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Abstract

Theoretical models of personality disorders can be complex and multifaceted, making it difficult to validate such models in a comprehensive, empirical fashion. One such model of borderline personality disorder (BPD) is the Emotional Cascade Model (Selby & Joiner, 2009), which has garnered empirical support in piecemeal fashion, but has not been examined in a gestalt fashion. One way to test comprehensive models of personality pathology is with Temporal Bayesian Network (TBN) modeling, in which the relations between multiple subcomponents of a model can be specified and examined over a dynamic time frame, allowing for the modeling of positive feedback processes in addition to comprehensive model utility. In this study we applied TBN modeling to examine the Emotional Cascade Model in a sample of adolescents and young adults who actively self-injure, including those with BPD. TBN modeling was applied to ecological momentary assessment data provided via participant smartphone assessments for a period of two weeks. TBN analysis suggested that the emotional cascade model has considerable predictive utility, demonstrating substantial accuracy in predicting BPD diagnosis (with accuracy estimates around 90%) and momentary prediction of rumination, negative emotion, and dysregulated behaviors (with accuracy estimates consistently above 70% and reaching up to 100%, depending on the level of momentary prediction specificity). These findings provide support and validity to the notion that BPD may emerge from a dynamic interplay between emotional cascades and dysregulated behaviors. Implications of TBN modeling of BPD and personality disorders, in general, are discussed.

Keywords: borderline personality disorder; emotional cascade model; Bayesian network modeling, ecological momentary assessment, personality disorder modeling

A critical component of the scientific process within the field of personality psychopathology is the generation and evaluation of evidence-driven models of psychological dysfunction. Until recently, research approaches to personality psychopathology models have been primarily restricted to theoretical and logical evaluation, paired with piecemeal empirical testing of limited parts of these models. Fortunately, even with such limited approaches, researchers have established many useful models of personality dysfunction that have evidentiary support, using data derived from multiple methodologies (e.g., longitudinal, biological, experimental). However, despite such progress, the field continues to face limitations in the way that it can evaluate complex models, especially in a manner that incorporates data from various model components simultaneously. One major restraint to the evaluation of our models is that traditional statistical hypothesis testing (e.g., classical or frequentist approaches) requires certain assumptions about models, but in reality, such restrictions often make the real world conform to our modeling methods, rather than the other way around. Specific problems with frequentist assumptions include: challenges related to non-normally distributed outcome variables, nonlinearity of variable relationships, inability to model bidirectional feedback of variables, and a static versus dynamic view of variable relationships over time. Essentially, trying to test complex, dynamic models of psychopathology within traditional analytic frameworks may result in unnecessary, unfavorable, or even adverse model constraints.

In comparison to classical statistical approaches, Bayesian modeling techniques do not require many of these same assumptions, and instead aim to piece the data together in a model that maximizes consistency with what the data are actually revealing. Such an approach allows for investigation of the model as a *whole*, evaluation of one part of the model while constraining another part of the model, and investigation of specific outcomes or accuracy of the predictive model. Fortunately, the field is beginning to incorporate more Bayesian-style techniques into psychopathology modeling. For example, Bayesian Networks, and their ability to support causal inference, were recently discussed as part of an overview of *Network Modeling* applications in psychopathology (McNally, 2016). However, while Network Modeling represents a significant advance in the field, it is really just the tip of the iceberg, so to speak, for the power that Bayesian Network approaches promise. The purpose of the present investigation was to apply Temporal Bayesian Network (TBN)[1] modeling techniques, which are particularly well suited to incorporating time and feedback features, to an investigation of the *Emotional Cascade Model* of borderline personality disorder (Selby, Anestis, & Joiner, 2008; Selby & Joiner, 2009), a model with a growing evidence base and which lends itself well to investigation with TBN techniques.

The Emotional Cascade Model and Borderline Personality Disorder

The *Emotional Cascade Model* (ECM) has been postulated as a broad model for understanding the interplay between intense negative emotional states and dysregulated behaviors, including but not limited to binge eating, nonsuicidal self-injury, substance use, and aggressive behavior (Selby, Anestis, & Joiner, 2008). Specifically, the model postulates that a process may occur in which a vulnerable individual experiences negative emotion in response to an event, and then ruminates in response to that negative emotion. Rumination (Nolen-Hoeksema, 1991) refers to a cognitive process in which an individual engages in repetitive thinking about the negative event, including focusing on the causes, consequences, and internal reactions to the event. The process of rumination is thought to increase the amplitude of negative emotion, and as the intensity of negative emotion increases, the intensity of rumination increases

[1] Please note that we use the specifier "Temporal" to describe a Bayesian Network (BN) model that incorporates time dependence. A similar term "Dynamic BN" is sometimes applied to a TBN with additional restrictions on its parameters (Koller, & Fiedman, 2009). Leaving the technical details of the difference between TBNs and DBNs outside the scope of this paper, the more general term TBN is used throughout this paper.

as well. Ultimately, this positive feedback process between negative emotion and rumination results in progressively intensifying levels of both negative emotion and rumination, resulting in a particularly aversive experience termed an “emotional cascade” (Selby, Anestis, & Joiner, 2008). It is at the height of such an emotional cascade that many dysregulated behaviors may play a role, as many people often report utilizing dysregulated behaviors in moments of elevated emotional distress (Selby & Joiner, 2009). The intense physical sensations of dysregulated behaviors (e.g., taste from food or physical pain from self-injury; Selby et al., 2019; Kranzler et al., 2017) may then shift cognitive attention away from the ruminative process, and onto the physical sensation. By shifting cognitive attention to physical sensations, the emotional cascade is short-circuited, resulting in a reduction in negative emotion and immediate feelings of relief.

