Machine Learning Models Predicting Daily Affective Dynamics Via Personality and
Psychopathology Traits

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Abstract

To date, numerous studies have examined personality and psychopathology indexes as predictors of affective dynamics, i.e. measures of how emotions change across time. Yet, little research has examined individual differences in personality, pathology, and affective dynamics constructs comprehensively, accounted for non-linear relationships, or examined the out-of-sample generalizations of the predictions. To address these gaps, the current research utilized machine learning models to predict affective dynamics. A large variety of baseline personality and psychopathology traits (pathological personality measures, clinical anxiety, depression, anger, sleep, affective instability scales, the big five personality traits, interpersonal circumplex measures, and control beliefs) were used to predict the affective dynamics derived from person-specific modeling of affect across a 50-day daily diary study. The results showed that baseline personality traits significantly predicted the strength of day-to-day affective dynamics for emotional variability, relative emotional variability, emotional instability, emotional inertia, and emotional cyclicity for both positive and negative affect (r s 0.152-0.444). Although broadly neglected in prior research, the results suggested that interpersonal circumplex measures most strongly predicted a number of affective dynamics.

Keywords: affective dynamics, interpersonal circumplex, machine learning

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Affect, the experience of feelings, emotions, or moods often fluctuates as a result of outside stimuli (e.g., events that have occurred) and internal stimuli (e.g., cortisol levels). Fluctuation of affect can occur involuntarily, and such fluctuation differs from person to person (Kuppens et al., 2010). Although the experience of affect fluctuation is common, extreme fluctuation of affect, termed affective instability, is much less common across persons. Affective instability can be broadly defined as rapid, intense shifts in mood with a difficulty in controlling such changes in mood and/or the consequences (Marwaha et al., 2014). Consequently, such involuntary, rapid fluctuations of affect often lead to self-harming behaviors, both suicidal and non-suicidal (Peters et al., 2016; Yen et al., 2004). Affective instability is also heavily correlated with anhedonic depression and predicts interpersonal relationship problems such as disagreements with friends and family as well as divorce (Bowen et al., 2017; Thompson et al., 2011).

Affective instability likely influences how a person behaves and has been robustly associated with various personality traits (Ebner-Priemer & Sawitzki, 2007; Hopwood et al., 2009; Kalokerinos et al., 2020; Kamen et al., 2010a; D. J. Miller et al., 2009a; J. D. Miller & Pilkonis, 2006). Although the relationship between affective instability and personality traits such as openness, extraversion, and agreeableness has been studied, neuroticism has been studied the most thoroughly (J. D. Miller & Pilkonis, 2006). Many studies looking at neuroticism and affective instability conclude that the relationship between the two is unambiguous, as neuroticism and affective instability show significant positive correlation (Kamen et al., 2010b; Maples et al., 2014; D. J. Miller et al., 2009b). However, the overall logic and approach behind

these studies looking at the association between neuroticism and affective instability are flawed in our view. That is, when measuring neuroticism, assessment approaches often directly incorporate affective instability. For example, the Big Five Inventory-2 (BFI-2) measures ‘negative emotionality’ (i.e. neuroticism) by including a facet-level subdomain of ‘emotional volatility’ (Soto & John, 2017a). Therefore, the relationship between neuroticism and affective instability could be a result of neuroticism being explicitly defined as a measure of affective instability (rather than a separate construct). In the present work, we assess trait negative emotionality with a broad array of questionnaires some of which directly assess emotional volatility, and situate any potential unique findings between neuroticism and affective instability within this array.

Turning to the relationship between psychopathology and affective instability, existing studies have examined the relationship between affective instability and psychopathologies such as borderline personality disorder (BPD) and bipolar disorder (Ebner-Priemer et al., 2007; Henry et al., 2001; Koenigsberg et al., 2002; Links et al., 2008; Tragesser et al., 2007; Tragesser & Robinson, 2009; Trull et al., 2008). The link between BPD and affective instability seems explicit as patterns of affective instability are more prominent in BPD patients (Koenigsberg et al., 2002; Tragesser et al., 2007). Notwithstanding this significant association, examining these relationships as if they are external also is tautological, given that affective instability is integrated in the measurement of BPD itself, meaning affective instability is one of the measurements that determines whether or not one has BPD (Distel et al., 2009). In fact, one of the diagnostic criteria of BPD by the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), which contains criteria for diagnosing mental disorders, states ‘affective instability due to a marked reactivity of mood’ (Biskin & Paris, 2012). Thus, the relationship between

personality pathology and affective instability is also fraught with measurement confounds and remains limited in scope. We seek to expand the literature by assessing a more comprehensive battery of personality pathology questionnaires, including trait measures of affective instability.

