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Adolescent Emotion Network Dynamics in Daily Life and Implications for Depression

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Abstract
Emotion network density describes the degree of interdependence among emotion states across time. Higher density is theorized to reflect rigidity in emotion functioning and has been associated with depression in adult samples. This paper extended research on emotion networks to adolescents and examined associations between emotion network density and: 1) emotion regulation and 2) symptoms of depression. Data from a daily diary study ($t = 21$ days) of adolescents ($N = 151$; 61.59% female; *mean age* = 14.60 years) were used to construct emotion network density scores. Emotion regulation was measured using The Difficulties in Emotion Regulation Scale Short Form (DERS-SF). Depression was measured using the Revised Child Anxiety and Depression Scale-Short Version (RCADS-SV). Associations between emotion network density and DERS-SF were examined through Pearson correlations. Multiple regression analyses examined associations between emotion network density and depression. Emotion network density was not associated with the DERS-SF. Follow-up analyses showed that it was positively associated with non-acceptance of emotions (a subscale of the DERS-SF). Emotion network density was positively associated with RCADS-SV depression. Non-acceptance of emotions may encourage the spread of emotion across time and states given that a feature of non-acceptance is to have secondary emotional responses to one's emotions. Emotion networks that are self-predictive may be a risk factor for adolescent depression.

Keywords Emotion network density · Intensive repeated measures · Emotion regulation · Adolescence · Depression

Emotional disturbances are a prevalent feature in models of psychopathology (Cicchetti et al. 1995; Mennin and Farach 2007) and difficulties in the ability to regulate emotions appropriately predict numerous forms of psychopathology (Aldao et al. 2010). Depression and anxiety disorders, for example, have as core symptoms excessive and persistent levels of sadness and anxiety, respectively (American Psychiatric Association 2013). However, models of psychopathology do not only focus on higher average levels of negative affect; emotions and their regulation are dynamic processes (e.g., Gross 2015; Kuppens and Verduyn 2015). How emotions unfold during daily life also plays an important role in understanding psychopathology risk (Csikszentmihalyi and Larson 2014; Trull et al. 2015). The purpose of the present study was to investigate individual differences in emotion network density in day-to-day life and their association with symptoms of depression during adolescence. Emotion network density describes the degree of interdependence among emotion states across time, is theorized to provide insight into emotion functioning, and has recently been shown to be associated with psychopathology in adults (Kuppens and Verduyn 2015; Pe et al. 2015). We provide an overview of research related to emotion dynamics and emotion networks specifically before turning to the potential insights a consideration of emotion networks may confer to our understanding of depression in adolescents.

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Emotional Rigidity and Depression

Emotions have multiple aspects – the subjective experience of emotional events, emotion behaviors, and emotion physiology – that all work to motivate and organize responses to stimuli and situations, but they may serve different functions (Cicchetti et al. 1995; Gross, & Munoz, 1995). For example, the physiological states that accompany emotions prepare organisms to act in certain ways while associated behavioral expressions serve communicative functions (Campos et al. 1989). While emotions alert us to important changes in our environments and facilitate responding to these changes (Kashdan and Rottenberg 2010; Izard 2009), their influence on behavior may be modulated. In other words, “people not only have emotions, they also handle them” (Frijda 1986, p. 401). The modulation of emotion is a necessary process, enabling optimal engagement in situations or responding to stimuli (Cole et al. 2004). Emotional reactions often reflect the up-regulation of emotions to motivate engagement to enact change or respond to a situation or stimulus, but must be balanced with adequate down-regulation to ensure appropriate responses that can avoid undesirable consequences for the well-being of the individual and/or those around the individual (Berenbaum et al. 2003). Emotion regulation research highlights processes that modulate the occurrence, intensity, and duration of emotional experiences (Cicchetti et al. 1995; Cole et al. 2004; Thompson 1990). Emotion regulation is thought to be adaptive when emotions persist until goals are achieved but respond flexibly (e.g., rise and fall when appropriate) to accommodate changing environmental demands (Thompson 1994).

Flexibility or rigidity in emotional responding also is an important feature in understanding how emotion regulation serves as a key underlying factor in depression. Individuals capable of managing their experiences and their expressions of emotion in a context-sensitive manner appear most able to respond to life’s demands (Lougheed and Hollenstein 2012; Mennin et al. 2007). Emotion regulation processes are less successfully deployed in depression (Aldao et al. 2010; Schäfer et al. 2017; Sheppes et al. 2015). Emotions in depression are characterized by rigidity rather than flexibility, manifesting as a contextually inappropriate persistence in emotions across time despite changes in contexts, goals, and demands (Hollenstein et al. 2013; Houben et al. 2015). Without the flexibility (rigidity’s counterpart) in emotion that is important for promoting an adaptive interplay between the individual and changing environmental demands, individuals are at elevated risk for depression and other psychopathology outcomes (Brose et al. 2015; Koval et al. 2013).

A Network Perspective on Emotion Processes

To capture within-person variability in emotions, many have turned to experience-sampling methods, in which individuals are repeatedly measured as they go about their daily lives (Bolger et al. 2003; Larson and Csikszentmihalyi 1983; Shiffman et al., 2008). The repeated assessment of individuals allows researchers to capture fluctuations in emotion (Ram and Gerstorf 2009). In this dynamic perspective of emotions, emotional rigidity is manifest as the extent to which individuals perseverate in an emotional state from moment to moment, or day to day. This has been described in terms of emotion inertia, an index of the temporal dependency of a time series (Jahng et al. 2008). Higher inertia values signify greater perseveration in an emotion state over time and indicate a decoupling of emotions from their adaptive functions (Kuppens et al. 2010). Rather than responding flexibly in a context-sensitive manner, an individual with high inertia values has predictable responses to their emotions from one time point to the next. Consistent with theory, both laboratory and experience-sampling paradigms have observed a positive association between greater emotion inertia (rigidity) and depressive symptoms (Brose et al. 2015; Koval et al. 2013). These findings demonstrate the value of the dynamic perspective of emotions for testing theories of the role of emotion rigidity in risk for depression.

