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Temporal and contemporaneous network structures of affect and physical activity in emotional disorders

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ABSTRACT

Background: High negative affect, low positive affect, and limited physical activity figure prominently in psychopathology, but little is known about the interrelatedness of affect and physical activity in emotional disorders.
Methods: We combined ecological momentary assessment data with a network approach to examine the dynamic relations among positive affect, negative affect, and smartphone-based estimates of physical activity in 34 participants with anxiety and depressive disorders over a 2-week period.
Results: In the contemporaneous networks, the positive affect nodes exhibited greater overall strength centrality than negative affect nodes. The temporal networks indicated that the negative affect node 'sadness' exhibited the greatest out-strength centrality. Furthermore, physical activity was unconnected to the affect nodes in either the temporal or contemporaneous networks.
Conclusions: Whereas positive affect plays a greater role in the contemporaneous experience of emotions, negative affect contributes more so to future affective states.

In recent years, considerable interest has been devoted to understanding mental disorders with models that better appreciate their complexity and dynamic behavior (Hofmann et al., 2020). Networks offer one such promising framework for modeling psychopathology (Borsboom and Cramer, 2013; Hofmann et al., 2016; McNally et al., 2015). Rather than presuming that symptoms or features of mental disorders reflect a latent, common cause – an underlying disease entity – network approaches model disorders as emergent phenomena issuing from causal interactions among their constituent symptomatic elements (Borsboom and Cramer, 2013). Features or symptoms of pathology can be represented as *nodes* in the network, and connections or associations between nodes can be modeled as *edges* in the network.

To date, most network studies on psychopathology have employed a cross-sectional design (Bos et al., 2017; Haslbeck and Fried, 2017). Such cross-sectional network research has focused on the symptom structure of individual disorders (Fried et al., 2016; McNally et al., 2015), exploring comorbidity between disorders (Beard et al., 2016; Curtiss et al., 2019), and identifying nodes most central to the network (i.e., the extent to which a node is connected to other nodes in the network; Robinaugh et al., 2016; Curtiss et al., 2019). Although cross-sectional network methodology affords advantages over traditional latent variable approaches, its atemporality precludes modeling of the dynamic characteristics of mental disorders (Epskamp et al., 2018a, 2018b; Hofmann and Curtiss, 2018).

Contemporary theories acknowledge that mental disorders are not static entities that persist over time with uniform structure, but rather dynamic systems with interacting features that vary over time (Hofmann et al., 2020). Intensive time-series designs using data collection approaches such as ecological momentary assessment (EMA) are necessary to model how psychopathology unfolds over time. Time-series network approaches permit examination of both the contemporaneous network structure (i.e., connections between nodes within the same time window) and temporal network structure (i.e., connections between nodes assessed via time lagged regression coefficients; Epskamp et al., 2018b).

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Several studies have used this approach (Epskamp et al., 2018a; Curtiss et al., 2019).

Bringmann et al. (2015) estimated the temporal network structure of symptoms of depression, which revealed that anhedonia (i.e., 'loss of pleasure') was the most central node exhibiting high levels of connectivity with other symptoms. Furthermore, the network structure revealed two communities of nodes, which were consistent with presentations of the melancholic and atypical subtypes of depression. Conducting a time-series study in a heterogeneous sample of individuals with mood and anxiety disorders, Fisher et al. (2017) found that negative and positive moods were highly central in the contemporaneous network, but the cardinal symptoms of depression and anxiety were not in the temporal network. In fact, a positive affect node exhibited the greatest out-strength centrality, predicting several other nodes at the next time point. In one of our studies (Curtiss et al., 2019), we examined the temporal network structure of affect and actigraphy-derived physical activity in people with bipolar disorder and healthy controls. Results revealed no significant differences in the centrality of positive affect and negative affect nodes in the temporal networks in either group. Furthermore, physical activity exhibited more connectivity in the temporal network of the healthy control participants than in that of participants with bipolar disorder, suggesting physical activity plays a prominent role in influencing affect in emotional psychopathology.

With few exceptions (e.g., Curtiss et al., 2019), network studies using intensive time-series methodology have primarily emphasized self-reported survey responses that measure disorder-specific symptoms. Although most research examining emotional psychopathology has been circumscribed to symptoms stipulated in the Diagnostic and Statistical Manual of Mental Disorders (5th ed.; DSM-5; American Psychiatric Association, 2013), prominent models of emotional psychopathology emphasize the importance of positive and negative affect (Hofmann et al., 2012). Hofmann et al. (2012) posit that emotional psychopathology is characterized primarily by the dysregulation of negative affect and deficits in positive affect. DSM-5 depression and anxiety syndromes are characterized by marked comorbidity issues and questionable nosological validity and reliability (Brown and Barlow, 2009; Watson, 2005; Rosellini and Brown, 2019). Accordingly, a better framework for examining the time-series network properties of emotional disorders would transcend beyond individual DSM-5 disorders by targeting transdiagnostic populations with pathologically high levels of negative affect.

