Personalized models of personality disorders: Using a temporal network method to understand symptomatology and daily functioning in a clinical sample

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Abstract

Background: An ongoing challenge in understanding and treating personality disorders (PDs) is significant heterogeneity in disorder expression, stemming from variability in underlying dynamic processes. These processes are commonly discussed in clinical settings, but are rarely empirically studied due to their personalized, temporal nature. The goal of the current study was to combine intensive longitudinal data collection with person-specific temporal network models to produce individualized symptom-level structures of personality pathology. These structures were then linked to traditional PD diagnoses and stress (to index daily functioning).

Methods: Using about 100 daily assessments of internalizing and externalizing domains underlying PDs (i.e., negative affect, detachment, impulsivity, hostility), a temporal network mapping approach, group iterative multiple model estimation, was used to create person-specific networks of the temporal relations among domains for 91 individuals (62.6% female) with a PD. Network characteristics were then associated with traditional PD symptomatology (controlling for mean domain levels) and with daily variation in clinically-relevant phenomena (i.e., stress).

Results: Features of the person-specific networks predicted paranoid, borderline, narcissistic, and obsessive-personality disorder symptom counts above average levels of the domains, in ways that align with clinical conceptualizations. They also predicted between-person variation in stress across days.

Conclusions: Relations among behavioral domains thought to underlie heterogeneity in PDs were indeed associated with traditional diagnostic constructs and with daily functioning (i.e., stress) in person-specific networks. Findings highlight the importance of leveraging data and models that capture person-specific, dynamic processes, and suggest that person-specific networks may have implications for precision medicine.

The etiology, typical progression, accurate assessment, and effective treatment of personality disorders (PDs) have been challenging to establish, contributing to suboptimal patient outcomes. This is because PDs are heterogeneous and highly comorbid with other forms of psychopathology (Silverman and Krueger, 2018, Bateman et al., 2015). Moreover, within the *Diagnostic and Statistical Manual of Mental Disorders* (DSM; American Psychiatric Association, 2013), PDs continue to be conceptualized as discrete categories despite strong evidence of limitations of this approach and benefits of a dimensional perspective (Hopwood et al., 2018, Krueger et al., 2014). Although DSM diagnoses were organized around key clinical processes, such as contextualized and dynamic symptoms (Wright and Hopwood, 2016), efforts to integrate a dimensional perspective into clinical settings, as exemplified by the “Alternative Model for Personality Disorder” (AMPD) in the latest version of the DSM, has significant potential to accommodate the inherent heterogeneity in manifestations of personality pathology. An important step toward this goal is to determine how an empirically-based dimensional model of personality can capture within-person processes that underlie traditional diagnostic groupings.

Structuring Dimensionality: Temporal Network Approaches to Personality

Mental disorders may be fruitfully represented as a network of “interacting symptoms” (Fried et al., 2017), composed of a set of elements (‘nodes’) and the connections (often referred to as ‘edges’) between those elements. A variety of network models are widely used in other fields (reviewed in Bringmann and Eronen, 2018) and differ in suitability for research questions, inferences that can be made, and statistical accuracy (Boccaletti et al., 2006).

Person-specific temporal network models are especially appealing to PD research. They leverage *intensive longitudinal data* (many observations per person) to represent *person-specific dynamic psychological processes*, and contrast with structural models of psychopathology that

are based on cross-sectional data and do not distinguish between exacerbations and diminutions of pathology over time (Forbes et al., 2017). Although PDs (and pathological traits as described in the AMPD) have demonstrated long-term stability *across individuals* (i.e., rank order, mean-level change) (Hopwood and Bleidorn, 2018, Morey and Hopwood, 2013, Wright et al., 2015b), expressions of PDs and pathological traits exhibit short-term fluctuation *within individuals* (Wright et al., 2015a, Wright and Simms, 2016). Indeed, the person-specific, dynamic nature of PDs is key to treatment, as clinicians seek to understand the mechanisms of symptom expression to determine when and how to interrupt these processes for a unique individual (Wright and Hopwood, 2016). Person-specific temporal network models speak to this, producing an individualized symptom-level structure of personality pathology dynamics, which could then be used to better predict behavior and clinical outcomes.

To capture PD symptom dynamics, researchers can use study designs that incorporate frequent real-time data collection in an individual's natural environment (i.e., ambulatory assessments). Daily diaries or Ecological Momentary Assessment (EMA) approaches are characterized by a series of repeated measurements (often via phone, tablet, or computer) of current experiences (including emotional states and behaviors) while participants engage in normal daily activities (Trull and Ebner-Priemer, 2013). For example, Wright and colleagues (2015a) examined daily covariation among domains of internalizing (i.e., negative affect and detachment) and externalizing (i.e., hostility and impulsivity) behavior in individuals with personality pathology via an online survey every day for 100 days. They modeled associations among these daily manifestations of PDs using a person-specific temporal network approach called unified structural equation modeling (uSEM; Gates et al., 2010, Kim et al., 2007). uSEMs combine traditional SEM and vector-autoregressive (VAR) approaches in order to model

contemporaneous (i.e., domains predicted by domains on the same day; from SEM) and lagged (i.e., domains predicted by domains on previous days; from VAR models) connections. The resulting networks provided insight into how the domains predicted one another on the same and different days uniquely for each participant; these inter-relations were not evident from the descriptive data typically used in group-level analyses, such as item means (Wright et al., 2015a).

Although person-specific temporal networks can illuminate heterogeneous phenomena, there is clear clinical value in being able to understand homogenous processes to the extent that they exist. Thus, ideal models of PDs and psychopathology should be able to generalize somewhat across individuals, while leaving room for personalized elements (Wright et al., 2015a, Wright and Zimmermann, 2019). Indeed, research has begun to demonstrate the utility of person-specific temporal approaches in understanding psychopathology (e.g., Epskamp et al., 2018, Fisher et al., 2017). For instance, in an illustrative analysis, Beltz and colleagues (2016) used group iterative multiple model estimation (GIMME; Gates and Molenaar, 2012) to generate network maps for 25 participants with PDs representing daily dynamic processes of a network including the same four personality pathology domains examined by Wright and colleagues (2015a). GIMME implements uSEMs with a grouping element to account for both homogeneity (in group-level connections) and person-specific heterogeneity (in individual-level connections). Beltz and colleagues (2016) identified two contemporaneous group-level connections between domains (i.e., disinhibition predicted hostility; negative affect predicted detachment), which can be interpreted as evidence for homogeneity in network functioning, even among participants with differing diagnoses and demographic characteristics. Yet, there was also considerable heterogeneity in network functioning across participants, as represented by unique individual-

level connections between domains within individuals' maps (Beltz et al., 2016). Taken together, this exemplar paper demonstrated that GIMME can successfully integrate group- and individual-level features of dimensional personality pathology, with potential clinical implications.

GIMME: A Temporal Network Model of Homogeneity and Heterogeneity

Features of GIMME networks, including connections (represented by regression coefficients), can be extracted to characterize meaningful psychological processes. For instance, nodes (domains in the studies above) in the networks of some individuals can have significant auto-regressive coefficients, which indicate time-lagged self-prediction (e.g., yesterday's negative affect predicts today's negative affect). Positive auto-regressive coefficients may reflect a clinical 'inertia,' or the extent to which emotional states are resistant to change, which has been associated with maladjustment and psychopathology (Houben et al., 2015). Additionally, the number of connections into and out of a node, referred to as "degree centrality," reflect the extent to which a domain predicts or is predicted by others. For example, certain domains can be identified as having particularly high "in-degree" (i.e., *predicted by* other domains), whereas other domains may have particularly high "out-degree" (i.e., *predicting* other domains) (Boccaletti et al., 2006). Thus, GIMME captures differential patterns of temporal network functioning and the person-specific organization of personality pathology. Further research is needed to examine the utility of GIMME in a larger, more heterogeneous sample – beyond illustrative and exemplar studies (Beltz et al., 2016, Wright et al., 2015a). Moreover, no studies have examined whether GIMME network features reflect traditional PD symptomatology or provide insight into daily outcomes typically assessed by clinicians to understand risk, such as stress.

Current Study

Here we take an empirically-based dimensional approach to the study of heterogeneity in personality pathology by employing GIMME to examine person-specific, day-to-day phenomenology of personality pathology measured by the “big-4” of personality pathology (i.e., negative affect, detachment, impulsivity, and hostility; Widiger and Simonsen, 2005). In a large, heterogeneous sample of individuals with prior PD diagnoses, we leveraged the GIMME demonstration of Beltz et al. (2016) and extend the person-specific models of Wright et al. (2015a). We then determined whether temporal network characteristics were differentially associated with traditional PD symptomatology (beyond average levels of the “big-4”) and whether they have predictive utility for understanding daily variation in clinically-relevant phenomena like stress.