Novel insights into emotion dynamics and their associations with symptoms of depression have recently been gained by considering dynamics *between* as well as *within* emotion states across time. This *emotion network* perspective, in which connections between emotion states are considered, extends inertia’s focus on rigidity in one emotion state by allowing for the possibility that one’s current emotion state may give rise to other emotions. For example, one may feel embarrassment over an angry outburst. This possibility has long been emphasized in emotion theory (e.g., Gross and Muñoz 1995) and there is also empirical support for the moment-to-moment transfer of emotions across time and states (Anand et al. 2016; Fredrickson and Joiner 2002; Pe and Kuppens 2012).

Some degree of emotion transfer across time and states is expected. However, just as inertia has been viewed as rigidity in emotion functioning at the level of individual emotions, network density – an indication of the strength of the temporal connections within and between emotions – can be conceived of as rigidity at the network level. Substantial spread of emotions across time and states (operationalized as high network density values) manifests in the form of a network of interdependent states, suggestive of an emotion system that is self-predictive (Kuppens and Verduyn 2015). In a self-predictive emotion system, it is theorized that individuals respond to their emotions rather than to ongoing events of potential importance, undermining the context-sensitive flexibility that characterizes healthy and adaptive emotional functioning. For example, in the case of an increase in the experience of sadness, an individual with an emotion network with relatively strong connections between sadness and anger may be likely to experience anger following the experience of sadness. In an individual with weaker connections between sadness and anger, the impact of an increase in sadness on the emotion network may die out much more quickly (Wichers 2014), allowing the individual to resume normal functioning, rather than persisting in negative emotion states.

Preliminary Evidence Linking Network Density and Depression in Adults

Support for the network perspective of emotions in depression has emerged in a number of studies of adults. These studies applying network methods offer support for the notion that a denser (e.g., self-predictive) network is a risk factor for depression. One study by Wigman and colleagues (Wigman et al. 2015) examined "mental state" networks (comprised of: cheerful, content, down, insecure, and suspicious mental states). Their findings revealed that individuals with depression were more likely to have denser, more self-predictive mental state networks relative to healthy controls, with negative states reinforcing negative states and negative states reducing positive states to a greater extent than in healthy controls. In a similar study examining connections across negative affect, positive affect, and paranoia in women, denser connections across time were observed with greater symptom severity measured by the Symptom Checklist-90-R (Wigman et al. 2013). Other work has focused specifically on emotion networks and examined connections among affect items exclusively. Pe and colleagues (Pe et al. 2015) compared emotion networks for 53 adults with major depression and 53 control adults (defined as individuals who experienced no current or past mental-health disorders and with a score of 9 or less on the Beck Depression Inventory-II). Emotion network density was higher in adults with major depressive disorder than in comparison adults, again highlighting that an underlying process in depression is that emotions are self-predicting and perhaps not responding flexibly to the environment (e.g., Koval et al. 2013; Kuppens et al. 2010).

Emotion Network Density and Adolescent Depression

Emotion network density provides a summary index of emotion dynamics that matches perspectives considering the self-predictive quality of emotions across time and other emotion states. There is also promising evidence for the ability for emotion network density to provide insight into depression. At this time, researchers await the application of emotion network processes to adolescent developmental risk for depression. Adolescence is a time of normative increases in the prevalence of depression (Birmaher et al. 1996; Kessler et al. 2001). Interestingly, emotion dynamics may be particularly salient during adolescence. For example, normative samples of adolescents tend to report a greater range of emotion (Larson et al. 1980) and exhibit more extreme mood swings (e.g., Maciejewski et al. 2015) relative to adults. These normative differences between adolescents and adults may stem from adolescence being a time of increased exposure to stressors (Larson and Ham 1993), increases in the intensity of parent-child conflict (Laursen et al. 1998), and a time during which emotion regulation capacities are still developing (Casey et al. 2008; Zimmermann and Iwanski 2014). Thus, applying dynamic methods to the study of adolescent emotion processes may offer fruitful new in-roads to understanding depression risk.

The limited research on emotion dynamics in adolescents with varying levels of depression supports the view that rigidity may be a key risk factor for depression. Kuppens and colleagues (Kuppens et al. 2010) compared inertia in angry, happy, and dysphoric behaviors (at intervals of 5 s) during family interaction tasks in 72 depressed and 64 non-depressed adolescents. Greater emotion inertia was observed in depressed relative to control participants. In terms of the predictive nature of emotion inertia for the emergence of clinical depression, greater inertia in both negative and positive emotional behaviors during videotaped interactions with a parent predicted the emergence of clinical depression 2.5 years later in a sample of 165 early adolescents (Kuppens et al. 2012). These findings suggest that rigidity in emotions as captured by emotion inertia is characteristic of depression during adolescence as well as adulthood and acts as a risk factor for subsequent depression. The extent to which depression during adolescence is characterized by rigidity in emotion network functioning is unclear.

The Present Study

In this study, we sought to examine adolescent emotion networks in the service of two major aims. The first aim was to begin the task of examining the processes associated with individual differences in emotion network density. Previous studies have speculated that emotion network density may partially result from difficulties in emotion regulation (Pe et al. 2015), with emotions becoming unresponsive to efforts to modulate the emotion system. To explore this possibility, we examined associations between emotion network density based on daily reports of emotion and a widely used measure of emotion regulation difficulties. We hypothesized that emotion network density would be positively associated with difficulties in emotion regulation. The second aim was to evaluate whether emotion network density was associated with symptoms of depression. Guided by recent work in the adult literature (Pe et al. 2015), we hypothesized that denser emotion networks would be associated with greater symptoms of depression. By considering the association between emotion network density and a measure of emotion regulation, the added value of emotion network density in understanding adolescent depression above and beyond standard measures of emotion dysregulation was examined.