In addition, most of the studies that have explored the relationship between affective instability and either personality traits or psychopathology do not examine the relationships of interest across a broad array of personality and psychopathology traits simultaneously. Instead, the research discusses such questions restrictively, focusing on the link between affective instability and one or two personality traits or specific psychopathologies. Such studies are limited in that they isolate one or two aspects of a person and examine the relationship between personality pathology and affective instability in a vacuum. This approach cannot capture a holistic perspective of the person. Little to no research has observed affective instability in a more integrated model of personality and psychopathology. Such an approach may be beneficial not only because it expands our understanding of affective instability, but also because it allows us to quantify the *relative* importance of various individual differences as predictors of affective instability.

Given limitations in the relevant literature, the current study investigated a comprehensive array of personality and psychopathology traits as predictors of an equally comprehensive variety of affective dynamics. Such dynamics include: emotional variability, relative emotional variability, emotional instability, emotional inertia, and emotional cyclicity. We also examined these dynamic patterns in positive and negative affect. Using machine learning, we aimed to: extend existing affective dynamics research to a large variety of personality traits and psychopathology constructs simultaneously, and to examine predictive performance via out-of-sample predictions while accounting for potential non-linear

relationships. Out-of-sample modeling is a key strength of machine learning approaches. Such an approach assesses model fit without the typical practice of using the exact same data to both build/train models and assess the accuracy of these models. Thus, we sought to address the following research questions:

- (1) Does personality and psychopathology data significantly predict emotional variability, relative emotional variability, emotional instability, emotional inertia, and emotional cyclicity for both positive and negative affect?
- (2) What are the most important personality and psychopathology constructs in predicting emotional variability, relative emotional variability, emotional instability, emotional inertia, and emotional cyclicity for both positive and negative affect?

Methods

Participants

Participants ($N = 175$, 18% Male, 81% Female, 1% Transgender, $M_{\text{age}} = 19.90$, Age range 18-31, 66% White/Caucasian, 7% African American/Black, 7% Hispanic/Latino, 1% Arab/Middle Eastern/Arab American, 14% Asian/Asian-American, 2% Asian Indian, 1% Pacific Islander, 2% Multiple/Mixed Ethnicities, 1% Other) were recruited from introduction to personality psychology courses.

Daily Diary Measures

Positive Affect Negative Affect Schedule (PANAS). We used a modified version of the PANAS 20-item scale where participants reported the extent to which they experienced a list of emotions “today” (e.g. negative affect, positive affect, fear, hostility, guilt, sadness, joviality, self-assurance, attentiveness, shyness, fatigue, serenity, and surprise) (Watson & Clark, 1994).

The item order was randomized to control for potential order effects. Participants rated each item on a 0 (Not at All) to 100 (Extremely) scale using a continuous slider.

Personality Trait Measures

Big Five Inventory-2 (BFI-2). The 60-item BFI-2 was used to measure the big five personality traits (Soto & John, 2017b). The measure asked participants on a 1 (Disagree Strongly) to 5 (Agree Strongly) to assess extraversion (e.g. “is outgoing, sociable”), agreeableness (e.g., “is compassionate, has a soft heart”), conscientiousness (e.g. “is dependable, steady”), negative emotionality (i.e. neuroticism, e.g. “is moody, has up and down mood swings”), and open-mindedness (e.g., “is curious about many different things”). Each of the corresponding scales have correlations between 0.71-0.80 with the NEO Five-Factor-Inventory (Soto & John, 2017b).

Affective Lability Scale (ALS). The 18-item ALS used a 1 (very unresponsive of me) to 4 (very responsive of me) Likert scale to measure anxiety lability (e.g. “At times I feel just as relaxed as everyone else and then within minutes I become so nervous that I feel light-headed and dizzy.”), anxiety-depression lability (e.g. “Many times I feel nervous and tense and then I suddenly feel very sad and down.”), depression lability (e.g. “At times I feel that I’m doing everything at a very slow pace but then soon afterwards I feel that I’m no more slowed down than anyone else.”), elation lability (e.g. “There are times when I feel absolutely wonderful about myself but soon afterwards I often feel that I am just about the same as everyone else”), anger lability (e.g. “I frequently switch from being able to control my temper very well to not being able to control it very well at all.”), and total lability (Oliver & Simons, 2004). The scales have shown good convergent validity, having greater convergent validity with cluster B personality disorders than clusters A or C (Look et al., 2010).

