Self-Dislike and Sadness are Central Symptoms of Depression in College Students: A Network
Analysis

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Abstract

Depression in college students is an important public health issue. There is growing recognition that some depression symptoms may have a more central role in the disorder than others. We use network analyses to identify the most central symptoms of depression in college students. In a cross-sectional network the BDI-SF was collected at a single time point ($N = 10,005$) and in a symptom change network the BDI-SF was collected at two time points separated on average by approximately two months ($N = 700$). In both samples, the most central depression symptoms were *self-dislike* and *sadness*. Centrality scores for the cross-sectional network were highly correlated ($r = .86$) with the centrality scores for the symptom change network. *Self-dislike* and *sadness* may have important roles in college student depression. Additional work experimentally targeting and changing these central symptoms is needed to determine whether they have a causal role in the disorder.

Self-Dislike and Sadness are Central Symptoms of Depression in College Students: A Network Analysis

College student samples are often treated as analog or samples of convenience, but depression among college students is a growing public health concern. A recent review indicates that the point prevalence rate of depression is 30.6% in college students (Ibrahim, Kelly, Adams, & Glazebrook, 2013), which is much higher than even the 16.2% lifetime prevalence rate in the general population (Kessler et al., 2003). Further, the incidence (Center for Collegiate Mental Health, 2017) and severity (Xiao et al., 2017) of depression in college students presenting for treatment significantly increased from 2010 to 2015.

Depressed college students make worse grades (Hysenbegasi, Hass, & Rowland, 2005), may be more likely to take medical leave (Meilman, Manley, Gaylor, & Turco, 1992), and drop out more frequently than non-depressed students (Hunt, Eisenberg, & Kilbourne, 2010). Even among students who are not clinically depressed or treatment seeking, the severity of depression appears to have increased over time (Erdur-Baker, Aberson, Barrow, & Draper, 2006). Students who endorse greater depression severity without meeting criteria for a diagnosis also make worse grades (Haines, Norris, & Kashy, 1996) and have more alcohol related problems (Bravo, Pearson, & Henson, 2017). Therefore, a better understanding of depression and its symptoms in college students could help improve a variety of outcomes in that population.

To date, most studies of depression in college students (and in general) have taken a sum score approach to the measurement of depression. Some have persuasively argued that this practice may be problematic from psychometric (Fried, 2015) and conceptual (Borsboom, 2008) perspectives. Further, given the tremendous symptom heterogeneity that is typically observed among depressed individuals (Fried & Nesse, 2015; Lewis, 1938; Olbert, Gala, & Tupler, 2014),

there is growing recognition that examining associations among depression symptoms, rather than a singular focus on depression total scores, may provide new insights into which symptoms are particularly important for the maintenance of depression (St Quinton & Stain, 2019).

Network analyses have recently been developed and applied to describe the dynamics between symptoms (Borsboom, 2017). Network analysis calculates the unique associations between each pair of measured symptoms while controlling for all other symptoms and shrinking potentially spurious associations to zero (Epskamp & Fried, 2018). Individual symptoms that are most strongly associated with other symptoms (*strength*), are most strongly associated with the greatest number of other symptoms (*closeness*), and sit on the shortest path between other symptoms most often (*betweenness*) are considered the most central symptoms in the network (Valente, 2012).

Central symptoms are theoretically more important to outcomes both inside and outside the symptom network (Borsboom, 2017). Indeed, adults who endorse more central symptoms of depression at baseline are more likely to experience a major depressive episode in the following six years compared to adults who endorse more peripheral symptoms of depression (Boschloo, van Borkulo, Borsboom, & Schoevers, 2016). Importantly, this symptom level analysis does not require symptoms to load onto one latent factor over time or imply a belief in an underlying, unidimensional depression.

Previous network analyses of depression may provide a sense of which depression symptoms will be most central in college students. When strength of symptoms is used to identify central symptoms, network analyses in adult, clinical samples have identified *sadness* (Beard et al., 2016), *anhedonia* (Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015), and *fatigue* (van Borkulo et al., 2015) as central symptoms. A recent network analysis in a

non-selected sample of adolescents found that *sadness*, *self-dislike*, *pessimism*, and *loneliness* were the most central symptoms of adolescent depression (Mullarkey, Marchetti, & Beevers, 2018). This network analysis also contained a comparison of network structure across sexes, which was not included in the adult samples, indicating that the link between self-dislike and negative body image was stronger in girls than in boys.