Ongoing research on the ECM has provided growing support for the validity of the model. Studies using cross-sectional data with high risk and clinical populations have found evidence for connections between rumination, negative emotion, and dysregulated behaviors using model-based traditional statistical approaches (Selby, Anestis & Joiner, 2008; Selby, Anestis, Bender, & Joiner, 2009; Tuna & Bozo, 2014). Experimental data (including those with diagnoses of borderline personality disorder) has demonstrated that those at high risk demonstrated a stronger reaction to a lab-based rumination induction than control participants did (Selby, Anestis, Bender, & Joiner, 2009). The ECM has also been tested with longitudinal data through the use of ecological momentary assessment (EMA) methods, in which participants provide “real world” data from their lives by responding to multiple assessments every day via mobile device (such as a smartphone), typically for a period of one to two weeks. Selby & Joiner (2013) demonstrated that increases in negative emotion and rumination reported at one time during the day worked in a synergistic fashion to predict the occurrence of a subsequent dysregulated behavior within a period of just a few hours later. Utilizing these same data, Selby and colleagues (2016) further demonstrated that rumination and negative emotion indeed had positive feedback effects on each other over time, such that an exponential growth function was supported to describe the effects of rumination and negative emotion on each other. In these situations, risk for behavioral dysregulation increased exponentially as well, especially for those with a borderline personality disorder diagnosis. Finally, although the ECM has been postulated to be a broad model for dysregulated behavior, it has also been applied specifically to borderline personality disorder, with Selby & Joiner (2009) hypothesizing that this disorder may arise when an individual has frequent experiences with emotional cascades and dysregulated behaviors. The potential for emotional cascades to be particularly important in BPD has been supported by numerous studies (Selby et al., 2009; 2013; 2016; Martino et al., 2018; Meaney et al., 2016; Tuna & Bozo, 2014). Thus, there may be some degree of diagnostic specificity of the ECM to borderline personality, relative to other disorders such as depression or posttraumatic disorder.

Though existing data support the ECM, the findings are still far from conclusive that emotional cascades exist or that they are a primary cause of dysregulated behaviors. Support for the ECM would improve with additional research and replications, but current statistical approaches used to evaluate the model remain limited in important ways. One particular challenge is that the ECM posits that there are simultaneous, bidirectional effects of rumination and negative emotion on each other over time, which remains difficult to provide evidence for. Most past research has examined the connection between rumination and negative emotion across just two consecutive time points, however, there may also be residual effects between these variables from one recording to the next over multiple recordings. No studies to date have examined the dynamic interplay between rumination and negative emotion, as well as their residuals, on dysregulated behaviors across multiple daily observations. One of the reasons that such a model has not yet been explored is because it represents too many observed variables, autocorrelation between those variables, and differential effects over time that may be incompatible with traditional latent growth curve modeling approaches. Essentially, it is very difficult to study a model at a "gestalt" level, examining how macro-level factors like BPD affect momentary-level factors like momentary emotion, and vice versa.

TBN modeling techniques may provide one way to address these challenges, by capturing important time-dependence features of the ECM. Because Bayesian modeling techniques do not make as many assumptions about the underlying data and hypotheses, they represent a new opportunity in the field of psychopathology in the evaluation of complex models of psychopathology in frontiers that traditional statistical models have been unable to travel.

Bayesian Network Modeling Approach

Bayesian Network models (Kjærulff & Madsen, 2012), both time dependent and time independent, have been applied to the investigation of complex phenomena in many other fields, including risk analysis in engineering and industrial settings (Khakzad, 2015), organ failure in medical research (Sandri et al., 2014), effective brain connectivity based on functional MRI (Rajapakse & Zhou, 2007), medical decision making (Rose, Smaili, & Charpillet, 2005), and even traffic condition evaluation (Hofleitner, Herring, Abbeel, & Bayen, 2012). Because of the substantial difference between Bayesian techniques and traditional techniques, some general remarks on the Bayesian Network modeling approach are useful (see the monograph by Kjærulff and Madsen [2012] for a comprehensive technical description).

The bulk of the psychological field has been trained primarily in classical/frequentist statistical approaches. Although classical approaches have helped the discipline make much progress, they may also be limiting both conceptualization and evaluation of complex psychological models with classical approaches. For example, classical statistical approaches require the fulfillment of many assumptions during analyses, which may or may not be true. Common classical assumptions, most of which tend to be violated repeatedly in the "real world," include: random sampling of the population, independence of observations from each other, independence of observational error, homoscedasticity, and approximate normality of observations and error. Classical techniques also tend to rely on linear associations and ignore potential for feedback (positive or negative) processes. Finally, even the very logic of using p-value significance tests is coming under increased scrutiny as a flawed practice (Wagenmakers, Verhagen, Ly, Matzke, Steingroever, Rouder, & Morey, 2017). Thus, any conclusion that is drawn from these approaches may only be accurate in certain situations.

Bayesian techniques, on the other hand, represent an alternative view of the underlying assumptions we make about probability, and these methods have started to gain steam in psychological, social, and organization research (Kruschke, Aguinis, & Joo, 2012). Bayesian approaches are not necessarily better than frequentist methods, or vice versa, but rather each approach serves as a tool that can be used to make potential conclusions about observed data.

The core of Bayesian techniques revolves around the use of the Bayes Theorem (Bayes & Price, 1763) (for a recent article in the context of psychological applications, see [Etz & Vandekerhove, 2018] and references therein). A Bayesian Network (BN) consists of nodes, each node representing a random variable,[2] and arrows, each arrow representing a direct conditional dependence between a pair of nodes. A BN thus represents a joint probability distribution over a

[2] A random (or uncertain) variable can be in two or more of its possible states. If the total number of states is finite, the random variable is discrete; if a continuum of possible states is considered, the variable is continuous. Only discrete uncertain variables are considered in the work presented in this paper.

set of K uncertain variables: $p(X_1, X_2, X_3, \ldots, X_K)$, and the structure of the BN encodes conditional dependencies among subsets of these random variables. The details of dependencies among the variables are described by the BN parameters, which are the values of the conditional probabilities of dependent nodes given states of the nodes on which they depend (in BN parlance, the conditional probabilities of "children" given states of their "parents"). Typically, conditional dependencies in BNs are interpreted as causal dependencies. The causal interpretation is consistent with the demand that—by definition—no set of arrows in a BN (followed from tail to head, with nodes in between) can form a directed closed cycle.

A BN model allows one to graphically represent one's knowledge about a set of uncertain variables. This knowledge can be extracted from "hard" data (including, e.g., multiple measurements or observations of quantities of interest, either as numerical or as categorical values), but it can also reflect a subjective level of uncertainty about some of the variables. BN modeling is a powerful methodology with which to reason in domains with uncertainty; this is because the prior probabilities of any set of variables can be systematically updated by taking into account evidence about the states of other variables. If, for example, in a K-node BN that represents a joint probability distribution $p(X_1, X_2, X_3, \ldots, X_K)$, one obtains evidence that $X_2 = x_2, X_K = x_K$ (i.e., that variable X_2 is in its state x_2 and variable X_K is in its state x_K), then one can take into account that evidence and thus update one's knowledge of other variables by calculating the posterior probability distribution over the remaining variables $X_1, X_3, X_4, \ldots, X_{K-1}$ given the obtained evidence: $p(X_1, X_3, X_4, \ldots, X_{K-1} | X_2 = x_2, X_K = x_K)$. This would systematically improve one's level of knowledge of variables $X_1, X_3, X_4, \ldots, X_{K-1}$. Although any calculation in BN models can be in principle carried out by a sequential application of the Bayes Theorem and the Law of Total Probability, computations in BNs containing many nodes and arrows rely on a variety of efficient algorithms that save computing time and memory (see, e.g., Kjærulff, & Madsen, 2012). Thus, the application of BNs to a set of uncertain variables can be thought of as updating one's knowledge about variables of interest with evidence about other variable(s) being in its (their) specific state(s). Successive updating with additional evidence systematically increases the accuracy of a BN model.