Positive Affect Negative Affect Expanded Trait Version (PANAS-X). The PANAS-X trait version, a 60-item questionnaire that uses a 1 (very slightly or not at all) to 5 (extremely) Likert scale, measured: negative affect, positive affect, fear, hostility, guilt, sadness, joviality, self-assurance, attentiveness, shyness, fatigue, serenity, and surprise (Watson & Clark, 1994). The PANAS-X has strong convergent validity (r range 0.85 – 0.91) with matched scales on the Profile of Mood States (Watson & Clark, 1994).

Single-Item Self-Esteem Scale (SISES). The SISES asks one question that measures self-esteem. The question “I have high self-esteem” is answered from 1 (not very true of me) to 5 (very true of me) (Robins et al., 2001). The scale has shown strong convergent validity (r range 0.72 to 0.76) with the Rosenberg Self-Esteem scale (Robins et al., 2001).

Defense Style Questionnaire-40 (DFS). The DFS-40 is a questionnaire on a 1 (strongly disagree) to 9 (strongly agree) Likert scale, is designed to measure defense styles such as, somatization, autistic fantasy, denial, dissociation, devaluation, splitting, acting out, passive aggression, displacement, projection, isolation, rationalization, idealization, reaction formation, undoing, pseudo altruism, suppression, anticipation, humor, and sublimation (Andrews et al., 1993).

Inventory of Personality Organization – Revised (IPO-R). The IPO-R, a 32-item questionnaire with a 1 (never true) to 5 (always true) Likert scale, measures identity diffusion (Smits et al., 2009). Showing its clinical validity, identity diffusion was found to be highest in those with personality disorders, moderate in a sample with anxiety/depression pathology, and lowest in a normative sample (Smits et al., 2009).

Behavioral Inhibition and Behavioral Activation Scales Revised (BIS/BAS-R). The BIS/BAS-R is a 20-item questionnaire on a 0 (not true) to 3 (very true) scale, measuring:

behavioral inhibition system (e.g. “I usually get very tense when I think something unpleasant is going to happen.”); behavioral activation system – reward responsiveness (e.g. “I feel excited and full of energy when I get something that I want.”); behavioral activation system – drive (e.g. “When I want something, I usually go all the way to get it.”); behavioral activation system fun seeking (e.g. “I often do things for no other reason than that they might be fun.”) (Muris et al., 2005).

Experiences in Close Relationships Scale Short Form (ECR-S). The ECR-S has 12 items each with a 1 (strongly disagree) to 7 (strongly agree) Likert scale, measuring attachment anxiety and attachment avoidance (Wei et al., 2007). With related items, the scale shows good convergent validity, such as the relationships between attachment anxiety and reassurance seeking ($r = 0.45$) and between attachment avoidance and fear of intimacy ($r = 0.74$) (Wei et al., 2007).

Control Belief Scales (CBS). The CBS, a 42-item questionnaire on a 1 (strongly disagree) to 7 (strongly agree) Likert scale, measuring realistic control beliefs, CBS Realistic Control Beliefs, (e.g. “Hard work and following through are the best means of realizing one’s goals.”) and unrealistic control beliefs, CBS Unrealistic Control Belief, (e.g. “There is no such thing as misfortune; everything that happens to us is the result of our own doing.”) (Zuckerman et al., 2004).

Interpersonal Sensitivities Circumplex (ISC). The ISC is 64-item questionnaire on a 1 (not at all, never bothers me) to 8 (extremely, always bothers me) Likert scale, measuring sensitivity to control (e.g. “it bothers me when a person thinks they are my boss”), sensitivity to antagonism (e.g. “it bothers me when a person disregards my feelings”), sensitivity to remoteness (e.g. “it bothers me when a person doesn’t show any feelings”), sensitivity to timidity

(e.g. “it bothers me when a person won’t engage in conversation”), sensitivity to passivity (e.g. “it bothers me when a person cannot assert themselves”), sensitivity to dependence (e.g. “it bothers me when a person avoids conflict at all costs”), sensitivity to affection (e.g. “it bothers me when a person wants to spend lots of time with me”), and sensitivity to sensation seeking (e.g. “it bothers me when a person doesn’t respect my privacy”) (Hopwood et al., 2011).