College students are often in a developmental period conceptualized as emerging adulthood, which involves more independence than adolescence but less role specificity than adulthood (Arnett, 2000). Depression may differ in form and function among emerging adults compared to adolescents and adults, but will share some similarities (Galambos, Barker, & Krahn, 2006). For example, emerging adults experience first incidence of a major depressive episode more often than adults, fewer suicidal attempts than adolescents, and similar levels of comorbidity compared to both adolescents and adults (Rohde, Lewinsohn, Klein, Seeley, & Gau, 2013). Therefore, we might expect some central symptoms and network structure differences based on sex to be shared between emerging adults, adolescents, and adults while others might be unique to this developmental period.

Given that our sample predominantly consists of first and second year college students, we expect our sample will have more in common with adolescent depression than adult depression. We therefore hypothesize that *sadness* (a central symptom in both adolescents and adults), *self-dislike*, and *pessimism* (identified as central symptoms in adolescents) will be among the most central symptoms of depression in college students. We further hypothesize that the *negative body image* - *self-hatred* association will be a stronger edge in female college students than males. We will also test whether network structures differ between students who report clinically elevated levels of sum scores and those who do not. These cross-sectional analyses

were conducted in a large sample ($N = 10,005$) and will also allow us to evaluate other exploratory hypotheses.

Although cross-sectional network analyses provide insight into relationships between symptoms at a single time point, an important issue is whether symptom centrality measured at one point has predictive utility (Lutz et al., 2018). For instance, can symptom centrality scores from a cross-sectional network identify which symptoms are most important for predicting symptom change? Such evidence would also be particularly compelling if this prediction was performed in a new sample (i.e., out-of-sample predictive utility, Yarkoni & Westfall, 2017). Thus, the final goal of this study was to examine whether depression symptom centrality measured in a cross-sectional network provided predictive validity for identifying the most central symptoms in a symptom change network in an independent sample. Although there is a dearth of research demonstrating the predictive utility of cross-sectional symptom centrality, prior work suggests that centrality in a cross-sectional network can predict future onset of depression (Boschloo et al., 2016) and out-of-sample symptom change among people with social anxiety (Rodebaugh et al., 2018). Thus, we expected centrality in the cross-sectional depression network would predict symptom centrality out-of-sample in a depression symptom change network.

Methods

Cross-sectional Network (Sample 1)

Participants

The current data was collected as a part of a screening process for depression related studies for students enrolled in an Introduction to Psychology course at the University of Texas at Austin. The sample ($N = 10,005$) was racially diverse (Race/Ethnicity: 51.22%

White/Caucasian, 19.93% Asian or Pacific Islander, 18.70% Hispanic, 4.79% Black, 0.13% American Indian or Alaskan Native, 3.16% Multi-Racial, 0.45% Other, 1.62% missing) college students (Age 18.77 ± 1.82 years old; range 16 – 60 years; 18-22 = 94.22%) and was predominantly female (63.24% female, 35.23% male, 1.53% missing).

Measure

Depressive symptoms were assessed using the Beck Depression Inventory – Short Form (BDI-SF; Beck & Beck, 1972). The BDI-SF is a 13 item self-report questionnaire that measures the presence and severity of cognitive, motivational, affective, and somatic symptoms of depression. Items are measured on a 4-point Likert scale, ranging from 0 (i.e. “I do not feel sad”) to 3 (i.e. “I am so sad or unhappy that I can't stand it”). The BDI-SF is highly correlated with the long form of the BDI ($r = .89$ to $.97$ in Beck, Rial, & Rickels, 1974; $r = .93$ in Reynolds & Gould, 1981). The BDI-SF has been shown to correlate highly with clinicians' ratings of depression ($r = .55-.67$) and has demonstrated good convergent validity with UCLA Loneliness scale ($r = .47$ in Beck, Steer, & Carbin, 1988). The scale has also demonstrated discriminant validity; for example, it is not significantly associated with the Marlowe-Crowne Social Desirability Scale ($r = -.27$ in Aaron T. Beck et al., 1974).

