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USING DYNAMIC FACTOR ANALYSIS TO MODEL INTRAINDIVIDUAL VARIATION IN BORDERLINE PERSONALITY DISORDER SYMPTOMS

A Dissertation in
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by

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ABSTRACT

Borderline personality disorder (BPD) is a highly prevalent, debilitating, and costly form of mental illness that involves instability in self-concept, emotions, and behavior, including chronic suicidality and self-injury. The essential psychological dynamics underlying the disorder are poorly understood. In particular, the role of identity disturbance in the disorder is largely unexplained, although several prominent theories have been advanced. Psychodynamic theories posit that identity disturbance underlies emotional and behavioral dysregulation, whereas biosocial theory suggests that identity disturbance is the result and largely not the cause of these other symptoms. Research to date has been largely cross-sectional and based on retrospective report, making it difficult to untangle the temporal dynamics of BPD symptoms. In addition, new research based on ecological momentary assessment (EMA), which could potentially shed light on this question, has focused on groupwise hypotheses and analyzed interindividual data. This approach does not account for potential heterogeneity in these processes, whereas person-specific methods based on intraindividual variation can account for this heterogeneity. The current study uses dynamic factor analysis, a person-specific modeling approach, to investigate the longitudinal covariation of anger, impulsivity, and identity disturbance. 11 psychiatric outpatients who were diagnosed either with BPD (n = 4) or with a mood or anxiety disorder, but not BPD (n = 7) completed a 21-day EMA protocol by rating these symptoms six times per day at quasi-random times at roughly 2-hour intervals. Cubic spline interpolation was used to produce time series with equal spacing between measurements, and models were created to describe the relationship between these symptoms, both in synchronous ratings and at successive time points. Models were created using examination of modification indices from a baseline autoregressive model, and multiple fit indices were used to determine good fit. Results revealed
extensive variability between individuals in the dynamics of anger, impulsivity, and identity disturbance, although a simple autoregressive model fit data well for six participants. The results support neither psychodynamic nor behavioral theories of BPD symptom dynamics but imply that each may account for symptom variation in different individuals with the disorder. Results also show that a person-specific approach to modeling EMA data is feasible and may support the development of theories of psychological processes in BPD. This class of methods may also be useful for the study of psychotherapy process and outcome and may aid in treatment planning, outcome monitoring, and diagnostic assessment in clinical settings.
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Chapter 1

Introduction

Borderline Personality Disorder

Borderline personality disorder (BPD) is a costly, debilitating, and common psychiatric disorder. Studies estimate its prevalence at about 3% of the general population (Coid, Yang, Tyrer, Roberts, & Ullrich, 2006; Lenzenweger, Lane, Loranger, & Kessler, 2007; Samuels et al., 2002; Torgersen, Kringlen, & Cramer, 2001; Trull, Jahng, Tomko, Wood, & Sher, 2010). Individuals with BPD are also highly prevalent in clinical practice, making up about 10-20% of psychiatric outpatients (Korzekwa, Dell, Links, Thabane, & Webb, 2008; Zimmerman, Chelminski, & Young, 2008; Zimmerman, Rothschild, & Chelminski, 2005) and 15-40% of inpatients (Grilo et al., 1998; Widiger & Frances, 1989; Zimmerman, Chelminski, & Young, 2008). In general, those with BPD consume a large amount of costly mental health services in comparison with individuals with other disorders (Ansell, Sanislow, McGlashan, & Grilo, 2007; Bender et al., 2001; Hörz, Zanarini, Frankenburg, Reich, & Fitzmaurice, 2010; Sansone, Zanarini, & Gaither, 2003; Zanarini, Frankenburg, Khera, & Bleichmar, 2001; Zanarini, Frankenburg, Hennen, & Silk, 2004). A high proportion of individuals with BPD commit repeated self-injurious acts (Clarkin, Widiger, Frances, Hurt, & Gilmore, 1983; Gunderson et al., 2011), and up to 10% eventually commit suicide (Stone, 1993). BPD is frequently comorbid with other mental disorders (Nurnberg et al., 1991; Skodol et al., 2002; Zanarini et al., 1998, 2004), and the presence of BPD negatively affects outcome in the treatment of depression (Levenson, Wallace, Fournier, Rucci, & Frank, 2012; Shea, Widiger, & Klein, 1992), anxiety disorders (Chambless et al., 1992; Cloitre & Koenen, 2001; Feeny, Zoellner, & Foa, 2002; Mennin & Heimberg, 2000), and eating disorders (Cooper, Coker, & Fleming, 1996). Recent
developments in the treatment of BPD itself have given clinicians empirically-supported psychotherapeutic options to use with this demanding population (Bateman & Fonagy, 2008, 2009; Blum et al., 2008; Clarkin, Levy, Lenzenweger, & Kernberg, 2007; Giesen-Bloo et al., 2006; Gregory et al., 2008; Linehan et al., 2006; McMain et al., 2009; McMain, Guimond, Streiner, Cardish, & Links, 2012). Nevertheless, treatment remains a significant challenge, and only about 50% of individuals respond to any given psychotherapy (Levy, 2008). Given these facts, it is evident that BPD is a serious public health concern and that understanding this severe form of psychopathology is important.

Current conceptualizations of BPD suggest a multifaceted disorder involving emotion dysregulation, impulsive and self-harming behaviors, and instability in relationships and self-concept. The description of BPD in the American Psychiatric Association’s Diagnostic and Statistical Manual of Mental Disorders (DSM; American Psychiatric Association, 1994, 2013) is the most influential description of the disorder. It specifies 9 symptoms of BPD: behavioral efforts to ward off abandonment by others; intense and unstable relationships; unstable self-image or sense of self; impulsivity, such as reckless driving, substance abuse, impulsive spending or sex, and binge eating; recurrent suicidal behavior or gestures, or self-mutilating behavior without suicidal intent; affective instability or excessive mood reactivity; chronic feelings of emptiness; inappropriate, intense anger; and transient, stress-related paranoia or dissociation. Five or more of these symptoms, or criteria, are required to be present in order make a diagnosis of BPD. In addition, the symptomatic pattern should be deviant from cultural norms and expectations, inflexible and pervasive across situations, distressing or impairing to a clinically significant degree, temporally stable, and of early developmental origin.
Thus, BPD is understood to involve instability in several domains, namely affect, behavior, and self-concept. However, it is not at all clear how these different aspects of the disorder interrelate. In particular, the role in the disorder of “identity disturbance,” defined in the *DSM-5* as a “markedly and persistently unstable self-image or sense of self” (American Psychiatric Association, 2013, p. 663), is not well understood, but a few prominent theories have been proposed from varying theoretical perspectives. One possibility is that individuals with BPD have a temperamental vulnerability to emotional extremes, which makes impulsive and self-harming behaviors more likely. This erratic emotional and behavioral experience, in turn, leads to relationship instability and also makes it difficult for these individuals to construct a coherent view of themselves when they reflect on their experiences. This view is most consistent with behavioral or “biosocial” models of the disorder that hold emotion regulation difficulties to be the core symptom of the disorder (Crowell, Beauchaine, & Linehan, 2009; Linehan, 1993; Zanarini & Frankenburg, 2007). From this perspective, the identity disturbance observed in individuals with BPD is secondary to emotional vulnerability and behavioral dysregulation and would not serve as a good prospective predictor of impulsivity, emotionality, and other important features of the disorder when other symptoms are taken into account. Accordingly, treatments developed with this model of psychopathology intervene to help the individual modulate affect and regulate behavior, assuming that change in the rest of the individual’s symptoms will follow (e.g., Linehan, 1993).

In contrast, psychoanalytic and psychodynamic theories of BPD, most notably those from an object-relations framework, posit that having an incoherent and diffuse sense of self decreases the ability of those with BPD to consistently use positive self-relevant thoughts to modulate their emotional reaction to even minor stressors. Thus, the lack of a coherent self-concept is thought
to result in extreme affect, erratic behavior, and greater vulnerability to self-harm (Bender & Skodol, 2007; Clarkin, Yeomans, & Kernberg, 2006; Fonagy & Target, 2006; Levy et al., 2006). These theories regard the emotional and behavioral symptoms of the disorder as secondary to identity disturbance in individuals with BPD. In these models, both self-concept instability and erratic affective experience would be important prospective predictors of impulsivity.

Psychoanalytic treatments for BPD, which are based on this general model of the disorder, intervene to help the individual develop a more coherent sense of self, which then theoretically leads to more adaptive emotional and behavioral patterns (e.g., Bateman & Fonagy, 2004; Clarkin, Yeomans, & Kernberg, 2006). In short, psychodynamic and biosocial theories posit an opposite role for identity disturbance in the overall mechanism of BPD pathology: one as the cause, and the other as the result, of the affective and behavioral dysregulation that is typical of the disorder.

Complicating these models is a possible distinction between identity disturbance as a stable and lasting individual-differences variable and identity disturbance as a subjective sense of self-incoherence that can vary over time within an individual. The former variable is described in the psychodynamic literature as a consequence of temperamental vulnerability to aggression, the use of immature defensive strategies, and insecure attachment (e.g., Fonagy, Target, Gergely, Allen, & Bateman, 2003; Kernberg, 1975; Levy, Meehan, Weber, Reynoso, & Clarkin, 2005), which produce a chaotic and incoherent representation of self. This self-structure is thought to be relatively permanent and to leave the individual vulnerable to BPD, and its presence is generally assessed via clinical observation of conflicting self-representations (Kernberg, 1984).

At the same time, many clinical authors and researchers have also suggested that individuals with BPD can experience a temporary clarity in their self-concept at certain times.
For example, Fonagy and colleagues propose that “a stable sense of self is illusorily achieved” for a short time in those with BPD when their maladaptive defenses allow them to disavow aspects of their self-concept that are painful (Fonagy et al., 2004, p. 359). The authors also point out that these temporary states of self-clarity eventually exact a heavy price, as these defenses may bring about negative interpersonal consequences. Likewise, Kernberg (1984) theorizes that individuals with BPD tend to keep conflicting representations of self separate, leading to oscillations between contradictory self-concepts that may temporarily be held with rigid conviction until outside reality disrupts the active self-representation. In a study of clinical observations of identity disturbance, Wilkinson-Ryan and Westen (2000) found that a major component of the construct, as observed by clinicians in everyday practice, was “a tendency to make temporary hyperinvestments in roles, value systems, world views, and relationships that ultimately break down” (p. 529). It is reasonable to postulate that these temporary hyperinvestments in self-defining roles and values might temporarily lend an individual a subjective sense of clarity in their self-concept, in line with the views advanced by clinical writers. These accounts converge in the idea that this seemingly coherent sense of self is maladaptive, as it reflects an unstable and unrealistic self-representation that may lead to poorly modulated behavior.

In social-personality psychology, a similar plurality of self-structure variables has developed. The consciously accessible, subjective sense of clarity and stability in the self-concept is generally referred to as “self-concept clarity.” This variable is usually operationalized via self-report (Campbell et al., 1996) and is very similar to identity disturbance; in fact, measures of self-concept clarity show some validity as measures of identity disturbance in BPD (Pollock et al., 2001; Roepke et al., 2011). Although originally thought of as a stable individual-
differences variable, self-concept clarity has been shown to vary from day to day within individuals and in dynamic relationship with life events and mood (Ayduk, Gyrak, & Luerssen, 2009; Lavallee & Campbell, 1995; Nezlek & Plesko, 2001), suggesting that fluctuations in this variable may be important. In contrast, structural and more enduring aspects of stability in the self-concept structure are often assessed through laboratory tasks, such as card-sort procedures thought to evoke representations of implicit self-structure (e.g., Linville, 1987).

At least one research study suggests that these trait-like and state-like self-concept variables have a dynamic relationship similar to the psychodynamic models described above. Boyce (2008) has found that individuals with low trait self-concept clarity (i.e., high trait-level identity disturbance) could be temporarily induced to experience a state of high self-concept clarity. When this happened, they showed a compartmentalized structure of self-representations – the hypothesized organization underlying borderline personality pathology, according to Kernberg (1984) – as assessed by a laboratory card-sorting measure. In contrast, when individuals with high trait self-concept clarity were in a state of high self-concept clarity, they showed an integrated self-structure, which is associated with resilience (Showers & Kling, 1996). Thus, it is possible that momentary states of low subjective identity disturbance, or high self-concept clarity, may leave individuals with BPD vulnerable to negative outcomes by distorting their representations of themselves and of others.