Additionally, as a circumplex measure, we also coded the overall elevation of sensitivities, ISC Elevation, sensitivity to dominance, ISC Dominance, (a dimensional rating weighting the total degree to which a participant is bothered by dominance or submissiveness across a single continuum), and sensitivity to warmth, ISC Warmth.

Circumplex of Interpersonal Values (CIV). The CIV is a 64-item questionnaire on a 1 (not important to me) to 4 (extremely important to me) Likert scale, measuring: agentic values (e.g. “how important is it that I appear confident”), agentic and separate values (e.g. “how important is it that I appear forceful”), separate values (e.g. “how important is it that I keep my guard up”), submissive and separate values (e.g. “how important is it that I not reveal my positive feelings for them”), submissive values (e.g. “how important is it that I conform to their expectations”), submissive and communal values (e.g. “how important is it that I put their needs before mine”), communal values (e.g. “how important is it that I feel connected towards them”), and agentic and communal values (e.g. “how important is it that I express myself openly”) (Locke, 2000). Additionally, as a circumplex measure, we also coded the overall elevation of values, values to dominance, and values to warmth.

Inventory of Interpersonal Strengths-32 (IIS). The Inventory of Interpersonal Strengths-32 is a 32-item questionnaire on a 0 (very little like me) to 5 (almost always like me) Likert scale, measuring: leading strengths (e.g. “I can take charge in a group”), direct strengths

(e.g. “I am comfortable disagreeing with others”), balance strengths (e.g. “I realize I don’t have to be friends with everyone”), restraint strengths (e.g. “I can listen and think before I act in a relationship”), cooperative strengths (e.g. “I am a good listener”), consider strengths (e.g. “It makes me happy when others are happy”), connected strengths (e.g. “I enjoy being with other people”), and engage strengths (e.g. “I really shine in the spotlight”) (Hatcher & Rogers, 2012). Additionally, as a circumplex measure, we also coded the overall elevation of strengths, strengths related to dominance, and strengths related to warmth.

Inventory of Interpersonal Problems -32 (IIP). The IIP-32 is a 32-item questionnaire on a 0 (not at all distressed) to 5 (completely distressed) Likert scale, measuring: domineering problems (e.g. “I can take charge in a group”), vindictive problems (e.g. “I am comfortable disagreeing with others”), cold problems (e.g. “I realize I don’t have to be friends with everyone”), socially avoidant problems (e.g. “I can listen and think before I act in a relationship”), nonassertive problems (e.g. “I am a good listener”), exploitable problems (e.g. “It makes me happy when others are happy”), overly nurturant problems (e.g. “I enjoy being with other people”), and intrusive problems (e.g. “I really shine in the spotlight”) (Barkham et al., 1996). Additionally, as a circumplex measure, we also coded the overall elevation of problems, problems related to dominance, and problems related to warmth.

Level of Personality Functioning – Self Report (LPFS-SR). Participants finished a 12-item Likert style measure of personality functioning using the LPFS-SR (American Psychiatric Association, 2013), that has been validated and demonstrated predictive validity in prior studies (Roche et al., 2016).

Level of Personality Functioning – Observer Report (LPFS-OR). Using the same 12-item Likert measure of LPFS, independent raters and a team of undergraduate observers rated

participants self-written psychological life-history narratives using the abbreviated version of the Life Stories Interview (American Psychiatric Association, 2013; McAdams, 2008). The raters received good interrater reliability with an average ICC of between 0.74-0.78 across teams for the total). This method demonstrated predictive validity in negative correlation with use of less mature defenses, and in higher relations with personality dysfunction measures (see (Roche et al., 2018) for more information).

Personality Inventory for the Diagnostic and Statistical Manual-5 Brief Form (PID-5-BF). The PID-5-BF, a 25-item measure of personality pathology for the alternative model of personality disorders for the DSM-5, measures negative affectivity personality pathology, detachment personality pathology, antagonism personality pathology, disinhibition personality pathology, and psychoticism personality pathology (Krueger et al., 2012). Each PID-5 scale shows strong convergent validity (r range 0.58 – 0.70) with related personality disorders (Hopwood et al., 2012).

PROMIS Anxiety Scale – Short Form (PROMIS Anxiety). The PROMIS Anxiety Scale-Short Form, a 7-item questionnaire on a 1 (never) to 5 (always) Likert scale, measures anxiety pathology in the past seven days (Pilkonis et al., 2011), and shows strong convergent ($r = 0.80$) validity with the Mood and Anxiety Symptom Questionnaire (Pilkonis et al., 2011).