Statistical Analysis

We first inspected mean, standard deviation, kurtosis, and skewness of all the BDI-SF items. We then used the R package *qgraph* (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) to estimate and visualize a Gaussian graphical model using polychoric correlations given the ordinal nature of the BDI-SF with each symptom coded 0-3 (Epskamp & Fried, 2018). To remove potentially spurious associations from the model we applied a lasso regularization technique. We used the Extended Bayesian Information Criterion (EBIC) tuning

parameter for this lasso procedure, as that tuning parameter performs well at recovering the true network structure as sample size increases (Foygel & Drton, 2010). We set the gamma hyperparameter of this penalty to 0.50 and tested 100 potential lambda hyperparameter values to conform with standard practice in psychopathology GGMs (Epskamp & Fried, 2018).

Symptom centrality can be operationalized with three major indices. *Betweenness* indicates the number of shortest paths connecting any two symptoms, while *Closeness* is computed as the inverse of the sum of the total length of all the shortest paths between a specific node and the rest of the network. Finally, *Strength* amounts to the sum of the absolute weights of the edge connecting the node to all the other nodes (Valente, 2012).

We tested the stability and accuracy of our network via both a case-dropping bootstrap test for centrality stability and bootstrap confidence intervals for the accuracy of network edges (Epskamp, Borsboom, & Fried, 2017). Centrality stability was operationalized with the correlation stability coefficient (i.e., *CS-coefficient*). CS-coefficient represents the maximum proportion of cases that can be dropped to still obtain a 95% probability that the correlation of the ranking between the centrality indicator in the original network and the case-subset network will amount to 0.7, with CS-coefficients being required to match at least 0.25, but preferentially above 0.5 (Epskamp et al., 2017). In addition, internode centrality difference test was computed with 95% non-parametric bootstrap confidence intervals (CIs; 1,000 bootstrap samples). If zero is included in CI, the two nodes do not differ with respect to that centrality index.

Second, edge-weights accuracy was estimated with 95% bootstrap CIs. Larger CIs around individual edge-weights indicate reduced precision in the estimation of the edges, whereas narrower CIs around individual edge-weights imply a more trustworthy network. Significantly stronger edges were identified by examining the CIs of the difference between each pair of

edges. If zero is included in CI, the two nodes do not differ. All stability and accuracy analyses described above were performed using the *R*-package bootnet 1.0 (Epskamp, 2015).

Then, we calculated correlations between centrality indexes and both mean and standard deviation of symptoms in the full sample network. This test allows us to determine whether symptom centrality indexes are substantially influenced by symptoms' differential variability or mean values (Terluin, de Boer, & de Vet, 2016).

We also tested for differences in network connectivity and structure between both males and females and individuals above and below the BDI-SF cut point. We used the cut point of scoring 8 or above on the BDI-SF as indicating clinical status, as this score has been found to be an optimal trade-off between positive predictive value and negative predictive value (Sultan, Luminet, & Hartemann, 2010; Terluin et al., 2016). We conducted all of these tests using the *R*-package NetworkComparisonTest 2.0.1 (van Borkulo & Millner, 2016).

Results

Descriptive statistics

Mean, standard deviation, skewness, kurtosis, and frequency of the BDI-SF symptoms are reported in Table 1. The overall mean and standard deviation of the traditional sum score of all symptoms is $M = 4.01$, $SD = 4.30$.

Depressive symptoms network estimation, centrality stability tests, and strength comparison

The cross-sectional network of depressive symptoms, as estimated with the Gaussian graphical model, is shown in Figure 1. The ranking of the symptoms as indexed by strength and closeness are taken as strongly robust and trustworthy while betweenness was not as robust based on having a *CS*-coefficients below 0.5. However, there has been recent evidence

challenging the appropriateness of applying closeness to psychopathology networks, as the assumptions required for interpreting closeness may not hold (Bringmann, Elmer, & Snippe, 2018). Therefore, we interpreted only strength (See Supplemental Material Sections S1-S2 for Details on Item Informativeness and Robustness Tests). We also tested for any potentially redundant nodes using the ‘goldbricker’ function from the networktools package (Jones, 2018) and found no statistically redundant nodes (See Supplemental Material or <https://osf.io/gf8mx/> for all R Code and Data for the main and supplemental analyses).

In terms of strength, *self-dislike* was statistically stronger than all of the other symptoms in the network. *Sadness* and *anhedonia* were statistically stronger than 50% or more of the symptoms in the network (Figure S1). In contrast, several symptoms appeared to be rather marginal, such as *negative body image*, *appetite*, and *crying*.