As pointed out above, the specific modeling approach of this paper falls more narrowly within the scope of Temporal Bayesian Network Modeling (TBN) TBN is an extension of the Bayesian approach to incorporate time dependence (see Koller, & Fiedman, 2009). In a TBN approach, a time period of interest is discretized into two or more time steps that are relevant to the data being modeled. Pieces of information contained in the data are associated with these time steps. A TBN model consists of several connected clusters of nodes, one cluster corresponding to one time step. The clusters of nodes at different time steps are identical in structure, i.e. they are interconnected in the same way within each cluster.[3] The connections among the clusters of nodes correspond to the time-dependence of the variables being modeled. The time dependence may in general extend over more than one time step. Time dependencies extending over multiple time steps can occur if the dynamic process being modeled is characterized by significant "time lag," or "memory," effects.

Current Study

The purpose of the current study was to utilize TBN methodology with experience sampling data to model multiple time points over a daily basis and examine key, but previously untested, components of the ECM. In this study we utilized EMA data from a sample of

[3] If an additional restriction is imposed on a TBN, namely that the parameters that define the nodes, i.e. the conditional probabilities that parametrize the connection among the nodes, are the same in each cluster, then such a TBN would be called a Dynamic BN (DBN). However, the models considered in this paper are TBNs without this additional restriction.

adolescents and young adults who actively self-injure to construct a TBN model from five EMA time assessments across a single day, which were then used to model multiple feedback processes between negative emotion, rumination, and dysregulated behaviors. Of note, the focus of this study on adolescents and young adults with BPD is justified by a growing recognition in the field that BPD represents a lifespan developmental diagnosis that is as reliable and valid in adolescence as it is in adulthood (Chanen & McCutcheon, 2013). Accordingly, the construction of this ECM TBN allowed for the following four features of the ECM to be modeled simultaneously and then used in model prediction evaluation: 1) rumination and negative emotion increase each other over time (i.e., generate positive feedback on each other), 2) rumination and negative emotion increase themselves over time (i.e., generate positive feedback on themselves), 3) these positive feedback processes provoke dysregulated behavior (i.e., positive feedback on dysregulated behavior, and 4) dysregulated behavior then reduces rumination and negative emotion (i.e., negative feedback onto negative emotion and rumination). In this TBN, time was specified as successive time steps per day, with several assessments of multiple participants taking place across multiple days. Time invariant variables for psychiatric diagnosis were specified in the model, specifically: BPD, major depressive disorder (MDD), and posttraumatic stress disorder (PTSD). These variables were used in determining model predictive accuracy of BPD diagnosis, state rumination, negative emotion, and dysregulated behaviors, reflecting the complex system that the ECM represents (Selby & Joiner, 2009).

Methods

Participants: Participants included 47 self-injuring adolescents and young adults ages 15-21 (*M* = 19.1, *SD* = 1.77), drawn from the general community, recruited via referrals from local treatment centers and print and online ads placed throughout the community (Kranzler et al., 2017)). As described below, many in this sample also exhibited elevated symptoms and diagnoses of BPD. This study was IRB approved, and all participants provided written informed consent prior to participation in the study, and parental consent along with participant assent was obtained for participants under the age of 18. Participants were eligible if they: 1) were age 15 to 21 and 2) had self-injured two or more times in the past two weeks. Exclusion criteria were: 1) non-fluent English speakers; 2) rated at severe or extreme risk for suicide during baseline assessment (as indicated by presence of a suicide plan and intent to act); and 3) diagnoses of a psychotic disorder, life-threatening anorexia, or developmental delays. Thirty-two participants (68%) identified as female, 14 (30%) as male, with one (2%) identifying as transgendered. Eighteen (38%) participants identified as white, seven (15%) as black/African American, nine (19%) as Asian, eight (17%) as Hispanic/Latino, and five (11%) as multi-racial.

Procedures: Eligible participants were recruited from mental health outpatient clinics, through flyers placed in public settings throughout the community, and via online ads. After screening, participants completed an initial baseline assessment that consisted of self-report questionnaires and clinical diagnostic interviews. During the baseline assessment participants were also trained in how to use the "Track It" EMA app, an Android-based EMA program that could be used either on the participant's personal smartphone or on one provided to them for the duration of the study. Participants completed two days of EMA practice assessment, for which data were not used, followed by two weeks of EMA monitoring. During that time, participants completed five signal-contingent EMA entries daily as well as self-initiated event-contingent entries after experiencing an NSSI thought or behavior. During these momentary assessments, participants were asked questions about their behaviors, cognitions, and affect since the last assessment, details for which are further explained below. Signal-contingent entries were scheduled to prompt participants to respond at random times within five pre-determined windows: 9:00am-11:30am, 11:30am-2:00pm, 2:00pm-4:30pm, 4:30pm-7:00pm, and 7:00pm-9:00pm. Random signals were utilized to prevent participants from "anticipating" an assessment signal. At the conclusion of the two-week monitoring period, participants were debriefed and compensated for their participation.

Clinical Diagnostic Interviews: All participants completed the following diagnostic interviews for the current study, with all interviews being completed by a trained Ph.D. or Psy.D. student in clinical psychology, all of whom were trained to competency by the study principal investigator (EAS).

Borderline Personality Disorder Assessment: All participants completed the Structured Clinical Interview for DSM-IV Axis II Disorders (SCID-II; First, Gibbon, Spitzer, Williams, & Benjamin, 1997) to establish a potential diagnose of BPD, which required positive endorsement of at least five above-threshold symptoms during the interview. In the current sample, 27.7% met full diagnostic criteria for BPD (n=13). Although 13 participants met full threshold for BPD diagnosis, an additional 7 participants endorsed three (N=3) to four (N=4) out of the five necessary symptoms for BPD, indicating approximately 42% of the sample had a moderate or higher level of BPD pathology. A subset of participants' (N=20) interviews were audio recorded and evaluated by novel diagnostic raters, which when compared to the original raters indicated an inter-rater reliability of kappa=.85, which indicated good reliability.