Despite the prominent standing of these different models of BPD and the possible theoretical importance of identity disturbance in BPD, direct empirical tests of the proposed processes within the disorder are scant, and the essential nature of the disorder is still poorly understood. There is also no indirect evidence for the suitability of either psychodynamic or biosocial models of the disorder in terms of differential efficacy or effectiveness of
psychotherapies developed in accordance with them (Levy, 2008). Limitations of the DSM definition of BPD and of the methodology of most of the research to date leave open these questions and will be described below. These limitations are high levels of heterogeneity within DSM-IV BPD and a research literature based primarily on retrospective, cross-sectional data.

**Heterogeneity within the BPD Category**

First, it is unclear whether Borderline Personality Disorder as defined in the DSM has a single essential nature. Latent class analyses using the BPD criterion set generally show evidence for a single class of individuals who can be diagnosed with the disorder among large samples (Clifton & Pilkonis, 2007; Fossati et al., 1999; Shevlin, Dorahy, Adamson, & Murphy, 2007), although the distinction between those who have the disorder and those who do not is difficult to draw given the frequency of many of the BPD symptoms among those who do not formally qualify for the diagnosis (Shevlin et al., 2007). Nevertheless, there is abundant evidence for heterogeneity among individuals with BPD in studies that take variables outside the DSM system into account. Many variables have been shown to delineate BPD subtypes, including specific patterns of interpersonal problems (Leihener et al., 2003; Salzer et al., 2013; Wright et al., 2013), dependency and self-criticism (Kopala-Sibley et al., 2012), psychopathic traits (Newhill, Vaughn, & DeLisi, 2010), effortful control (Hoermann, Clarkin, Hull, & Levy, 2005), personality variables (Bradley, Conklin, & Westen, 2005; Tramantano, Javier, & Colon, 2003), attachment style (Levy, Meehan, Weber, Reynoso, & Clarkin, 2005), demographic characteristics (Johnson et al., 2003; Stevenson, Meares, & Comerford, 2003), other co-occurring disorders (Ferrer et al., 2008) and various combinations of these factors (Digre et al., 2009).
This heterogeneity is not surprising given the polythetic nature of the *DSM* diagnostic algorithm for BPD. No symptom must be present for the diagnosis to be made, and instead the presence of any five is considered sufficient. This approach to diagnosis was the result of a decision by authors of the third edition of the manual to group disorders by descriptive features, rather than by putative etiological factors or underlying mechanisms, in order to achieve acceptability by researchers and clinicians of differing theoretical backgrounds (Spitzer, 2001). Thus, for example, neither emotional variability nor identity disturbance must be part of the overall symptom picture of someone with BPD. The result of the American Psychiatric Association’s decision is that there are 256 unique ways for an individual to meet criteria for BPD within the *DSM* diagnostic system, and in fact, many of these criterion combinations actually occur in practice. For example, Johansen, Karterud, Pedersen, Gude, and Falkum (2004) found 136 different criterion patterns among 252 individuals with *DSM-IV* BPD in Norwegian day hospitals. This variety within the diagnostic category seems to be important: individuals with the disorder who meet differing numbers of BPD criteria (Asnaani, Chelminski, Young, & Zimmerman, 2007) or different criterion patterns among the 256 combinations (Cooper, Balsis, & Zimmerman, 2010) have been shown to differ in terms of their levels of pathology and functioning. In all, then, it is evident that a diagnosis of BPD does not hold the same implications for every individual to which it is applied. This high degree of heterogeneity raises the possibility that BPD symptoms might interact in different ways in different individuals and that different theories affording primacy to one factor or another might apply to different subgroups of individuals with the diagnosis.
Research Based on Retrospective Self-Report

Scientific knowledge about the mechanisms of BPD is also constrained by limitations of research design. One important such limitation of research into the validity of various models of BPD is that much of it is based on retrospective self-report. In this method of data collection, individuals are asked to recall and summarize their past experience and to characterize their general thoughts, feelings, and behaviors, most often in the context of an unstructured or semi-structured interview or using a questionnaire measure. This strategy is cost-effective and easy to implement, and it also mirrors the typical diagnostic encounter in clinical practice. However, retrospective recall for psychological experiences can be biased and inaccurate (Bolger, Davis, & Rafaeli, 2003; Ebner-Priemer & Trull, 2009; Fahrenberg, Myrtek, Pawlik, & Perrez, 2007; Ptacek, Smith, Espe, & Raffety, 1994; Solhan et al., 2009; Shiffman, Stone, & Hufford, 2008; Smith, Leffingwell, & Ptacek, 1999; Todd et al., 2003). Interviewees and survey respondents are often unable to recall with accuracy the frequency, sequence, or quality of their experiences. This is true for the sort of inner emotional experiences that characterize many of the symptoms in the DSM (Robinson & Clore, 2002) but also holds for relatively objective events, such as the number of cigarettes smoked within a certain period (Shiffman, 2009). More complex information, such as the context in which an experience occurs or the individual’s reasons for carrying out a certain behavior, is also notably difficult to relate to a clinician or researcher with accuracy (e.g., Todd et al., 2003; Todd et al., 2005). Indeed, linkages between symptoms and their context and between behaviors and their motivations are often the focus of DSM criteria (e.g., “frantic efforts to avoid... abandonment” or “stress-related paranoid ideation” in the case of BPD; American Psychiatric Association, 2013, p. 663) and of interview questions and questionnaire items based on the DSM criteria. Thus, it is questionable whether retrospective
interview-based or questionnaire data result in an accurate picture of an individual’s psychological problems as they actually occur in the person’s life.

Difficulties in retrospective recall on questionnaires and in interviews may be particularly problematic for self-report data from individuals with BPD due to their chaotic, rapidly shifting inner experience. Ebner-Priemer and colleagues (2006), for example, gathered the quality and intensity of self-reported emotional experience in individuals with BPD and healthy control participants every 10-20 minutes over a 24-hour period. Afterwards, they asked participants to rate the intensity of various positive and negative emotions. Individuals with BPD showed a negative recall bias: they retrospectively recalled their negative emotions as more intense, and their positive emotions as less intense, than they had indicated at the time. Importantly, this tendency was not due to comorbid major depressive disorder or post-traumatic stress disorder, as it was present regardless of these other diagnoses. Other investigations comparing retrospective recall of affective states and immediate ratings of these states in individuals with BPD have revealed similarly low correspondence between the two (Links, Heisel, & Garland, 2003; Solhan, Trull, Jahng, & Wood, 2009).

Other recent research suggests that inconsistency in endorsement of questionnaire items may also be particularly pronounced in BPD. Hopwood and colleagues (Hopwood & Morey, 2007; Hopwood et al., 2009; Hopwood & Zanarini, 2010) have found that individuals with BPD or clinically significant BPD features tend to show inconsistent response patterns within personality questionnaires relative to individuals with other personality disorders, even when controlling for the presence of a major depressive disorder diagnosis. The authors note that these findings may reflect a defensive response pattern among individuals with BPD, actual trait instability, or other factors.
Finally, as a recent review paper notes (Santangelo, Bohus, & Ebner-Priemer, in press), retrospective recall is a particularly problematic data-collection strategy when dealing with unstable psychiatric symptoms, as concordance between retrospective and immediate ratings for this type of experience is particularly low. Several symptoms of BPD are characterized by particular instability over time, especially behavioral manifestations of the disorder such as self-injury and frantic efforts to avoid abandonment (McGlashan et al., 2005; Shea et al., 2002). These experiences often have acute environmental determinants (Gunderson et al., 2003), whereas other symptoms, and indeed functional impairment, are more stable (Skodol et al., 2005) and may be easier for the individual to summarize with accuracy. In addition, because many symptoms of BPD involve variability, change, and instability in other variables (e.g., affect or self-concept), retrospectively reporting on them involves rating changes or differences between separate experiences rather than rating a single experience (Ebner-Priemer & Trull, 2009). Research has shown that retrospective ratings of change and instability are more prone to inaccuracy than ratings of mean values or general frequencies (Ebner-Priemer, Bohus, & Kuo, 2007, as cited in Ebner-Priemer & Trull, 2009; Stone, Broderick, Shiffman, & Schwartz, 2004). For all of these reasons, it is not clear that an empirical literature that relies heavily on retrospective report can allow researchers to come to an accurate picture of the dynamics and mechanisms of BPD.

**Research Based on Cross-Sectional Data**

A final limitation of previous research into the relationships between different BPD symptoms is that most findings are based on cross-sectional data, reflecting ratings of BPD symptoms across many individuals at one point in time. For example, numerous factor analyses and correlational studies of BPD criteria have been conducted, but the results vary with respect
to the relationships between affective lability, instability in self-concept, and behavioral disturbances. Some research suggests that instability of affect and identity show a closer relationship with each other than with other symptoms, such as impulsivity and suicidality (Benazzi, 2006), whereas other studies suggest that self-concept instability is related to both impulsivity and affective instability to a greater degree than the latter two relate to each other (Becker, McGlashan, & Grilo, 2006). Still other studies are not able to discriminate between the strength of these relationships (Blais, Hilsenroth, & Castlebury, 1997; Fossati et al., 1999; Johansen et al., 2004; Koenigsberg et al., 2001; Sanislow et al., 2002). One recent cross-sectional study directly tested the unique contributions of different constructs to BPD symptoms. Cheavens, Strunk, and Chriki (2012) measured self-reported emotion dysregulation, interpersonal problems, and sense of self among college students and Internet users and found that only emotion dysregulation uniquely predicted variance in self-reported BPD symptoms.

Because cross-sectional research consists only of the analysis of responses at a single point in time, it cannot illuminate how various phenomena unfold and interrelate over time within individuals. The lion’s share of research into the nature of BPD has been cross-sectional, and accordingly, the temporal interplay between different symptoms of BPD has largely been neglected. Moment-to-moment variability in emotion, self-concept, and impulsivity is especially important to understand in BPD, as at least one empirical account suggests that diurnal variance in these symptoms tends to be more extreme in BPD than either day-to-day variance within individuals or interindividual variability (Nisenbaum, Links, Eynan, & Heisel, 2010).

**Ecological Momentary Assessment in BPD**

One method for circumventing both the biases of retrospective recall and the limitations of cross-sectional data is ecological momentary assessment (EMA). In this type of assessment,
individuals complete repeated, unobtrusive records of their experiences, close in time to the events that are being rated. Thus, EMA both minimizes error due to recall bias and allows for the longitudinal analysis of multivariate psychological processes (Bolger et al., 2003; Shiffman et al., 2008; Conner, Tennen, Fleeson, & Barrett, 2009). As such, it is a promising set of methods for studying psychopathology (Myin-Germeys et al., 2009), and this advantage is particularly helpful for BPD, which by definition involves variability over time in several presumably interrelated symptoms.

The study of affective variability in BPD using intensive, repeated paper-and-pencil measures of mood has a modest history, especially in inpatient settings (e.g., Cowdry, Gardner, O’Leary, Leibenluft, & Rubinow, 1991; Stein, 1995). In recent years, EMA studies have taken advantage of the proliferation of handheld digital organizers and mobile “smartphone” devices to study these processes in outpatients and community samples. These electronic devices have several advantages: they allow researchers to deliver random prompts to participants to enter self-report data, reducing practice and habituation effects. They also allow for responses to be electronically time-stamped, which increases participant adherence to the survey regimen and helps researchers model responses with greater temporal fidelity. EMA studies of BPD have grown more common in the past decade (for reviews of previous studies, see Nica & Links, 2009 and Santangelo, Bohus, & Ebner-Priemer, in press), and this method is generally seen as promising due to improvements in the quality, availability, and price of mobile devices and to advances in approaches to modeling the resulting data (e.g., Miller, 2012).

Most of the studies using EMA in BPD have focused on the nature of affective dysregulation in the disorder. For example, Trull and colleagues (2008) used electronic diaries to prompt outpatients with BPD and outpatients with major depressive disorder (MDD), but
without BPD, to complete records of their mood at random intervals six times per day for one month. They found similar mean levels of positive and negative affect across the two groups. However, overall variability of positive and negative affect was greater in the BPD group, as was the instability (differences between successive ratings) of hostility, fear, and sadness. Ebner-Priemer and colleagues (2007) found that individuals with BPD reported more complex emotions (i.e., the presence of more than one emotion at a time), with greater intensity of complex negative emotions, than healthy control participants. In general, the best-conducted studies suggest that individuals with BPD show greater instability in affect than healthy controls or individuals with MDD (Santangelo, Bohus, & Ebner-Priemer, in press).