Method

The present study made use of data from The Family Life Optimizing Well-being (FLOW) study, an intensive longitudinal study designed for the study of day-to-day intraindividual variability across a range of domains of functioning in parents and their adolescent children, including emotions, family functioning, school experiences, and well-being. Detailed information on the larger study is available in Brinberg et al. (2017) and Fosco and Lydon-Staley (2017). Ethics approval for the study procedures was obtained from the Institutional Review Board at The Pennsylvania State University.

Participants

Participants were 151 families of 9th and 10th grade adolescents (93 female, 58 male) recruited through high schools in Pennsylvania. Families were eligible for participation if they met six criteria: (1) a family with one 9th or 10th Grade student, (2) status as a "two-parent" family, defined as having two caregiving adults living in the same house for at least two years, (3) youth were required to live in one household continuously, (4) all participants were required to be able to read and write English fluently, (5) internet access and means to complete daily surveys at home, and (6) consent and assent to participate from the parent and adolescent, respectively. Adolescent participants were between 13 and 16 years of age ($M = 14.60$, $SD = 0.83$) and identified (via parent report) as White (83.4%), Asian (4.6%), African American/Black (4.6%), Native American/American Indian (0.7%), Hispanic/Latino (0.7%), Multiracial (5.3%), missing information (0.7%). Caregivers (92.7% mothers, 4.64% fathers, 1.30% stepmothers, 0.7% aunts, 0.7% foster mothers) had an average age of 43.4 ($SD = 6.9$) years and self-identified as White (90.1%), Asian (3.3%), African American/Black (2.6%), Native American/American Indian (0.7%), Hispanic/Latino (0.7%), Multiracial (2.0%), and missing information (0.7%). Adolescent participants reported GPAs of 'Mostly A's' ($n = 97$), 'Mostly B's' ($n = 35$), 'Mostly C's' ($n = 16$), 'Mostly D's' ($n = 1$), and 'Mostly lower than D's" (n=2). Caregivers had a yearly family income ranging from '$20,000' to '$125,000 or more' (*Median* = '70,000–79,999′). Caregivers' education spanned graduate or professional training (23.2%), college degree (27.8%), associate's degree or > one year college (30.5%), and high school degree or similar (15.2%), less than a high school degree (2.7%), or missing information (0.7%).

Procedure

Families were recruited through emails sent to parents from school principals. Interested parents received a web link with study information and a consent form. After confirming that the family met inclusion criteria, adolescents were contacted with a description of the study and an opportunity to assent or decline participation. If the adolescent assented, an email was sent to the youth with a baseline survey which contained demographic questionnaires, the DERS-SF, and the RCADS-SV used in the present study. The baseline survey contained additional scales related to global family functioning and well-being that were not the focus of the present study. Once the youth completed the baseline survey, the caregiver received his/her baseline survey which also contained scales on family functioning and demographics. Upon completion of the baseline survey, a 21-day daily diary protocol was initiated. Links to daily questionnaires were emailed separately to parents and adolescents at 7:00 PM each night in their time-zone, followed by a reminder text message or phone call to notify that the survey links had been sent. Participants were instructed to complete the daily survey before going to bed, although access links remained open until 9:00 AM the next morning. In cases where participants completed surveys the following morning, they were instructed to report on the previous day. Daily questionnaires took approximately 5 min to complete. The surveys included questions on family functioning (e.g., cohesion and conflict) and school experiences in addition to the emotion items reported in the present manuscript. Parents and adolescents were compensated with gift cards to Amazon.com or Wal-Mart (based on preference) at each study phase: $25 each after completing the baseline assessment; $2.50 for the first 4 daily surveys of each week, and $5 for the last 3 surveys of each week (up to $25 per week). Continued participation through the daily diary was further incentivized through the use of a raffle for which an iPad mini was available as a prize. Every week in which all daily questionnaires were completed resulted in one entry into the raffle drawing.

Measures

The present study made use of adolescents' reports of daily emotion from the daily diary component of the study as well as demographic, depression, and trait emotion regulation characteristics from the baseline surveys completed by the adolescent participants prior to the daily diary protocol.

Depression Adolescent depression was measured using the depression subscale of the Revised Child Anxiety and Depression Scale-Short Version (RCADS-SV; Ebesutani et al. 2012). The measure was scored indicating the frequency with which symptoms of depression were experienced, with scores ranging from 1 ("Never") to 4 ("Always"). Higher values on this scale reflected higher levels of depressive symptoms. The depression subscale has shown excellent internal reliability in previous work (Esbjorn et al., 2012) and for the current sample the measure demonstrated high reliability ($\alpha = 0.91$). Participants reported a mean score of 1.53 ($SD = 0.58$).

Difficulties in Emotion Regulation Emotion regulation was measured using The Difficulties in Emotion Regulation Scale Short Form (DERS-SF; Kaufman et al. 2016), a short version of the Difficulties in Emotion Regulation Scale (DERS; Gratz and Roemer 2004). The DERS is one of the most widely used self-report measures of emotion regulation deficits and has shown good internal reliability and convergent validity with adolescents (Neumann et al. 2010; Weinberg and Klonsky 2009). The DERS-SF has been shown to capture dimensions of emotion regulation deficits measured by the original DERS, exhibit correlations with clinically relevant scales in a way that mirrors correlations observed when using the full DERS, and has shown good internal reliability (Kaufman et al. 2016).