Furthermore, a wealth of literature attests to the relevance of altered physical activity in depression and anxiety (Burton et al., 2013; Stubbs et al., 2017). In general, cumulative evidence suggests that low levels of overall physical activity are associated with depression and anxiety (Burton et al., 2013; Stubbs et al., 2017) and that acute levels of stress may confer risk for more sedentary lifestyles (Stults-Kolehmainen and Sinha, 2014). That notwithstanding, little research has examined the role of physical activity in emotional disorders from a time-series perspective, which would foster a more idiographic understanding of physical activity as it relates to positive and negative affect. Prior research has suggested that physical activity is more strongly related to positive affect than negative affect (Clark and Watson, 1988; Watson, 1988; Wichers et al., 2012), and prior time-series network research indicated that higher levels of shame was prospectively associated with less physical activity (Curtiss et al., 2019). Given the theoretical and empirical support for including objective measurements of physical activity, a multi-modal approach to examining the temporal relationship between affect and physical activity is warranted.

In the current study, we used a time-series network approach to examine the temporal and contemporaneous network structure of positive and negative affect, as well as physical activity, in a heterogeneous sample of patients with emotional disorders. One of our primary aims was to determine whether positive affect or negative affect nodes would exhibit greater centrality in the time-series networks. Another aim was to investigate the role of physical activity in the temporal and contemporaneous affect networks. Consistent with prior research (Clark and Watson, 1988; Watson, 1988; Wichers et al., 2012), we hypothesized that physical activity would be more strongly associated with positive affect than negative affect. Our study is the first to examine the time-series network structure of positive affect, negative affect, and smartphone-derived physical activity in a heterogeneous clinical sample of patients with emotional disorders.

1. Methods

1.1. Inclusion and exclusion characteristics

Participants were included in the study if they exhibited the following characteristics: 1) were at least 18 years old, 2) satisfied criteria for high negative affect (i.e., a score ≥ 22 on the negative affect subscale of the Positive and Negative Affect Schedule; PANAS), 3) were stable on current psychotropic medication with the same dose and same regimen for a minimum of 6 weeks and were willing to maintain stable dose, OR off concurrent medication for at least 2 weeks prior to first study visit. There was no restriction on the type of medication used as long as the dosage and frequency of use remained stable for the appropriate time period, 4) were stable on current psychotherapy for a minimum of 6 weeks prior to first study visit, OR were not receiving psychotherapy, and 5) had access to a smartphone.

Participants were ineligible if they: 1) were unable to understand study procedures or participate in informed consent process, 2) had a serious medical or neurological illness known to influence daily activity patterns (e.g., Alzheimer's disease, Parkinson's disease, etc.), 3) had significant suicidal ideation within 2 weeks of first study visit (Beck Depression Inventory-II, Q9 > 1), 4) had a history of head trauma causing loss of consciousness resulting in ongoing cognitive impairment, 5) had a history of psychotic disorder, bipolar disorder, or developmental disorder, 6) had a current substance abuse disorder, or 7) had significant personality dysfunction likely to interfere with study participation (as assessed during the clinical interview).

1.2. Participants

Participants were referred directly from an outpatient anxiety and depression clinic. Thirty-four participants completed all aspects of the study and were included in the final data analyses. Although another participant completed both baseline and follow-up surveys, the participant's EMA data were lost because of smartphone error. Participants included 25 women, 8 men, and one individual who identified as non-binary. They ranged in age from 18 to 55 years old ($M = 28.97$, $SD = 9.83$). Their demographic and clinical characteristics are in Table 1.

The mean baseline PANAS (Watson et al., 1988) negative affect score was 31.76 ($SD = 5.59$), and the mean baseline PANAS positive affect score was 21.76 ($SD = 5.00$). These scores indicate that the sample had higher negative affect than 97 % of the general adult population and lower positive affect than 90 % of the general adult population (Crawford and Henry, 2004). The sample's mean baseline depression and anxiety scores, as measured by the Beck Depression Inventory II (BDI-II; Beck et al., 1996) and trait scale of the State Trait Anxiety Inventory (STAI; Spielberger, 1983), were 25.65 ($SD = 8.15$) and 60.82 ($SD = 7.03$), respectively. Such scores suggest that the current population exhibited symptoms of depression and anxiety at the 97th and 99th percentiles, respectively (Crawford and Henry, 2004; Spielberger, 1983). The average EMA self-report data completion rate for the 34 subjects was 47.03 time-points ($SD = 12.26$).

1.3. Procedures

Referred individuals were asked to complete a brief phone screen to determine the likelihood that they were eligible for the study. At the screening visit, the participant was provided with informed consent and

Table 1
Demographic and clinical characteristics.

	Mean (*SD*)
Age	28.97 (9.83)
Gender (%, *n*)	
Male	23.53 (8)
Female	73.53 (25)
Non-binary	2.94 (1)
Race and ethnicity (%, *n*)	
White	79.41 (27)
Hispanic/Latino	8.82 (3)
Black or African American	5.88 (2)
Asian	5.88 (2)
Marital status (%, *n*)	
Single	73.53 (25)
Living with partner	17.65 (6)
Married	8.82 (3)
Education status (%, *n*)	
Graduate school	20.59 (7)
College	52.94 (18)
Partial college	14.71 (5)
High school	5.88 (2)
Partial high school	2.94 (1)
Unknown	2.94 (1)
Primary diagnosis (%, *n*)	
GAD	44.12 (15)
PDD	17.65 (6)
MDD	14.71 (5)
SAD	8.82 (3)
OCD	5.88 (2)
PD	2.94 (1)
IAD	2.94 (1)
OCPD	2.94 (1)
CSR	5.65 (0.77)
PANAS-NA	31.76 (5.59)
PANAS-PA	21.76 (5.00)
BDI-II	25.65 (8.15)
STAI-T	60.82 (7.03)