Other symptoms of BPD are less frequently studied but include instability in interpersonal behavior (Russell, Moskowitz, Zuroff, Sookman, & Paris, 2007), dissociation and paranoia (Glaser, van Os, Thewissen, & Myin-Germeys, 2010; Stiglmayr et al., 2008), suicidality (Links et al., 2007; Links, Eynan, Heisel, & Nisenbaum, 2008) and rejection and rage (Berenson, Downey, Rafaeli, Coifman, & Paquin, 2011). A few studies have also examined the contexts in which BPD symptoms arise. For example, Stiglmayr and colleagues (2008) linked dissociative symptoms to states of stress in BPD patients as well as in clinical and healthy control participants; the BPD group experienced more stress-linked dissociation than either control group. Likewise, Glaser et al. (2010) found that stress was related to psychotic experiences in individuals with BPD to a greater extent than those with active psychosis, cluster C personality disorders, or healthy controls. These studies have thus provided support for the validity of the “stress-related paranoid ideation or severe dissociative symptoms” criterion of DSM-5 BPD (American Psychiatric Association, 2013, p. 663). Berenson and colleagues (2011) have used EMA methods to relate momentary feelings of rage (which the authors conceptualized
as the experience of BPD criterion of intense, uncontrolled anger) and perceptions of rejection in
individuals from the community with BPD and healthy control participants. Results showed that
the experience of intense rage in the context of perceived rejection was much stronger in the
BPD group than in the healthy control group. Although the EMA data did not allow the authors
to determine the directionality of the rejection-rage contingency, a priming task in the laboratory
with the same sample suggested that the mental activation of rejection-related constructs
triggered cognitions associated with rage.

Thus, a number of studies have examined symptoms of BPD using EMA methods, which
have helped to validate clinical observations that the disorder involves affective instability,
extreme anger responses to interpersonal slights, and dissociation and paranoia under distress.
Further studies have elucidated the naturalistic context of the emotional and behavioral
experiences associated with BPD. To date, however, no studies have examined impulsivity or
identity disturbance in BPD using EMA. In addition, very few studies have examined the
relationships between different BPD symptoms, although some EMA studies have examined the
social, environmental, and psychological contexts that give rise to a single symptom.

In addition, the extant EMA studies of borderline personality pathology have examined
groupwise hypotheses, comparing a BPD group with a group of healthy control participants or a
clinical group with other diagnoses. These studies generally use multilevel modeling,
generalized linear modeling, or another approach to modeling variation in the symptom or
process of interest. In the most common approach, mean levels of these variables are compared
across groups in order to test hypotheses about the uniqueness of the borderline personality

1 In their review, Santangelo, Bohus, & Ebner-Priemer (in press) cite two EMA studies examining variability in self-
esteeem and its relationship to BPD features (Tolpin, Gunthert, Cohen, & O’Neill, 2004; Zeigler-Hill & Abraham,
2006). However, variability of self-esteem is not very consistent with the description of identity disturbance in
DSM-IV or DSM-5, where it is described as involving shifts in goals, values, roles, sexual identity, aspirations, and
other non-evaluative aspects of self and identity.
syndrome. However, this groupwise approach to the analysis of EMA data does not account very well for the high levels of potential, and actual, heterogeneity within the class of individuals with BPD. Multilevel modeling using longitudinal data, for example, may account for individual variation around certain parameters of interest, but this variation is generally understood as quantitative variation around a mean value. Thus, this approach does not allow for qualitative variation in the characteristic processes of BPD (Sterba & Bauer, 2010). Nevertheless, despite this pervasive focus on groupwise hypotheses and interindividual variation, it is clear that intensive longitudinal data collected through EMA have the potential to illuminate heterogeneity within diagnostic categories through the examination of intraindividual variation in BPD symptoms as they occur over time.

**Person-specific analysis of intraindividual variation**

In recent years, it has become more apparent that the relationships between variables within individuals over time are not necessarily the same as the relationships between variables when these constructs are measured in several persons at one point in time (Kenny, Kashy, & Bolger, 1998; Tennen & Affleck, 2002). For example, it has been shown that the personality factors of Neuroticism and Conscientiousness are generally negatively related in factor analyses of interindividual variation (Mount, Barrick, Scullen, & Rounds, 2005), but they tend to be positively correlated over time within individuals (Beckmann, Wood, and Minbashian, 2010). Similar divergence has been shown for the interpersonal dimensions of agency and communion, which are unrelated in cross-sectional studies but positively associated over time within individuals (Roche, Pincus, Hyde, Conroy, & Ram, 2013). Thus, the dynamics of interindividual (or intergroup) variation, where patterns of behaviors, emotions, or other responses are compared between persons, and the structure of intraindividual variation, where different responses are
compared over time within persons, are very often distinct (Borsboom, Mellenbergh, & van Heerden, 2003; Molenaar, 2004).

Importantly, it is also often the case that substantial heterogeneity exists between individuals in the intraindividual covariation of variables over time, so that the nomothetic models that describe individual or group differences do not generally hold implications for the processes that obtain for a single person, even when the same sample is used for both types of analysis. It has been shown, for example, that the intraindividual covariance structure of responses to questionnaires that are designed to assess the Five-Factor Model of personality does not usually resemble the five factors that are derived from the analysis of their interindividual variation, and substantial differences between subjects have been found in terms of the number and composition of the factors required to describe the intraindividual data (Hamaker, Dolan, & Molenaar, 2005; Molenaar & Campbell, 2009). The same has been shown of items on the PANAS, a common and robustly replicated measure of positive and negative affect (Rovine, Molenaar, & Corneal, 1999), and in simulated behavioral genetics data (Molenaar, Huizenga, & Nesselroade, 2003). Empirical studies (e.g., Hamaker et al., 2005) and a mathematical proof (Kelderman & Molenaar, 2007) demonstrate that a single, stable, well-fitting model of between-subjects variation can be derived that does not apply to the intraindividual variation of any of the individuals in the sample.

Because previous investigations of BPD symptom dynamics using EMA have relied on between-persons and between-groups approaches to data analysis, they have not revealed the extent to which these relationships vary across individuals. A person-specific approach to modeling EMA data would allow for the examination of this heterogeneity and would still produce meaningful tests of the models put forth in the clinical literature. The current study
seeks to apply a person-specific modeling approach (dynamic factor modeling; Molenaar, 1985) to EMA ratings of disturbances in affect, behavior, and identity among individuals with BPD and among clinical control participants. Within each individual, competing hypotheses are tested that derive from clinical theories of BPD from the psychodynamic and behavioral/biosocial traditions. These hypotheses are: 1) identity disturbance will prospectively predict later self-reported affective and behavioral dysregulation, as predicted by psychodynamic theory and 2) affective and behavioral dysregulation will predict later identity disturbance, as “biosocial” theory predicts. In addition, the person-specific approach and diagnostically mixed sample allows for an exploration of two additional hypotheses: 3) that the relationships among identity disturbance, anger, and impulsivity will not uniformly resemble hypotheses 1 and 2 but will instead vary between individuals; and 4) the relationships between these symptoms will be unique to individuals with DSM-IV borderline personality disorder and not present in individuals with other DSM-IV disorders.
Chapter 2

Method

Participants

Participants were 11 adult individuals participating in outpatient treatment at the Penn State Psychological Clinic, a community mental health center and the primary training clinic for the graduate program in clinical psychology at the Pennsylvania State University. In order to be eligible to participate in the study, participants had to be aged at least 18 years; could not be diagnosed with schizophrenia, schizoaffective disorder, bipolar I disorder, delusional disorder, delirium, dementia, amnestic disorder, cognitive disorder NOS, current substance dependence, mental retardation, or borderline intellectual disability; and had to self-report normal or corrected-to-normal vision (in order to read questionnaires on the smartphone’s LCD screen). Characteristics of the participants can be found in Table 1.

Participants were recruited from two separate studies with slightly different diagnostic inclusion criteria. In the first study, clinicians who were conducting routine diagnostic interviews with individuals presenting for treatment were asked to mention a study about “personality in daily life” to clients. If a client indicated interest in the study, he or she could sign a consent form giving research staff permission to access their diagnostic interview data to verify their eligibility based on diagnosis and to contact them for additional eligibility screening over the telephone. The diagnostic inclusion criterion for this study, in addition to the diagnostic exclusion criteria above, was the presence at intake of either BPD or a DSM-IV anxiety disorder. The second group of participants was recruited from among outpatient clients from the same clinic who had participated in previous studies and had asked to be contacted about further
Table 1

Demographic and Diagnostic Characteristics of the Current Sample (N = 11)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>N</th>
<th>%</th>
<th>M</th>
<th>SD</th>
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<tr>
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<td></td>
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<td></td>
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<td>0</td>
<td></td>
<td></td>
</tr>
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<td></td>
<td></td>
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<tr>
<td>Caucasian</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>0</td>
<td></td>
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</tr>
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<td>ALS total score, baseline</td>
<td></td>
<td></td>
<td>2.47</td>
<td>0.81</td>
</tr>
</tbody>
</table>

<sup>1</sup>Participants could list more than one ethnicity.

<sup>2</sup>Participants could list more than one marital status (e.g., divorced and dating).

<sup>Note</sup>. IPDE = International Personality Disorder Examination; BPD = Borderline Personality Disorder; GAPD = General Assessment of Personality Disorder; SCCS = Self-Concept Clarity Scale; MSI-BPD = McLean Screening Inventory for BPD; BSCS = Brief Self-Control Scale; ALS = Affective Lability Scales.
research. These individuals were called and, if they expressed interest, were screened for the study via telephone in the same way as the first group. Diagnostic eligibility for these previous studies was based on the presence of either BPD or a *DSM-IV* MDD or dysthymia diagnosis, in addition to the same exclusion criteria as above. Thus, participants were eligible for the current study if they met criteria for either BPD or a unipolar mood or anxiety disorder (but not BPD). Figure 1 shows the flow of the 25 recruited individuals through the current study. In all, 11 eligible individuals agreed to participate and submitted enough EMA data to be analyzed.

*Figure 1. Flow chart of participants through the study.*
Procedure

After being recruited as above, participants completed baseline questionnaire measures and received extensive training in the use of the smartphone device. For 21 days following this laboratory session, participants completed three kinds of surveys on their smartphones: surveys in response to block-randomized auditory prompts from the device (“prompted surveys”), surveys after every interpersonal interaction lasting at least three minutes, and surveys within an hour of going to sleep for the night. The three types of surveys varied in their content, and the current report only concerns the prompted surveys.

Before the 21-day EMA sampling period, participants chose between three 12-hour intervals for daily prompts: 6:00am to 6:00pm, 8:00am to 8:00pm, or 10:00am to 10:00pm. Participants received 6 prompts per day to complete surveys, each of which occurred at a pseudo-random time within a 2-hour block during the overall 12-hour interval. Participants were instructed to complete a prompted survey immediately upon hearing the prompt, although they could decline to do so if they were engaged in an activity that would make it dangerous to attend to the survey (for example, driving a car). In this case, they had the option of completing a survey at a later time. Each survey was time-stamped by the date and time it was begun. Once a survey was begun, the participant had 10 minutes to complete it before the phone “timed out.” Surveys were transmitted to a central, encrypted server as soon as they were completed, as long as the participant had access to a wireless data network. Compliance with all surveys was monitored by the research team, and phone calls were placed to participants who had completed a low number of surveys to resolve any technological problems that might have interfered with survey completion.
At the end of the 21-day EMA sampling period, participants returned to the laboratory to return the phone and receive payment. They could receive up to $150 in compensation for this portion of the study: $50 for the baseline questionnaires and training session and $2.35 for each day of participation, which increased to $100 if they met a threshold of compliance with the survey protocol (participation for 18 of 21 days, with 85% completion of prompted surveys and an average of 6 interaction-contingent surveys per day). The study was approved by the Institutional Review Board of the Pennsylvania State University.

Materials

**Diagnostic Interviews.** Participants completed semi-structured diagnostic interviews as part of their clinic intake or as part of previous research studies.