In line with the multidimensional nature of emotion regulation (e.g., Cole et al. 2004; Gratz and Roemer 2004), the DERS-SF incorporates 6 subscales in the measurement of emotion regulation, including 1) awareness and understanding of emotional responses, 2) acceptance of emotions, 3) the ability to control impulsive behaviors when experiencing negative emotions, 4) the ability to employ situationally appropriate emotion regulation strategies to meet one's goals, 5) the ability to engage in goal-directed behavior while experiencing negative emotions, and 6) the extent to which one is clear about which emotions one is experiencing. The total scale and subscales were scored to provide a score indicating the frequency with which emotion dysregulation is typically experienced, with scores ranging from 1 ("Almost never") to 5 ("Almost always"). The total scale exhibited high reliability (α = 0.91) and the subscales exhibited satisfactory reliability: awareness (α = 0.76), non-acceptance (α = 0.84), impulse control (α = 0.89), goal-directed behavior (α = 0.83), strategies (α = 0.88), and clarity (α = 0.85). Participants reported a mean total score of 2.05 (*SD* = 0.73). Mean scores for subscales are presented in Table 1.

Daily Emotion Daily emotion was measured at the end of each day using items adapted from the Profile of Mood States - Adolescents (POMS-A; Terry et al. 2003) of the form, "How much of the time today did you feel…?" Four emotion scales, each consisting of two items – happiness (happy, content), depression (depressed, sad or blue), anxiety (worried, afraid), and anger (angry, annoyed) – were computed. Participants rated how much they felt each emotion that day, using a slider scaled 0 ("None of the time") to 10 ("All of the time") with 0.1 increments. A generalizability theory approach was taken to assess the reliability of the multi-item affect scales (see Bolger and Laurenceau 2013). Happiness, depression, anger, and anxiety scales all exhibited reliable within-person variability in emotion over the course of the study, with reliability scores of 0.80, 0.81, 0.72, and 0.75, respectively. Taking the mean of each participants' daily reports, participants reported a mean happiness of 8.03 (*SD* = 1.87), a mean anger of 1.74 (*SD* = 1.63), a mean depression of 1.20 (*SD* = 1.67), and a mean anxiety of 1.31 (*SD* = 1.73).

Out of a possible 3171 days, complete data on daily emotion scales were available for 2823 days (89.03%). Complete data for the scales was available for an average of 18.70 (*SD* = 2.65) days across participants. Pearson correlations between number of days completed and key study variables revealed that participants completing more days exhibited fewer emotion dysregulation difficulties as assessed by the DERS-SF ($r = -0.20$, $p = 0.01$) and were older ($r = 0.18$, $p = 0.03$) relative to participants completing fewer days. Number of days completed was not significantly correlated with symptoms of depression ($r = -0.14$, $p = 0.08$). Independent samples *t*-tests revealed no significant difference in the number of days completed across genders ($t = -0.10$, $p = 0.92$).

Table 1 Emotion network density, symptoms of depression, and emotion regulation: Correlations and descriptive statistics

Variables	1	2	3	4	5	6	7	8	9
1. Network Density	1								
2. Depression	0.22**	1							
3. DERS-SF Total	0.13	0.64**	1						
4. Non-Acceptance	0.23**	0.57**	0.78**	1					
5. Goals	0.09	0.50**	0.76**	0.54**	1				
6. Strategies	0.08	0.65**	0.87**	0.66**	0.69**	1			
7. Clarity	0.07	0.47**	0.78**	0.63**	0.44**	0.62**	1		
8. Impulse	−0.01	0.39**	0.77**	0.52**	0.56**	0.68**	0.49**	1	
9. Awareness	0.08	0.19*	0.36**	0.06	0.03	0.09	0.24**	0.13	1
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Mean	1.33	1.53	2.05	1.94	2.48	1.88	1.84	1.67	2.50
Standard Deviation	0.27	0.58	0.73	1.00	1.08	1.06	0.95	0.93	1.03

Notes: DERS-SF = Difficulties in Emotion Regulation Scale Short Form; $N = 151$; *$p < .05$; **$p < .01$

Data Analysis

The daily emotion scales were lagged by one day to create previous day (*t-1*) happiness, depression, anxiety, and anger scores. Days with missing data on daily emotion were removed leaving a total of 2444 days of data. The intensive repeated measures data (2444 days nested within 151 persons) were analyzed using multilevel models (Snijders and Bosker 2012). Both outcome and predictor variables were within-person standardized before the analysis to minimize the extent to which associations between symptoms of depression and network density were driven by individual differences in emotion variance (Pe et al. 2015). By creating within-person standardized variables, each individual's emotion time series had a mean of 0 and a standard deviation of 1. A second motivation for using within-person standardized variables was to render the coefficients representing different edges in the network comparable to one another, as raw regression coefficients are sensitive to scale and variance differences across variables (see Bringmann et al. 2016; Bulteel et al. 2016; Pe et al. 2015; Schuurman et al. 2016 for further discussions of this approach).

Separate multilevel models for each emotion outcome were used to estimate time-lagged associations among all emotions in order to create the emotion network density term. This emotion density term combines within-emotion associations over time that have been used to assess emotion inertia (e.g., Kuppens et al. 2010) with cross-emotion associations over time that have assessed the interplay of different emotions over time (e.g., Pe and Kuppens 2012). Using happiness as an example, models for emotion network density were constructed as.