PROMIS Depression Scale – Short Form (PROMIS Depression). The PROMIS Depression Scale-Short Form, an 8-item questionnaire with 1 (never) to 5 (always) Likert scale, measures depression pathology in the past seven days (Pilkonis et al., 2011), and shows strong convergent validity ($r = 0.83$) with the Center for Epidemiologic Studies Depression Scale (Pilkonis et al., 2011).

PROMIS Anger Scale – Short Form (PROMIS Anger). The PROMIS Anger Scale-Short Form, a 5-item form with a 1 (never) to 5 (always) Likert scale, measures depression problems in the past seven days (Pilkonis et al., 2011). The questionnaire shows adequate convergent validity ($r = 0.51$) with the Aggression Questionnaire (Pilkonis et al., 2011).

PROMIS Sleep Disturbance Scale –Short Form (PROMIS Sleep Disturbance). The PROMIS Sleep Disturbance –Short Form, an 8-item questionnaire with a 1 to 5 Likert scale (Likert anchors vary throughout the scale) measures sleep disturbance in the past seven days, and shows strong convergent validity with long forms and has greater precision than other related disturbance scales (Yu et al., 2011).

Procedure

Participants were recruited from Introduction to Personality Psychology and received extra credit for their participation. Participants were also given an alternative extra-credit opportunity if they did not wish to participate. Participants were asked to complete the personality measures during a pre-assessment and complete the PANAS at the end of every day for 50 days. At the end of each day, participants were instructed to go online, enter their unique participant identification number, and complete the 20 items on the PANAS. An average of 89.3% of the total surveys were completed by participants (mean = 44.7 surveys complete, median = 45 surveys, range 30 – 50 surveys).

Analyses

Calculating Affective Dynamics. We utilized the following measures of affective dynamics, calculated for both positive affect and negative affect: (1) *emotional variability* as defined by the individual standard deviation (iSD), (2) *relative emotional variability* as defined by the relative individual standard deviation (iSDr), (3) *emotional instability* as defined by the

individual root mean square of successive differences (iRMSSD), (4) *emotional inertia* as defined by the individual autoregressive relationships (iAR) using idiographic models, and (5) *emotional cyclical*ity as defined by weekly oscillatory dynamics (iCycle) using Lomb-Scargle periodograms. Note that emotional variability (iSD) describes the total amount of variability across the daily diary study. Relative emotional variability (iSDr) represents the total amount of variation possible given the mean of the affect. Emotional instability (iRMSSD) represents average immediate changes of affect from day to day. Emotional inertia captures the degree to which affect carries over from one day to the next, reflecting resistance to change. Emotional cyclical

Machine Learning Models. All models were trained and evaluated using out-of-sample predictions by using four-fold cross-validation. All models were based on extreme gradient boosting regression trees (“xgboost”). Models utilized all personality and psychopathology traits to predict each of the affective dynamics for negative affect and positive affect. The out-of-sample correlation between the predicted and individual affect dynamics was utilized as the primary outcome.

Model Feature Importance and Interpretability. To test our research questions, we examined the explainability of each of the models. Shapley values were utilized to visualize the drivers of each prediction. These values are generated based on perturbation to the saved models to determine how each model is making predictions. Shapley values represent an individual subjects’ predicted outcome, quantifying both magnitude and directionality on the prediction. Shapley values are valuable in part because, in a traditional bi-variate analysis, a given direction of association (e.g., positive correlation) can be driven by an almost infinite array of phenomena. For instance, a positive correlation can result from individuals scoring low on the predictor who

also score low on the outcome, individuals scoring high on the predictor scoring high on the outcome, or any combination of these factors. Shapley values allow one to rapidly perceive the underlying patterns that are driving a given bivariate relationship while accounting for all other predictors.

Results

Predictive Performance

Negative Affect Dynamics. Machine learning models were capable of significantly predicting (1) negative affect *emotional variability* (iSD, $r = 0.444$, 95% CI [0.317, 0.555]), (2) negative affect *relative emotional variability* (iSDr, $r = 0.201$, 95% CI [0.055, 0.339]), (3) negative affect *emotional instability* (iRMSSD, $r = 0.419$, 95% CI [0.289, 0.534]), (4) negative affect *emotional inertia* (iAR, $r = 0.152$, 95% CI [0.005, 0.293]), and (5) negative affect *emotional cyclical*ity (iCycle, $r = 0.178$, 95% CI [0.030, 0.317]). This suggests that personality and psychopathology variables were capable of predicting the negative affect dynamics for all types of measures, with moderate to large effects for emotional variability and emotional instability, and small effects with relative emotional variability, emotional inertia, and emotional cyclical