Methods

Data came from a daily diary study in a sample of individuals with personality pathology, as discussed above (Beltz et al., 2016; Wright et al., 2015). Other data from this study have also been published in work with different research aims. Lane et al. (2019) was primarily a simulation study to validate the subgrouping component of GIMME aiming to map the core features of borderline personality disorder (BPD), and only included participants from this sample who met the clinical threshold for BPD. Wright et al. (2019) also used the subgrouping component of GIMME aiming to map the interplay among stress, interpersonal behavior, and affect. The current manuscript is conceptually and methodologically distinct from this past work: We used the multiple solutions version of GIMME and variables concerning the broader forms of personality pathology aiming to go beyond network mapping by using network features to predict personality disorder symptoms and daily stress.

Participants

Participants were 91 individuals (62.6% female) with a PD selected from the daily diary portion of a parent study aimed at refining measurement in personality pathology (Wright et al., 2015a). All procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. Participants completed online diaries including clinically-relevant behaviors for 100 consecutive evenings. Although 116 participants attended a baseline assessment, only participants providing at least 60 days of data were included in the present analyses to ensure reliable parameter estimates ($n=95$), based on simulation-derived cut-offs (Lane et al., 2019). An additional 4 participants were excluded due to low variance in item endorsement (i.e., consistently marking only '0' for relevant items).

The final sample of 91 participants primarily reported being either White (83.5%) or African American (13.2%), and had a mean age of 45.13 years ($SD=13.37$). They were heterogeneous in PD diagnoses: 56% avoidant, 6.6% dependent, 48.4% obsessive compulsive, 18.7% narcissistic, 39.6% borderline, 4% histrionic, 7.7% antisocial, 36.3% paranoid, 16.5% schizotypal, and 13.2% schizoid. The average number of PD diagnoses per participant was 2.5. Additionally, 63.7% were diagnosed with mood disorders, 72.5% with anxiety disorders, 9.9% with psychotic disorders, and 23% with substance/alcohol use disorders. Participants provided a mean of 97.19 data points (i.e., 97.19 completed daily diaries; $SD=6.82$). Detailed demographics are presented in Table 1. Participants received financial compensation for their participation: see Wright et al. (2015a).

Measures

Daily domains of PD. Four factor-analytically derived domains of daily personality pathology were created from 16 daily diary items that were designed to capture day-to-day

expressions of PDs (Wright et al., 2015a). Briefly, participants rated items on an 8-point response scale (0=“Not at all”; 7=“Very much so”). The statements were designed to reflect the personality facets of negative affect, detachment, disinhibition, and hostility. Scores were created by averaging relevant items. When participants were missing a data point, the score was typically imputed by averaging the scores from the previous and following two days (Supplemental Materials); when the amount of missing time series data is low (<20%), imputation method has little influence on results (Rankin and Marsh, 1985). The resulting four-variate time series were used in subsequent analyses.

Baseline PD symptom counts. PD symptom counts were determined from clinical diagnostic interviews conducted at the baseline assessment. On average, time between diagnostic interview and the first diary in this study was 1.4 years ($SD=0.16$ years). Although 11 PDs were assessed in this sample, we specifically focused on disorders with higher prevalence rates in the current study (>15%) to ensure sufficient representation: avoidant, obsessive compulsive, narcissistic, borderline, paranoid, and schizotypal.

Stress. A latent factor score was computed using seven stress indicators reported daily. Each indicator captured broad experiences of stress (e.g., “Did you have an argument or disagreement with anyone since this time yesterday?”) and was estimated as a product of the number of events occurring in that category and the severity rating for that category on a 4-point response scale (0=“Not at all”; 3=“Very”).

Data Analysis

First, the 91 time series were submitted to GIMME-MS, a version of GIMME that generates multiple solutions in order to facilitate the accurate estimation of the direction of prediction among variables (Beltz and Molenaar, 2016). Within GIMME, two connections can

equally improve model fit at a given iteration. To address this, multiple solutions are generated, each following a path originating at one of the equal connections. For instance, if the contemporaneous connection from variable A to variable B would improve model fit as much as the contemporaneous connection from B to A, then one solution would estimate the A-to-B connection and continue to iterate, while a separate solution would estimate the B-to-A connection and continue to iterate. A single solution is then selected based on the AIC (Supplemental Materials; Beltz and Molenaar, 2016). At the group-level, the standard 75% criterion was used: A connection between two domains was required to be significant (according to a chi-square difference test with one degree of freedom for an individual's model) for at least 69 (of 91) participants to be estimated for everyone in the sample. At the individual-level, an optimal solution – when multiple were generated – was selected according to the Akaike Information Criterion (AIC; Akaike, 1974); see Supplemental Materials. Final maps (containing group- and individual-level connections for each participant) were evaluated with alternative fit indices, with two of four required to meet cut-offs to indicate excellent fit (Brown, 2014): root mean square error of approximation (RMSEA) $\leq .05$, standardized root mean square residual (SRMR) $\leq .05$, comparative fit index (CFI) $\geq .95$, and non-normed fit index (NNFI) $\geq .95$. White noise tests were conducted on each map to determine whether all temporal information was captured by the modeled connections (i.e., whether residuals were uncorrelated white noise); see Supplemental Materials.

Extraction of network features. We extracted several features from the individual-level networks to characterize person-specific patterns of connections among the domains that could be linked to diagnoses and daily behavior.

Auto-regressive coefficients. For each participant, we examined whether a given domain had a relatively large first order auto-regressive coefficient. The presence of a positive, significant auto-regressive coefficient can be interpreted as temporal stability in that domain.

Degree. For each participant, we calculated the within-internalizing degree (i.e., total number of connections between negative affect and detachment regardless of their direction or whether they were contemporaneous or lagged), within-externalizing degree (i.e., between impulsivity and hostility), and between internalizing and externalizing degree (i.e., total number of connections between an externalizing domain and an internalizing domain). Within-degree reflects the extent to which facets within the same domain influence one another. For example, higher within-internalizing degree would indicate that levels of negative affect and detachment are highly dependent on one another. Degree between internalizing and externalizing, instead, represents cross-talk across internalizing and externalizing domains.

Regressions. We tested associations between PD symptomatology and network features to determine whether associations between externalizing and internalizing domains uniquely underlie diagnoses; specifically, the goal was to determine whether network features predict dimensional symptoms above and beyond average levels of the “big-4” typically used in clinical research. A multiple regression model was run for each network feature (predictor) and symptom count (outcome), with age and average daily ratings for each domain included as covariates; see Table 2 for zero-order correlations among covariates and PD symptom counts. The daily ratings statistically control for *levels* of externalizing and internalizing domains, and therefore isolate effects of the *dynamic interplay* among the domains, as represented by the network features. There were no significant differences between male and female participants for any of the symptom counts, and thus, sex was not covaried. The resulting standardized beta weights are

interpreted as dimensional indices of the strength and direction of the relation between a symptom and a given network feature. We note results that are statistically significant at $p < .05$ (uncorrected), but focus on the variation of the indices because we did not have *a priori* hypotheses.

Multilevel models. We examined whether network features were predictive of stress to illustrate the utility of network features for understanding daily processes linked to clinically-relevant outcomes. We used multilevel growth models (with an unstructured covariance matrix of the random effects) to examine changes in stress across the course of the study, and the extent to which daily stress was predicted by dynamics within and between internalizing and externalizing domains. Age and average domain levels were time-invariant covariates. Gender was also a time-invariant covariate because of sex differences in stress experiences and responses (Bale and Epperson, 2015, Kudielka and Kirschbaum, 2005). Day was nested within participants (using unstructured covariance matrix of the random effects), and both random intercepts and slopes were modeled.

Results

GIMME

Final network models generally fit the data well (Average: $\chi^2=15.49$, $df=17.93$, CFI=1.00, NNFI=.99, RMSEA=.01, SRMR=.05). However, a small percentage of models (7.69%) only met standards of acceptable fit (i.e., only one index met criteria for excellent fit). Interestingly, GIMME-MS did not detect any group-level connections; that is, there were no identical connections of the same directionality present across the majority of the sample. Thus, GIMME-MS only mapped person-specific connections.

GIMME-MS results were manually reviewed for multiple solutions (see Supplemental Materials) to identify the best-fitting model (using primarily the AIC as validated in Beltz & Molenaar, 2016). Selected models for each individual were then submitted to *a posteriori* model validation to ensure that their temporal order (i.e., the covariation accounted for by the contemporaneous and lag 1 connections) was sufficient for capturing sequential dependencies. Specifically, if residuals were not white noise, lag 2 or lag 3 connections were fit to the data (Supplemental Materials).