*Anxiety Disorders Interview Schedule (ADIS; Brown, DiNardo, & Barlow, 1994).* Those recruited for the study from clinic intakes were diagnosed with Axis I disorders using an augmented version of the ADIS, a semi-structured interview for the diagnosis of substance use disorders, anxiety disorders, mood disorders, eating disorders, somatoform disorders, and psychotic disorders. Within the clinic, interrater reliability of diagnoses based on the ADIS is good (Cohen’s $\kappa = .673$ for mood disorders and .655 for anxiety disorders; Nordberg, McAleavey, Castonguay, & Levy, 2009).

*Structured Clinical Interview for DSM-IV Axis I Disorders, Clinician Version (SCID-I; First, Spitzer, Gibbon, & Williams, 1997).* Individuals recruited from previous research studies were diagnosed with Axis I disorders using the SCID-I, a semi-structured interview covering mood disorders, psychotic disorders, substance use disorders, anxiety disorders, somatoform disorders, and eating disorders. Previous analyses of interrater reliability within this
research sample have shown high concordance of SCID-I diagnoses between raters (κ ranges from .64 to 1.0; Scott, Levy, & Granger, 2013).

**International Personality Disorders Examination (IPDE; Loranger, 1999).** All individuals in the sample, whether recruited from clinic intakes or previous research studies, were diagnosed with personality disorders using the IPDE. The IPDE provides both a criterion count and a dimensional score for each personality disorder. The dimensional score for BPD includes both symptoms above criterion level (which receive a score of 2) and symptoms that are elevated but below the criterion threshold (which receive a score of 1). The interrater reliability of these diagnoses within the clinic is good (Cohen’s κ = .677 for all Axis II disorders and .679 for BPD; Nordberg et al., 2009). Interrater reliability of these diagnoses within the research sample (Scott et al., 2013) was excellent (Cohen’s κ values ranged from .71 to 1.0 for all Axis II disorders; for BPD, κ = .88), as was the reliability of the number of BPD criteria met (ICC = .94) and of the BPD dimensional scores (ICC = .98).

**Baseline Questionnaires.** Participants completed baseline questionnaires during the laboratory session at which they received training in use of the smartphone. They completed these questionnaires via an online survey-hosting website (surveymonkey.com). The following questionnaire measures are considered in the current study:

**General Assessment of Personality Disorder (GAPD; Morey et al., 2011).** The GAPD is a 65-item self-report questionnaire rated on a 4-point Likert-type scale ranging from 1 (“Strongly Disagree”) to 4 (“Strongly Agree”). The measure is designed to assess a general level of personality functioning, as articulated by the DSM-5 Personality Disorders Work Group (e.g., Skodol et al., 2011). This construct is not part of the diagnosis of personality disorders in DSM-5 but is contained within the manual’s alternative model for personality disorders (American
An initial study of the GAPD (Morey et al., 2011) showed that the 65-item scale could be described with a unidimensional structure and discriminated between individuals with differing numbers of DSM-IV personality disorders. Its latent trait dimension also showed strong relationships with the identity disturbance and impulsivity criteria of BPD, even taking other DSM-IV PD criteria into account. In the current study, the unweighted mean of responses was used to characterize individuals’ level of personality functioning. Responses were keyed so that higher numbers indicated a higher level of personality functioning (i.e., less personality pathology). The internal consistency of the GAPD in the current sample was excellent (α = 0.97).

**Self-Concept Clarity Scale (SCCS; Campbell et al., 1996).** The SCCS is a 12-item self-report measure designed to assess the extent to which a person's self-beliefs are clearly and confidently defined, internally consistent, and stable. Items are rated on a 5-point Likert-type scale ranging from “Strongly disagree” to “Strongly agree.” The SCCS has been shown to relate to the actual consistency of individuals’ self-attribute ratings (Campbell et al., 1996). Although the measure was developed for use with normal samples (Campbell et al., 1996; Campbell, Assanand, & Di Paula, 2003), it has also been used as a self-report measure of self-concept stability among individuals with BPD (Pollock et al., 2001; Roepke et al., 2011). The internal consistency of the SCCS is good, both in the initial validation study (α = 0.86; Campbell et al.) and in the current study (α = 0.88).

**Affective Lability Scales (ALS; Harvey, Greenberg, & Serper, 1989).** The ALS is a 54-item self-report instrument designed to measure lability in anxiety, depression, anger, and hypomania, and labile shifts between anxiety and depression and hypomania and depression. Items are rated on a 4-point Likert-type scale ranging from “Very characteristic of me, extremely
descriptive” to “Very uncharacteristic of me, extremely undescriptive.” Scores on the ALS have been found to differentiate individuals with BPD from those with bipolar II disorder (Henry et al., 2001) and depression (Solhan, Trull, Jahng, & Wood, 2009). In addition, large-scale research shows strong correlations between the ALS and other markers of borderline personality traits (Ellison & Levy, 2012; Trull, 2001). The individual scales of the ALS are highly intercorrelated, suggesting that they measure a general tendency toward emotional lability (Harvey et al., 1989), and the overall scale had high internal consistency in the current sample (α = 0.99). Scores were coded so that higher values on the 1-4 scale would indicate more affective lability.

**Brief Self-Control Scale (BSCS; Tangney, Baumeister, & Boone, 2004).** The BSCS is a 13-item self-report measure of effortful self-control. It has most often been used in non-clinical samples, where it shows a robust relationship with measures of adjustment, self-esteem, substance abuse, and interpersonal skills (Tangney, Baumeister, & Boone, 2004) and relates to real-world outcomes such as academic performance (Duckworth, Tsukayama, & May, 2010) and criminal and deviant behavior (Holtfreter, Reisig, Piquero, & Piquero, 2010; Reising & Pratt, 2011). Importantly, self-control scores on the BSCS are negatively related to self-reported symptoms of BPD (Tangney et al., 2004). The internal consistency of the BSCS was good in Tangney et al. (α = 0.84) and adequate in the current sample (α = 0.68).

**McLean Screening Inventory for Borderline Personality Disorder (MSI-BPD; Zanarini et al., 2003).** The MSI-BPD is a 10-item screening questionnaire for BPD that can be used in interview or self-report contexts. Its items are face-valid inquiries about *DSM-IV* BPD criteria (with one additional item relating to interpersonal mistrust), scored on a yes/no basis. Research generally supports its validity and utility as a screener for BPD (Noblin, Venta, &
Sharp, in press; Patel, Sharp, & Fonagy, 2011; Zanarini et al., 2003), although its performance as a screener in a recent study was mixed (Chanen et al., 2008). The MSI-BPD has also been used as an outcome measure in a study of psychotherapy for BPD (Williams, Hartstone, & Denson, 2010). Zanarini et al. (2003) found the MSI-BPD had an optimal combination of sensitivity and specificity with a “caseness” cutoff of 7 endorsed items for adults. The internal consistency of the MSI-BPD was good in validation studies ($\alpha = 0.74$ in Zanarini et al., $0.73$ in Noblin et al., and $0.94$ in Patel et al.) and adequate in the current sample ($\alpha = 0.66$).

**Prompted smartphone surveys.** Participants completed 6 randomly-prompted smartphone surveys per day, which contained 46 questions and were designed to take about 5 minutes each. Participants completed smartphone surveys on Motorola Droid Razr devices. Questions asked about participants’ current affect, symptoms and functioning, repetitive thoughts, cravings to use substances, self-control capacity, values, thoughts of suicidality and self-harm, and self-concept and self-concept clarity. The current study concerns questions relating to 3 symptoms of BPD: anger, impulsivity, and self-concept disturbance.

Anger data was collected using the prompt, “How angry do you feel right now?”, which was rated on a visual analog scale (VAS) on the touch-sensitive screen of the smartphone. Participants chose a point along a continuum ranging from “Not at all” to “Extremely,” which was encoded as an integer value from 0 to 100. Impulsivity was operationalized as participants’ answers to the prompt, “Please rate how you see yourself RIGHT NOW using the following scales” on a VAS ranging from “Impulsive” to “In control.” These responses were encoded on a 0-100 scale, with 100 representing “in control.” Responses to this question were then reverse-scored so that higher scores would represent higher levels of impulsivity. Identity disturbance was measured using the prompt, “RIGHT NOW I have a clear sense of who I am and what I
Respondents used a VAS with the anchor points “Strongly disagree” and “Strongly agree,” and a 0-100 scale was used to encode responses. This item was also reverse scored, so that higher scores represented higher levels of identity disturbance (lower levels of self-concept clarity). This item was adapted from the 12-item SCCS (Campbell et al., 1996) to refer to state (not trait) identity disturbance. A similar modification has been used in a daily diary study to study fluctuations in self-concept clarity (Ayduk, Gyurak, & Luerssen, 2009).

Single-item measures were used to measure the constructs of interest in the current study because the primary advantage of EMA studies is their ecological validity relative to laboratory-based retrospective report. For this reason, questionnaire batteries in EMA studies tend to be brief to allow unobtrusive measurement of phenomena of interest, under the presumption that larger batteries of questions would disrupt the participant’s natural, lived experience. However, brief instruments run the twin risks of unreliability and inadequate coverage of important constructs. As methodologies for ecologically valid assessment have been developed, researchers have increasingly commented on the tension between maximizing reliability and content validity of assessments by using psychometrically sound measures and maximizing ecological validity by minimizing burden to participants (Bolger et al., 2003; Csikszentmihalyi & Larson, 1987; Shiffman et al., 2008). Relative priority in the current study was given to maximizing ecological validity.

Data preparation

The dynamic factor analyses used in the current project require data with equal time intervals between measurement occasions (Molenaar & Rovine, 2011). Because the smartphones used in the current project prompted participants to complete surveys at random times within 2-hour blocks, and because participants varied in how quickly they responded to
prompts, this requirement was violated. Thus, cubic spline interpolation (Forsythe, Malcolm, & Moler, 1977) was used to generate evenly-spaced data points to be used in the current analyses. To do this, the data were divided by participant and then by day. An initial zero point was chosen for each day’s data for each participant at the quarter hour time (e.g., 8:45am, 9:00am, 9:15am) before that day’s initial survey start timestamp. An endpoint for the interpolation was then chosen for each participant in order to best cover the group of observation intervals across days and produce even time intervals for all data points. Separate interpolations were then performed for each participant’s data on each day, yielding 6 evenly-spaced data points per day per participant per variable. Days with at least 5 completed surveys were submitted to interpolation, and a visual comparison of the raw and interpolated data was used to ensure that the interpolation produced an accurate representation of the original time series. The interval between interpolated observations varied slightly between participants depending on participants’ actual timing of survey completion. Cubic spline interpolation was carried out within the R program, version 2.11.1, using the splines package (Bates & Venables, 2010).

Each participant’s interpolated data across the 3-week diary period was used to derive estimates of the sequential covariance of identity disturbance, impulsivity, and anger. To do this, each participant’s data were treated as a 3-variate time series of length 6 (the number of observations per day) with a number of replications $K$ equal to the number of days. Block-Toeplitz covariance matrices were created describing the intraindividual covariation of anger, impulsivity, and identity disturbance across successive time points ($t$ and $t + 1$). The block-Toeplitz matrices were created under the assumption of “weak stationarity,” meaning that the means and variances of the data were assumed not to vary depending on location in the time series, and covariances of variables with equal relative spacing were constant over time. Thus,
the covariance matrices contained equal variance and covariance values for the three variables of interest regardless of their position at time $t$ or at $t + 1$. This stationarity assumption is necessary for dynamic factor modeling (Molenaar & Rovine, 2011). The total number of observations within each factor was calculated as

$$N_{obs} = K + 1$$

in order to account for the mean levels estimated when creating the block-Toeplitz covariance matrix (that is, a loss of $K – 1$ degrees of freedom). These covariance matrices were then used to evaluate the fit of the models to each participant’s data.