Major Depressive Disorder and Posttraumatic Stress Disorder: Current major depressive disorder (MDD) and posttraumatic stress disorder (PTSD) were included to provide potential comparisons for the BPD group. Both current MDD and PTSD diagnoses were determined from the DSM-IV Mini International Neuropsychiatric Interview (MINI; Sheehan et al., 1998), a research-based structured clinical interview. In the current sample, 53.2% met criteria for current major depression (n=25), and 10.3% met criteria for PTSD (N=5). Diagnoses on the MINI demonstrated good inter-rater reliability in this sample for MDD (kappa=1.0) as well as PTSD (kappa=.79).

Ecological Momentary Assessment Measures: All participants completed assessments multiple times every day, typically taking 3-5 minutes to complete each response. During these assessments, participants provided information on the following experiences as they occurred over the previous 2-3 hours:

Momentary Negative Emotion: In each EMA assessment participants were asked to rate their current affective state by responding to 19 specific affect items, rating them each on a 0-10 Likert-type scale. Affect items included eight positive affect items (not used in the present study's analyses) and 11 negative affect items (sad, angry, hurt/emotionally rejected, frustrated, anxious/afraid, lonely, empty/numb, guilty, physically numb, ashamed, overwhelmed; summed to compute a total negative affect score; range = 0-102, Cronbach's alpha in present sample = .87). For the present study negative emotion was person-centered to reflect the following ratings: 0= momentary emotion less than one standard deviation above personal mean or lower (i.e., low), 1= momentary emotion one standard deviation above personal mean but less than two standard deviations (i.e., high), and 2= momentary emotion two standard deviations or more above personal mean (i.e., very high). This categorical representation of the data is more amenable to BN modeling than a continuous measure with a large range of values.

Momentary Rumination: During each EMA assessment participants rated eight items assessing their rumination since the previous assessment on a 0-10 Likert-type scale and items were then summed to compute a total momentary rumination score (range = 0-80). Items were based on the core characteristics of rumination: thinking that is repetitive, passive, difficult to control, and negatively focused (Ehring & Watkins, 2008; "I am experiencing many thoughts that are repeating over and over," "I am experiencing many repetitive thoughts about how I am currently feeling," "My thoughts are flowing from one thought to the next more quickly than they usually do," and "I am experiencing many thoughts that are difficult for me to control or change."). Given the fact that specific content and temporal direction are the most significant distinction between the different types of rumination (Ehring & Watkins, 2008), items were past, present, *and* future focused ("I am experiencing many thoughts about past personally-relevant problems," "I am experiencing many thoughts about current personally-relevant problems," "I am experiencing many thoughts about how a current problem may impact my future," and "I am experiencing many thoughts about personally-relevant problems that may occur in the future.") and were not specific about the content of thoughts. In the current sample, the scale demonstrated strong internal consistency: with an overall Cronbach's alpha of .91. With regard to the construct validity of the momentary rumination scale, as reported in Hughes et al. (2019), the total scale demonstrated an Intraclass Correlation Coefficient of .70 (within person variance accounted for 70% of the scale's total variance in the sample). Inter-item correlations were also significant and moderate, ranging from .45 to .83. Furthermore, an exploratory factor analysis in which items were restricted to one factor indicated that all items loaded well onto a single factor, with an Eigen value of 4.93 and factor weights ranging from.52 to .85. Thus, the momentary rumination measure demonstrated substantial internal consistency and face validity (Hughes et al., 2019).

For the present study rumination was person-centered to reflect the following ratings: 0= momentary rumination less than one standard deviation above personal mean or lower (i.e.., low), 1= momentary rumination one standard emotion above personal mean but less than two standard deviations (i.e.., high), and 2= momentary rumination two standard deviations or more above personal mean (i.e., very high).

Dysregulated Behaviors Assessment: Participants were asked whether they had engaged in any of the following dysregulated behaviors since the completion of their previous EMA assessment: NSSI, any alcohol use, any illicit drug use, impulsive shopping, or a binge-eating episode. Participants were provided with common definitions of each behavior during the baseline training. All behaviors were coded such that the presence of ANY dysregulated behavior at each momentary assessment was coded (1) or no dysregulated behaviors were reported (0). These behaviors were then summed into a single, dysregulated behaviors count variable that indicated the follow: no behaviors occurred (coded as 0), one behavior occurred (coded as 1), and two or more behaviors occurred (coded as 2). Although these behaviors may seem unrelated, past research has found that these behaviors have underlying common traits relevant to emotion dysregulation and impulsivity, and counting them together as one scale is justifiable conceptually and analytically (Selby et al., 2009; Tuna & Bozo, 2014).

Data Analytic Strategy

Our approach is to use TBN modeling of real-world data extending over a period of time during which measurements were collected. For the current study, TBN models were built and tested in the GeNIe 2.2 software environment developed by BayesFusion LLC (https://www.bayesfusion.com/).

The model development proceeded as follows. A number of interim models were initially built. For each of the models, a model structure was first specified in terms of causally connected nodes corresponding to the momentary negative emotion, rumination, dysregulated behavior, measured at five time steps during each day, and also including nodes corresponding to the diagnostic statuses of the study participants. As described above, we reduced momentary variables for negative emotion, rumination and dysregulated behavior in terms of three states each, which streamlined the model and improved its interpretability. The parameters describing the causal connections among those nodes were determined from the data, i.e. conditional probability distributions for each connection were learned from data.

The predictive accuracy of each interim model was then evaluated based on real-world data and using the *k*-fold cross-validation method (Geisser, 1993; Rodriguez, Perez, & Lozano, 2010). As a model optimization procedure, interim models were modified to improve their accuracy. The best-performing model most successfully classifies variables of interest, such as possible diagnoses, based on available evidence about person's behavior and emotions over time and in this way. Leaving a description of interim TBN model outside the scope of this paper for brevity, the next two subsections describe the best-performing TBN model and the results of its *k*-fold cross-validation. All of these features provide novel avenues for the exploration of emotional cascades, dysregulated behaviors and BPD.