Final models contained between 1 and 12 connections ($M=6.24$, $SD=1.89$), with all models including contemporaneous connections (Range: 4-9) and most including lagged connections (Range: 0-6). Figure 1 depicts individual-level maps from four participants selected to represent networks at high levels of paranoid (Figure 1A), borderline (Figure 1B), narcissistic (Figure 1C), and obsessive-compulsive symptoms (Figure 1D). These participants had at least one auto-regressive component, suggesting some day-to-day stability in domains; this also was evident in the full sample (Range of first order auto-regressive coefficients: 0-4). The majority of auto-regressive coefficients (98.7%) across all participants had positive beta weights ($n=2$ significant negative auto-regressive coefficients), consistent with the interpretation that these coefficients reflect temporal stability. Except for Participant C, the depicted participants also had connections within the internalizing domains (i.e., negative affect and impulsivity were related); this was true for the nearly the entire sample (94.5% had within-internalizing connections). Additionally, the depicted participants had connections within the externalizing domains (i.e., detachment and hostility were related) and between the internalizing and externalizing domains; this was also true for nearly all the sample (90.1% had within-externalizing connections; 95.6% had between internalizing and externalizing connections).

Associations Among Personality Networks and Symptomatology

Multiple regression analyses revealed unique temporal network signatures for different PD symptoms; see Supplemental Table 1. Average R^2 for models predicting each symptom count were as follows: borderline=.17, narcissistic=.13, avoidant=.24, obsessive-compulsive=.09, paranoid=.30, schizotypal=.12. Results are shown in Figure 2 and Supplemental Figures 1 and 2, which includes all beta weights from each model, depicting the differential prediction of each PD symptom by age, average levels of the domains, and the network features. For instance, Figure 2A depicts the prediction of paranoid symptomatology. After controlling for age (green) and average levels of detachment (gray), negative affect (orange), disinhibition (yellow), and hostility (purple), network features (blue and listed on the y-axis) still uniquely predicted symptoms, specifically connections within the internalizing domain. Bars to the left represent negative prediction magnitudes; bars to the right represent positive prediction magnitudes.

Network features uniquely predicted four of the six PD symptoms considered. First, paranoid symptomatology (Figure 2A) was uniquely predicted by lower within-internalizing degree, suggesting that reduced cross-talk between negative affect and detachment is linked to higher levels of mistrustfulness. Second, borderline symptomatology (Figure 2B) was uniquely predicted by disinhibition auto-regression, such that greater symptomatology was linked to the absence of this connection in the network, reflecting greater variability in disinhibition across time. Symptoms were also uniquely predicted by greater degree between internalizing and externalizing domains, potentially reflecting dynamic interpersonal processes, such as reactive aggression in response to feelings of anxiety within the disorder (Hopwood, 2018). Third and similar to borderline symptomatology, narcissistic symptomatology (Figure 2C) was uniquely predicted by degree between internalizing and externalizing domains, which may underlie

fluctuations between expressions of vulnerability and grandiosity. Fourth, obsessive-compulsive symptomatology (Figure 2D) was uniquely predicted by the presence of disinhibition and hostility auto-regressive coefficients, as well as by greater within-externalizing degree.

Covariates. As expected, there were numerous significant bivariate associations among age, average domain levels, and PD symptoms (Table 2). For the most part, when included as covariates in models of network features predicting symptomatology, however, the influence of average domain levels were reduced and not significant (Figure 2). There were two notable exceptions, such that avoidant symptoms were significantly associated with greater average levels of negative affect in most models, and paranoid symptoms were significantly associated with greater average levels of detachment. Additionally, age was significantly negatively associated with three symptom counts: borderline, avoidant, and paranoid personality symptoms (i.e., being younger was associated with more symptoms in this sample).

Associations Among Personality Networks and Daily Stress

Multilevel model results are shown in Table 3. Person-specific network features for connections within internalizing and externalizing domains predicted between-person variation in rate of change in stress over time. Interestingly, significant interactions with day revealed opposite patterns for within-internalizing compared to -externalizing degree. Specifically, more connections within externalizing domains were related to increased stress over time, while more connections within internalizing domains were related to decreased stress over time. Inter-individual variation in connections between internalizing and externalizing domains did not account for differences in stress over time.

Discussion

The aim of this study was to characterize the heterogeneity in personality pathology by leveraging intensive longitudinal data consisting of about 100 daily reported detachment, negative affect, disinhibition, and hostility ratings from 91 individuals with PDs. Person-specific temporal networks captured the daily interplay among these four domains of personality pathology, and features of the networks predicted paranoid, borderline, narcissistic, and obsessive-personality disorder symptom counts, even above average levels of the domains. Both internalizing and externalizing network features also predicted daily stress. Findings are especially noteworthy because detected associations span methods (i.e., interview and self-report; cross-sectional and intensive longitudinal) and are separated by some length of time; thus, estimates of effects are likely quite conservative. Taken together, the current study outlines an approach for quantifying the behavioral processes underlying personality pathology and has potential clinical utility.

The networks were detected with GIMME-MS, a person-specific network modeling technique that maps contemporaneous and lagged connections among domains. Although GIMME-MS can detect group-level connections, no connections common across participants were detected, likely reflecting the sample's heterogeneity (e.g., high and differential patterns of comorbidity). Thus, a unique temporal network map was estimated for each participant, and these maps generally fit each person's data well. As GIMME-MS produces sparse networks through a data-driven method, only statistically meaningful connections were included in each individual's network.

Differential Prediction of Network Features

Although GIMME-MS has been previously applied to a subset of these data ($n=25$) in order to illustrate how to map dynamic processes between internalizing and externalizing

behaviors (Beltz et al., 2016), the current study extends this work to the full sample and demonstrates how network features map on to traditional clinical data. For example, both borderline and narcissistic symptomatology were associated with greater degree between externalizing and internalizing, such that detachment or negative affect predicted or was predicted by disinhibition or hostility. This is consistent with clinical descriptions of these disorders, noting that expressions of negative affect are strongly linked to expressions of hostility (American Psychiatric Association, 2013, Hopwood, 2018). Moreover, borderline symptomatology, which is uniquely characterized by emotional dysregulation and unpredictability, was also linked to instability of disinhibition levels (i.e., absence of disinhibition auto-regressive coefficients). In contrast, paranoid symptomatology, which includes hostile aloofness and hypersensitivity to criticism and threat, was uniquely predicted by increased daily levels of detachment but lower within-internalizing degree (i.e., fewer connections between detachment and negative affect). Finally, obsessive-compulsive symptomatology, which is characterized by inflexibility, stubbornness, and reactive anger in response to loss of control or need for compromise, was associated with the presence of externalizing auto-regressive coefficients, reflecting greater stability of externalizing domains, and greater within-externalizing degree, reflecting more cross-talk between disinhibition and hostility. Thus, associations between network features from GIMME-MS models and traditional PD symptom counts were in line with clinical conceptualizations of the disorders.

Importantly, network features were predictive of personality pathology even when accounting for average daily levels of externalizing and internalizing domains, as well as age. Daily levels of some domains and age predicted some symptoms, though. Younger participants were more likely to have higher levels of avoidant, paranoid, and borderline symptoms,

consistent with the age range in the sample (i.e., 19 to 79; $M=45.13$) and evidence that PD symptomology tends to decline in middle adulthood (age 40s) (Skodol, 2008). Additionally, higher average levels of negative affect predicted avoidant symptoms and higher average levels of detachment predicted paranoid symptoms, consistent with characteristics of negative emotionality and anxiety within avoidant PD and social withdrawal within paranoid PD. Thus, domain levels seemed to predict specific sets of symptoms, while network features predicted across symptom sets (e.g., degree between internalizing and externalizing was predictive of both narcissistic and borderline symptoms, perhaps revealing novel commonalities between them).

Models that included network features, average daily levels, and age, predicted 9-30% of the variance in symptom counts. Network feature prediction suggests that the dynamics they reflect provide important information beyond average levels of pathology, which are typically used in clinical research and practice. Network features may therefore uniquely reflect some behavioral processes underlying clinical diagnoses of personality pathology and serve as effective targets for intervention within treatment settings. To this point, network features also predicted rates of change daily stress, a key experience that is often assessed in clinical settings and has been shown to negatively impact both daily functioning and long-term outcomes (Lupien et al., 2009). It was measured, in part, using counts of daily stressful events here. Interestingly, greater cross-talk among externalizing domains predicted increases in stress, but greater cross-talk among internalizing domains predicted decreases in stress. Greater cross-talk between negative affect and detachment may result in increased isolation and withdrawal, limiting exposure to stressful events (Foster et al., 2018). In contrast, greater cross-talk between hostility and impulsivity could increase the likelihood of provoking stressful events.

