Analysis Classes	Number in Original LCA Class	Asymptomatic (*n* = 13,881)	Impulsive (*n* = 3,720)	Identity Disturbed (*n* = 2,232)
Asymptomatic	12,787	12,203 (95.4%)	366 (2.9%)	218 (1.7%)
Mild	1,939	57 (2.9%)	1,712 (88.3%)	170 (8.8%)
Angry	1,719	1,460 (84.9%)	259 (15.1%)	0 (0%)
Moderate Internalizing	952	34 (3.6%)	36 (3.8%)	882 (92.7%)
Moderate Dysregulated	967	1 (0.1%)	966 (99.9%)	0 (0%)
Severe w/ Interpersonal Functioning	680	127 (18.7%)	157 (23.1%)	396 (58.2%)
Severe w/o Interpersonal Functioning	789	0 (0%)	227 (28.8%)	562 (71.2%)

Note. Numbers sum to 100% of the total prevalence of each latent class by row. LCA = latent class analysis; FMM = factor mixture modeling.

Table 11

*Correlations Among the MSI-BPD Items – BPD Sample (*N *= 66)*

	Fear of abandonment	Relationship chaos	Identity disturbance	Impulsivity	Suicidality/ self-harm	Affective instability	Emptiness	Anger
MSI-BPD								
Fear of abandonment								
Relationship chaos	.29*							
Identity disturbance	.14	.17						
Impulsivity	.17	.08	.39**					
Suicidality/self-harm	.36**	.07	.30*	.08				
Affective instability	.33**	.10	.18	.31*	.31*			
Emptiness	.42***	.14	.38**	.40**	.42***	.44***		
Anger	.39**	.08	.32**	.37**	.30*	.39**	.43***	
Paranoia/dissociation	.23	.06	.41***	.51***	.14	.45***	.43***	.59***

Note. Correlations among MSI-BPD items are tetrachoric correlations. Number of observations vary by correlation, depending on available data; sample size reported is highest number of valid observations for a bivariate correlation. MSI-BPD = McLean Screening Instrument for Borderline Personality Disorder.

* $p < .05$, ** $p < .01$, *** $p < .001$.

Table 12

*Factor Analytic, Latent Class, and Factor Mixture Model Results – BPD Sample (*N *= 66)*

Model	Log-Likelihood	Parameters	AIC	AIC_c	BIC	BIC_{adj}	VLMR LRT ($2LL_{diff}$)	*p*	LMR $LRT_{Adj.}$	*p*	BLRT *p*
Factor analysis											
One-factor	**-310.69**	**18**	**657.37**	**671.92**	**696.79**	**640.12**	--	--	--	--	--
Two-factor	-307.74	19	653.48	670.00	695.08	635.27	--	--	--	--	--
Latent class analysis											
One class	-364.49	9	746.97	750.19	766.68	738.35	--	--	--	--	--
Two classes	**-312.12**	**19**	**662.23**	**678.75**	**703.84**	**644.02**	**104.74**	**<.001**	**102.30**	**<.001**	**<.001**
Three classes	-300.84	29	659.68	708.01	723.18	631.88	22.55	.09	22.03	.09	.09
Four classes	-290.37	39	658.74	778.74	744.14	621.36	20.94	.02	20.45	.02	.25
Five classes	-283.92	49	665.84	972.09	773.13	618.87	12.90	.41	12.60	.42	1.00
Factor mixture analysis											
One-factor, two-class											
FMM-1	**-312.12**	**19**	**662.23**	**678.75**	**703.84**	**644.02**	**--**	**--**	**--**	**--**	**--**
FMM-2	-310.06	21	662.12	683.12	708.10	641.99	1.25	.74	1.12	.75	1.00
FMM-3	-301.27	28	658.53	702.42	719.84	631.69	18.84	.45	16.40	.45	.67
FMM-4	-300.51	29	659.02	707.35	722.52	631.22	20.36	.35	19.92	.36	.60
FMM-5	-293.05	37	660.09	760.52	741.11	624.63	35.28	.04	34.85	.04	<.001