Positive Affect Dynamics. Machine learning models were capable of significantly predicting (1) positive affect *emotional variability* (iSD, $r = 0.297$, 95% CI [0.156, 0.426]), (2) positive affect *relative emotional variability* (iSDr, $r = 0.392$, 95% CI [0.259, 0.510]), (3) positive affect *emotional instability* (iRMSSD, $r = 0.282$, 95% CI [0.140, 0.412]), (4) positive affect *emotional inertia* (iAR, $r = 0.177$, 95% CI [0.030, 0.316]), and (5) positive affect *emotional cyclical*ity (iCycle, $r = 0.154$, 95% CI [0.006, 0.295]). This suggests that personality and psychopathology variables were capable of predicting the positive affect dynamics for all

types of measures, with moderate to large effects for emotional variability, relative emotional variability, and emotional instability, and small effects with emotional inertia and emotional cyclicity.

Feature Importance and Interpretability

Negative Affect Dynamics. The model results suggested that the most important features were: (1) DFS Anticipation for negative affect *emotional variability*, (2) ISC Warmth for negative affect *relative emotional variability*, (3) neuroticism for negative affect *emotional instability*, (4) IIS Leading for negative affect *emotional inertia*, and (5) IIS Warmth negative affect *emotional cyclicity*. With the exception of ISC warmth on negative affect relative emotional variability, the relationships were suggestive that higher values of the predictor were associated with higher values of the response variables (i.e. high neuroticism corresponded with higher predicted negative affect *emotional instability*). See Table 1 and Figure 1.

Positive Affect Dynamics. The model results suggested that the most important features were: (1) BAS Fun-Seeking for positive affect *emotional variability*, (2) BAS Fun-Seeking for positive affect *relative emotional variability*, (3) ISC Dominance for positive affect *emotional instability*, (4) IIS Dominance for positive affect *emotional inertia*, and (5) conscientiousness for positive affect *emotional cyclicity*. The relationships were suggestive that higher values of the predictor were associated with higher values of the response variables (i.e. high conscientiousness corresponded with higher predicted *emotional cyclicity*). See Table 1 and Figure 2.

General Discussion

This paper investigates day-to-day affective dynamics constructs in the context of a comprehensive array of individual differences, and identifies the relative importance of these

traits in predicting the ways in which people's affect changes from day-to-day. Taken together, the results suggest that for both positive and negative affective dynamics, the implemented machine learning models significantly predicted each of the affective dynamic constructs considered in this analysis, specifically: emotional variability, relative emotional variability, emotional instability, emotional inertia, and emotional cyclicity.

The present results are derived from machine learning models capable of identifying non-linear relationships between our predictors (baseline personality and psychopathology traits) and affective dynamics outcomes, as well as assessing model fit using a “test set” of data that was not used for “training” the ML models (i.e., estimating key coefficients). Such a statistical approach should at once be more sensitive to patterns in the data and avoid the inflated effect sizes that can be caused by determining and evaluating the significance of coefficients using the same data points. The current results generally align with the results of more conventional approaches to examining relationships between individual difference constructs and affective dynamics. Specifically, we show relationships between (1) greater depression symptoms and more blunted or perseverative negative affect over time (i.e., higher affective inertia; iAR), (2) depression symptoms and more reactive/unstable negative affect (emotion variability: iSD), (3) greater anxiety and more unstable or variable negative affect (iRMSSD, iSD), (4) trait negative emotionality and both greater negative affect instability (iRMSSD) and positive emotion variability (both iSDr and iSD). Such findings and related theoretical significance have been reported elsewhere (Houben et al., 2015).

Affective Dynamics and Interpersonal Dominance

Notably, interpersonal interaction style measures were among the top five most significant predictors in eight of the ten affective dynamic models (see Figure 1). The

prominence of interpersonal styles is significant given that, to date, relatively few studies have examined the manner in which emotion dynamics relate to social behavior. We find links between affective dynamics constructs and (1) indexes reflective of comfort and experience with dominant interpersonal behavior (IIS Dominance, IIS Leading), and (2) indexes reflective of interpersonal sensitivity/reactivity towards both the dominance/submissive (ISC Dominance) and warmth/cold (ISC Warmth) dimensions.