Note. GAD = generalized anxiety disorder; PDD = persistent depressive disorder; MDD = major depressive disorder; SAD = social anxiety disorder; OCD = obsessive compulsive disorder; PD = panic disorder; IAD = illness anxiety disorder; OCPD = obsessive compulsive personality disorder; CSR = clinical severity rating; PANAS-NA = Negative Affect subscale of Positive and Negative Affect Schedule; PANAS-PA = Positive Affect subscale of Positive and Negative Affect Schedule; BDI-II = Beck Depression Inventory-II; STAI-T = Trait Anxiety subscale of State-Trait Anxiety Inventory.

asked to complete baseline questionnaires and diagnostic screening assessments to obtain DSM-5 diagnoses. Participants then underwent a two-week EMA phase, during which positive affect, negative affect, and physical activity was measured five times per day. EMA procedures were implemented with the Ethica app, available on both IOS and Android platforms. Ethica permits assessment of self-reported questions and sensor-based data such as motion sensors for physical activity. After the two-week EMA phase, participants were re-administered the baseline questionnaires.

1.4. Measures

1.4.1. Screening Measure

1.4.1.1. Positive and Negative Affect Schedule (PANAS; Watson et al., 1988). The PANAS is a 20-item instrument that assesses positive and negative affect. This is the principal screening measure used for the current study. According to norms derived from a large population study, the mean of the negative affect scale is 16 with a standard deviation of 5.9 (Crawford and Henry, 2004). Eligible participants were required to have a score one standard deviation above the mean (i.e., a score of 22) to represent high negative affect. According to the normative data from Crawford and Henry (2004), a score of 22 indicates that an individual would have higher levels of negative affect than 86 % of a general adult population.

1.4.2. Clinician administered measure

1.4.2.1. Adult Anxiety Disorders Interview Schedule for DSM-5 (Adult ADIS-5; Brown and Barlow, 2014). The Adult ADIS-5 interview was used to assess emotional psychopathology (i.e., major depressive disorder, persistent depressive disorder, generalized anxiety disorder, social anxiety disorder, panic disorder, agoraphobia, obsessive-compulsive disorder, specific phobia, and posttraumatic stress disorder).

Baseline and Post-EMA Measures.

1.4.2.2. Beck Depression Inventory-II (BDI-II; Beck et al., 1996). The BDI-II is a 21-item instrument that measures the presence and severity of depressive symptoms.

1.4.2.3. The State Trait Anxiety Inventory (STAI; Spielberger, 1983). The STAI trait anxiety subscale consists of 20-items measuring trait anxiety.

1.4.3. EMA measures

1.4.3.1. Positive and negative affect items. Consistent with the van de Leemput et al. (2014) study, the following four nodes assessed positive and negative affect: cheerful, contentment, sad, and anxious. These items represent each quadrant of the affective space defined by valence and arousal: cheerful (positive valence, high arousal), contentment (positive valence, low arousal), anxious (negative valence, high arousal), and sad (negative valence, low arousal). They were answered on a 7-point Likert scale from not at all (0) to extremely (6)

1.4.3.2. Ethica sensor data. Smartphone sensors obtained the time-stamped objective accelerometer data for 14 consecutive days to measure smartphone-derived physical activity. Our methodological approach to integrating physical activity sensor data parallels that of prior time-series network research (Curtiss et al., 2019), which has successfully modeled both self-report and sensor data by ensuring that the final time points of the sensor dataset were estimated on the same time scale as the self-report data. Preprocessing was accomplished by submitting accelerometer data to principal component analysis, whereby the factor scores from the first factor were used for subsequent network analyses.

1.5. Data analysis

The primary aims required estimation of temporal and contemporaneous networks. To explore the network structure, we used affect items and sensor data scores to model the relationship between positive affect, negative affect, and physical activity by using the R package *mlVAR* (Epskamp et al., 2018b). Each affect item, as well as the sensor data, was a *node*. *Edges* between nodes reflected directed partial regression coefficients. That is, each directed edge reflects a unique association between two nodes controlling for all other relationships in the network. Temporal and contemporaneous network structures were modeled for two node sets: (1) positive and negative affect nodes, and (2) positive affect, negative affect, and physical activity nodes.

Specifically, temporal networks are constructed by using multilevel vector autoregressive (VAR) analyses (Epskamp et al., 2018b). In these models, a given node at time t was regressed onto all other time lagged $t - 1$ independent variables. All models were analyzed with procedures defined by the *mlVAR* package. The fixed effect coefficients produced a weighted directed network, in which the temporal connections can be construed as signifying Granger causality (Bringmann et al., 2015; Granger, 1969). Furthermore, contemporaneous networks were also estimated. Contemporaneous networks estimate edges between nodes within the same measurement window rather than across measurement windows, as occurs in temporal networks. Visualizations of each network omitted nonsignificant edges to reduce superfluous detail. The mlVAR models used the default *lmer* estimator, performing listwise deletion for missing data.