**Periodic Trends**

The presence of periodic trends in the time series data is a potential concern, because if the variables are influenced by such a trend within the time period sampled, estimates of relationships between variables across time points could be affected. Research has also demonstrated trends in affective variables within days for individuals with BPD (Nisenbaum et al., 2010). Periodic trends were checked by a visual inspection of the time series data (see Figure 2) and by a trend analysis. The trend analysis was conducted by regressing the interpolated time series data for each participant simultaneously onto sine and cosine functions. These functions were given a period equal to that participant’s window for prompted surveys, or roughly 12 hours (Refinetti, Lissen, & Halberg, 2007). Statistically significant coefficients relating these sine and/or cosine functions to anger, impulsivity, or self-concept clarity point to the possible presence of periodic trends in these variables. This method also allows for the derivation of descriptive statistics regarding each participant’s periodic oscillation in these symptoms. For example, the amplitude $A$ of the periodic oscillation is given by the formula

$$A = \sqrt{b_1^2 + b_2^2},$$
where $b_1$ and $b_2$ are the unstandardized regression coefficients for the sine and cosine functions, respectively. The time of day $t_0$ at which the estimated minimum or maximum of the function occurs is

$$t_0 = \tan^{-1} \left( \frac{b_1}{b_2} \right) \times \frac{1}{2\pi},$$

where $t_0$ is in fractions of a day. Given the frequency of 1 day for these functions, the opposite extreme is then given by $t_0 + \frac{1}{2}$ (Stolwijk, Straatman, & Zielhuis, 1999). If the regression analysis suggested the presence of circadian trends in the data, a sensitivity analysis was performed in the model-fitting step by substituting the regression residuals from the trend analysis for the original time series data and comparing the model fit results with the original model’s results.

Figure 2. Interpolated control/impulsivity data across 19 days of responses for participant 9. The trend analysis showed a circadian trend in these data with an amplitude of 7.98 and a maximum impulsivity about 2/3 of the way between the first and second rating of the day.
**Dynamic Factor Models**

Model fitting was conducted using LISREL, version 8.12 (Jöreskog & Sörbom, 1993). An autoregressive model with a lag of 1 occasion, or an AR(1) model, was used as the baseline model for each participant. In the AR(1) models, levels of identity disturbance, impulsivity, and anger at each time point were used to predict levels of these variables at the next survey. Correlations between simultaneously rated variables were allowed. If this baseline model did not show good fit to the data, modification indices were used to guide the addition of additional parameters (i.e., cross-lagged regression weights between one variable at time $t$ and another variable at time $t + 1$). These less-restricted models are termed vector autoregressive models, or VAR(1) models when a lag of 1 occasion is used. Each model was evaluated via a combination of fit statistics, namely the Standardized Root Mean Square Residual (SRMR), Root Mean Square Error of Approximation (RMSEA), Non-Normed Fit Index (NNFI), and Comparative Fit Index (CFI). These fit statistics were used in place of the chi-square statistic in dynamic factor modeling because the sequential dependence in the ratings violates the assumption of independence underlying the distribution of chi-square (Molenaar, 1985). In contrast, these alternative indices do not have a theoretical sampling distribution and performed well in a small simulation study (Molenaar & Rovine, 2011). Models were considered adequate fits to the data when the following conditions were met: RMSEA $\leq 0.08$, SRMR $\leq 0.1$, NNFI $\geq 0.95$, and CFI $\geq 0.95$. Chi-square values are reported as supplementary information. Figure 3 represents the baseline AR(1) model as implemented in LISREL.
Figure 3. 3-variate autoregressive dynamic factor model (AR[1] model) describing the relationship between anger, impulsivity, and identity disturbance, simultaneously and at successive time points, as implemented in LISREL (y submodel).
In the dynamic factor modeling approach, the residual variance of variables at time $t + 1$, $\zeta_{t+1}$, represents the degree to which an individual’s anger, impulsivity, and self-concept clarity are predicted by earlier levels of these variables. These “innovation” parameters thus quantify the level of sequential structure in these three BPD symptoms and can, in extensions of the current methodology, be used to quantify the effects of interventions upon the idiographic processes (e.g., Fisher, Newman, & Molenaar, 2011) and can be treated as individual difference variables in their own right (Ram, Brose, & Molenaar, 2013). In the current study, the innovation parameters are used as an index of the stability of the processes modeled.
Chapter 3

Results

Sample Characteristics

Thirteen participants volunteered for the study, completed baseline measures, and began the smartphone portion of the protocol. Of these, two participants stopped providing prompted survey responses shortly into the 3-week smartphone data collection period (after two and six days of participation, respectively). The remaining 11 participants constitute the sample for the current study. Their demographic, diagnostic, and baseline psychological characteristics can be found in Table 1. Figure 4 shows participants’ scores on baseline surveys.

![Figure 4. Scores on baseline self-report questionnaires for study sample (N = 11). GAPD = General Assessment of Personality Disorder; SCCS = Self-Concept Clarity Scale; BSCS = Brief Self-Control Scale; ALS = Affect Lability Scales. Higher scores on the GAPD, SCCS, and BSCS and lower scores on the ALS indicate better functioning in these domains.](image-url)
Compliance with Prompted Surveys

Because participants were explicitly told that they could forego responding to a smartphone prompt if they could not do so safely and could initiate a survey at a later time to compensate for the omission, compliance was measured as the percentage of the expected 126 prompted surveys (21 days with 6 surveys per day) completed. Surveys completed outside of the 21-day sampling window (for example, before the laboratory visit on the day when the phone was to be returned) were not counted in this total, because they were not used in data analysis. Compliance ranged from 61.9% to 100%, with a mean of 89.0% and a median of 90.4%. Table 2 shows compliance for each participant, as well as the fit statistics for each participant’s final dynamic factor model.

Person-Specific Results

Participant 1.

Diagnosis and baseline characteristics. Participant 1 was a 32-year-old married Caucasian woman who identified as heterosexual. She was recruited through previous participation in research and diagnosed via the SCID with major depressive disorder and past PTSD. She met two BPD criteria (unstable and intense interpersonal relationships and affective instability) and had an IPDE dimensional score of 5 (with one subthreshold score in addition to the two BPD criteria) and a Global Assessment of Functioning (GAF) score of 65. Her scores on baseline self-report measures were as follows: GAPD = 2.83, SCCS = 2.5, BSCS = 2.69, ALS = 2.94. She endorsed 4 items on the MSI-BPD.

Dynamic factor model. Participant 1’s data were described after interpolation by data points with lags of 6000s. According to the fit indices chosen a priori for the evaluation of dynamic factor models in LISREL, the autoregressive model (AR[1]) fit the data poorly, $\chi^2(6) =$
Table 2

*EMA Compliance and Fit of Dynamic Factor Models*

<table>
<thead>
<tr>
<th>Participant</th>
<th>Days</th>
<th>Compliance (%)</th>
<th>$\chi^2$</th>
<th>df</th>
<th>p</th>
<th>CFI</th>
<th>NNFI</th>
<th>SRMR</th>
<th>RMSEA</th>
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<td>1.00</td>
<td>0.055</td>
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<td>4.72</td>
<td>4</td>
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<td>0.99</td>
<td>0.021</td>
<td>0.042</td>
</tr>
<tr>
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<td>5</td>
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</tbody>
</table>

*Note.* Days = number of days with EMA data usable for dynamic factor analyses; Compliance = percentage of 126 expected prompted surveys completed; CFI = Comparative Fit Index; NNFI = Non-Normed Fit Index; SRMR = Standardized Root Mean Residual; RMSEA = Root Mean Square Error of Approximation.
21.98, CFI = 0.80, NNFI = 0.50, SRMR = 0.14, RMSEA = 0.20. Two additional cross-lagged parameters were required to achieve good fit on all fit indices. In the final model (Figure 5), a vector autoregressive model (VAR[1] model), anger at time \( t \) positively predicted levels of impulsivity at time \( t + 1 \), unstandardized \( \beta = 0.17, t = 2.21, p = .03 \). In addition, identity disturbance at time \( t \) negatively predicted levels of impulsivity at time \( t + 1 \), unstandardized \( \beta = -0.25, t = 3.16, p < .001 \). All autoregressive parameters were significant with the exception of anger, which did not show a relationship between values at successive time points, unstandardized \( \beta = -0.04, t = 0.31, p = .76 \). In addition, all synchronic correlations between variables (that is, correlations between variables measured at the same occasion) were significant with the exception of the relationship between identity disturbance and impulsivity (at time \( t \), unstandardized \( \psi = 12.30, t = 1.67, p = .10 \). The residual variance parameters suggested that time \( t \) ratings accounted for a negligible portion of the variance in anger at time \( t + 1 \), 25% of the variance in impulsivity at time \( t + 1 \), and 20% of the variance in identity disturbance at time \( t + 1 \).

**Periodic trends.** No significant periodic trends were observed in this participant’s anger, impulsivity, or identity disturbance data.

**Participant 2.**

**Diagnosis and baseline characteristics.** Participant 2 was a 60-year-old single Caucasian man who identified as heterosexual. He was recruited through clinic intake and diagnosed via the ADIS with mood disorder NOS and alcohol abuse on Axis I. On Axis II, he was diagnosed with narcissistic personality disorder and BPD. He met five criteria for BPD: identity disturbance, chronic feelings of emptiness, inappropriate anger, unstable interpersonal relationships, and
Figure 5. Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #1. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model (p > .05). ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between \( t \) and \( t + 1 \) is 6000s.

* \( p < .05 \). ** \( p < .01 \). *** \( p < .001 \).

...affective instability. He had no other subthreshold scores on the IPDE, giving him a BPD dimensional score of 10. He endorsed 9 items on the MSI-BPD and had a GAF score of 45. His scores on baseline self-report measures were as follows: GAPD = 2.29, SCCS = 2.42, BSCS = 2.92, ALS = 2.91.

**Dynamic factor model.** The autoregressive model fit participant 2’s data well (see Figure 5), so no further modifications were made to the AR(1) model. However, most individual parameter estimates in the model were not significantly different from zero, including the autoregressive relationships between impulsivity and identity disturbance and these variables at
the next measurement occasion (an interval of 6840s separated time points for this participant).

Anger at time $t$ did predict levels of anger at the next time point, unstandardized $\beta = 0.25$, $t = 2.68$, $p = .009$. Anger was also positively related to impulsivity in synchronic ratings, $\psi = 72.55$, $t = 3.02$, $p = .003$.

**Periodic trends.** A significant periodic trend was found for participant 2’s identity disturbance data over the 20 days of the diary period, $b_{\text{cos}} = 2.79$, $t = 2.30$, $p = 0.02$. The trend analysis suggested that this participant’s identity disturbance peaked roughly halfway through the day and that the oscillation had a fairly small amplitude (2.95 on a 0-100 scale). A sensitivity analysis of this participant’s data using the residuals from the trend analysis suggested that the above dynamic factor model did not fit as well after taking this trend into account, $\chi^2(6) = 7.81$, $p = 0.25$, CFI = 0.94, NNFI = 0.85, SRMR = 0.060, RMSEA = 0.055. The greatest modification index from this analysis was the lagged relationship between identity disturbance (at time $t$) and anger at time $t + 1$. Adding this parameter to the model improved fit to acceptable levels, $\chi^2(6) = 7.81$, $p = 0.25$, CFI = 0.94, NNFI = 0.85, SRMR = 0.060, RMSEA = 0.055, although the added parameter was not significantly different from zero, $\beta = 0.08$, $t = 1.65$, $p = .10$. Time $t$ variance accounted for a relatively small portion of $t + 1$ variance in anger, impulsivity, and residual identity disturbance ratings (6%, 2%, and 1%, respectively). Figure 6 shows participant 2’s final model.

**Participant 3.**

**Diagnosis and baseline characteristics.** Participant 3 was a 46-year-old married Caucasian woman who identified as heterosexual. She was recruited through clinic intake and diagnosed with BPD without a diagnosis on Axis I. She met six BPD criteria: unstable and intense interpersonal relationships, identity disturbance, chronic suicidality, affective instability,
feelings of emptiness, and intense anger. She also received subthreshold scores on two other
criteria, giving her a dimensional score of 14 on the IPDE, and she endorsed 9 items on the MSI-
BPD. Her GAF score was 55. Her scores on baseline self-report measures were as follows:
GAPD = 1.82, SCCS = 1.92, BSCS = 2.08, ALS = 3.19.

Dynamic factor model. The AR(1) model for participant 3’s data showed poor fit on
most fit indices, $\chi^2(6) = 22.32$, CFI = 0.95, NNFI = 0.88, SRMR = 0.15, RMSEA = 0.16. A step-
by-step modification of the model based on modification indices resulted in the addition of two
cross-lagged parameters. This partial VAR(1) model suggested that, for this participant, higher levels of anger predicted higher levels of impulsivity and higher levels of identity disturbance 6480 seconds later. All variables were positively related in synchronic ratings. In addition, this model suggested that participant 3 was not consistent in levels of anger, impulsivity, and identity disturbance from one occasion to the next, as autoregressive relationships were not significant.