Taken together, we used an exploratory approach to illustrate how person-specific networks of personality that capture dynamic interplay between domains of personality pathology can be linked to clinical data, revealing novel insights. Of note, our four-factor structure of personality was derived from between-person analyses. Although these four factors are meaningful at the within-person level (Wright et al., 2015a), in future studies, it will be important to verify this structure for each participant. Additionally, we did not have strong *a priori* hypotheses, and thus, do not make claims about significance in the context of null hypothesis testing. Network results do, however, seem to have important clinical implications for understanding and treating PDs, and thus warrant further hypothesis-driven examination. Further, in future work GIMME could be used to map the interplay among clinical features (e.g., personality pathology and stress). An example application of GIMME-MS in testing personality theory hypotheses using intensive longitudinal data is provided in the Supplemental Materials.

Conclusion

This study illustrates an under-used and novel way to collect and analyze clinically-relevant data that reflects the dimensional, dynamic, and heterogeneous nature of personality pathology, drawing from an emerging body of work on the clinical utility of such behavioral processes (Beltz et al., 2016, Bringmann et al., 2016, Fisher and Boswell, 2016). Using daily assessments of internalizing and externalizing domains, we applied a temporal network mapping approach to identify unique individual-level behavioral processes. These processes were associated with both traditional diagnostic categories and aspects of daily functioning (i.e., stress). In fact, these processes predicted outcomes above and beyond daily domain levels. Findings emphasize the importance of leveraging models that capture person-specific, dynamic processes in concert with traditional approaches that rely on averages.

Table 1. Sample Demographics

	<i>N/M</i>	<i>%/SD</i>
Age	45.13	13.37
<u>Gender</u>		
Male	34	37.4
Female	57	62.6
<u>Race/Ethnicity</u>		
White	76	83.5
Black	12	13.2
Native American	3	3.3
Hispanic	4	4.4
<u>Education</u>		
No high school diploma	6	6.6
High school diploma	34	37.4
Some college	15	16.5
College degree	33	36.3
Graduate/Professional	38	41.8
<u>Employment</u>		
Employed	30	33
Unemployed	12	13.2
Disabled	30	33
Retired	8	8.8
Student	4	4.4
Homemaker	4	4.4
<u>Income</u>		
Less than \$15,000	26	28.6
\$15,000-\$29,999	20	22
\$30,000-\$44,999	17	18.7
\$45,000-\$59,999	13	14.3
More than \$60,000	15	17
<u>Marital Status</u>		
Married	24	26.4
Widowed	5	5.5
Divorced	17	18.7
Separated	3	3.3
Never Married	42	46.2

Note. *M* = Mean. *SD* = Standard deviation. Sample size of 91.

Table 2. Bivariate Correlations between Average Ratings of Daily Domains of Personality Pathology, Age, and Baseline Personality Disorder Symptom Counts

	Age	Daily Negative Affect	Daily Detachment	Daily Impulsivity	Daily Hostility
Daily Negative Affect	-.02				
Daily Detachment	-.10	.76***			
Daily Impulsivity	-.07	.58***	.49***		
Daily Hostility	-.06	.58***	.43***	.72***	
Schizotypal	-.08	.28**	.17	.19 ⁺	.28**
Paranoid	-.26*	.38**	.44***	.32**	.40***
Narcissistic	-.15	.20 ⁺	.19 ⁺	.21*	.30**
Borderline	-.23*	.30**	.30**	.17	.22*
Obsessive-Compulsive	.07	.09	.06	.16	.14
Avoidant	-.31**	.32**	.31***	.06	.05

Table 3. Multilevel Model Analyses for Person-Specific Prediction of Stress from Within-Degree Network Features

	Externalizing	Internalizing
<u>Fixed Effects</u>		
Intercept	-0.48 (0.34)	-0.25 (0.38)
Day	-0.004 (0.001)**	0.003 (0.002)
Within-factor Degree	0.10 (0.08)	0.02 (0.08)
Day x Within-factor Degree	0.002 (0.0006)*	-0.002 (0.0007)*
Age	0.00 (0.00)	0.00 (0.00)
Gender	0.15 (0.16)	0.15 (0.16)
Average Level	0.01 (0.12)	0.00 (0.05)
<u>Random Effects</u>		
<u>Intercept</u>	0.46 (0.07)	0.48 (0.08)
<u>Day</u>	0.00 (0.00)	0.00 (0.00)

Note. *** $p < .001$; ** $p < .01$; * $p < .05$; no adjustments for multiple tests and robust standard errors are reported for all estimates. Intercept values reflect day 1 scores. Random effects are estimated for the intercept and slope; all other parameters were fixed.

Figure 1. Final GIMME networks for four participants with differing levels of personality pathology symptomatology. Solid lines depict contemporaneous connections and dashed lines depict lagged connections. There was no group-level structure; thus, all lines depict individual-level connections (uniquely estimated for the participant) that also have associated β weights. All four models had excellent fit and were of the first order (i.e., only lag 1 connections estimated).

1A) Participant with notable paranoid symptomatology (8 symptoms; Range in the sample 0 – 8); Model fit: $\chi^2 = 9.67$, $df = 14$, CFI= 1.00, NNFI = 1.00, RMSEA= .00, SRMR= .04. 1B) Participant with notable borderline symptomatology (15 symptoms; Range in the sample 0 – 15); Model fit: $\chi^2 = 6.28$, $df = 16$, CFI= 1.00, NNFI = 1.00, RMSEA= .00, SRMR= .03. 1C) Participant with notable narcissistic symptomatology (11 symptoms; Range in the sample 0 – 12); Model fit: $\chi^2 = 13$, $df = 13$, CFI= 1.00, NNFI = 1.00, RMSEA= .00, SRMR= .04. 1D) Participant with notable obsessive-compulsive symptomatology (8 symptoms; Range in the sample 1 – 9); Model fit: $\chi^2 = 11.20$, $df = 14$, CFI= 1.00, NNFI = 1.00, RMSEA= .00, SRMR= .05.

A)

B)

C)

D)

Figure 2. Temporal network signatures of personality disorders. 2A) Temporal network signature of paranoid symptomatology. 2B) Temporal network signature of borderline symptomatology. 2C) Temporal network signature of narcissistic symptomatology. 2D) Temporal network signature of obsessive-compulsive symptomatology. Each panel includes the resulting standardized beta weights of the associations between the six predictor variables (i.e., network feature: blue bar; average daily level of negative affect: orange bar; average daily level of detachment: grey bar; average daily level of disinhibition: yellow bar; average daily level of hostility: purple bar; age: green bar) and the criterion (i.e., PD symptom count). Each panel

includes the results for seven separate models (i.e., one model for each network feature, indicated by the vertical labels).

References

- AKAIKE, H. 1974. A new look at the statistical model identification. *IEEE transactions on automatic control*, 19, 716-723.
- AMERICAN PSYCHIATRIC ASSOCIATION 2013. *Diagnostic and statistical manual of mental disorders* Washington, DC, American Psychiatric Association.
- BALE, T. L. & EPPERSON, C. N. 2015. Sex differences and stress across the lifespan. *Nature Neuroscience*, 18, 1413-1420.
- BATEMAN, A. W., GUNDERSON, J. & MULDER, R. 2015. Treatment of personality disorder. *The Lancet*, 385, 735-743.
- BELTZ, A. M. & MOLENAAR, P. C. 2016. Dealing with multiple solutions in structural vector autoregressive models. *Multivariate behavioral research*, 51, 357-373.
- BELTZ, A. M., WRIGHT, A. G., SPRAGUE, B. N. & MOLENAAR, P. C. 2016. Bridging the nomothetic and idiographic approaches to the analysis of clinical data. *Assessment*, 23, 447-458.
- BOCCALETTI, S., LATORA, V., MORENO, Y., CHAVEZ, M. & HWANG, D.-U. 2006. Complex networks: Structure and dynamics. *Physics reports*, 424, 175-308.
- BRINGMANN, L. F. & ERONEN, M. I. 2018. Don't blame the model: Reconsidering the network approach to psychopathology. *Psychological review*, 125, 606-615.
- BRINGMANN, L. F., PE, M. L., VISSERS, N., CEULEMANS, E., BORSBOOM, D., VANPAEMEL, W., TUERLINCKX, F. & KUPPENS, P. 2016. Assessing temporal emotion dynamics using networks. *Assessment*, 23, 425-435.
- BROWN, T. A. 2014. *Confirmatory factor analysis for applied research*, Guilford Publications.