Description of the ECM TBN Model

Structure of the Model

The best-performing TBN model developed in this study (which we call the "ECM TBN model") is displayed in Figure 1It was specified based on ECM hypothesized relations between emotion and cognitive construct variables. Each of the five time steps at which the variables of negative emotion, rumination and dysregulated behavior were measured throughout the day served as a piece of a larger model in which the five successive time steps were structured in serial fashion, such that variables at each time step could influence variables at a later time step, as depicted in Figure 1. The diagnostic variables, on the other hand, do not depend on the time step, since the subjects' clinical statuses are assumed to be stable in the course of the study.

To explain the structure of the model in some detail, we utilize the following shorthand notation for the time-dependent nodes: R(n), NE(n) and DB(n) (for each time step n=1, 2, 3, 4, 5) denote the nodes "Rumination_at_Time_Step_n", "Negative_Emotion_at_Time_Step_n" and "Dysregulated_ Behavior_at_Time_Step_n", respectively. The three nodes at the bottom of the network were specified as time-independent diagnostic variables: PTSD_Diagnosis , BPD_Diagnosis and MDD_Diagnosis (for PTSD, BPD and MDD, respectively). To elucidate the structure of the TBN model shown in Figure 1, we note that "_at_Time_Step_1" nodes are connected to nodes at all subsequent time steps during the day, all the way to the fifth time step; and the only connecting arrows within the same time steps are R(n)→NE(n) (for each time step n=1, 2, 3, 4, 5). A detailed list of all connections among the nodes of this TBN model is below:

Each of MDD, PTSD and BPD → {R(n),NE(n),DB(n) (for all n=1,2,3,4,5)},
R(1)→{NE(1), R(2),R(3),R(4),R(5), NE(2),NE(3),NE(4),NE(5), DB(2),DB(3),DB(4),DB(5)},
NE(1)→{R(2),R(3),R(4),R(5), NE(2),NE(3),NE(4),NE(5), DB(2),DB(3),DB(4),DB(5)},
DB(1)→{R(2),R(3),R(4),R(5), NE(2),NE(3),NE(4),NE(5), DB(2),DB(3),DB(4),DB(5)},
R(2)→{NE(2), R(3),R(4),R(5), NE(3),NE(4),NE(5), DB(3),DB(4),DB(5)},
NE(2)→{R(3),R(4),R(5), NE(3),NE(4),NE(5), DB(3),DB(4),DB(5)},
DB(2)→{R(3),R(4),R(5), NE(3),NE(4),NE(5), DB(3),DB(4),DB(5)},
R(3)→{NE(3), R(4),R(5), NE(4),NE(5), DB(4),DB(5)},
NE(3)→{R(4),R(5), NE(4),NE(5), DB(4),DB(5)},
DB(3)→{R(4),R(5), NE(4),NE(5), DB(4),DB(5)},
R(4)→{NE(4), R(5), NE(5), DB(5)},
NE(4)→{R(5), NE(5), DB(5)},
DB(4)→{R(5), NE(5), DB(5)},
R(5)→NE(5),
NE(5)→ nothing,
DB(5)→nothing.

Thus, in this TBN model, a causal effect has been specified between momentary rumination and negative emotion, which allows for modeling of self-compounding effect for both of these variables, consistent with previous work on the ECM (Selby et al., 2016). Diagnostic statuses, for BPD, PTSD and MDD, were modeled to influence each of these variables at all assessment time steps. Thus, each diagnostic variables was modeled as a time-independent common cause contributor to the degree of rumination, negative emotion and dysregulated behavior during the day. In general, the specified structure of the TBN model implies that rumination, negative emotion and dysregulated behavior at any time step during the day could influence the probability of their occurrence at later time steps. Such influence can be either direct (e.g. due to causal connections like NE(n)→DB(n+1), DB(n)→R(n+2), etc.) or indirect, i.e. mediated through probabilities of diagnostic statuses. Quantitative details of the causal influences among all the variables of the TBN model, and in particular whether or not, and to what degree, they may include positive or negative feedback effects during the day, depend crucially on parametric contents of the model, which is the subject of the next subsection.

Parameters of the Model

After specifying the structure of the TBN model, its parameters (i.e. conditional probabilities associated with the connecting arrows) were learned from data. The parameter learning was based on a subset of data from the total dataset, such that only the cases with exactly five measurements per day were retained. Selecting only the days that contained exactly five measurements meant that the physical time separation of any two consecutive time steps of the TBN model can be interpreted more strictly, in that the physical time between any two consecutive measurements is actually about 2 to 3 hours. The total number of days included in this strict database was 232 (the full database including days with missing values and with more or fewer than 5 measurement was 737). From this, we were able to machine-learn all the parameters from the selected data subset using the Expectation-Maximization (ME) algorithm implemented in the GeNIe software.

Results

EMA methods with this sample were successful in capturing numerous BPD-relevant behaviors and events during the two-week data collection period. During this time, participants reported 1,024 rumination events at one standard deviation (SD) higher than their personal average, and 624 events two SDs higher. 994 negative emotion events were reported at one SD higher than personal average, while 536 were two SDs higher. The average number of dysregulated behaviors reported during EMA per person was 14.65 (SD=14.06; range = 0-58).

Model Outcome Evaluation

Once the ECM TBN model was fully specified, with the structure depicted in Figure 1 and the parameters learned from data, the model was then evaluated to assess its predictive accuracy. Relative to classical statistical methods, which rely on evaluation of a hypothesis via statistical tests, p-values, and effect sizes, Bayesian Networks can be evaluated based on what they will be used for – in other words, in terms of the accuracy of the model's predictions given the data available.[4] Thus, the ECM TBN model was tested as a possible tool for predicting outcomes of particular interest, such as diagnostic status (BPD diagnosis present or absent), or the prediction of an event, such as a behavior occurring. To test the ECM TBN we examined the model performance with respect to three different goals: 1) using EMA data to predict multiple "unknown" diagnostic statuses (e.g. presence or absence of MDD, PTSD, and BPD), 2) predicting BPD diagnosis specifically using EMA data in combination with information about diagnostic comorbidity, and 3) using BPD diagnostic status in combination with EMA data from earlier in one day to predict constructs like negative emotion, rumination, and dysregulated behaviors later in the same day.

[4] Note that some traditional performance measures, such as p-values, etc. are applicable to other types of Bayesian Networks, e.g. to BNs whose nodes correspond to continuous probability distributions, which are essentially equivalent to graphical representations of structural equation models. However, as explained above, the nodes of the ECM TBN have discretized states, for which traditional statistical tests less useful.