Node centrality for temporal networks was determined by computing three centrality indices: in-strength (IS), out-strength (OS), and betweenness (B). A node's in-strength parameter denotes the sum of all the absolute values of the weighted edges that are directed toward it, whereas a node's out-strength parameter denotes the sum of the absolute values of all weighted edges that proceed from it to another node. The betweenness centrality parameter indicates the number of times that a node lies on the shortest path between any other pair of nodes. Node centrality for contemporaneous networks was determined by computing strength. We opted to emphasize strength centrality parameters over expected influence parameters, which do not use absolute values, because our nodes signify variables that are inversely correlated (i.e., positive affect and negative affect items). Although expected influence parameters convey nuanced information when all nodes have a similar interpretation such as symptoms (i.e., higher scores indicate worse severity), these metrics seem less suitable for nodes having opposite measurement interpretations (e.g., such as positive and negative affect). Our aim is to examine the overall influence of one node on other nodes irrespective of directionality, which is better accomplished with the absolute values of strength parameters.

For our first aim, temporal and contemporaneous networks of positive and negative affect were estimated. For the temporal network, the out-strength centrality parameter (i.e., a metric indicating how strongly a node predicts other nodes) was estimated for each node. Permutation tests were used to determine whether positive affect nodes exhibit greater out-strength than do negative affect nodes. For the contemporaneous network, the standard strength centrality parameter for each node was estimated, and, again, permutation tests were used to compare centrality across nodes of positive and negative affect.

For our second aim, temporal and contemporaneous networks were estimated with nodes reflecting positive affect, negative affect, and physical activity. Bootstrapping tests compared the magnitude of the edges connecting positive affect nodes and physical activity and the magnitude of the edges connecting negative affect nodes and physical activity. Stronger edges between positive affect and physical activity than negative affect and physical activity in both the temporal and contemporaneous networks would provide support for the proposed hypothesis.

1.6. Sample size justification

The number of participants was determined from a simulation power analysis using the *SIMR* package in R (Green & MacLeod, 2016). A priori power analyses revealed that for 30 subjects with 70 time points, the power would be at least 99.80 %. The power analyses were informed by the auto-correlation coefficients obtained by a study from Curtiss et al. (2019), as there is no gold-standard method of estimating power for networks involving temporal and contemporaneous regression coefficients. Accordingly, 34 subjects were included in the final sample, and the average EMA self-report data completion rate was 47.03 time-points ($SD = 12.26$). This level of completion would still yield a statistical power rate of at least 95.5 %.

2. Results

2.1. Time-series diagnostics

For all nodes, data was screened for multicollinearity to assess potential node redundancy. None of the contemporaneous bi-variate correlations exceeded standard cut-offs thresholds for multicollinearity ($r \geq 0.80$; Berry and Feldman, 1985). Also, all nodes were screened for potential time trends. Individual multilevel models were estimated such that each variable was regressed on a time variable. None of the models exhibited a statistically significant relationship between the respective node and time (p's > 0.30).

2.1.1. Temporal and contemporaneous network structure of positive and negative affect

In the temporal network structure, results of the mlVAR network analyses revealed robust directed relationships both within and between nodes of a particular valence (Fig. 1A). The node reflecting *contentment* at $t - 1$ significantly predicted elevated levels of *cheerfulness* at the next measurement window ($\beta = 0.19$, $p < 0.001$). Furthermore, *contentment* evinced a significant and positive auto-correlation coefficient ($\beta = 0.17$, $p < 0.01$), suggesting that prior increases in *contentment* are associated with subsequent elevations in *contentment*. Similarly, a significant and positive auto-correlation emerged for *sadness* ($\beta = 0.26$, $p < 0.001$). The node representing *sadness* inversely and prospectively predicted the positive affect nodes *contentment* ($\beta = -0.13$, $p < 0.01$) and *cheerfulness* ($\beta = -0.15$, $p < 0.01$); however, it did not significantly predict or was significantly predicted by the other negative affect node, *anxiety*. The only significant parameter associated with the node *anxiety* was an autocorrelation coefficient ($\beta = 0.26$, $p < 0.001$), suggesting higher levels of anxiety are prospectively associated with more anxiety at later time points.

Regarding centrality in the temporal network, the nodes *sadness* (OS $= 0.28$) and *contentment* (OS $= 0.19$) had the highest out-strength centrality values. This is sensible as the *sadness* node had two directed edges directed to other nodes and the *contentment* node had one directed edge predicting another node. The node for *cheerfulness* exhibited the strongest in-strength centrality parameter (IS $= 0.34$), which suggests that this node is the one most influenced by the behavior of other nodes at earlier time points. Centrality estimates of the temporal network are presented in Supplementary Fig. 1.

In the contemporaneous network, the structure was denser, as all nodes exhibited connections with each other within the same time window (Fig. 1B). Again, nodes within the same valence demonstrated positive edges, whereas nodes of opposite valence exhibited negative edges. The partial correlation between the positive affect nodes *cheerfulness* and *contentment* ($r_{partial} = 0.53$, $p < 0.001$), as well as that between the negative affect nodes *sadness* and *anxiety* ($r_{partial} = 0.22$, $p < 0.001$), was positive and significant. The contemporaneous relationship was negative between *sadness* and both *contentment* ($r_{partial} = -0.13$, $p < 0.01$) and *cheerfulness* ($r_{partial} = -0.21$, $p < 0.001$). Likewise, a similar pattern emerged between *anxiety* and both *contentment* ($r_{partial} = -0.19$, $p < 0.001$) and *cheerfulness* ($r_{partial} = -0.13$, $p < 0.01$).