- EPSKAMP, S., VAN BORKULO, C. D., VAN DER VEEN, D. C., SERVAAS, M. N., ISVORANU, A.-M., RIESE, H. & CRAMER, A. O. 2018. Personalized network modeling in psychopathology: The importance of contemporaneous and temporal connections. *Clinical Psychological Science*, 6, 416-427.
- FISHER, A. J. & BOSWELL, J. F. 2016. Enhancing the personalization of psychotherapy with dynamic assessment and modeling. *Assessment*, 23, 496-506.
- FISHER, A. J., REEVES, J. W., LAWYER, G., MEDAGLIA, J. D. & RUBEL, J. A. 2017. Exploring the idiographic dynamics of mood and anxiety via network analysis. *Journal of abnormal psychology*, 126, 1044-1056.
- FORBES, M. K., WRIGHT, A. G., MARKON, K. E. & KRUEGER, R. F. 2017. Evidence that psychopathology symptom networks have limited replicability. *Journal of Abnormal Psychology*, 126, 969-988.
- FOSTER, K. T., HICKS, B. M. & ZUCKER, R. A. 2018. Positive and negative effects of internalizing on alcohol use problems from childhood to young adulthood: The mediating and suppressing role of externalizing. *Journal of abnormal psychology*, 127, 394-403.
- FRIED, E. I., VAN BORKULO, C. D., CRAMER, A. O., BOSCHLOO, L., SCHOEVERS, R. A. & BORSBOOM, D. 2017. Mental disorders as networks of problems: a review of recent insights. *Social Psychiatry and Psychiatric Epidemiology*, 52, 1-10.
- GATES, K. M. & MOLENAAR, P. C. 2012. Group search algorithm recovers effective connectivity maps for individuals in homogeneous and heterogeneous samples. *Neuroimage*, 63, 310-319.
- GATES, K. M., MOLENAAR, P. C., HILLARY, F. G., RAM, N. & ROVINE, M. J. 2010. Automatic search for fMRI connectivity mapping: an alternative to Granger causality

- testing using formal equivalences among SEM path modeling, VAR, and unified SEM. *Neuroimage*, 50, 1118-1125.
- HOPWOOD, C. J. 2018. Interpersonal dynamics in personality and personality disorders. *European Journal of Personality*, 32, 499-524.
- HOPWOOD, C. J. & BLEIDORN, W. 2018. Stability and change in personality and personality disorders. *Current opinion in psychology*, 21, 6-10.
- HOPWOOD, C. J., KOTOV, R., KRUEGER, R. F., WATSON, D., WIDIGER, T. A., ALTHOFF, R. R., ANSELL, E. B., BACH, B., MICHAEL BAGBY, R. & BLAIS, M. A. 2018. The time has come for dimensional personality disorder diagnosis. *Personality and mental health*, 12, 82-86.
- HOUBEN, M., VAN DEN NOORTGATE, W. & KUPPENS, P. 2015. The relation between short-term emotion dynamics and psychological well-being: A meta-analysis. *Psychological bulletin*, 141, 901-930.
- KIM, J., ZHU, W., CHANG, L., BENTLER, P. M. & ERNST, T. 2007. Unified structural equation modeling approach for the analysis of multisubject, multivariate functional MRI data. *Human Brain Mapping*, 28, 85-93.
- KRUEGER, R. F., HOPWOOD, C. J., WRIGHT, A. G. & MARKON, K. E. 2014. DSM-5 and the path toward empirically based and clinically useful conceptualization of personality and psychopathology. *Clinical Psychology: Science and Practice*, 21, 245-261.
- KUDIELKA, B. M. & KIRSCHBAUM, C. 2005. Sex differences in HPA axis responses to stress: a review. *Biological psychology*, 69, 113-132.

- LANE, S. T., GATES, K. M., PIKE, H. K., BELTZ, A. M. & WRIGHT, A. G. 2019. Uncovering general, shared, and unique temporal patterns in ambulatory assessment data. *Psychological methods*, 24, 54-69.
- LUPIEN, S. J., MCEWEN, B. S., GUNNAR, M. R. & HEIM, C. 2009. Effects of stress throughout the lifespan on the brain, behaviour and cognition. *Nature reviews neuroscience*, 10, 434-445.
- MOREY, L. C. & HOPWOOD, C. J. 2013. Stability and change in personality disorders. *Annual review of clinical psychology*, 9, 499-528.
- RANKIN, E. D. & MARSH, J. C. Effects of missing data on the statistical analysis of clinical time series. *Social Work Research and Abstracts*, 1985. Oxford University Press, 13-16.
- SILVERMAN, M. H. & KRUEGER, R. F. 2018. Taking Stock of Relationships among Personality Disorders and Other Forms of Psychopathology. *Handbook of Personality Disorders: Theory, Research, and Treatment*.
- SKODOL, A. E. 2008. Longitudinal course and outcome of personality disorders. *Psychiatric Clinics of North America*, 31, 495-503.
- TRULL, T. J. & EBNER-PRIEMER, U. 2013. Ambulatory assessment. *Annual review of clinical psychology*, 9, 151-176.
- WIDIGER, T. A. & SIMONSEN, E. 2005. Alternative dimensional models of personality disorder: Finding a common ground. *Journal of personality disorders*, 19, 110-130.
- WRIGHT, A. G., BELTZ, A. M., GATES, K. M., MOLENAAR, P. & SIMMS, L. J. 2015a. Examining the dynamic structure of daily internalizing and externalizing behavior at multiple levels of analysis. *Frontiers in psychology*, 6, 1914.

- WRIGHT, A. G., CALABRESE, W. R., RUDICK, M. M., YAM, W. H., ZELAZNY, K., WILLIAMS, T. F., ROTTERMAN, J. H. & SIMMS, L. J. 2015b. Stability of the DSM-5 Section III pathological personality traits and their longitudinal associations with psychosocial functioning in personality disordered individuals. *Journal of Abnormal Psychology*, 124, 199-207.
- WRIGHT, A. G. & HOPWOOD, C. J. 2016. Advancing the assessment of dynamic psychological processes. *Assessment*, 23, 399-403.
- WRIGHT, A. G. & SIMMS, L. J. 2016. Stability and fluctuation of personality disorder features in daily life. *Journal of Abnormal Psychology*, 125, 641-656.
- WRIGHT, A. G. & ZIMMERMANN, J. 2019. Applied ambulatory assessment: Integrating idiographic and nomothetic principles of measurement. *Psychological assessment*, Advance online publication.

Supplemental Methods

Measures

Daily domains of PD. Four factor-analytically derived domains of daily personality pathology were created from 16 daily diary items that were designed to capture day-to-day expressions of PDs (Wright et al., 2015). When participants were missing a data point, typically the score was imputed by averaging the scores from the previous and following two days. Of all of the data points across participants, less than 7% were imputed. Across the sample, the percentage of missing data points ranged from 0 to 19.4% ($M = 6.52\%$; $SD = 5.26\%$), and 23 participants had over 10% missing. Only four participants had two or more adjacent data points missing; three of them had one instance of two adjacent missing data points, one of them had one instance of two adjacent missing data points and one instance of three adjacent missing data points. When one of the two prior data points was an imputed value, we took an average of the two prior data points and the two latter data points. When one of the two data points after were missing, we took an average of the two prior data points and one data point after (the value that was not missing). For data points that were followed by two missing data points, we imputed the value by taking an average of the two previous data points only.

Data Analysis

GIMME model selection. Since GIMME model fitting is data-driven, multiple solutions can occur when two connections (e.g., usually contemporaneous connections from A to B or B to A) could equally improve model fit at a given iteration. To address this, each solution path (i.e., A to B and B to A) is followed (until it fits the data well), and then solutions are compared (Beltz and Molenaar, 2016). Out of the 91 time series (91 participants) submitted to GIMME analyses that were included in the final sample, 77 time series resulted in multiple solutions. In each case, each model structure that was produced was reviewed to determine whether two of four

alternative indices met criteria that indicate excellent fit (Brown, 2014): root mean square error of approximation (RMSEA) $\leq .05$, standardize root mean residual (SRMR) $\leq .05$, comparative fit index (CFI) $\geq .95$, and non-normed fit index (NNFI) $\geq .95$. All solutions must also be identified. Following recommended procedures (Beltz and Molenaar, 2016), model structures that did not meet these requirements were discarded. The Akaike Information Criterion (AIC; Akaike, 1974) was used to compare the remaining solutions, which has been validated in previous simulation studies (Beltz and Molenaar, 2016). The model solution with the lowest AIC was selected as the final model solution for that participant. In rare cases ($n=5$), model solutions demonstrated equivalent AICs, but included different significant connections. In these instances, we examined the standard errors and chose the model solution with the lowest values or that would have presumably been selected by the original GIMME program (that does not generate multiple solutions).