Predictive accuracy of the ECM TBN model was evaluated by conducting *k-fold cross-validation* (Geisser, 1993; Rodriguez, Perez, & Lozano, 2010), which is implemented in the GeNIe software. In this method, the 232 days of the data set used in machine learning were split into *k* equal parts ("folded *k* times"). After that, the parameters of the model were then "re-learned" from the first *k*-1 folds, and that model was then tested against the last *k*-th fold, and the results of the test are recorded. Then the data folds are reshuffled, and the parameters of the model are again re-learned from the new *k*-1 fold and the model is re-tested against the next *k*-th fold, and recorded. This process is repeated so that *k* results of *k* tests of *k* re-learned models are obtained. These results are then averaged for the final result of the *k*-fold cross-validation.

Section 1. Using the ECM TBN Model to Predict Multiple Diagnostic Statuses

The results of the validation depend on what variables a researcher desires to predict. For example, in one of the three performance goals listed above, we wanted to test the quality of the prediction of the diagnostic statuses of BPD, MDD, and PTSD. In the context of *k*-fold cross-validation, these diagnostic variables are referred to as "class variables" (or class nodes). The goal is to assess how well the ECM TBN model is expected to predict the class variables based on the known states of the remaining fifteen variables (i.e., the levels of rumination, negative emotion and dysregulated behaviors at all five time steps), which are taken from the data set.

The accuracy of prediction is then a measure of the performance of the model: it is the ratio of the number of times the BN model predicted the actual state correctly to the total number of times that class variable appears in the data set. The results of *k*-fold cross-validations do depend on the number of folds *k*, but having compared the results of 10-fold, 20-fold, 60-fold and 116-fold cross-validations, we found that this dependence is not strong. In Table 1 we compare the results of 10-fold, 20-fold, 60-fold and 116-fold cross-validations for the three class nodes: BPD, PTSD and MDD. The expected prediction accuracy is expressed both in terms of the percentages of cases that the ECM TBN Model predicted correctly and—in prantheses—in terms of ratios of correclty predicted cases to the total number of cases in the database.

One conclusion from the above tests is that if a researcher or clinician has evidence about levels of a person's rumination, negative emotion and dysregulated behaviors during all five time steps during a day, then one could be expected to be able to correctly identify if the person has status "BPD Present" in about 89% of cases, on average, while also being able to confirm a "BPD Absent" status of the person in about 96% of cases, on average. (These percentages are not to be confused with the standard frequentist statistical measures such as the p-value or the α confidence level.) These findings suggest that the ECM TBN model might have potential utility as a screening tool for BPD, MDD and PTSD: a person provides evidence of his or her levels of rumination, negative emotion and dysregulated behaviors taken five times during one day, and the ECM TBN model tool could possibly accurately determine that the person's statuses are negative with respect to those disorders, and also to suggest to the clinician that the person may need to be further evaluated as to other positive diagnostic statuses. While the results in Table 1 show somewhat different predictive accuracies of the ECM TBN model for BPD, MDD and PTSD diagnoses, these differences were relatively small, but seemed to favor prediction of BPD. However, it is more significant that the accuracies for all three diagnoses are high (above 80%).

Section 2. Using the ECM TBN Model to Predict BPD Diagnostic Status Specifically

In general, when using TBN modeling, the more variables we have evidence about, the more accurately we can predict the desired class variables. This is further illustrated in this section, where we *k*-fold cross-validated the ECM TBN model as a predictor of the state of only one class variable, namely BPD, while evidence about all other seventeen variables was available. In particular, in this prediction scenario, it was assumed that the statuses of the person with respect to MDD and PTSD were known in addition to his or her measured levels of rumination, negative emotion and dysregulated behaviors at all five steps during EMA.

In a 10-fold cross-validation of this model we obtained the following outcomes regarding accuracy of BPD diagnosis. The accuracy of predicting the BPD variable overall (regardless of the BPD status) was 95% (220/232); whereas the accuracies of predicting the specific BPD statuses were 96% (137/142) for the status “BPD Absent”, and 92% (83/90) for the status “BPD Present”. Relative to the results presented in Section 1, where simultaneous predictions of BPD, MDD, and PTSD statuses were evaluated, the model has superior predictive power of BPD diagnosis alone. In this sense, information on the presence of a potential comorbid diagnosis such as MDD, which is present in most cases of BPD, provided for more accurate estimation of BPD diagnosis in conjunction with ECM relevant variables. Thus, if a clinician knows not only the levels of a person’s rumination, negative emotion and dysregulated behaviors throughout a day, but also MDD and PTSD statuses, then the ECM TBN model could be used as a diagnostic support tool for identifying the BPD status of the person.

Section 3. Predicting Negative Emotion, Rumination, and Dysregulated Behaviors in the ECM TBN

In this third and final section of results, we investigated a k-fold cross-validation in which BPD status of a person is assumed to be known. The class nodes included not only the diagnostic variables MDD, and PTSD, but also the nodes for rumination, negative emotion and dysregulated behavior at time steps 4 and 5. The fact that in this *k*-fold cross-validation there were eight class nodes, instead of three as in Section 1 above, means that the available evidence was entered into the six remaining nodes, namely, in rumination, negative emotion and dysregulated behaviors at time steps 1 and 2. Since the BPD status of the person is assumed to be known, we considered two scenarios: one in which the BPD status is fixed to be “BPD Absent”, and the other where the assumed BPD status was “BPD Present”. The results of 10-fold cross-validation of the ECM TBN Model are presented below in Table 2 for both scenarios considered (as in Section 2, very similar accuracies were obtained for any number of folds). It is worth noting that, since we have eight class variables (compared with three class variables in Section 1 and only one class variable in Section 2), the 10-fold cross-validation described in this section is quite ambitious because eight nodes were predicted based on evidence for only six nodes.

Finally, the predictive accuracy was somewhat better when the ECM TBN model was specified with BPD status being positive (total model accuracy for all eight class variables being 91%) relative to the ECM TBN model in which BPD status being negative (total model accuracy being 88%). These findings indicate that if we know a patient has BPD, and we were to obtain momentary data on negative emotion, rumination, and dysregulated behaviors across a few time points, our prediction of the levels of those variables would range from “respectable” to “good.”

Discussion

Models of personality disorders are inherently complex, with the ultimate goal of describing predictable patterns of emotional and behavior responding across diverse situations. The field’s reliance on linear models utilizing limited variables and dynamic states may limit our ability to truly develop and test strong, evidence driven models. Incorporating Bayesian Network (BN) approaches may serve as one promising route to examining complex, dynamic models of personality characteristics and environmental responses.