Level 1:

$$\begin{aligned} Happiness_{i,t} = \beta_{0i} + \beta_{1i}Happiness_{i,t-1} \\ + \beta_{2i}Depression_{i,t-1} + \beta_{3i}Anxiety_{i,t-1} \\ + \beta_{4i}Anger_{i,t-1} + e_{it} \end{aligned} \quad (1)$$

where $Happiness_{i,\ t}$ is the emotion of interest (anxiety, depression, and anger were modeled in separate models of the same form) for person *i* on day *t*; β_{1i} indicates within-person differences in happiness on day *t* associated with happiness at day *t-1*; β_{2i} indicates within-person differences in happiness on day *t* associated with depression at day *t-1*; β_{3i} indicates within-person differences in happiness on day *t* associated with anxiety at day *t-1*; β_{4i} indicates within-person differences in happiness on day *t* associated with anger at day *t-1*; and e_{it} are day-specific residuals that are allowed to autocorrelate (AR1). Parameters β_1 to β_4 allowed an estimation of the unique contribution of each emotion at day *t-1* on happiness at day *t*.

Person-specific intercepts and associations (from the Level 1 model) were specified (at Level 2) as.

Level 2:

$$\begin{aligned} \beta_{0i} &= \gamma_{00} \\ \beta_{ki} &= \gamma_{k0} + u_{ki} \end{aligned} \quad (2)$$

where γs are sample-level parameters and the us are residual between-person differences. The random effects were assumed to come from a multivariate normal distribution, estimating an unstructured covariance matrix of the random effects. It was assumed that the day-to-day emotion processes were stable over time (i.e., that the data were weakly stationary). The Kwaitkowski-Phillips-Schmit-Shin test from the tseries package in R (Trapletti & Hornik, 2017) was used to examine the extent to which the data met the assumption of stationarity. The assumption was met for 571 of the 604 (4 emotions X 151 participants) instances, with only 33 (5.46%) instances not meeting this assumption. Findings reported below were robust to the exclusion of participants with at least one emotion time series that violated the assumption of stationarity.

Individual participants' slopes were then extracted from the four multilevel models, taking the form $\beta_{ki} = \gamma_{k0} + u_{ki}$. As the interest was in the strength of the connections between emotion states regardless of directionality, the sum of the absolute value of the 16 slopes was calculated to represent the density of the emotion network for each participant. Models were fit using the nlme package in R (Pinheiro et al. 2015) using maximum likelihood estimation. Pearson correlations were then computed to examine the associations between emotion network density, symptoms of depression, and difficulties in emotion regulation before forced-entry multiple, Poisson regression analyses were employed to examine the association between emotion network density and symptoms of depression while controlling for difficulties in emotion regulation, age, and gender. Gender was a factor variable with female as the reference category. The choice of Poisson regression reflected the positive skew of the RCADS-SV variable. We additionally examined potential effects of missing data by reanalyzing the data after days with missing data were imputed with participants' mean emotions across their time series. The results were unchanged and, as such, the original results were obtained and presented below.

To examine the robustness of the findings, an additional emotion network density index was created by substituting the within-person standardized scores with person-mean deviated scores and controlling for the mean level of the emotion scales across the 21 days at level 2 of the multilevel models. The use of person-mean deviated variables has been taken in previous studies (e.g., Bringmann et al. 2016; Pe et al. 2015) The association between network density and both symptoms of depression, $r(149) = 0.37$, $p < 0.001$, and the DERS-SF overall score, $r(149) = 0.42$, $p < 0.001$, were significant when using the within-person standardized versus within-person deviated variables. In light of concerns of the role of variability in emotion scores across both persons and emotions on edge strength (Pe et al. 2015; Schuurman et al. 2016), we continued with the more conservative, within-person standardized version of emotion network density. An additional emotion network density index was created by controlling for time of day in the multilevel models (eqs. 1 and 2). No associations between emotion and time of day emerged and the results for associations among emotion network density and depression were unchanged.

To further examine the robustness of the findings, a dichotomous depression variable was created based on previous research (Chorpita et al. 2005). Participants with scores of 21 or greater on the RCADS-SV were classified as a depressed group ($n = 26$). Participants with scores lower than 21 on the RCADS-SV ($n = 125$) were classified as a non-depressed group. Independent samples t-tests were used to test for differences in emotion network density across the two groups.

Results

Emotion Network Density: Descriptive Statistics

The mean emotion network density for the sample was 1.33 ($SD = 0.27$). To examine associations between emotion network density and missing data, Pearson correlations revealed that the number of days completed by participants was not systematically associated with emotion network density ($r = 0.11$, $p = 0.17$). Figure 1 provides an illustration of emotion network density for two participants. Each emotion state at time t is represented by a node in the network and relations between emotion states from time t-1 to time t are represented by weighted arrows (indicating connection strength) between nodes. The arrow from emotion state k to emotion state j is a visual depiction of the weight β_{kj}, expressing the strength of the association between emotion state k at time t-1 and emotion state j at time t. The thickness of the arrows indicates the strength of the association: the thicker the arrow between two nodes, the stronger the association. Table 2 presents correlations between emotion network density and the mean values of all emotions for each participant across the daily diary study. Emotion network density was positively associated with the experience of negative emotions (anxiety, anger, and depression) and negatively associated with the experience of happiness.

Emotion Network Density: Associations with Emotion Regulation

Table 1 presents the correlations between emotion network density, symptoms of depression, as well as the DERS-SF total scale and subscales. Emotion network density was not significantly correlated with the DERS-SF total score ($r = 0.13$, $p = 0.12$). Examining correlations among emotion network density and subscales of the DERS-SF, emotion network density was associated with non-acceptance ($r = 0.23$, $p < 0.01$) but not with the other subscales (all ps > 0.05).