Note. Factor analysis model derived via maximum likelihood estimation. Latent class and factor mixture models run with 600 random starts and 120 final stage iterations to ensure identification of global, not local, maxima in the likelihood function. Optimal factor analytic, latent class, and factor mixture model presented in **bold** font. Although the 2-factor factor analytic model revealed lower information criteria than the 1-factor model, differences in these indices of less than 10 suggest relatively equivalent fit between models, suggesting the preferability of the more parsimonious (i.e., fewer estimated parameters) model (Burnham & Anderson, 2002). Optimal latent class model selected based on first nonsignificant BLRT statistic (LRT show the difference between a model with *k* classes and a model with *k* – 1 classes; Nylund et al., 2007). Optimal factor mixture model selected based on lowest BIC (Nylund et al., 2007). Optimal factor mixture model selected based on significant BLRT and lowest AIC_c and BIC (Nylund et al., 2007). AIC = Akaike Information Criterion; AIC_c = corrected Akaike Information Criterion ($AIC_c = AIC + [(2 * k) * (k + 1) / (N – k – 1)]$; BIC = Bayesian Information Criterion; BIC_{adj} = sample-size adjusted BIC (n* = (n +2) / 24); VLMR LRT = Vuong-Lo-Mendell-Rubin likelihood ratio test; $2LL_{diff}$ = 2 times the log likelihood difference; LMR LRT_{adj} = Lo-Mendell-Rubin adjusted likelihood ratio test; BLRT = bootstrapped likelihood ratio test; FMM = factor mixture model.

†Lowest log-likelihood not replicated, suggesting identification of local, rather than global, maximum.

Table 13

*One-Factor CFA Factor Loadings and Item Thresholds and Observed Item Response Probabilities – BPD Sample (*N *= 66)*

	Standardized Factor Loadings	*p*	Unstandardized Item Thresholds	*p*	Observed Item Response Probabilities
MSI-BPD Item					
Fear of abandonment	.58	<.001	-0.92	.01	.67
Relationship chaos	.26	.10	-0.66	.02	.65
Identity disturbance	.63	<.001	-0.07	.85	.51
Impulsivity	.70	<.001	-1.61	.002	.74
Suicidality/self-harm	.49	.001	-0.76	.02	.65
Affective instability	.71	<.001	-1.41	.004	.71
Emptiness	.80	<.001	-1.11	.04	.64
Anger	.84	<.001	-2.16	.007	.74
Paranoia/dissociation	.87	<.001	-2.79	.014	.77

Note. Item response probabilities reflect overall proportion of participants endorsing each item.

MSI-BPD = McLean Screening Instrument for Borderline Personality Disorder.

Table 14

*Probability of Class Membership and Indicator Responses in a Two-Latent-Class Model of MSI-BPD Items – BPD Sample (*N *= 66)*

		Latent Class	
		1	2
Assigned Class Label	Marginal Probabilities	Mild BPD	Severe BPD
Class Prevalence	--	30% (20)	70% (46)
Conditional probability of a "True" response			
Fear of abandonment	.67	.36	.80
Relationship chaos	.65	.54	.70
Identity disturbance	.51	.12	.68
Impulsivity	.74	.40	.89
Suicidality/self-harm	.65	.37	.78
Affective instability	.71	.37	.86
Emptiness	.64	.17	.85
Anger	.74	.25	.96
Paranoia/dissociation	.77	.31	.98

Note. Probabilities of class membership represent the proportion of the overall sample with most likely class membership in each mutually exclusive latent class. Marginal probabilities represent the overall item endorsement across the classes. Conditional item response probabilities suggest that likelihood that individuals in a given class (as indicated by the column label) will endorse a given item (as indicated by the row label). MSI-BPD = McLean Screening Instrument for Borderline Personality Disorder.

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