Regarding centrality in the contemporaneous network, both of the positive affect nodes, *cheerfulness* and *contentment*, exhibited the highest strength estimates (S = 86; S = 84, respectively). This indicates that both the positive affect nodes exhibit the highest levels of connectivity in the contemporaneous network. Centrality estimates of the contemporaneous network are presented in Supplementary Fig. 2.

To directly address the primary aim, we conducted Monte-Carlo permutation tests for both the temporal and contemporaneous networks. In the temporal network, the combined out-strength of the positive affect nodes ($M = 0.09$) was not significantly different from the combined out-strength of the negative affect nodes ($M = 0.13$; Monte-Carlo permutation $p = 0.33$). In the contemporaneous network, the combined strength of the positive affect nodes ($M = 0.85$) was significantly greater than the combined strength of the negative affect nodes ($M = 0.54$; Monte-Carlo permutation $p < 0.001$). Positive affect nodes may not exhibit higher levels of connectivity with respect to prospective associations, yet they do demonstrate greater connectivity with other nodes during the same time window.

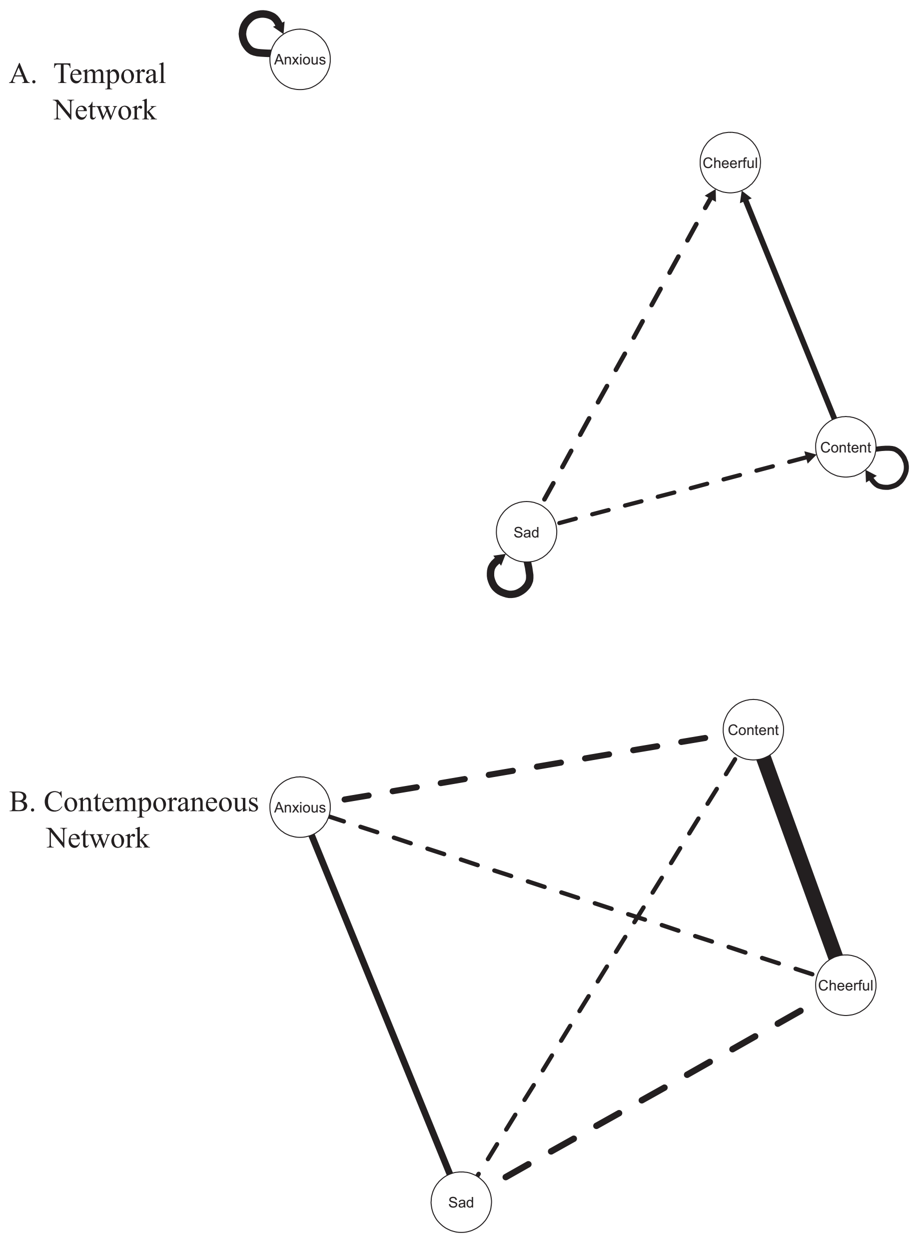

Fig. 1. Temporal and contemporaneous networks of positive and negative affect.
Note. Non-significant edges are omitted. In the temporal network, all edges are directed, and edges connecting to the same node indicate significant autocorrelation. Edges are non-directed in the contemporaneous network. Thickness of edge indicates strength of association. Solid edges denote positive associations, whereas dashed edges denote negative associations.

2.1.2. Temporal and contemporaneous network structure of positive affect, negative affect, and physical activity

To examine the role of physical activity in the dynamic network structure of positive and negative affect, we included a node encoding accelerometer information from a smartphone-based sensor in the network to represent physical activity We transformed the accelerometer data, preprocessing it by using principal component analysis before including the factor scores from the single principal component into the network prior to analysis.