Emotion Network Density: Associations with Depression

As hypothesized, emotion network density was correlated with symptoms of depression ($r = 0.23$, $p = 0.01$), with larger

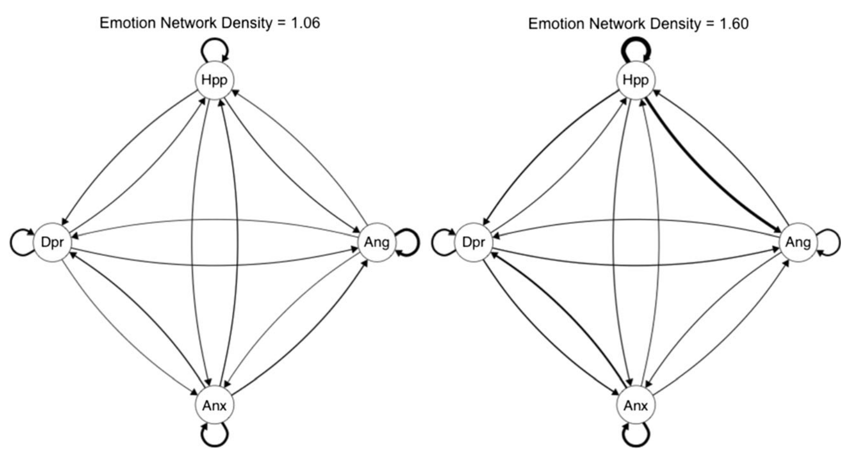

Fig. 1 Graphic display of emotion network dynamics for two participants. The 4 emotion states are: Hpp = happiness, Anx = anxiety, Ang = anger, Dpr = depression. The thickness of the arrows represents the strength of the connections between any two pairs of emotions (one emotion state at time t-1 and the other at time t across days). To facilitate comparisons between both networks, the maximum thickness of the arrows was set to the maximum connection strength across both networks (a value of 0.38). The network on the left is associated with an overall affect network density score of 1.06 while the network on the right has a score of 1.60. These values were chosen to represent networks with density values at ± 1 standard deviation (0.27) around the mean (1.33). Thus, the network on the left is a less dense emotion network relative to the network on the right. The networks were constructed using qgraph in R (Epskamp et al. 2012)

Table 2 Correlations of mean emotions during the daily diary, symptoms of depression, and emotion network density

Variables	1	2	3	4	5
1. Network Density	1				
2. RCADS-SV	0.22**	1			
3. Mean Anger	0.18*	0.57***	1		
4. Mean Anxiety	0.28***	0.66***	0.76***	1	
5. Mean Happiness	−0.21**	−0.58***	−0.60***	−0.52***	1
6. Mean Depression	0.19*	0.68***	0.83***	0.85***	−0.69***

Notes: RCADS-SV = Revised Child Anxiety and Depression Scale-Short Version; $N = 151$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$. Emotions are the mean of the participant time series for each emotion across the daily diary phase of the study

emotion network density values associated with more symptoms of depression (Table 1). Similar findings emerged when the dichotomous depression variable was used. There was a difference in overall network density for participants in the non-depressed group ($M = 1.31$, $SD = 0.27$) compared to the depressed group ($M = 1.45$, $SD = 0.25$), $t(37.90) = 2.72$, $p = 0.01$, with depressed participants exhibiting higher network density relative to non-depressed participants.

Forced entry, Poisson multiple regression analysis (Table 3) indicated that depressive symptoms were associated with emotion network density, DERS-SF total score, gender, and age, $\chi^2(4) = 133.76$, $p < 0.001$. Adolescents exhibiting more depressive symptoms had higher emotion network density scores ($\beta = 0.22$, $p = 0.004$) and greater difficulties in emotion regulation ($\beta = 0.29$, $p < 0.001$). Neither gender ($\beta = 0.4$, $p = 0.38$) nor age ($\beta = 0.01$, $p = 0.76$) were associated with symptoms of depression.

Post-Hoc Analyses of the Components of Emotion Networks

To probe the regression results further, we conducted post-hoc exploratory analyses of specific metrics reflecting aspects of the global network density score: self-loops, instrength, and outstrength. *Self-loops* reflect the association between values of an emotion at time *t-1* to time *t* and are often used as an indication of emotion inertia, or rigidity (e.g., Jahng et al. 2008). It was calculated as the absolute value of the slope in which the value of an emotion scale at time *t-1* was predicted by its value at time *t*. *Instrength* reflects a given emotion's susceptibility to being affected by other emotions. It was calculated as the sum of the absolute value of the three slopes in which other emotions predicted a given emotion. *Outstrength* refers to the degree to which a given emotion provides input to other emotions in the network and is calculated as the sum of the absolute value of the three slopes in which a given emotion predicted other emotion. Both instrength and outstrength have been used as more fine-grained indices of emotion network functioning in previous work (Bringmann et al. 2016; Fisher et al. 2017).

Table 3 Results of the Poisson multiple regression analyses examining the associations between emotion network density and symptoms of depression

	Depression			
	Estimate	*Standard Error*	*p* value	*Exp*(B)
Intercept	1.80***	0.12	<0.001	6.04
Emotion Network Density	0.22**	0.08	<0.01	1.07
DERS-SF Total Score	0.29***	0.03	<0.001	0.96
Gender	0.04	0.04	0.38	1.27
Age	0.01	0.03	0.76	0.95

Notes: All predictors were sample-mean centered to facilitate interpretation of the intercept as level of depression for the prototypical participant. Gender was a factor with female as the reference category. $N = 151$. $**p < 0.01$, $***p < 0.001$

Table 4 presents the correlations between self-loops, instrength, outstrength, and symptoms of depression. Anger and anxiety self-loops were not associated with symptoms of depression ($ps > 0.05$). The self-loops for both depression ($r = 0.25$, $p = 0.002$) and happiness ($r = 0.22$, $p = 0.01$) were positively associated with symptoms of depression. Instrength for anxiety and happiness were not associated with symptoms of depression ($ps > 0.05$). The instrength of both anger ($r = 0.17$, $p = 0.03$) and depression ($r = 0.23$, $p = 0.01$) were positively associated with symptoms of depression. Outstrength for anger, depression, and happiness were not associated with symptoms of depression (all $ps > 0.05$). Outstrength for anxiety was associated with symptoms of depression ($r = 0.16$, $p = 0.05$).