Emotion and behavior are inextricably linked and components of emotion should motivate people to adjust their behavior to match the environment (Frijda & FRIDJA, 1986). Consistent with this, Berkowitz and Harmon-Jones (2004) suggest that the emotions one experiences should influence the way in which individuals interact with others. In particular, people who experience more positive emotion (i.e., less negative emotion) should tend to behave more agreeably toward others (Berkowitz & Harmon-Jones, 2004). From such a perspective, positive emotionality should be associated with approach tendencies (including social affiliation) while negative affect should be linked to anger (Berkowitz & Harmon-Jones, 2004), which can motivate people to act more dominantly (Cabral & de Almeida, 2019)

The present findings are consistent with Berkowitz and Harmon-Jones's (2004) theory in that more reactive positive emotion systems should be linked to more agreeable or less dominant/interpersonally aggressive behavior. Concretely, we show that reduced positive affective inertia, in the form of more variable and less blunted positive affect (i.e., lower iAR), is associated with decreased tendencies to act in dominant ways (e.g., disagree with others; IIS Dominance). Given links between higher autocorrelations and more blunted emotion reactions (Kuppens et al., 2010), as well as links between lower autocorrelations and positive emotionality (Houben et al., 2015), the present results support and extend Berkowitz' theory and suggest that

people who experience more positive emotions may be less inclined to adopt a dominant interpersonal style.

Interestingly, the present results suggest that more variable, and less blunted *negative* affect (i.e., lower iAR or affective inertia) is also predictive of reporting decreased tendencies to enact interpersonal dominance (IIS Leading). This cross-valence effect is quite consistent with previous research given that individuals who exhibit more variable positive *or* negative emotion over time tend to report increased mental health/happiness, and happier individuals have been less accustomed to disagreeable behavior such as interpersonal aggression or dominance (Ziapour et al., 2018). Specifically, Houben et al. (2015) show that lower autoregressions of both positive and negative affect over time are linked to enhanced psychological well-being, including happiness (Houben et al., 2015), and existing evidence points to a significant positive relationship between happiness and the tendency to adopt a more agreeable, less aggressive interpersonal style (Ziapour et al., 2018).

Affective Dynamics and Interpersonal Sensitivity

Turning to our findings concerning interpersonal sensitivity to the dominance dimension (ISC Dominance; the tendency to be “bothered” by dominance and/or submissiveness), we show a strong pattern across emotional valence where people who reported greater ISC Dominance also tended to report more extreme/variable and unstable fluctuations in emotion across days. Specifically, elevated ISC Dominance was associated with both negative and positive emotion instability (iMSSD) or reactivity (iSD, iSDr). This finding is consistent with existing affective dynamics research, and would be expected given that (1) emotional instability of both positive and negative affect have been linked to increased anxiety, neuroticism, and generally decreased mental health (Houben et al., 2015), (2) and individuals higher in neuroticism or trait anxiety

have consistently shown greater reactivity/sensitivity to the environment (Martin et al., 2000; Spielberger et al., 1999), and finally (3) as previously discussed, such sensitivity should manifest itself in social situations (Hopwood et al., 2011; D. J. Miller et al., 2009a). In other words, it is reasonable to expect that interpersonal sensitivity of this type could manifest itself as the emotionally reactive individual becoming more easily upset by both dominant or submissive individuals.

Based on the previous paragraph, one might assume that individuals showing greater affective variability/instability would also report being more easily bothered by extreme coldness or extreme warmth. However, we find the opposite pattern. The present ISC Warmth findings indicate that sensitivity towards the warmth dimension is negatively associated with emotional reactivity of both positive (RMSSD) and negative (iSDr) affect. Such a pattern suggests that individuals who experience more unstable/variable affect tend to be less easily bothered by others who exhibit extreme warmth or extreme coldness.

One plausible explanation for this pattern of findings is that individuals with high emotional reactivity may also tend to have a colder interpersonal style, and colder individuals should be less bothered by others who also show cold interpersonal behaviors ((Hopwood et al., 2011). An assumption made in this explanation is that higher scores on the current ISC Warmth index are generally reflective of people being more bothered by excessive coldness than by excessive warmth. The present explanation is plausible given that (1) individuals with higher affective reactivity have been more likely to experience anxiety, depression, general negative emotionality, and lower positive emotionality (Houben et al., 2015), (2) such individuals have tended to behave more coldly toward others (Smith et al., 2010), and finally (3) people tend to be less bothered by others who exhibit interpersonal behaviors similar to their own (Hopwood et

al., 2011). Thus, individuals who are more emotionally reactive may be less bothered by others adopting a colder interpersonal style. Conversely, individuals who have lower emotional variability show lower levels of anxiety or depression and higher levels of well-being and happiness, and thus warmer interpersonal behavior. From this perspective, such individuals would exhibit greater sensitivity towards others who have colder interpersonal styles.