Accuracy and edge comparisons

The analysis of the accuracy of 68 edges, as implemented by means of non-parametric CIs, suggested that the precision of the edges was acceptable, with smaller CIs indicating more accurate estimation of the edges (Figure S2). Consequently, the parameters represented in the network model can be considered as reasonably accurate (See Section S3 for further detail on strongest edges).

Symptoms mean levels, variability, and association with strength centrality index

In the whole sample, the depressive symptoms with the highest mean levels (i.e., fourth quartile) were *fatigue*, *sadness*, and *anhedonia*. Strength centrality was not strongly related to symptom mean and was moderately inversely related to symptom standard deviation (See Section S4 for more detail).

Network and symptom mean levels comparisons between sexes

We compared the networks of female ($n = 6,327$) and male participants ($n = 3,525$). While the test for network connectivity differences showed no statistical difference (global strength difference = 0.07; females global strength = 5.30, males global strength = 5.23; $p = 0.30$), the two networks were significantly different in terms of structure (maximum difference = 0.20; $p < .001$).

To understand this finding, we checked the statistical difference of each single edge, between males and females, after applying the Bonferroni-Holm correction at $p < .005$ (Benjamin et al., 2018) as the results may be more likely to replicate in future samples (See Section S5 for suggestive results between $p = .005$ and $.05$). The edges that were stronger in females than males were *sadness-crying* (Female: 0.08, Male: 0.00; $p < 0.001$), *self hatred-negative body image* (Female: 0.22, Male: 0.02; $p < 0.001$), and *crying-fatigue* (Female: 0.09, Male: 0.00; $p = 0.001$). The edge that was stronger in males than females were *pessimism-social loss* (Male: 0.06, Female: -0.001; $p < 0.001$). In sum, three edges were stronger in females than males, while one edge was stronger in males than in females (Section S6 for Sample Size Sensitivity Tests).

There were also sex differences in mean levels of individual symptoms. Compared to males, females reported higher mean levels of the *sadness*, *crying*, *indecision*, *negative body image*, *effort to work*, *fatigue*, and *appetite* (Table S1). Females reported a higher mean level of a majority of symptoms, while males did not report higher mean levels in any of the BDI-SF symptoms. These findings present a different picture than the network findings, where males and females both demonstrated stronger associations between certain sets of symptoms.

Network comparison between clinical status groups

We also compared the networks of individuals above ($n = 1,665$) and below ($n = 8,340$) the clinical cut point on the BDI-SF. Networks did not differ in terms of global strength (global strength difference = 0.12; subclinical global strength = 3.12, clinical global strength = 2.97; $p = 0.12$) or network structure (maximum difference = 0.09; $p = 0.37$). So despite the inherent differences in the groups in symptom sum scores, there is no evidence that the network structures differ across the severity groups in this sample (Section S7 for Sample Size Sensitivity Tests).

Symptom Change Network (Sample 2)

Participants

There were 700 college student participants (M age = 19.17, $SD = 2.26$). 59.0% were female, 41.0% were male. 56.1% were Caucasian, 24.1% were Asian/Pacific Islander, 4.6% were African-American, 0.7% were Native American, 4.9% were Multiracial, and 9.6% chose not to answer or race/ethnicity was missing. Participants completed the same short-form of the Beck Depression Inventory as in the cross-sectional network analyses, Sample 1. No participants from Sample 2 were included in Sample 1; thus, there is no sample overlap.

Analytic Plan

We then estimated a network using a Gaussian Graphical Model (GGM; Epskamp, Waldorp, Möttus, & Borsboom, 2018) with the residual changes in symptoms over two weeks to one year ($M = 7.56$ weeks) as the nodes in Sample 2. To create change scores for each symptom of the BDI-SF, we used linear regression models to residualize follow-up scores for each individual symptom on the matching symptom at baseline (e.g., follow-up *sadness* residualized on baseline *sadness*) and the amount of time elapsed in weeks between assessments. Using residual change scores rather than raw change scores allows us to avoid the confound of regression to the mean for particularly high or low initial scores. These residualized scores can be treated as continuous.

Further, using residualized scores makes the change scores statistically independent from the baseline assessment, removing the possibility that cross-sectional centrality is associated with network change centrality simply because both include a baseline assessment.