***a posteriori* model validation.** GIMME produces models with contemporaneous and first order lagged connections, meaning that the lagged connections represent estimates at one time point prior (i.e., 1 day before), with the assumption that the model residuals are white noise (i.e., all temporal information is captured by the modeled connections). The individual-level models must be submitted to *a posteriori* validation to verify this assumption (as described in Beltz and Molenaar, 2015). If the validation process indicates that the first order connections did not sufficiently capture all sequential dependencies in each participant's data (according to white noise tests), then higher order lagged connections (i.e., estimates at two or three days prior) are added to the model. White noise tests were carried out in LISREL (Joreskog and Sorbom, 1992). The tests were evaluated with the same alternative fit indices and criteria as the final models. When residuals were not white noise, Lagrange Multiplier equivalents (modification indices;

Sörbom, 1989) were used to add second order connections to individual-level maps, then white noise tests were repeated. If residuals were still not white noise, modification indices were used to add third order connections to individual-level maps. If the third order connections did not significantly improve model fit, then we used the second order model that met standards of acceptable fit (i.e., one, but not two, of the four alternative fit indices met the criteria for excellent fit). The first order connections were sufficient for 78 participants (85.7% of sample). A minority of participants required lag 2 connections (12.1%) or lag 3 connections (2.20%). When estimating higher order models, we similarly generated multiple model solutions and chose the model solution that met the criteria for alternative fit indices and had the lowest AIC for each individual. Although higher-order lagged connections were included within individual maps to accurately represent network connectivity, network features were calculated only using first-order connections, as these parameters were present across all participants. Participants with first order models did not statistically differ in gender, age, daily levels of domains, or any PD symptom count, from participants with second or third order models (all $p > .05$). To determine whether associations were driven by participants with higher-order models, all analyses were also repeated excluding the few individuals who had lags of 2 or 3 in their models. In the smaller sample ($n=78$), the pattern of results was the same in terms of the effect sizes of associations; see Supplemental Table 2.

Supplemental Discussion

Future Applications: Applying GIMME to Narcissistic Personality Disorder

GIMME-MS is particularly well-suited to explicitly test hypotheses within recent models on the interpersonal dynamics of PDs (Hopwood, 2018). Interpersonal models of PD emphasize the relevance of social situations that occur frequently within an individual's day-to-day life, which are influenced by and trigger specific expressions of pathology. For instance, clinical reports of narcissistic personality disorder describe distinct states of both grandiosity and vulnerability (Wright and Edershire, 2018, Hopwood, 2018). In the interpersonal model of PD, narcissistic personality disorder is thought to be characterized by perceptions of threat to one's feelings of superiority, resulting in feelings of anxiety and envy and a desire to assert one's self, which leads to displays of grandiosity (Hopwood, 2018). The other person would likely respond negatively to such displays, and perhaps become competitive, reinforcing this sequence (i.e., individual with narcissistic personality disorder perceives a status threat) (Wright et al., 2017). Thus, GIMME-MS could be used to study the extent to which an individual fluctuates between grandiosity and vulnerability, and factors that impact this fluctuation.

To implement this in a study, individuals would receive several specific queries throughout the day (i.e., morning, afternoon, and evening) about any interpersonal situations that they encountered. For each encounter, participants would respond to probes regarding their interaction, emotional state, goals during the interaction, and resulting behavior; they would also be asked about the response of the other individual (informed by the elements of the interpersonal sequence described by Hopwood, 2018). In line with previous applications of GIMME, 100 completed encounter surveys, would be collected (see Beltz and Gates, 2017 for a GIMME tutorial). Responses would be coded and used in a GIMME network that included nodes

for the extent to which different types of perceptions (e.g., status threat, abandonment), affect (e.g., anxiety, anger), motives (e.g., agency, communion), and behaviors (e.g., grandiosity, vulnerability) were present in the situation, and results would demonstrate whether the proposed connections ('edges') were both present and in the expected direction and temporal order.

In the proposed interpersonal model, for individuals with narcissistic symptoms, we hypothesize the detection of a group-level contemporaneous connection (reflecting homogeneity) for the perception of status threat predicting anxiety affect, and a contemporaneous connection of anxious affect predicting agency motives. Individual-level connections would reveal the extent to which interpersonal sequences predict either expressions of grandiosity (i.e., contemporaneous connection from agency motive to grandiose) or vulnerability (i.e., contemporaneous connection from agency motive to vulnerable), and the interplay between these behaviors (i.e., contemporaneous or lagged connections between grandiosity and vulnerability). Moreover, the presence of lagged connections of behaviors predicting perceptions (i.e., grandiose behavior from a previous interpersonal encounter predicts current perception of status threat) would indicate that interpersonal sequences were reinforcing for a given individual.

Further, beyond providing more insight into the underlying dynamic processes and heterogeneity of clinical expression, GIMME networks could be reviewed to identify potential targets of treatment and to develop more effective strategies tailored to an individual's unique network of pathology. For example, based on the interpersonal sequences within GIMME networks, clinicians may focus on evaluating specific automatic thoughts reflecting the perceptions that precipitate interpersonal sequences (e.g., "He thinks he's better than me. I'll show him.") or may introduce specific emotion regulation strategies depending on the type of affect that is predictive of harmful behaviors (e.g., emotion regulation for anger versus sadness).

Supplemental Table 1. Regression Analyses between Network Features and Baseline Personality Disorder Symptom Counts, Controlling for Average Ratings of Daily Domains of Personality Pathology and Age in the Entire Sample (N = 91)

	Borderline			Narcissistic			Avoidant			Obsessive-compulsive			Paranoid			Schizotypal		
	B	SE	β	B	SE	β	B	SE	β	B	SE	β	B	SE	β	B	SE	β
Model: Auto-regressive NA	-1.39	.79	-.18 ⁺	-.34	.68	-.05	-.07	.41	-.02	.65	.41	.17	-.84	.45	-.17 ⁺	-.89	.65	-.15
Daily average NA	.47	.44	.19	-.05	.38	-.02	.58	.23	.43*	-.07	.23	-.05	.02	.25	.01	.56	.36	.28
Daily average DET	.35	.39	.14	.16	.34	.07	.11	.20	.08	-.01	.21	-.01	.50	.23	.31*	-.22	.32	-.11
Daily average DIS	-.54	.96	-.10	.21	.82	.05	-.55	.49	-.20	.78	.50	.30	-.22	.55	-.07	-.22	.79	-.05
Daily average HOS	.79	.89	.15	1.08	.76	.25	-.24	.46	-.09	-.23	.46	-.09	1.06	.51	.33*	.97	.73	.24
Age	-.07	.03	-.24*	-.03	.02	-.14	-.05	.01	-.31**	.01	.02	.10	-.04	.02	-.24*	-.02	.02	-.09
R^2, F	.18, 3.04*			.12, 1.91 ⁺			.24, 4.47**			.08, 1.15			.32, 6.53***			.13, 2.08 ⁺		
Model: Auto-regressive DET	1.23	.74	.17	.87	.63	.14	-.20	.38	-.05	.53	.39	.15	.13	.43	.03	.77	.61	.13
Daily average NA	.49	.44	.19	-.02	.38	-.01	.57	.23	.42*	-.03	.23	-.03	.01	.26	.00	.56	.36	.28
Daily average DET	.30	.39	.12	.12	.34	.06	.12	.20	.09	-.03	.21	-.02	.49	.23	.31*	-.25	.32	-.12
Daily average DIS	-.37	.95	-.07	.26	.81	.06	-.55	.49	-.19	.71	.50	.27	-.13	.56	-.04	-.11	.78	-.03
Daily average HOS	.63	.88	.12	1.09	.75	.25	-.27	.45	-.10	-.08	.46	-.03	.92	.51	.28 ⁺	.86	.72	.21
Age	-.06	.03	-.20*	-.03	.02	-.12	-.05	.01	-.31**	.01	.01	.09	-.04	.02	-.22*	-.02	.02	-.07
R^2, F	.18, 2.97*			.14, 2.23*			.24, 4.52**			.07, 1.03			.29, 5.74***			.13, 2.03 ⁺		
Model: Auto-regressive DIS	-2.40	.86	-.31**	-.18	.76	-.03	.18	.45	.04	1.11	.45	.29*	-.28	.51	-.06	-.32	.73	-.05
Daily average NA	.73	.44	.29	-.03	.39	-.02	.55	.23	.41*	-.19	.23	-.15	.04	.27	.02	.57	.38	.29
Daily average DET	.30	.38	.12	.15	.34	.07	.12	.20	.08	.01	.20	.01	.50	.23	.31*	-.22	.33	-.11
Daily average DIS	-.05	.94	-.01	.28	.83	.06	-.57	.49	-.20	.55	.49	.21	-.09	.56	-.03	-.07	.80	-.02
Daily average HOS	.40	.85	.08	1.01	.76	.24	-.24	.45	-.09	-.05	.45	-.02	.89	.51	.28 ⁺	.78	.73	.19
Age	-.07	.03	-.26*	-.03	.02	-.14	-.04	.01	-.20**	.02	.01	.13	-.04	.02	-.23*	-.02	.02	-.08
R^2, F	.22, 3.95**			.12, 1.88 ⁺			.24, 4.49**			.11, 1.76			.29, 5.79***			.11, 1.76		
Model: Auto-regressive HOS	.33	.91	.04	.64	.77	.10	.25	.46	.06	1.16	.46	.30*	-.44	.52	-.09	-1.01	.74	-.16
Daily average NA	.43	.45	.17	-.08	.38	-.04	.57	.23	.42*	-.09	.23	-.08	.02	.26	.01	.57	.36	.28
Daily average DET	.34	.40	.13	.15	.34	.07	.11	.20	.08	-.02	.20	-.02	.51	.23	.31*	-.21	.32	-.10
Daily average DIS	-.30	1.00	-.06	.44	.85	.10	-.47	.51	-.17	1.04	.50	.40*	-.26	.57	-.08	-.41	.81	-.10
Daily average HOS	.39	.98	.08	.73	.83	.17	-.37	.50	-.13	-.64	.49	-.25	1.11	.56	.34 ⁺	1.26	.79	.31
Age	-.06	.03	-.21*	-.03	.02	-.12	-.05	.01	-.30**	.01	.01	.10	-.04	.02	-.22*	-.02	.02	-.09
R^2, F	.14, 2.46*			.13, 2.00 ⁺			.24, 4.53**			.12, 1.84			.30, 5.89***			.13, 2.08 ⁺		
Model: Within-Degree Int	-.31	.38	-.08	-.27	.33	-.09	-.01	.20	-.00	.35	.20	.19 ⁺	-.43	.22	-.18*	-.10	.32	-.03
Daily average NA	.39	.45	.15	-.10	.38	-.05	.57	.23	.42*	.01	.23	.01	-.07	.25	-.05	.52	.37	.26
Daily average DET	.40	.40	.16	.20	.34	.09	.11	.20	.08	-.07	.21	-.05	.57	.23	.36*	-.20	.33	-.10
Daily average DIS	-.37	.97	-.07	.27	.82	.06	-.55	.49	-.19	.68	.50	.26	-.10	.54	-.03	-.11	.79	-.03