In the temporal network, the structure exhibited a nearly identical structural configuration and pattern of associations as estimated in the prior temporal network that excluded physical activity (Fig. 2A). That is, *sadness* negatively predicted *contentment* ($\beta = -0.12$, $p < 0.01$) and *cheerfulness* ($\beta = -0.14, p < 0.01$) at the next time window. The positive directed edge from *contentment* to *cheerfulness* was also significant ($\beta = 0.19, p < 0.001$), and significant auto-correlations emerged for the same affect nodes, including *sadness* ($\beta = 0.25$, $p < 0.001$), *contentment* ($\beta = 0.16, p < 0.01$), and *anxiety* ($\beta = 0.26, p < 0.001$). Again, *anxiety* was not associated with any of the other nodes in the network. Regarding the physical activity node, it only exhibited a significant autocorrelation ($\beta = 0.19$, $p < 0.001$) and was not connected with any other nodes in the network.

Centrality estimates in this temporal network were congruent with the pattern of results obtained in the prior temporal network excluding physical activity. The nodes *sadness* (OS = 0.26) and *contentment* (OS = 0.19) demonstrated the highest out-strength centrality parameters, and the node *cheerfulness* exhibited the highest 'in-strength' (IS = 0.33) parameter estimate. The physical activity node was associated with a value of 0 for each centrality parameter estimate calculated. Please refer to Supplementary Fig. 3 for the full results of the centrality estimates.

In the contemporaneous network with physical activity, the physical activity node was isolated and did not exhibit any significant associations with the other affect nodes within the same time window (Fig. 2B). Yet again, the contemporaneous network was characterized by nodes of the same valence being positively associated with each other and nodes of the opposite valence being negatively associated. The partial correlation between the positive affect nodes *cheerfulness* and *contentment* ($r_{partial} = 0.53$, $p < 0.001$), as well as that between the negative affect

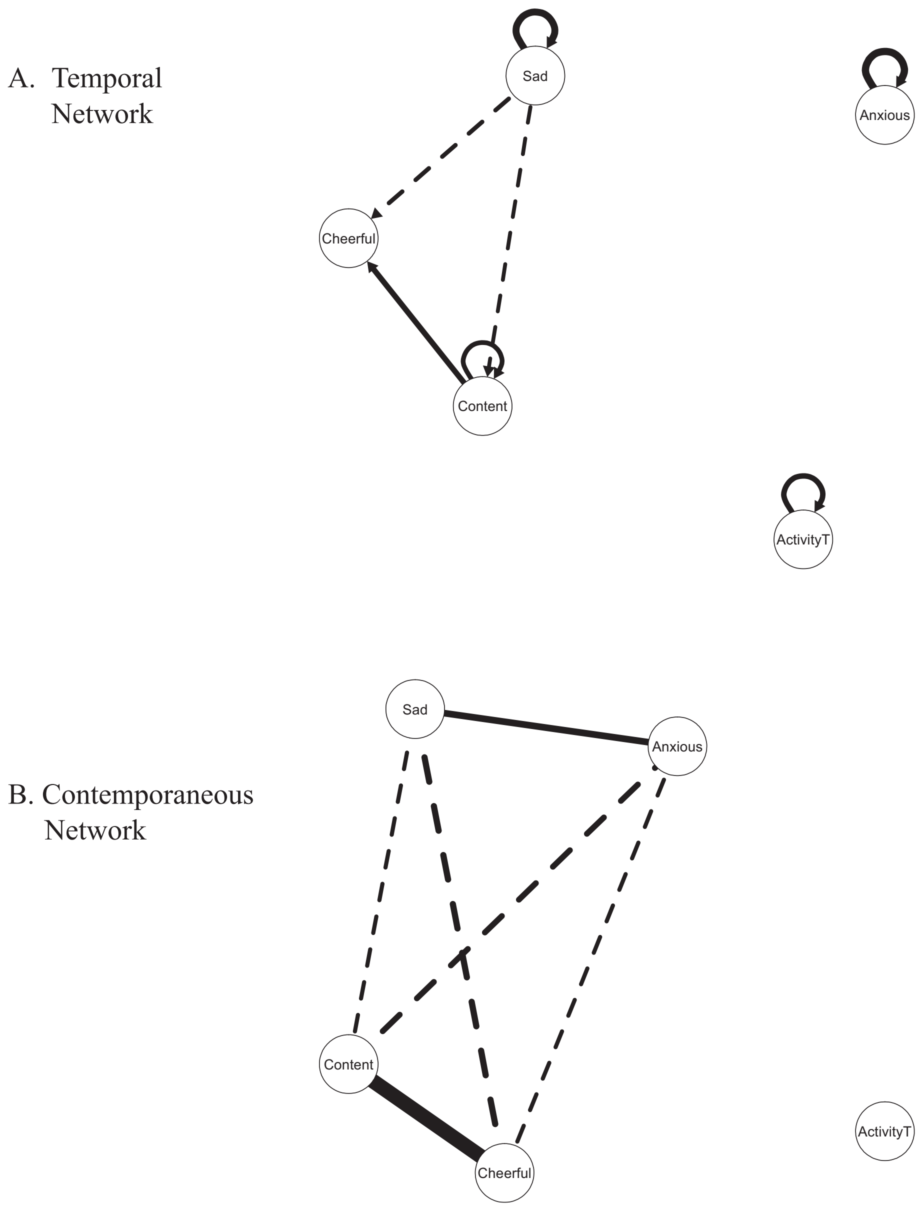

Fig. 2. Temporal and contemporaneous networks of positive affect, negative affect, and physical activity. *Note*. Non-significant edges are omitted. In the temporal network, all edges are directed, and edges connecting to the same node indicate significant auto-correlation. Edges are non-directed in the contemporaneous network. Thickness of edge indicates strength of association. Solid edges denote positive associations, whereas dashed edges denote negative associations. ActivityT refers to the transformed physical activity accelerometer variable.