**Periodic Trends.** The trend analysis showed a significant periodic trend in participant 3’s identity disturbance scores, $b_{\sin} = -4.38$, $t = 3.01$, $p = 0.003$. The trend predicted a peak in identity disturbance in mid-morning with an amplitude of 4.5 additional units of identity disturbance on a 0-100 scale. In addition, a significant periodic trend was observed in this participant’s impulsivity scores, $b_{\sin} = -2.76$, $t = 2.16$, $p = 0.03$, with an amplitude of 3.02 units and a maximum in impulsivity about one-third of the way through the day. The dynamic factor model fit to participant 3’s raw data also showed good fit when the residual identity disturbance and impulsivity values were used, $\chi^2(4) = 2.80$, CFI = 1.00, NNFI = 1.00, SRMR = 0.024, RMSEA = 0.0. Thus, the model was retained (Figure 7). Time $t$ variance accounted for a negligible portion of variance in participant 3’s $t + 1$ anger ratings but did account for substantial portions of $t + 1$ impulsivity (15% of the variance) and identity disturbance (23% of the variance).

**Participant 4.**

**Diagnosis and baseline characteristics.** Participant 4 was a 34-year-old single Caucasian woman who identified as bisexual. She was recruited through clinic intake and diagnosed with recurrent MDD of mild severity, chronic PTSD, and generalized anxiety disorder on Axis I. She also met three criteria for BPD on Axis II (impulsivity, suicidality or parasuicidality, and chronic
Figure 7. Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #3. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model (p > .05). ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between t and t + 1 is 6480s.

feelings of emptiness) and received subthreshold scores on five other criteria, giving her an IPDE dimensional score of 11. She endorsed 4 items on the MSI-BPD and had a GAF score of 65. Her scores on baseline self-report measures were: GAPD = 3.22, SCCS = 3.67, BSCS = 2.92, ALS = 2.06.

**Dynamic factor model.** The baseline AR(1) model showed inadequate fit to participant 4’s data, $\chi^2(6) = 16.10$, CFI = 0.92, NNFI = 0.79, SRMR = 0.070, RMSEA = 0.13. Modification led the addition of three cross-lagged parameters. In the final model (Figure 8), participant 4’s initial levels of impulsivity predicted impulsivity 5520 seconds later, and impulsivity also
predicted anger at the later time point. Although identity disturbance at time $t$ did not significantly predict identity disturbance at time $t + 1$, it did negatively predict later anger. There was a significant autocorrelative relationship between anger at successive time points. The model also required a cross-lagged regression of identity disturbance on earlier anger scores, although this parameter value itself was not significantly different than 0, unstandardized $\beta = 0.13$, $t = 1.75$, $p = .08$. Time $t$ values accounted for 20%, 4%, and 4% of time $t + 1$ variance in anger, impulsivity, and identity disturbance, respectively.

![Diagram](image)

**Figure 8.** Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #4. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model ($p > .05$). ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between $t$ and $t + 1$ is 5520s. * $p < .05$. ** $p < .01$. *** $p < .001$. 
**Periodic trends.** The trend analysis did not suggest the presence of a periodic trend in anger, impulsivity, or identity disturbance for participant 4.

**Participant 5.**

**Diagnosis and baseline characteristics.** Participant 5 was a 27-year-old Caucasian woman who identified as bisexual and gave her relationship status as “dating.” She was recruited through clinic intake and diagnosed with MDD and social phobia on Axis I and avoidant personality disorder on Axis II. She met two BPD criteria: chronic feelings of emptiness and recurrent suicidal behavior. Her BPD dimensional score on the IPDE was 7, and her GAF score was 45. Her scores on baseline self-report measures were as follows: GAPD = 2.37, SCCS = 2.75, BSCS = 1.85, ALS = 2.59. She endorsed 5 items on the MSI-BPD.

**Dynamic factor model.** The baseline AR(1) model showed good fit for participant 5’s data. However, the autoregressive parameter values were not significant, suggesting that participant 5’s levels of anger, impulsivity, and identity disturbance did not relate to levels of these variables 7000 seconds later. Anger was not significantly related to either synchronous impulsivity or synchronous identity disturbance in the final model, but impulsivity and identity disturbance were modestly and positively related.

**Periodic trends.** The trend analysis suggested a periodic trend in participant 5’s identity disturbance levels, $b_{\sin} = -4.45$, $t = 2.52$, $p = 0.01$. The periodic function had an estimated amplitude of 4.81 and a peak identity disturbance in late morning. Applying the residual values from this function to the dynamic factor modeling procedure, the AR(1) model no longer showed adequate fit on all indices, $\chi^2(6) = 6.97$, CFI = 0.92, NNFI = 0.81, SRMR = 0.060, RMSEA = 0.042. Modification indices suggested an additional cross-lagged relationship between identity disturbance at time $t$ and impulsivity at time $t + 1$, after which the model fit well on all indices,
\( \chi^2(5) = 3.23, p = 0.66, \text{CFI} = 1.00, \text{NNFI} = 1.00, \text{SRMR} = 0.042, \text{RMSEA} = 0.0. \) However, this additional parameter itself was not significant, unstandardized \( \beta = -0.27, t = 1.97, p = .052. \)

Overall, variance in time \( t \) values accounted for 2%, 5%, and 0% of the \( t + 1 \) variance in anger, impulsivity, and identity disturbance, respectively. Figure 9 shows participant 5’s final dynamic factor model.

**Figure 9.** Dynamic factor model describing the relationship between anger, impulsivity, and the residual values of identity disturbance (after accounting for the circadian trend in identity disturbance), at synchronous and successive time points, for participant #5. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model (\( p > .05 \)). ANG = anger; IMP = impulsivity; ID DIST resid. = residual values of identity disturbance from trend analysis. Interval between \( t \) and \( t + 1 \) is 7000s.

* \( p < .05 \).  ** \( p < .01 \).  *** \( p < .001 \).
Participant 6.

**Diagnosis and baseline characteristics.** Participant 6 was a 20-year-old single Caucasian woman who identified as heterosexual. She was recruited through clinic intake and was diagnosed with social phobia; additionally, bulimia nervosa and binge eating disorder were included as diagnoses to be ruled out. On Axis II, participant 6 qualified for obsessive-compulsive personality disorder and met one BPD criterion (impulsivity). She received a score of 2 on the IPDE BPD dimension. Her scores on baseline self-report measures were: GAPD = 2.75, SCCS = 3.25, BSCS = 2.38, ALS = 2.56. She endorsed 4 items on the MSI-BPD and had a GAF score of 80.

**Dynamic factor model.** The baseline AR(1) model showed good fit for participant 6’s data. However, impulsivity was the only autoregressive parameter to reach significance, unstandardized $\beta = 0.28, t = 2.29, p = .03$. In addition, anger was related to impulsivity in synchronic ratings, unstandardized $\psi = 245.08, t = 2.84, p = .006$. In all, time $t$ variance accounted for 3%, 8%, and 4% of variance in $t + 1$ anger, impulsivity, and identity disturbance, respectively. Figure 10 shows the final dynamic factor model for this participant.

**Periodic trends.** The trend analysis did not suggest a periodic trend in participant 6’s data.

Participant 7.

**Diagnosis and baseline characteristics.** Participant 7 was a 38-year-old single Caucasian woman who identified as heterosexual. She was recruited through previous participation in research and diagnosed with mood disorder NOS on Axis I, with past diagnoses of PTSD and eating disorder NOS. On Axis II, she received diagnoses of BPD and paranoid personality disorder. She met all nine BPD criteria, giving her an IPDE dimensional score of 18, and she
had a GAF score of 35. She endorsed 7 items on the MSI-BPD. Her scores on baseline self-report measures were: GAPD = 2.49, SCCS = 2.33, BCS = 1.85, ALS = 1.91.

Figure 10. Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #6. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model (p > .05). ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between $t$ and $t + 1$ is 6000s.

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

Dynamic factor model. The baseline AR(1) model fit participant 7’s data well, although only impulsivity showed a significant autoregressive character, unstandardized $\beta = 0.29$, $t = 3.17$, $p = .002$. Impulsivity was reliably (and positively) related to synchronous identity disturbance, unstandardized $\psi = 234.61$, $t = 3.99$, $p < .001$. Time $t$ values explained 18, 6, and 10 percent of
variance in $t+1$ ratings of anger, impulsivity, and identity disturbance, respectively. Figure 11 shows the final dynamic factor model for participant 7.

**Periodic trends.** The trend analysis did not reveal any evidence of periodic trends in participant 7’s data.

![Figure 11. Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #7. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model (p > .05). ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between $t$ and $t+1$ is 7000s. * $p < .05$. ** $p < .01$. *** $p < .001$.]
Participant 8.

Diagnosis and baseline characteristics. Participant 8 was a 50-year-old divorced Caucasian woman who identified as heterosexual and also noted that she was in a romantic relationship. She was recruited through previous participation in research. She was diagnosed with recurrent MDD of moderate severity, dysthymic disorder, social phobia, and eating disorder NOS. Although she qualified for an alcohol dependence diagnosis based on her recent history of alcohol use, she was not currently drinking. She met eight BPD criteria (the unmet criterion was inappropriate, intense anger) and received a dimensional score of 17 on the IPDE. However, she only endorsed 4 items on the MSI-BPD. She had a GAF score of 50. Her scores on baseline self-report measures were: GAPD = 2.65, SCCS = 3.33, BSCS = 2.23, ALS = 2.74.

Dynamic factor model. The baseline AR(1) model fit well for participant 8’s data. Each parameter was significant in the model, with reliable autoregressive relationships for anger, impulsivity, and identity disturbance across a 6400-second interval, as well as a positive and moderate correlation between synchronic ratings of anger and impulsivity and positive correlations between identity disturbance and anger and identity disturbance and impulsivity. Variance in time \( t \) values explained 18, 6, and 10 percent of variance in \( t + 1 \) ratings of anger, impulsivity, and identity disturbance, respectively.

Periodic trends. The trend analysis suggested a significant periodic trend in participant 8’s anger ratings, \( b_{\sin} = -6.13, t = 2.27, p = 0.02 \). The regression model showed a peak in participant 8’s anger ratings about 5 hours 20 minutes after the first rating of the day, with an amplitude of 7.02 points on a 0-100 scale. In addition, this participant’s identity disturbance values showed a periodic trend, \( b_{\cos} = 5.54, t = 2.84, p = 0.0053 \), with the wave function showing a peak identity disturbance value at about 9 hours after the first rating of the day with an
amplitude of 5.55 points. Accounting for these trends did not alter the dynamic factor model for this participant (Figure 12).

![Dynamic factor model diagram](image)

*Figure 12. Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #8. Numbers represent completely standardized maximum likelihood parameter estimates. ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between $t$ and $t + 1$ is 6400s. * $p < .05$. ** $p < .01$. *** $p < .001$.*

**Participant 9.**

**Diagnosis and baseline characteristics.** Participant 9 was a 32-year-old single Caucasian man who identified as heterosexual. He was recruited through clinic intake and diagnosed with social phobia. In addition, a single major depressive episode in partial remission was noted, along with a rule-out diagnosis of dysthymic disorder. He received no diagnosis on Axis II and
received a dimensional BPD score of 3 on the IPDE without meeting any BPD criteria. He endorsed 3 items on the MSI-BPD and had a GAF score of 55. His scores on baseline self-report measures were: GAPD = 3.06, SCCS = 4.33, BSCS = 2.23, ALS = 1.20.

**Dynamic factor model.** Participant 9 rated his identity disturbance at 0 on a 0-100 scale at every occasion during the three-week diary period, which was consistent with his score on the 12-item SCCS at baseline (the highest in the sample) and the fact that he did not endorse the identity disturbance item on the MSI-BPD nor meet this criterion based on the diagnostic interview. Because these ratings did not vary over the course of the three weeks, only anger and impulsivity were used in the dynamic factor model. An AR(1) model containing only these two variables at t and t + 1 fit well. Anger and impulsivity both showed significant stability from one occasion to the next (with a 6000-second interval), unstandardized $\beta_{\text{anger}} = 0.42$, $t = 4.95$, $p < .001$ and unstandardized $\beta_{\text{impulsivity}} = 0.31$, $t = 3.40$, $p < .001$. Anger and impulsivity were moderately and positively correlated, unstandardized $\psi = 129.59$, $t = 3.62$, $p < .001$. Approximately 18% and 9% of anger and impulsivity variance at $t + 1$, respectively, was accounted for by ratings at the previous occasion.