Daily average HOS	.51	.89	.10	1.00	.75	.23	-.26	.45	-.09	-.09	.46	-.03	.87	.50	.27 ⁺	.79	.73	.19
Age	-.06	.03	-.22*	-.03	.02	-.14	-.05	.01	-.31**	.01	.01	.10	-.04	.02	-.23*	-.02	.02	-.08
R^2, F	.15, 2.55*			.13, 1.99 ⁺			.24, 4.46**			.08, 1.24			.32, 6.67***			.11, 1.75		
Model: Within-Degree Ext	.00	.41	.00	.43	.34	.15	-.02	.21	-.01	.61	.20	.36**	-.11	.23	-.05	.04	.33	.02
Daily average NA	.44	.45	.17	-.11	.38	-.05	.58	.23	.43*	-.13	.22	-.10	.02	.26	.01	.53	.37	.26
Daily average DET	.35	.40	.14	.14	.34	.07	.11	.20	.08	-.03	.20	-.03	.50	.23	.31*	-.22	.33	-.11
Daily average DIS	-.39	.98	-.07	.42	.82	.10	-.56	.50	-.20	.95	.49	.36 ⁺	-.17	.56	-.05	-.10	.80	-.02
Daily average HOS	.54	.95	.11	.66	.80	.16	-.24	.48	-.09	-.62	.47	-.25	1.00	.55	.31 ⁺	.77	.78	.19
Age	-.06	.03	-.21*	-.02	.02	-.10	-.05	.01	-.31**	.02	.01	.15	-.04	.02	-.23*	-.02	.02	-.07
R^2, F	.15, 2.43*			.13, 2.16 ⁺			.24, 4.46**			.14, 2.31*			.29, 5.77***			.11, 1.73		
Model: Between-Degree Ext & Int	.75	.32	.24*	.57	.27	.22*	.00	.17	.00	-.15	.17	-.10	.18	.19	.09	.45	.27	.18 ⁺
Daily average NA	.63	.44	.16	.09	.38	.04	.57	.23	.43*	-.09	.24	-.07	.05	.26	.03	.65	.37	.32 ⁺
Daily average DET	.33	.39	.13	.14	.33	.07	.11	.20	.08	-.00	.21	-.00	.50	.23	.31*	-.23	.32	-.11
Daily average DIS	-1.01	.98	-.19	-.23	.83	-.05	-.55	.51	-.19	.83	.52	.32	-.28	.58	-.08	-.49	.81	-.12
Daily average HOS	.81	.87	.16	1.23	.74	.29	-.25	.45	-.09	-.17	.47	-.07	.98	.51	.30 ⁺	.96	.72	.24
Age	-.06	.03	-.23*	-.03	.02	-.15	-.05	.01	-.31**	.01	.02	.09	-.04	.02	-.22*	-.02	.02	-.09
R^2, F	.20, 3.48**			.16, 2.68*			.24, 4.46**			.06, .85			.30, 5.93***			.14, 2.25*		

Note. ⁺ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. NA = negative affect. DET= detachment. DIS= disinhibition. HOS= hostility. Int= internalizing. Ext= externalizing. 11 models were run separately with a given personality disorder as the outcome (i.e., 11 models, one per network feature, with borderline symptom count as the outcome). In each model, one network feature served as the predictor, and there were five covariates including each of the daily levels of the four personality domains (i.e., negative affect, detachment, disinhibition, and hostility) and age.

Supplemental Table 2. Regression Analyses between Network Features and Baseline Personality Disorder Symptom Counts, Controlling for Average Ratings of Daily Domains of Personality Pathology and Age Only in Participants with First Order Models (N = 78)

	Borderline			Narcissistic			Avoidant			Obsessive-compulsive			Paranoid			Schizotypal		
	B	SE	β	B	SE	β	B	SE	β	B	SE	β	B	SE	β	B	SE	β
Model: Auto-regressive NA	-1.62	.86	-.21 ⁺	-.08	.79	-.01	-.30	.45	-.07	.48	.46	.12	-.78	.48	-.16	-.1.18	.75	-.19
Daily average NA	.57	.48	.21	-.07	.44	-.03	.66	.25	.46*	.13	.26	.10	-.13	.27	-.08	.60	.42	.28
Daily average DET	.45	.39	.18	.17	.36	.08	.10	.21	.07	-.10	.21	-.08	.61	.22	.39**	-.27	.34	-.13
Daily average DIS	-.84	.94	-.16	.36	.87	.08	-.68	.50	-.24	.68	.50	.27	-.15	.53	-.05	-.26	.82	-.06
Daily average HOS	.97	.87	.19	1.00	.81	.23	-.17	.46	-.06	-.23	.47	-.09	1.24	.49	.40	.93	.76	.23
Age	-.08	.03	-.30**	-.03	.03	-.15	-.05	.02	-.35**	.01	.02	.04	-.04	.02	-.25*	-.03	.03	-.12
R^2, F	.23, 3.54**			.12, 1.68			.26, 4.19**			.08, .95			.37, 6.96***			.12, 1.61		
Model: Auto-regressive DET	.72	.78	.10	.66	.70	.11	-.70	.40	-.18 ⁺	.39	.41	.11	-.18	.44	-.04	.44	.67	.08
Daily average NA	.48	.49	.18	-.08	.44	-.03	.65	.25	.45*	.15	.26	.12	-.17	.27	-.10	.54	.42	.25
Daily average DET	.44	.40	.17	.16	.36	.07	.11	.20	.08	-.10	.21	-.08	.61	.22	.39**	-.28	.35	-.13
Daily average DIS	-.59	.95	-.11	.41	.86	.09	-.67	.49	-.24	.63	.50	.25	-.05	.53	-.02	-.08	.82	-.02
Daily average HOS	.74	.88	.15	1.03	.79	.24	-.27	.45	-.10	-.12	.46	-.05	1.09	.49	.35*	.76	.76	.19
Age	-.07	.03	-.25*	-.03	.03	-.14	-.05	.02	-.34	.00	.02	.02	-.04	.02	-.22*	-.02	.03	-.08
R^2, F	.20, 2.98*			.14, 1.84			.29, 4.78***			.07, .92			.35, 6.33***			.09, 1.23		
Model: Auto-regressive DIS	-2.01	.92	-.27**	.05	.86	.01	.33	.49	.08	.87	.49	.23	-.03	.53	-.01	.02	.82	.00
Daily average NA	.86	.50	.32 ⁺	-.08	.47	-.04	.58	.27	.41*	-.00	.27	-.00	-.16	.29	-.20	.54	.45	.25
Daily average DET	.35	.39	.14	.18	.37	.08	.11	.21	.08	-.05	.21	-.04	.60	.22	.39**	-.27	.35	-.13
Daily average DIS	-.36	.93	-.07	.37	.87	.08	-.68	.50	-.24	.50	.50	.20	-.04	.54	-.01	-.10	.83	-.02
Daily average HOS	.56	.86	.11	.99	.80	.23	-.20	.46	-.07	-.09	.46	-.04	1.10	.49	.36*	.73	.76	.18
Age	-.08	.03	-.31**	-.03	.03	-.14	-.05	.02	-.32**	.01	.02	.05	-.04	.02	-.22*	-.02	.03	-.08
R^2, F	.25, 3.84**			.12, 1.67			.26, 4.20**			.10, 1.32			.35, 6.29***			.09, 1.15		
Model: Auto-regressive HOS	.16	.96	.02	.38	.87	.06	.42	.49	.10	1.13	.49	.31*	-.71	.53	-.15	-1.37	.81	-.22
Daily average NA	.48	.49	.18	-.10	.44	-.04	.61	.25	.43*	.07	.25	.06	-.12	.27	-.07	.64	.42	.30
Daily average DET	.45	.40	.18	.18	.36	.08	.09	.21	.07	-.10	.20	-.08	.61	.22	.39**	-.27	.34	-.13
Daily average DIS	-.57	.99	-.11	.48	.89	.11	-.52	.51	-.19	.92	.50	.36 ⁺	-.24	.54	-.07	-.47	.84	-.11
Daily average HOS	.62	.98	.12	.82	.88	.19	-.41	.50	-.15	-.64	.50	-.26	1.42	.54	.46*	1.33	.83	.33
Age	-.07	.03	-.26*	-.03	.03	-.14	-.05	.02	-.32**	.01	.02	.04	-.04	.02	-.24*	-.02	.03	-.10
R^2, F	.19, 2.81*			.13, 1.71			.27, 4.26**			.13, 1.72			.36, 6.76***			.12, 1.68		
Model: Within-Degree Int	-.60	.41	-.16	-.29	.37	-.09	-.22	.21	-.11	.18	.22	.10	-.56	.22	-.24*	-.32	.36	-.10
Daily average NA	.46	.48	.17	-.08	.44	-.04	.64	.25	.44*	.16	.26	.12	-.19	.26	-.12	.53	.42	.25
Daily average DET	.54	.40	.21	.22	.37	.10	.12	.21	.09	-.12	.21	-.10	.68	.22	.44**	-.22	.35	-.11
Daily average DIS	-.61	.94	-.12	.38	.86	.09	-.63	.49	-.23	.61	.50	.24	-.03	.51	-.01	-.09	.82	-.02