nodes *sadness* and *anxiety* ($r_{partial} = 0.22$, $p < 0.001$), was positive and significant. The contemporaneous relationship was negative between *sadness* and both *contentment* ($r_{partial} = -0.12$, $p < 0.01$) and *cheerfulness* ($r_{partial} = -0.20$, $p < 0.001$). Likewise, a similar pattern emerged between *anxiety* and both *contentment* ($r_{partial} = -0.19$, $p < 0.001$) and *cheerfulness* ($r_{partial} = -0.13$, $p < 0.01$).

Regarding centrality in the contemporaneous network with physical activity, results were similar to the prior contemporaneous network without physical activity. Both of the positive affect nodes, *cheerfulness* and *contentment*, exhibited the highest strength estimates (S = 0.86; S = 0.84, respectively). Please refer to Supplementary Fig. 4 for the full centrality estimate results.

With regard to our primary hypothesis, which predicted that physical activity would have stronger edges with positive affect nodes than negative affect nodes, the results are unable to address that prediction. Because physical activity was isolated and unconnected to any other nodes in either the temporal or contemporaneous networks, the hypothesis was untestable.

3. Discussion

To elucidate the time-series characteristics of positive affect, negative affect, and physical activity, we used a time-series network approach in a sample of treatment-seeking individuals with high trait negative affect. The primary aims were to investigate the temporal and contemporaneous network structure of positive affect, negative affect, and physical activity. In the temporal network, the node representing sadness evidenced the greatest out-strength, both predicting itself and inversely predicting the positive affect nodes representing contentment and cheerfulness. This suggests that a person's overall level of sadness at one point is highly predictive of how much sadness and positive affect one will experience at future time points. Notably, the node representing anxiety was unconnected to other nodes in the temporal networks. Because these networks are derived from partial regression coefficients, which control for the influence of other nodes in the network, perhaps levels of anxiety do not prospectively predict the positive affect nodes above and beyond the contribution of sadness. Although sadness exhibited the greatest out-strength, there was no evidence that the combined out-strength of negative affect nodes was significantly greater than that of positive affect nodes in the temporal network. Thus, perhaps high levels of connectivity with respect to prospective relationships are more strongly associated with specific forms of negative affect (e.g., sadness) rather than negative affect as a whole.

In the contemporaneous networks, nodes of the same valence exhibited positive associations (e.g., between sadness and anxiety, etc.), and nodes of the opposite valence exhibited negative associations (e.g., between sadness and cheerfulness, etc.). Though not surprising, this result is consistent with many findings in affective science that attest to robust positive relationships between same-valence affect states and negative relationships between opposite-valence affect states at both the cross-sectional (Crawford and Henry, 2004; Watson et al., 1988) and time-series level (Gill et al., 2017).

That notwithstanding, these results differ somewhat from our prior study investigating the temporal network structure of positive affect, negative affect, and physical activity in people diagnosed with bipolar disorder and healthy controls (Curtiss et al., 2019). One of the principal findings from that study was that the associations between opposite-valence affect nodes were characterized by more positive edges and fewer negative edges in the clinical sample of people with bipolar disorder. Those results had implications that bore on prominent theories of positive and negative affect: the circumplex model (CM; Russell, 1980) and the evaluative space model (ESM; Cacioppo et al., 1999; Norris et al., 2010). Our previous study (Curtiss et al., 2019) suggested that affective systems in bipolar disorder are more associated with the co-activation patterns permitted by the ESM than the co-inhibition patterns posited by the CM. That is, those results indicated that increases in positive affect could lead to increases in negative affect and vice versa in bipolar disorder, whereas positive affect states would inhibit the expression of negative affect states in healthy controls.

In the current study, there was no support for such a co-activation mechanism of the dynamic behavior of affect. In all instances, opposite-valence affect states exhibited negative edges in both the temporal and contemporaneous networks. The ostensible discrepancy between these studies may be reconciled by considering the disparate patient populations. Therefore, perhaps co-activation patterns of affect states are distinct to clinical presentations associated with especially pronounced disturbances in both positive and negative affect. Bipolar disorder involves both disturbances in low mood and manic episodes, often invariant to context (Gruber, 2011; Johnson and Fulford, 2009). Disorders with such severe expressions of emotion dysregulation may confer more risk for co-activation of opposite-valence states of affect, whereas anxiety and unipolar depressive disorders may exhibit the co-inhibition patters of affect associated with less severity. Overall, this would indicate that the tenets of the CM (i.e., co-inhibition) may apply to emotional psychopathology characterized primarily by high negative affect, whereas the co-activation mechanisms permissible under the ESM may better represent emotional psychopathology characterized by both high negative affect and maladaptively elevated positive affect.

In addition to distinctive patterns of connectivity exhibited between positive and negative affect nodes, there were other noteworthy findings. Positive affect nodes had greater strength centrality than negative affect nodes in the contemporaneous network. This suggests that positive affect nodes exhibit higher levels of connectivity with other nodes during the same time window.