**Periodic trends.** Participant 9’s anger showed a significant periodic trend, $b_{\text{sin}} = 9.69$, $t = 3.23$, $p = 0.0016$. According to the regression model, the amplitude of the wave was 9.86 on a 0-100 scale and peaked about 6 hours after the first rating of the day (i.e., mid-afternoon). Impulsivity also displayed a periodic trend, $b_{\text{sin}} = -7.85$, $t = 2.75$, $p = 0.007$. According to the model, participant 8’s impulsivity peaked about 75 minutes after the first rating of the day with an amplitude above the mean of 7.98 points on a 0-100 scale. Adjusting for these trends by using residual values in dynamic factor models resulted in no changes to model parameters relative to the model using raw data, so this model was retained (Figure 13).
Figure 13. Dynamic factor model describing the relationship between anger and impulsivity, at synchronous and successive time points, for participant #9. Numbers represent completely standardized maximum likelihood parameter estimates. ANG = anger; IMP = impulsivity. Interval between $t$ and $t + 1$ is 6000s.

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

Participant 10.

**Diagnosis and baseline characteristics.** Participant 10 was a 28-year-old single woman. She identified as heterosexual and selected three ethnic categories to describe herself: African-American, American Indian/Alaska Native, and Hispanic or Latina. She was recruited through previous research participation. She was diagnosed with dysthymic disorder and received no diagnosis on Axis II. She did not meet any BPD criteria nor receive any subthreshold ratings on the IPDE. She had a GAF score of 75 and endorsed 4 items on the MSI-BPD. Her scores on baseline self-report measures were: GAPD = 3.32, SCCS = 4.17, BSCS = 3.00, ALS = 1.20.

**Dynamic factor model.** The baseline AR(1) model fit the data well for participant 10. However, only anger showed a significant autoregressive relationship across 7000-second intervals, unstandardized $\beta = 0.47$, $t = 5.24$, $p < .001$. In addition, impulsivity and identity
disturbance were positively correlated in synchronic ratings, unstandardized $\psi = 12.79$, $t = 2.45$, $p = .02$. None of the other model parameters were significantly different from 0. Anger at time $t$ accounted for 22% of the variance in anger at $t + 1$, whereas impulsivity and identity disturbance showed lower stability.

**Trend analysis.** The trend analysis did not reveal any evidence of periodic trends in participant 10’s data, and so the AR(1) model was retained (Figure 14).

* Figure 14. Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #10. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model ($p > .05$). ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between $t$ and $t + 1$ is 7000s.
  
  * $p < .05$. ** $p < .01$. *** $p < .001$. 
Participant 11.

**Diagnosis and baseline characteristics.** Participant 4 was a 40-year-old divorced African-American woman who identified as heterosexual. She was recruited through previous research participation and diagnosed with recurrent major depressive disorder of moderate severity. She met two BPD criteria, identity disturbance and stress-related paranoid ideation, and she received an IPDE dimensional score of 6. Her GAF score was 55, and her scores on baseline self-report measures were: GAPD = 2.05, SCCS = 2.17, BSCS = 3.31, ALS = 3.83. She endorsed 5 items on the MSI-BPD.

**Dynamic factor model.** The AR(1) model fit participant 11’s data well, although none of the autoregressive parameters were significantly different from 0. Only 2% of anger and impulsivity ratings at \( t + 1 \) were accounted for by earlier ratings, and a negligible portion of the variance in identity disturbance was accounted for by earlier ratings. Only impulsivity and identity disturbance showed significant relationships in synchronic ratings, unstandardized \( \psi = 104.10, t = 3.20, p = .002 \). Figure 15 shows the final dynamic factor model for Participant 11.

**Trend analysis.** The trend analysis did not reveal any evidence of periodic trends in participant 11’s data.

**General Results**

Dynamic factor modeling revealed a wide variety of relationships between anger, impulsivity, and identity disturbance, both in synchronous ratings and over time intervals of approximately 1.5-2 hours. For six individuals, an autoregressive model was sufficient to describe the variation in these symptoms from one measurement occasion to the next, although the parameter values of the autoregressive relationships themselves varied considerably. For the other five individuals, cross-lagged relationships between one symptom at one occasion and a
second symptom at the next occasion were required to achieve good model fit. Within these VAR(1) models, there was not a consistent relationship between identity disturbance and the other symptoms. In two individuals, identity disturbance negatively predicted later anger or impulsivity; in one, identity disturbance followed (but did not precede) feelings of anger; and in the remaining two participants, identity disturbance did not show a lagged relationship with the other BPD symptoms. In general, identity problems tended to be positively correlated with synchronous anger and impulsivity, although the magnitude of these relationships also varied. Overall, the results suggested that there was not a consistent relationship between identity  

Figure 15. Dynamic factor model describing the relationship between anger, impulsivity, and identity disturbance, at synchronous and successive time points, for participant #11. Numbers represent completely standardized maximum likelihood parameter estimates. Dashed lines indicate nonsignificant parameters retained in the final model ($p > .05$). ANG = anger; IMP = impulsivity; ID DIST = identity disturbance. Interval between $t$ and $t + 1$ is 7000s. * $p < .05$. ** $p < .01$. *** $p < .001$. 
disturbance and the BPD symptoms of anger and impulsivity, although isolated cases conformed to the theoretical models posited by psychodynamic (e.g., Kernberg, 1984) and behavioral (e.g., Linehan, 1993) theorists. The presence or absence of a DSM-IV BPD diagnosis did not seem to make a difference in the dynamic factor model adopted.
Chapter 4

Discussion

The present study represents a preliminary effort to apply person-specific modeling approaches to ecological momentary assessment data in individuals with BPD. The aims of the current study were to investigate the dynamic relationship of subjective identity disturbance to anger and impulsivity and to explore whether these relationships were similar across individuals with, and without, a diagnosis of BPD. The dynamic factor models varied in their resemblance to the models postulated on the basis of prior theories. Hypothesis 1, based on the psychodynamic notion that identity disturbance is a “core” symptom of BPD that accounts for the appearance of the other symptoms, was supported in two of 11 participants. For these individuals, the experience of identity disturbance negatively predicted the later appearance of anger or impulsivity. Hypothesis 2, that identity disturbance is primarily the result of behavioral and affective instability rather than their cause, was supported in one individual, whose sense of self-concept clarity decreased after an earlier increase in anger. Otherwise, there were no individuals for whom identity disturbance varied with anger and impulsivity in line with these prominent theories. Thus, the results failed to support either hypothesis in the majority of the sample. However, results suggested that there is a good deal of heterogeneity between individuals in the nature and strength of the relationships between these three BPD symptoms over time, in line with hypothesis 3. Finally, contrary to hypothesis 4, there was little indication in the present data that the type of model or the extent of the relationships between the three symptoms depended on the presence or absence of a BPD diagnosis.

The results showed that identity disturbance has a complex and varied temporal relationship with other BPD symptoms. Interestingly, identity disturbance was sometimes
negatively related to later expressions of anger and impulsivity in the dynamic factor models. The direction of this relationship is consistent with the notion that a temporary sense of self-concept clarity can precede affective and behavioral dysregulation (Fonagy, Gergely, Jurist, & Target, 2004). It may be for example, that a temporary, and illusory, subjective sense of self-concept clarity arises in some individuals with BPD because they engage in the defensive strategy of splitting (Kernberg, 1984): they keep positive and negative aspects of their self-concept separate and thus do not have access to self-information that might help them self-regulate (Lumsden, 1993). Thus, they may be more vulnerable to extreme behaviors when their sense of self is more secure.

The results also provide support for the notion that the subjective experience of self-concept clarity can be dissociated from the more trait-like and structural construct of “identity diffusion” or “identity disturbance” proposed by clinical authors and captured in the DSM. This distinction is in line with findings in social-psychological research (Ayduk, Gyurak, & Luerssen, 2009; Boyce, 2008; Nezlek & Plesko, 2001). The construct assessed in the current study is likely to conform to the former in its direct assessment of momentary and subjective sense of self, which did vary substantially in 10 of 11 participants. In contrast, the latter may be best assessed by an observer (such as a clinician), who can witness seemingly contradictory statements about goals, values, and other self-defining attributes over time, even as the individual may not be aware of this variation. A clinician may also infer the presence of structural identity disturbance from an individual’s history of erratic investment in different roles, vocational and social pursuits, and relationships (Kernberg, 1984, 2006; Stern et al., 2010), even if the individual draws a strong sense of identity from these activities at the time.
In addition, in one individual, identity disturbance was the sequel of earlier anger (and in another participant this relationship was present in the final model but did not reach significance). This relationship provides limited support for the idea that identity disturbance can be a temporary consequence of emotion dysregulation (Linehan, 1993). Longitudinal tests of this proposition would be helpful. Also useful would be direct experimental tests of the relationship between emotional and behavioral dysregulation and later self-concept. For example, recent studies have shown that impulsivity can be induced in laboratory tasks, producing a tendency to indulge in maladaptive eating and substance use (Guerrieri, Nederkoorn, Schrooten, Martijn, & Jansen, 2009; Jones et al., 2011). Anger inductions through exposure to provocative stimuli, harassment by a confederate, punishment by another participant, stress interview, and environmental manipulation also have a rich history in laboratory settings (Lobbestael, Arntz, & Wiers, 2008). It would be instructive to see how momentary self-concept clarity is affected by these experimental manipulations.

Despite the presence of a few individuals in the sample who showed these hypothesized relationships, most participants did not show a lagged relationship between identity disturbance and the other variables, although synchronous relationships were common. For them, symptoms did not show a dynamic relationship across the time intervals in the current study. This seems consistent with the model of BPD presented in DSM, in which the disorder is described by a temporally stable cluster of symptoms that do not necessarily influence one another. However, the stability of these models, as indicated by the residual variance of anger, impulsivity, and identity disturbance at \( t + 1 \), was generally fairly low, suggesting that the autoregressive models did not account very well for these variables’ values over time. In addition, the autoregressive parameters themselves were often not significantly different from zero. It could be that the
experience of anger, impulsivity, and identity disturbance is not stable for these individuals or that it depends on contextual factors or other psychological experiences not measured in the current study.

It did not seem that the models describing the dynamic relationships between anger, impulsivity, and identity disturbance depended on the presence or absence of a DSM diagnosis of BPD, as some participants without BPD demonstrated dynamic relationships between anger, impulsivity, and identity disturbance, and some participants with the diagnosis did not show evidence of these relationships. The significance of this finding is unclear, however, given the small sample size and the absence of explicit statistical comparisons between individuals or groups. It is also true that many participants without BPD in the current study met some number of criteria for the disorder. In fact, the median number of BPD criteria met by these seven individuals was 2. Research indicates that the presence of even one BPD criterion is associated with greater levels of functional impairment and suicidality and a greater likelihood of psychiatric hospitalization (Zimmerman, Chelminski, Young, Dalrymple, & Martinez, 2012), suggesting that even at subthreshold levels, BPD symptoms may have important consequences. It should also be noted that the DSM differentiates individuals with BPD on the basis of symptomatic level, not on the covariation of symptoms with one another (as in the current study). This leaves open the possibility that diagnostic groups could be differentiated in the current data by the severity of these symptoms or in their functional consequences for the individual, both of which are clearly important considerations.

Nevertheless, given the presence of subthreshold BPD traits in much the sample and the fact that dynamic relationships between these symptoms could sometimes be found in the absence of the disorder itself, the current results raise the possibility that the pathological
processes involved in BPD may cross diagnostic lines. This finding has implications for evolving nosological systems. Disorders in the *DSM* are often presumed to operate as latent entities, based in underlying physiological, neuroanatomical, or psychological mechanisms, that cause the appearance of observable “symptoms.” This assumption is made explicit, for example, in factor analyses of the symptom clusters that purport to test the validity of these diagnoses (e.g., Blais, Hilsenroth, & Castlebury, 1997). However, influential critics of the *DSM* diagnostic system have recently argued that a scientific nosology should reflect fundamental neurobiological and psychological mechanisms of dysfunction (e.g., Cuthbert & Insel, 2012; Kendler, Zachar, & Craver, 2011). The present findings suggest that relationships between anger, impulsivity, and identity pathology may cut across *DSM-IV* categories.