Daily average HOS	.62	.87	.12	.95	.79	.22	-.25	.45	-.09	-.13	.46	-.05	1.04	.47	.34*	.69	.76	.17
Age	-.08	.03	-.28*	-.04	.03	-.16	-.05	.02	-.35**	.00	.02	.03	-.04	.02	-	-.02	.03	-.10
R^2, F	.22, 3.25**			.13, 1.78			.27, 4.33**			.07, .89			.40, 7.95***			.10, 1.30		
Model: Within-Degree Ext	.45	.44	.13	.63	.39	.21	.15	.23	.08	.46	.23	.27*	.01	.25	.01	.11	.38	.16
Daily average NA	.39	.49	.15	-.22	.44	-.09	.61	.26	.43*	.05	.26	.04	-.17	.28	-.10	.52	.43	.24
Daily average DET	.46	.40	.18	.19	.36	.09	.10	.21	.07	-.08	.21	-.07	.61	.22	.39**	-.27	.35	-.13
Daily average DIS	-.43	.97	-.08	.64	.86	.14	-.58	.50	-.21	.80	.50	.32	-.04	.54	-.01	-.05	.84	-.01
Daily average HOS	.33	.95	.07	.48	.84	.11	-.34	.49	-.13	-.52	.49	-.21	1.10	.53	.36*	.64	.82	.16
Age	-.06	.03	-.22*	-.02	.03	-.10	-.05	.02	-.31**	.01	.02	.07	-.04	.02	-.22*	-.02	.03	-.07
R^2, F	.20, 3.02*			.16, 2.17 ⁺			.26, 4.19**			.11, 1.49			.35, 6.29***			.09, 1.17		
Model: Between-Degree Ext & Int	.54	.36	.16	.64	.32	.23*	-.01	.19	-.00	-.28	.19	-.18	.17	.20	.09	.51	.31	.19
Daily average NA	.57	.48	.21	.02	.43	.10	.64	.25	.45*	.11	.25	.09	-.14	.27	-.09	.62	.42	.29
Daily average DET	.44	.40	.17	.16	.35	.07	.10	.21	.07	-.09	.21	-.07	.60	.22	.39**	-.28	.34	-.14
Daily average DIS	-1.01	.98	-.19	-.09	.87	-.02	-.63	.51	-.23	.82	.52	.32	-.17	.55	-.05	-.47	.84	-.11
Daily average HOS	.85	.88	.17	1.18	.78	.27	-.22	.46	-.08	-.23	.46	-.10	1.16	.49	.38*	.88	.75	.22
Age	-.07	.03	-.25*	-.03	.03	-.14	-.05	.02	-.33**	.00	.02	.01	-.04	.02	-.22*	-.02	.03	-.08
R^2, F	.22, 3.26**			.17, 2.43*			.26, 4.10**			.09, 1.16			.35, 6.47***			.12, 1.65		

Note. ⁺ $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. NA = negative affect. DET= detachment. DIS= disinhibition. HOS= hostility. Int= internalizing. Ext= externalizing. 11 models were run separately with a given personality disorder as the outcome (i.e., 11 models, one per network feature, with borderline symptom count as the outcome). In each model, one network feature served as the predictor, and there were five covariates including each of the daily levels of the four personality domains (i.e., negative affect, detachment, disinhibition, and hostility) and age. Bolded values represent beta weights that were significant in the full sample but not significant in this smaller sample (Supplemental Table 1).

Supplemental Figure 1. Temporal network signature of avoidant symptomatology, including the resulting standardized beta weights of the associations between the six predictor variables (i.e., network feature: blue bar; average daily level of negative affect: orange bar; average daily level of detachment: grey bar; average daily level of disinhibition: yellow bar; average daily level of hostility: purple bar; age: green bar) and the criterion (i.e., PD symptom count). Shown are results for seven separate models (i.e., one model for each network feature, indicated by the vertical labels).

Supplemental Figure 2. Temporal network signature of schizotypal symptomatology, including the resulting standardized beta weights of the associations between the six predictor variables (i.e., network feature: blue bar; average daily level of negative affect: orange bar; average daily level of detachment: grey bar; average daily level of disinhibition: yellow bar; average daily level of hostility: purple bar; age: green bar) and the criterion (i.e., PD symptom count). Shown are results for seven separate models (i.e., one model for each network feature, indicated by the vertical labels).

References

- BELTZ, A. M. & GATES, K. M. 2017. Network Mapping with GIMME. *Multivariate behavioral research*, 52, 789-804.
- BELTZ, A. M. & MOLENAAR, P. C. 2015. A posteriori model validation for the temporal order of directed functional connectivity maps. *Frontiers in neuroscience*, 9.
- BELTZ, A. M. & MOLENAAR, P. C. 2016. Dealing with multiple solutions in structural vector autoregressive models. *Multivariate behavioral research*, 51, 357-373.
- BROWN, T. A. 2014. *Confirmatory factor analysis for applied research*, Guilford Publications.
- HOPWOOD, C. J. 2018. Interpersonal dynamics in personality and personality disorders. *European Journal of Personality*, 32, 499-524.
- JORESKOG, K. & SORBOM, D. 1992. LISREL VIII: Analysis of linear structural relations. *Moorestville, IN: Scientific Software*.
- SÖRBOM, D. 1989. Model modification. *Psychometrika*, 54, 371-384.
- WRIGHT, A. G., BELTZ, A. M., GATES, K. M., MOLENAAR, P. & SIMMS, L. J. 2015. Examining the dynamic structure of daily internalizing and externalizing behavior at multiple levels of analysis. *Frontiers in psychology*, 6, 1914.
- WRIGHT, A. G. & EDERSHILE, E. A. 2018. Issues resolved and unresolved in pathological narcissism. *Current Opinion in Psychology*, 21, 74-79.
- WRIGHT, A. G., STEPP, S. D., SCOTT, L. N., HALLQUIST, M. N., BEENEY, J. E., LAZARUS, S. A. & PILKONIS, P. A. 2017. The effect of pathological narcissism on interpersonal and affective processes in social interactions. *Journal of abnormal psychology*, 126, 898-910.