Taken together, the present affect and interpersonal findings extend our understanding of the ways in which emotion matters for social behavior. Interestingly, the results suggest links between interpersonal phenomenon and both blunted affect (affective inertia) and over-reactive affect (affective instability and variability), and the relative magnitude of these effects are comparable to more traditional covariates of affective instability such as negative emotionality.

Limitations

Some limitations should be considered when interpreting the current results. First, the sample population was composed of undergraduate students recruited from introduction to personality psychology courses, representing a predominantly White/Caucasian, female, and college-educated cohort. As a result, the participants in this study may not fully reflect the general population. For instance, younger participants have reported feeling less positive emotions such as content and calmness in comparison to older adults (English & Carstensen, 2014). Additionally, the present data was primarily gathered from women, which could decrease the generalizability of the models as women aged 15-25 can be twice as likely to report depression than men (Patten et al., 2006). A final potential limitation concerns the participants completing summary PANAS reports at the end of the day. Affect likely fluctuates during the day and the current protocol may not fully reflect intra-day affective dynamics (Crowe et al.,

2019). Future research could utilize more extensive Ecological Momentary Assessment to collect information on participant's affect multiple times throughout the day.

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Table 1

Variable Importance (variables listed are among the top 3 predictors of any affective outcome)

Predictor	Negative Affect						Positive Affect					
	iSD	iSDr	iRMSSD	iAR	iCycle	Total	iSD	iSDr	iRMSSD	iAR	iCycle	Total
BFI Conscientiousness	0	66	22	50	64	27	0	18	24	66	100	30
BFI Negative Emotionality	62	54	100	72	53	100	52	42	49	63	40	58
BAS Fun-Seeking	41	61	34	1	7	48	100	100	74	1	33	100
BAS Reward Responsiveness	94	35	33	10	24	75	0	17	0	22	0	11
CBS Unrealistic Control Belief	0	59	0	84	6	13	11	3	33	4	72	19
CIV Elevation	31	62	0	64	83	36	0	28	0	44	16	20
CIV PA Agentic	0	89	0	30	9	13	34	28	37	5	24	36
DFS Anticipation	100	45	0	17	35	65	0	7	0	3	5	4
DFS Isolation	0	0	0	22	2	2	0	0	16	79	40	15
DFS Rationalization	0	12	0	15	0	2	38	15	25	91	0	34
DFS Somatization	0	39	53	0	6	31	0	0	0	26	15	4
IIS Dominance	0	45	39	53	37	31	0	0	0	100	8	11
IIS Submissive	31	57	0	31	76	33	0	5	7	12	24	7
IIS Leading	0	13	0	91	36	11	0	16	6	11	0	11
IIS Warmth	0	0	0	11	100	10	0	9	28	17	68	18
ISC Dominance	26	84	38	72	59	53	18	53	100	15	38	62
ISC Elevation	29	68	32	18	18	43	61	65	54	7	50	69
ISC Warmth	66	100	19	58	28	64	39	15	57	25	44	39
PANASX Joviality	29	17	22	38	9	32	25	0	67	1	31	27
PANASX Shyness	0	17	0	95	26	10	0	0	0	4	23	2
PROMIS Anger	0	85	0	38	3	13	42	47	22	48	4	46
PROMIS Anxiety	100	16	53	34	42	90	0	16	0	34	2	12
PROMIS Depression	91	0	0	100	0	57	0	0	0	67	0	7

Note. The top three predictors (vertically) are bolded for each affective outcome. iSD = individual standard deviation (emotional variability); iSDr = relative individual standard deviation (relative emotional variability); iRMSSD = individual root mean square of successive

differences (emotional instability); iAR = individual autoregressive relationship (emotional inertia), iCycle = oscillatory dynamics (emotional cyclicity); Tot = total affective dynamics based on all other measures, weighted by predictive performance.

Figure 1: The most significant predictors for negative and positive emotion dynamics

Note: A purple feature value dot represents a subject scoring lower on the relevant individual difference (e.g., a model showing predominantly yellow subject dots with large positive

SHAP values would suggest that subjects scoring low on the outcome tend to report higher values on the predictor).