In the current study we evaluated a complex systems model of BPD, the emotional cascade model (ECM; Selby & Joiner, 2009), utilizing Temporal Bayesian Network (TBN) modeling of data derived from EMA methods. Using EMA data collected over a two-week period in a sample of youth who self-injured, we were able to incorporate five sequential daily recordings of variables of rumination, negative emotion, and behavioral dysregulation into a dynamic model characterized by complex causal dependencies among the variables extending across each day, allowing, e.g., for development of feedback loops. Model parameters were machine-learned from the EMA assessment data. Using the technique of *k*-fold cross-validation, we investigated the ability of the developed ECM TBN model to support predictive assessments of diagnostic status and dynamic levels of emotion, cognitions and behaviors. Ultimately the findings of TBN analysis demonstrate that the ECM model has predictive potential of both BPD diagnosis and dysregulated behaviors, suggesting that it should continue to be examined and tested as an informative model of BPD pathology.

One of the most powerful features of our TBN analyses of the ECM was that the ECM TBN model provided direct and differential predictive accuracy of BPD relative to depression (MDD) and trauma (PTSD) diagnoses. In Section 1 we explored differential diagnostic prediction accuracy with the TBN model informed by momentary rumination, negative emotion, and dysregulated behaviors across the day. Findings indicated that predictive accuracy was over 80% for all three diagnoses. Then, in Section 2, we extended the investigation of our predictive accuracy by incorporating MDD and PTSD diagnoses as predictive data into a model, i.e. they were assumed to be known, and BPD diagnosis was the only unknown. Under these conditions, the TBN model demonstrated 90% accuracy with regard to BPD diagnosis. It may be possible, then, for future work to incorporate TBN modeling with EMA data to augment traditional diagnostic screening tools and enhance prediction of BPD diagnostic status with patients.

Then, in Section 3, we demonstrated that the ECM TBN model had potential not only to predict diagnostic status, but also to predict personality level variables that occur at the daily level. Using the same TBN model, we assumed a known BPD diagnostic status, and we specified levels of rumination, negative emotion, and dysregulated behaviors earlier in the day (at time steps 1 through 3), to predict levels of these variables later in the day (at time steps 4 and 5). Findings indicated that with information about a participant's BPD diagnostic status, and earlier experiences in the day of negative emotion, rumination, and dysregulated behavior, the TBN model could predict later levels of these variables with considerable accuracy. For example, when the BPD status was assumed to be present, the model predicted later day levels of rumination with 81% to 92% accuracy, and levels of negative emotion with 88% and 92% accuracy. Even more impressively, the model predicted dysregulated behaviors with 95% and 100% accuracy, depending on whether BPD diagnosis was absent or present. Also, in these scenarios with BPD status assumed to be known, the model demonstrated superior predictive accuracy to a scenario (Table 2) in which BPD diagnostic status was not known. Such high-performance characteristics of this model indicate that we may be able to utilize real-time data provided via EMA methodology to predict dysregulated behaviors among those with BPD. Although the ECM TBN model showed higher accuracy in predicting dysregulated behaviors when BPD diagnostic status was known to be positive (91% accuracy) relative to the case when BPD diagnostic status was known to be negative (88% accuracy), it is not clear if this relatively small margin of difference represents a clinically useful or replicable difference in model prediction. This issue would be clarified in future samples in which participants with BPD are compared to those with psychiatric diagnoses who do not self-injure.

The findings of this study have essential clinical implications. First, the methods described here have potential to improve personality disorder diagnostic accuracy and efficiency. If patients were able to complete a brief EMA protocol (e.g. via smartphone app), prior to presenting to a clinician, it may be possible for a clinician to hypothesize a BPD diagnosis before even meeting the patient. Second, the methods described here have potential clinical utility in predicting momentary high risk for negative outcomes, such as rumination, negative emotion and dysregulated behaviors. It may even be possible for technological tools, such as smartphone apps, to help patients self-monitor by alerting them when at elevated risk for further emotional distress or impulsive behavior. The current study also has implications for innovating analysis of EMA data in research settings. EMA data is known for being complex and challenging, frequently requiring the use of mixed modeling methods. Furthermore, because EMA data involve so many data points over multiple timeframes, it is difficult to use EMA data in model testing, and procedures such as traditional structural equation modeling or time series analyses must be circumscribed to meet restrictive analytic requirements. However, using TBN methods seems ideal for using EMA data in model testing.

Although the current study has substantial strengths and potential for guiding future research, there are some limitations that should be noted. The primary limitation with this study is that prediction accuracy of the model was ultimately done on a post-hoc basis, even though micro-longitudinal data was utilized in the TBN modeling. For example, even though our models predicted diagnostic status with considerable accuracy, participants completed diagnostic interviews prior to engaging in the EMA protocol. The same applies to prediction of dynamic emotion and behavioral states. Future research could improve upon this limitation by using a brief EMA protocol to obtain data for usage in TBN model, and then use the TBN model to predict outcomes derived from a second subsequent EMA protocol. Such would ensure an even more rigorous test of predictive accuracy. Other limitations with the study include a relatively small sample size, diagnostic comorbidity with many BPD patients also having PTSD and MDD diagnoses, and the requirement of recent self-injury to participate in the study, which likely limited the relevance of the findings to BPD participants with regard to those who do not self-injure (roughly 50%; Selby et al., 2015) and may have resulted in restricted range of responses. Although this approach represents the best available method of addressing missing data, it doesn't rule out the possibility that days with more complete data were potentially biased relative to days with incomplete data. Finally, regarding the use of a youth sample, in combination with the current study's small sample size there is increased risk for potential developmental reliability or validity concerns. Future studies should aim to replicate the present analysis in large, adult samples to ensure these findings generalize to all adult populations.

Conclusion

Personality disorder researchers should be among the first in the field of clinical psychology to embrace Bayesian methodology, especially Bayesian Network analysis. There are numerous models of personality disorders that could benefit from and be informed by empirical examination with these methods. Notably, the Emotional Cascade Model has benefited from investigation with TBN methods, with evidence presented to support the ECM model when investigated in a dynamic, complex interplay of multiple model variables (e.g., negative emotion, rumination, behavioral dysregulation, BPD diagnosis). With further investigation along these lines it may be possible to eventually classify the ECM or other theoretical models of personality disorder as a "rigorously validated" model at a gestalt level.