Table 4 Pearson correlations among emotion network components and symptoms of depression by emotion

	Instrength	Outstrength	Self-loop
Anger	0.17*	0.05	−0.08
Anxiety	0.07	0.16^{+}	0.11
Depression	0.23**	0.12	0.25**
Happiness	−0.10	0.14	0.22**

Notes: $**p < 0.01$; $*p < 0.05$; $^{+}p = 0.05$

Following-up the association between non-acceptance and emotion network density, correlations between self-loops, instrength, outstrength, and non-acceptance were examined. Depression instrength ($r = 0.22$, $p = 0.007$) and happiness outstrength ($r = 0.17$, $p = 0.04$) were positively associated with non-acceptance. No other associations emerged.

Discussion

The present study examined individual differences in emotion network density during adolescence and their associations with symptoms of depression. Partial support for the hypothesis that emotion network density would be associated with emotion regulation ability emerged such that emotion network density was associated with one subscale – the non-acceptance subscale – of the emotion regulation scale, but was not associated with either the total score or other subscales of the measure. As hypothesized, greater emotion network density was associated with more symptoms of depression. Notably, the association between emotion network density and symptoms of depression was significant above and beyond a trait measure of emotion dysregulation that has been widely used to assess emotion regulation difficulties (Gratz and Roemer 2004; Kaufman et al. 2016).

Emotion Network Density and Emotion Regulation

Previous studies have speculated that emotion network density may partially result from difficulties in emotion regulation (Pe et al. 2015). Theory on emotion network density suggests that density indicates the extent to which the emotion system is rigid, resistant to both regulation efforts and situational demands (Kuppens and Verduyn 2015; Pe et al. 2015). The role of emotion regulation difficulties in individual differences in emotion network density was partially supported in that, while network density was not correlated with the total emotion regulation scale nor the majority of its subscales, it was correlated with the non-acceptance subscale.

Acceptance refers to openness to emotional experiences, even if those experiences are uncomfortable. The association between emotion network density and non-acceptance may be explained by the tendency for quicker recovery of emotions relative to other emotion regulation approaches such as suppression (Campbell-Sills et al. 2006; Liverant et al. 2008). In these studies, acceptance modulated the duration of emotion states, a characteristic that would result in lower coefficients *within* emotion states across time. In terms of the cross-lagged components of the emotion network (i.e., associations *between* affective states across time), a feature of non-acceptance is the tendency to have secondary emotional responses to one's emotions (Gratz and Roemer 2004), for example responding to the experience of anxiety with anger. Indeed, items on the DERS-SF non-acceptance scale capture the tendency to experience secondary emotion reactions (e.g., "When I'm upset, I become irritated with myself for feeling that way"). Thus, the tendency for participants high in non-acceptance to experience secondary emotional reactions may be a process through which between-person differences in non-acceptance resulted in higher coefficients *between* emotional states across time. Post-hoc analyses indicating significant correlations among non-acceptance and both depression in strength and happiness outstrength, indices of the extent of the interplay *between* emotion states across time, are in line with this interpretation.

Emotion Network Density and Symptoms of Depression

By demonstrating that emotion network density was associated with symptoms of depression in adolescents, our results extend findings in adults that denser emotion networks are associated with major depressive disorder (Pe et al. 2015). For both adolescents and adults, then, depression is characterized by dense temporal connections within and between emotions that may encourage the spread of emotion across time and states (Kuppens and Verduyn 2015). This self-predictive quality of dense emotion networks may indicate a rigidity of the emotional system that may undermine flexible responding to changing environmental demands.

The use of an emotion network density score reflected the interest in capturing the self-predictive nature of the emotion system as a whole. The approach allowed for heterogeneity across participants in terms of the edges that were contributing to high emotion network density, in line with recent findings of idiographic emotion dynamics (Fisher et al. 2017). By examining components of networks, depression and happiness self-loops, anger and depression instrength, and anxiety outstrength emerged as components that were systematically associated with symptoms of depression. Consistent with the diagnostic conceptualization of depression as persistent sadness, our findings indicated that adolescents who experienced more rigid depressed emotions across days (self-loops) were more likely to report higher levels of depression. More novel insights can be drawn from findings related to instrength and outstrength. Specifically, anger and depression instrength – their probability of being affected by other emotions – were associated with risk for depression. Likewise, anxiety outstrength also was correlated with depressive symptoms. These findings for anger and depression instrength, and anxiety outstrength reinforce theoretical treatments of emotion dynamics in which cross-emotion transfer has been highlighted (Gross and Muñoz 1995). The findings also suggest that understanding of the processes that may create risk for depression will entail the consideration of emotions beyond depression and the assessment of emotion networks. They also suggest the necessity of considering emotion regulation processes beyond those that aim to alleviate depression by impacting the duration of depressed mood in daily life (e.g., affect repair; Hemenover et al. 2008) and focusing on regulation strategies that will impact the effect of emotions beyond depression (e.g., anxiety) on the duration and experience of depressed mood (e.g., acceptance of emotions; Gratz and Roemer 2004).

Linking greater network density with greater symptoms of depression during adolescence adds to findings that have shown that, despite differences in emotion dynamics across developmental periods (e.g., Larson et al. 1980; Maciejewski et al. 2015), individual differences in emotion dynamics associated with depression in adults (e.g., inertia; Kuppens et al. 2010; Silk et al. 2003; Neumann et al. 2011) also demonstrate relevance for understanding depression during adolescence. A promising next step will be to examine whether changes in emotion network density within-person, over time can act as a warning sign for the onset of clinically relevant episodes of depression in adolescents as has been observed in adults (Wichers et al. 2016).