As noted above, this does not in itself argue against the validity of these diagnoses, which generally refer more to the mean levels of these symptoms within an individual rather than an essential pattern of their covariation over time. However, a number of researchers have recently begun to conceptualize psychopathology from the bottom up, viewing symptoms themselves as important entities that interrelate over time, may be reciprocally causal, and cross standard diagnostic boundaries (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011; Bringmann et al., 2013; Kendler, Zachar, & Craver, 2011; van Os, Delespaul, Wigman, Myin-Germeys, & Wichers, 2013; Wichers, in press; Wigman et al., 2013). Some of these researchers have proposed that these symptom networks might eventually supplant diagnostic systems such as the *DSM* (e.g., Wichers, 2013). EMA methods may aid in the construction of these symptom networks given that individual symptoms can be assessed more unobtrusively than disorders (the diagnosis of which requires inquiry about several symptoms at once), making them easy to capture in real-life contexts, and because causal modeling generally requires longitudinal
assessments of relatively high frequency. The severity of various symptoms could also be captured in these models (e.g., Bringmann et al., 2013), which would provide valuable information about which symptoms are most extreme. An approach taking both symptom severity and covariation into account would likely be of the greatest theoretical and clinical utility.

The results also point to the heterogeneity of longitudinal variation in BPD symptoms within individuals. Thus, the current results support the notion that models of intraindividual variation reveal heterogeneity among individuals that may not be apparent in nomothetic models of psychological processes. Identity disturbance may positively predict emotional and behavioral disturbance in some individuals, whereas it may relate negatively to these symptoms of BPD in others. It may also be a cause of these phenomena in some but an effect of them in others. In short, it is possible that multiple theoretically derived models of the mechanisms of BPD hold true simultaneously within different subgroups of BPD patients. In principle, it could be possible for some of the data derived from previous EMA studies of BPD (e.g., Berenson, Downey, Rafaeli, Coifman, & Paquin, 2011) to be re-analyzed using person-specific techniques. This could reveal whether the models derived from the interindividual and groupwise analyses also describe intraindividual variation with uniformity. The possibility of such a secondary analysis in any given study depends on the suitability of the data structure, adequate power, and longitudinal coverage of the variables of interest, but the heterogeneity revealed in the present data suggests that it could be scientifically important.

Thanks to recent developments in person-specific methods, it may now be possible to conduct analyses of intraindividual variation that both respect heterogeneity between individuals and lead to nomothetic models that can be applied to broader populations or subgroups. For
example, Gates and Molenaar (2012) describe an iterative method whereby overall group structures are first derived that work well for the majority of individuals, and then individual paths are allowed. This approach was shown to work for fMRI data from homogeneous and heterogeneous groups. In a similar vein, Bringmann et al. (2013) combined an intraindividual and interindividual approach by creating multilevel VAR models of emotion data, collected using EMA, among 129 participants with residual depression. The authors then submitted these models to a network analysis to estimate the average connection strength of the emotion variables, leading to an overall model of pathology. An approach similar to these, suitably applied to EMA data, might allow future researchers to account for the person-specificity of BPD dynamics while also creating models that apply generally to everyone with BPD, or to subgroups of individuals with the disorder.

The current results also have several clinical implications. First, they highlight that not every individual with BPD is the same and suggest that clinicians should pay attention to the idiographic, dynamic relationships between symptoms of the disorder. This would be fairly easy to integrate into several empirically-supported treatments for BPD, many of which already have therapists and clients monitor different phenomena as they unfold over time in order to plan interventions and foster insight. For example, clients participating in Dialectical Behavior Therapy (DBT; Linehan, 1993) are asked to complete “diary cards” by rating different symptoms of BPD, affective states, behaviors, impulsive urges, and the like on a daily basis. These records are then used to analyze chains of behavior in order to identify problematic patterns and to suggest ways of disrupting them. In this way, DBT interventions are tailored to each individual, but the process of gathering these diary data is lengthy, taking on the order of months. Using EMA data to monitor these patterns could make this system more time-effective, and dynamic
factor analysis could lend statistical rigor to the normally impressionistic system of behavioral chain analysis. Interventions could also be introduced into the statistical model to examine the effect of particular session-to-session therapist actions on the individual’s pathology (see, e.g., Gates, Molenaar, Hillary, & Slobounov, 2011).

The advent of increasingly affordable and powerful mobile technologies and the development of data-analytic techniques to model the resultant data have also led some researchers to advocate for an entirely person-specific approach to diagnosis, based on reciprocal interactions between affective states and behaviors instead of on symptom checklists (van Os et al., 2013). This “precision diagnosis” approach could potentially empower clients as they participate in collecting and interpreting experience-near diagnostic data and would also lead naturally into interventions to counter pathological relationships between symptoms. Similar appeals have been made for the development of person-specific methods of personality assessment (Caldwell, Cervone, & Rubin, 2008; Haynes, Mumma, & Pinson, 2009). The current results show that basic person-specific approaches to understanding the dynamics of psychopathology can be implemented fairly easily using readily available software. The utility of these methods for diagnosis and assessment in clinical settings may depend on clinicians’ ability to select a limited number of relevant symptoms for a given client, so that ecological validity can be maximized and intervals between assessments can be minimized.

Individual differences derived from these assessments might be very useful for the practice of psychotherapy. For example, variability in extraversion over time may reflect an individual’s reactivity to situational cues calling for extraverted behavior (Fleeson, 2001). Similarly, the stability of dynamic processes between BPD symptoms may indicate how amenable a client might be to disruptions in these processes by a skilled therapist (Fisher et al.,
If multiple processes are evident, a therapist might select a therapy target according to the process most likely to be affected by deliberate interventions. Similarly, EMA data might be used to derive prescriptive recommendations for one therapy over another, depending on the processes that might be targeted by different therapies. For example, if an individual’s self-concept incoherence appeared to be driving later impulsive or self-injurious behaviors or emotion dysregulation, a therapy targeting the client’s sense of self (such as Transference-Focused Psychotherapy; Clarkin, Yeomans, & Kernberg, 2006) might be most appropriate. On the other hand, a therapy targeting behavioral or emotional dysregulation directly (such as DBT) might be the best choice for a client whose identity disturbance appeared to be the product of these other symptoms. EMA data might also be profitably used to monitor the outcome of psychotherapy by examining the degree to which therapy clients’ pathological processes (measured before therapy) change as a result of therapeutic intervention (Fisher et al.; Piasecki, Hufford, Solhan, & Trull, 2007). Such data might also be used to understand psychotherapy process by helping to quantify dynamic processes that are hypothesized to mediate between therapy techniques and outcomes (e.g., Gunthert, Cohen, Butler, & Beck, 2005).

Several limitations of the current study deserve mention. One potential limitation is in the frequency of the observations taken during the EMA sampling period. In order to accurately model the processes of interest in BPD, data must be collected at an adequate frequency (Collins, 2006). More precisely, modeling a process requires sampling at twice the frequency of the process itself (e.g., Shannon, 1949/1998). The 1-2 hour interval between observations in the current study raises the possibility that important processes that occurred at a greater frequency were not captured. For example, Ebner-Priemer and Sawitski (2007) have demonstrated, using an EMA paradigm, that a specific affective process among individuals with BPD is only
captured when 15-30 minute sampling intervals are used. Although the current study did not seek to capture this particular process, future research with smaller sampling intervals, as well as techniques for analyzing process speed in EMA data (Shiyko & Ram, 2011), would be helpful in discerning whether smaller sampling intervals are necessary to tap important dynamics among the BPD symptoms involved in this study. Previous research has also uncovered the existence of several processes of affective instability at varying frequencies within BPD samples (Nisenbaum et al., 2010), and it is possible that the frequency of these processes varies from individual to individual. If the present data are robust, they point to the presence of potentially important psychological processes occurring over a span of 90-120 minutes involving anger, impulsivity, and identity disturbance in some individuals. However, it is also possible that at least some of the observed correlations between variables that were measured synchronously in the current study actually represent non-contemporaneous relationships between variables that occur at a smaller timescale.

A second limitation of the current study concerns measurement within the EMA sampling protocol. The psychometric properties (that is, the reliability and validity) of the self-report questions given during the EMA portion of the study are difficult to determine. In order to maximize ecological validity by minimizing the time burden of completing surveys, the constructs in the EMA surveys were operationalized with only one self-report question each. Single questions preclude the possibility of bolstering construct validity via aggregation and are thus not generally optimally reliable or valid measures of constructs. The current study adopted the single-item strategy in order to maximize the ecological validity of the EMA protocol, and the tradeoff between ecological validity and construct validity in EMA research is a widely recognized one (Bolger et al., 2003; Csikszentmihalyi & Larson, 1987; Shiffman et al., 2008).
without a consensus solution. However, multi-item measures of anger, impulsivity, and identity disturbance would be preferable as measures of these phenomena, at least in terms of reliability of measurement. In addition, the measurement of impulsivity by self-report is particularly challenging because these measures show an uncertain relationship with behavioral measures of impulsivity (Cyders & Coskunpinar, 2011; Meda et al., 2009; Reynolds, Ortengren, Richards, & deWit, 2006). Thus, the correspondence between the self-report ratings of impulsivity used in the current study and actual impulsive behaviors is not clear.

A third limitation of the current study is its power. The 11 participants in the sample each provided enough EMA data to estimate the fit of dynamic factor models. However, the power needed for examination of model fit is not necessarily the same as power needed to avoid type II errors in the detection of significant parameter values within the model. This might be a reason why several models required parameter estimates for good fit that were not themselves significantly different from zero. It is also possible that additional power would afford the opportunity to detect other synchronous and lagged relationships in these time series that were not apparent using the current data. In addition, the relatively limited sample of individuals in the current study precludes any direct statistical estimation of commonalities between these individuals in their model parameters. Techniques are being developed to allow for the estimation of parameters that apply across groups, even as person-specific parameters are also allowed (e.g., Gates & Molenaar, 2012), but the small sample size precludes their use in the current study.

Finally, the person-specific approach used in the current study is not without its limitations. For example, as stated above, the dynamic factor modeling approach required the assumption of weak stationarity in the data, which may not be strictly tenable given that several
individuals in the sample had just received preliminary attention in a psychiatric setting, which can be a time of rapid symptom change (Hansen, Lambert, & Forman, 2002; Howard, Kopta, Krause, & Orlinsky, 1986; Kopta, Howard, Lowry, & Beutler, 1994). Psychotherapy may have also had effects on the covariance of these symptoms over the three-week smartphone period. In addition, the relatively small number of participants in the current sample made comparison between models and generalization to the broader population difficult. Nevertheless, methods have been developed to retain a person-specific approach while dealing with several of these limitations. For example, Molenaar et al. (2009) describe an approach to time series modeling that does not require weakly stationary data. Another extension of the basic dynamic factor modeling approach used in the current paper allows for large numbers of variables (Zuur, Fryer, Jolliffe, Dekker, & Beukema, 2003), which might be helpful for examining transdiagnostic sets of symptoms instead of beginning from within the BPD criterion set, as in the current paper.

Given the prevalence of BPD as well as its debilitating nature and its direct and indirect costs, it is vital to understand properly and to treat effectively. The current study is, to my knowledge, the first to apply dynamic factor modeling to EMA data with individuals with BPD. As such, it presents a statistically rigorous method for modeling the dynamic processes of the disorder, one person at a time, using a promising data-collection technique. These models can then be aggregated to delineate subgroups or to create models that work optimally well for most individuals (e.g., Gates & Molenaar, 2012), a criterion that is scientifically important due to the high level of heterogeneity within BPD. This modeling approach also has the potential to fulfill recent appeals for a psychiatric nosology based on neurobiological and behavioral systems (e.g., Cuthbert & Insel, 2012) because of its data-driven, bottom-up construction, and it may be feasible as a diagnostic or outcome-monitoring system in clinical practice as well. Finally, this
approach also makes it possible to test hypotheses derived from clinical theory by modeling predicted patterns of symptom dynamics over time. The current results do not fully support the dynamic models derived from either prominent psychodynamic or behavioral conceptualizations of BPD, although they indicate that certain individuals may obey these patterns. Further research will be needed to ascertain how often theorized symptom dynamics can be recovered under different sampling conditions.
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