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Table 1. Expected Accuracy of Prediction of Diagnostic Variables BPD, MDD and PTSD, Assessed by *k*-Fold Cross-Validation for k=10, 20, 60 and 116.

Results of 10-Fold Cross-Validation			
Expected Accuracy of Prediction of Class Variable		**Expected Accuracy of Prediction of State of Class Variable**	
BPD	94% (217/232)		
		BPD: Absent	96% (136/142)
		BPD: Present	90% (81/90)
MDD	97% (226/232)		
		MDD: Absent	99% (197/199)
		MDD: Present	88% (29/33)
PTSD	95% (220/232)		
		PTSD: Absent	98% (190/194)
		PTSD: Present	79% (30/38)
Overall accuracy of prediction of all three class variables	95% (663/696)		
Results of 20-Fold Cross-Validation			
Expected Accuracy of Prediction of Class Variable		**Expected Accuracy of Prediction of State of Class Variable**	
BPD	93% (216/232)		
		BPD: Absent	96% (136/142)
		BPD: Present	89% (80/90)
MDD	98% (227/232)		
		MDD: Absent	99% (197/199)
		MDD: Present	91% (30/33)
PTSD	95% (221/232)		
		PTSD: Absent	97% (189/194)
		PTSD: Present	84% (32/38)
Overall accuracy of prediction of all three class variables	95% (664/696)		
Results of 60-Fold Cross-Validation			
Expected Accuracy of Prediction of Class Variable		**Expected Accuracy of Prediction of State of Class Variable**	
BPD	93% (216/232)		
		BPD: Absent	96% (136/142)
		BPD: Present	89% (80/90)
MDD	97% (226/232)		
		MDD: Absent	99% (197/199)
		MDD: Present	88% (29/33)
PTSD	95% (220/232)		

		PTSD: Absent	97% (189/194)
		PTSD: Present	82% (31/38)
Overall accuracy of prediction of all three class variables	95% (662/696)		

Results of 116-Fold Cross-Validation			
Expected Accuracy of Prediction of Class Variable		**Expected Accuracy of Prediction of State of Class Variable**	
BPD	93% (215/232)		
		BPD: Absent	95% (135/142)
		BPD: Present	89% (80/90)
MDD	97% (226/232)		
		MDD: Absent	99% (197/199)
		MDD: Present	88% (29/33)
PTSD	95% (220/232)		
		PTSD: Absent	97% (189/194)
		PTSD: Present	82% (31/38)
Overall accuracy of prediction of all three class variables	95% (661/696)		

Table 2. Expected Accuracy of Prediction of Diagnostic Variables MDD and PTSD, and of Rumination, Negative Emotion and Dysregulated Behavior at Time Steps 4 and 5, Assessed by *10*-Fold Cross-Validation for Two Scenarios of Known BPD Status

Results of 10-Fold Cross-Validation with Borderline Diagnosis Specified as "Present" (BPD-positive status)			
Expected Accuracy of Prediction of Class Variable		**Expected Accuracy of Prediction of State of Class Variable**	
MDD	92% (83/90)		
		MDD: Absent	96% (73/76)
		MDD: Present	71% (10/14)
PTSD	82% (74/90)		
		PTSD: Absent	89% (57/64)
		PTSD: Present	65% (17/26)
Negative Emotion at Time Step 4	88% (79/90)		
		Negative Emotion at T4: Low	92% (48/52)
		Negative Emotion at T4: High	78% (18/23)
		Negative Emotion at T4: Very High	87% (13/15)
Rumination at Time Step 4	92% (83/90)		
		Rumination at T4: Low	96% (48/50)
		Rumination at T4: High	93% (25/27)
		Rumination at T4: Very High	76% (10/13)
Dysregulated Behavior at Time Step 4	100% (90/90)		
		Number of DBs at T4: Zero	100% (84/84)
		Number of DBs at T4: One	100% (6/6)
		Number of DBs at T4: Two	Not Applicable
Negative Emotion at Time Step 5	92% (83/90)		
		Negative Emotion at T5: Low	96% (46/48)
		Negative Emotion at T5: High	93% (27/29)
		Negative Emotion at T5: Very High	77% (10/13)
Rumination at Time Step 5	81% (73/90)		
		Rumination at T5: Low	86% (44/51)
		Rumination at T5: High	70% (21/30)
		Rumination at T5: Very High	89% (8/9)
Dysregulated Behavior at Time Step 5	100% (90/90)		
		Number of DBs at T5: Zero	100% (80/80)
		Number of DBs at T5: One	100% (9/9)
		Number of DBs at T5: Two	100% (1/1)

Overall accuracy of prediction of all eight class variables	91% (655/720)		

Results of 10-Fold Cross-Validation with Borderline Diagnosis Specified as "Absent" (BPD-negative status)			
Expected Accuracy of Prediction of Class Variable		**Expected Accuracy of Prediction of State of Class Variable**	
MDD	96% (137/142)		
		MDD: Absent	99% (122/123)
		MDD: Present	79% (15/19)
PTSD	92% (131/142)		
		PTSD: Absent	98% (127/130)
		PTSD: Present	33% (4/12)
Negative Emotion at Time Step 4	83% (118/142)		
		Negative Emotion at T4: Low	90% (71/79)
		Negative Emotion at T4: High	81% (34/42)
		Negative Emotion at T4: Very High	62% (13/21)
Rumination at Time Step 4	83% (118/142)		
		Rumination at T4: Low	89% (64/72)
		Rumination at T4: High	77% (37/48)
		Rumination at T4: Very High	77% (17/22)
Dysregulated Behavior at Time Step 4	93% (132/142)		
		Number of DBs at T4: Zero	97% (113/117)
		Number of DBs at T4: One	70% (14/20)
		Number of DBs at T4: Two	100% (5/5)
Negative Emotion at Time Step 5	81% (115/142)		
		Negative Emotion at T5: Low	90% (70/78)
		Negative Emotion at T5: High	64% (27/42)
		Negative Emotion at T5: Very High	82% (18/22)
Rumination at Time Step 5	80% (114/142)		
		Rumination at T5: Low	89% (56/63)
		Rumination at T5: High	76% (41/54)
		Rumination at T5: Very High	68% (17/25)
Dysregulated Behavior at Time Step 5	95% (135/142)		
		Number of DBs at T5: Zero	98% (118/121)
		Number of DBs at T5: One	75% (12/16)
		Number of DBs at T5: Two	100% (5/5)
Overall accuracy of prediction of all eight class variables	88% (1000/1136)		