With respect to broader debates in the literature over the relative importance of positive affect versus negative affect in emotional disorders, results of the current study can contribute to the discrepant findings from recent studies examining this question from a dynamic time series approach. The results of our previous study (Curtiss et al., 2019) did not demonstrate that positive affect nodes exhibit statistically greater strength centrality measures than negative affect nodes, and the strongest nodes in both the clinical and healthy control sample were positive and negative affect nodes (i.e., attentiveness, upset, determination, and shame). In another time-series network study by Fisher et al. (2017), the primary results suggested that both negative and positive mood were highly central in the contemporaneous network, while a positive affect node exhibited the greatest out-strength centrality in the temporal network. The temporal network results of Fisher et al. (2017) are not in accord with those of Pe et al. (2015). Pe et al. (2015) found that negative mood nodes demonstrated greater levels of connectivity and density than nodes representing positive mood.

Our findings are noteworthy for underscoring the differential roles of both positive affect and negative affect in emotional disorders. The prominence of positive affect in contemporaneous networks may suggest that one's affective experience at any given time may be more strongly influenced by concurrent levels of positive affect than negative affect. However, negative affect may play a greater role in influencing the behavior of future affective experiences, consistent with Pe et al. (2015). Specifically, sadness might contribute to future affect more so than anxiety, consistent with longitudinal network studies suggesting that depressive symptoms are more central across time than anxiety symptoms (Curtiss et al., 2019).

In contrast to our hypothesis, physical activity was isolated in both the temporal and contemporaneous networks. Indeed, including the physical activity node barely altered the contemporaneous and temporal networks. However, physical activity at one time point did prospectively predict physical activity at the next one (i.e., a significant autocorrelation). The only other study that examined the time-series network characteristics of physical activity as it relates to positive and negative affect was our previous study (Curtiss et al., 2019). Results of the current study did not replicate the findings from our earlier study, which suggested that actigraphy-derived measurements of physical activity were negatively predicted by feelings of shame and positively predicted by subjective feelings of activeness in the temporal network. Several possible explanations may account for this inconsistency. First, differences in the connectivity of physical activity as a node may merely signify differences in how physical activity was measured. Whereas the current study recorded physical activity by means of smartphone accelerometers, we used actigraphy wrist watches that were worn continuously on the non-dominant hand in our previous study (Curtiss et al., 2019). Second, other differences in method might be relevant. In the current study, affect variables represented each of the four quadrants of the CM (i.e., high arousal-negative affect, low arousal-negative affect, high arousal-positive affect, and low arousal-positive affect), whereas we previously used broader set of affect nodes from the PANAS scale. Perhaps the inclusion of more affect nodes facilitated detection of significant edges between them and physical activity. Moreover, one node in our previous study – self-reported activeness – shared content with physical measurement of activity. Third, physical activity may play a different role as a function of diagnostic group: bipolar disorder in the early study, and depressive and anxiety disorders in this one. But in the previous study (Curtiss et al., 2019) physical activity was connected to only a few affect nodes. Indeed, physical activity had strong connections in the temporal network of healthy individuals, perhaps suggesting that it plays a less prominent role in affect dynamics in clinical samples than in non-clinical ones. Clinical disorders such as depression are associated with concurrent and prospective low levels of physical activity (Roshanaei-Moghaddam et al., 2009). Moreover, a study examining relationships between voluntary exercise and the time-series dynamics positive and negative affect in a non-clinical sample suggested that physical activity predicted the dynamics of negative affect (Bernstein et al., 2019). Perhaps clinical status is an important contextual factor affecting how physical activity influences positive and negative affect. Finally, differences in sampling frequency across the two studies might contribute to distinct findings.

It is important to acknowledge limitations of the current study. First, time-series network analyses assume stationarity (i.e., stability of means and variances during the measurement period). Especially for studies where clinicians aim to reduce the mean and variance of symptom measure over the course of treatment, we need to develop time-varying multilevel network models that can account for time trends.

Accordingly, we required treatment stability of these measures as an important inclusion criterion of the current study to mitigate significant time trend effects. Furthermore, physical activity was assessed with mobile smartphone sensors (i.e., accelerometer) as opposed to dedicated, sensitive actigraphic technology. Although participants were instructed to retain their smartphone on their person for accurate recording, they may have failed to do this consistently. This possibility renders ambiguous any null results. Future research may benefit from using wearable technology rather than smartphone sensors to collect sensor data with greater precision and integrity.

In conclusion, our study attests to the relevance of the time-series dynamics of affect and physical activity in emotional psychopathology. Our findings suggest that positive affect exhibits greater levels of network connectivity during contemporaneous time windows, and negative affect is more predictive of future affect states. Intensive time-series network studies afford promise for informing more process-based treatment approaches (Hofmann and Hayes, 2019). Results from the current study may inform treatments for emotional disorders by elucidating the differential role of positive and negative affect in the overall phenomenology of emotion. Future treatment research may consider the clinical utility of targeting negative affect to promote future psychological health and of targeting positive affect to enhance more contemporaneous health outcomes.

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CRediT authorship contribution statement

Joshua E. Curtiss: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Megan Pinaire:** Investigation, Writing – original draft, Writing – review & editing. **Daniel Fulford:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Richard J. McNally:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Stefan G. Hofmann:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jad.2022.07.061.

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