Limitations and Future Directions

It is important to consider the findings in light of the study's strengths and limitations. The use of online surveys was cost effective and reduced the burden of repeated laboratory visits. Survey links were sent to unique participant email addresses but it cannot be verified that the intended participants completed their surveys (see Fricker and Schonlau 2002 for discussion of online survey designs). Recruitment through schools constrained our ability to collect data on youth IQ, special education status, or diagnosis and treatment status, which would be helpful for future work. This information, as well as the recruitment of subpopulations with more specific characteristics, would allow a more thorough examination of how emotion network density may differ across subpopulations of adolescents relative to the examination that was possible given the wide array of participant demographics of the present sample. Depressive symptoms were measured concurrently with the intensive longitudinal data. As such, developmental inferences on the association between emotion network density and depression are not warranted without longitudinal analyses.

Emotion dynamics has been used as a catch-all term for both short-term emotional fluctuations and longer timescale mood swings (Kuppens 2015). The extent to which data collected across days are capturing emotion rather than mood has been raised (Hollenstein 2015). Notably, although inertia has typically been examined at timescales shorter than days, inertia of negative affect from day to day is positively associated with depressive symptoms (Brose et al. 2015). Going forward, multiple timescale designs will be required to examine the degree to which end of day reports are capturing the quick reactions that occur when individuals encounter stimuli and the slower-moving feeling states that are less strongly tied to specific stimuli (Beedie et al. 2005).

The current study used multiple-item emotion scales that allowed the reliable capture of within-person change. The inclusion of additional emotions—particularly positive emotions – would allow for analysis of the extent to which network density's association with depression is specific to the interplay among negative, positive, or all emotions. Previous work has shown that emotion network of negative but not positive emotions was associated with depression (Pe et al. 2015). Other work has shown that greater stability and, potentially higher persistence, of positive emotion is associated with better psychological health (Gruber et al., 2013; although see Houben et al. 2015; Koval et al. 2015).

The use of multilevel models matches the number of time points available in the present study, allowing individual differences in emotion dynamics to emerge by pooling data across participants and modeling heterogeneity as deviations from the prototypical individual (Beltz et al. 2016; Snijders and Bosker 2012). Greater length of time series will allow the application of approaches capable of modeling individual emotion dynamics without the need to pool data across participants (e.g., Fisher et al. 2017; see also Lydon-Staley and Bassett 2018 for discussion). Shorter time-intervals typically used to obtain longer time series will allow the consideration of both contemporaneous and temporal networks (see Epskamp et al. 2016), allowing an examination of emotion differentiation within time intervals (Erbas et al. 2014). Further considerations are the extent to which temporal associations beyond a lag of one may be appropriate as well as the need to consider non-linear associations.

Emotion network density is thought to reflect a self-predicting emotion system that is insensitive to changing contextual demands. However, context was not explicitly modeled in the present study nor in other studies of emotion network density (Pe et al. 2015). Thus, it is important to be cautious when interpreting emotion network density as an indication of insensitivity to changing contextual demands because it is possible that participants experienced different levels of demands during the assessment. Considering both individual and context will be essential for teasing apart the processes driving greater emotion network density. Moving forward, focusing on responses to single emotional experiences (e.g., Koval et al. 2015) will provide insight into the building blocks of the global metric of emotion network density.

To gain further understanding of emotion network density's association with emotion regulation, alternative measures beyond the DESR-SF will be fruitful. Such measures include indices of executive function which are highly relevant for understanding emotion regulation (Hale and Fitzer 2015;

Zelazo and Cunningham 2007). In addition to alternative measures, it would be valuable to examine the types of executive functions that are associated with emotion network density and, in turn, psychopathology. The present manuscript emphasized that flexibility in emotion dynamics would be associated with fewer depressive symptoms. However, it is likely that too much flexibility, in which emotions are completely unrelated to one's emotions of the previous day, may undermine health and well-being. This is in line with circuit balance theory (Hale et al., 2018; Hale et al., 2009). Circuit balance theory suggests that more is not always better in terms of executive functioning and that average executive functioning is optimal for health and well-being. Notably, additional analyses indicated no quadratic association between emotion network density and depressive symptoms. However, a robust test of theory in this context will require a sample with broader characteristics than available in the current sample. In particular, borderline personality disorder has been associated with relatively high fluctuations in affect, perhaps better characterized as instability rather than flexibility (Nica and Links 2009; Stein 1996). As such, one might expect to observe lower network density in participants with borderline personality disorder relative to healthy controls, indicative of instability rather than flexibility in their emotion dynamics. This will be especially important for adolescent research given that adolescent executive function ability, as well as emotion dynamics, may be particularly labile due to the normative maturation of brain circuitry underlying incentive motivation and executive functioning (Heller and Casey 2016; Lydon et al. 2015; Shulman et al. 2016).

Conclusions

In summary, the present study extends previous examinations of emotion network density in adults by demonstrating associations between emotion network density and symptoms of depression in adolescents. The finding that emotion network density offers additional predictive value in understanding risk for depression, above and beyond a trait measure of emotion regulation, highlights the added value of examining emotion regulation through emotion dynamics collected through intensive repeated measures. Finally, findings of associations between emotion network density and non-acceptance begin the task of teasing apart the processes that give rise to the emotion network density.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval The study was approved by the Institutional Review Board of The Pennsylvania State Unviersity.

Informed Consent Informed consent was obtained from all adult participants included in the study. For adolescent participants, consent and assent was obtained from the parent and adolescent, respectively.

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