This network model includes each variable as a “node” that is connected to other variables, or nodes, in the network via “edges”. Each network “edge” represents a unique partial association between two variables that accounts for all other nodes included in the network. To avoid the inclusion of spurious relationships in our model, we utilized the LASSO regularization technique (Tibshirani, 1996) to shrink all edge-weights based on a set parameter. Under this penalty, smaller, potentially spurious edge-weights shrink to a value of 0. We set the gamma hyperparameter of this penalty to 0.50 and tested 100 potential lambda hyperparameter values to conform with standard practice in psychopathology GGMs (Epskamp & Fried, 2018). We also tested for any potentially redundant nodes using the ‘goldbricker’ function from the networktools package (Jones, 2018) and found no statistically redundant nodes.

Previous analyses have correlated centrality with different outcomes like odds of having a major depressive episode in the following six years (Boschloo et al., 2016), but have reported only point estimates and have not reported estimates of uncertainty for these point estimates. This is because the strength centrality statistics for a network are not independent observations, so confidence intervals or p-values based on the assumption of independent and identically distributed observations (e.g., from running a standard correlation test) would not be valid. In other words, a correlation between *calculated* values from two *fixed* samples does not have the same sampling distribution as a correlation between *measured* values from two *random* samples. Moreover, the sampling distribution for centrality measures is non-parametric and typically

estimated by bootstrap (Epskamp et al., 2017; Epskamp & Fried, 2018). Thus, correlating centrality metrics with other outcomes, using standard methods, may not be appropriate.

Therefore, to properly account for the sampling error in the estimation of the correlation between centrality measures and other outcomes, we generated two independent sets of bootstrap-replicated centrality scores (1,000 replicates for cross-sectional centrality in Sample 1 and 1,000 separate replicates for change over time centrality in Sample 2). Then, to estimate the uncertainty in the correlation between the centrality scores of the two independent samples, we computed the correlations between each set of bootstrapped centrality scores from Sample 1 with each set of bootstrapped centrality scores from Sample 2 and calculated a 95% CI as the 2.5% and 97.5% quantiles of the resulting distribution of 1,000,000 correlations. This simulates the distribution of correlations we would observe if we collected 1,000 new samples of the same size as Sample 1 and 1,000 new samples of the same size as Sample 2. Importantly, this approach allows us to evaluate if central symptoms in a cross-sectional sample (Sample 1) predicted the strength centrality in a change over time network in a different sample, Sample 2.

This bootstrapping procedure also allows us to quantify the uncertainty around this estimate and determine if the prediction is significantly greater than zero. Exhaustively correlating all possible values from both samples allows us to avoid any potential cherry-picking of certain combinations of values and is computationally just as feasible as evaluating a random subset of potential correlations (which would also protect us against any potential cherry-picking). We also evaluated the median centrality ranks of each symptom across both networks to determine if the same symptoms were among the most central symptoms in both networks. We then repeated this bootstrapping and exhaustive correlation procedure to evaluate if

commonly endorsed symptoms in a cross-sectional sample (Sample 1) predicted strength centrality in a change over time network in a different sample, Sample 2.

Finally, to preliminarily test the replicability of the network structure differences observed in Sample 1, we also estimated separate male ($N = 286$) and female ($N = 412$) Gaussian Graphical Models at timepoint one. We then conducted Network Comparison Tests in the same manner as in Sample 1 and evaluated whether there were any differences across gender in global network connectivity or specific individual edges.

Results

Network Stability and Network Accuracy

All networks were stable and accurate, with *CS*-coefficients above 0.50 for strength centrality in all networks and many non-overlapping confidence intervals between edges.

Predicting Centrality Over Time with Cross-Sectional Centrality and Endorsement

As described above, to determine whether cross-sectional strength centrality predicted change over time strength centrality we calculated the exhaustive correlations between 1,000 bootstrap replicates of cross-sectional strength centrality in Sample 1 and 1,000 bootstrap replicates of change over time strength centrality in Sample 2. The correlation between strength centrality measures across samples was very strong ($r = 0.86$, 95% CI: 0.50, 0.89). This association implies that cross-sectional strength centrality from Sample 1 significantly predicts strength centrality out of sample in the change over time network in Sample 2. In other words, the most central symptoms in the cross-sectional network strongly identified the most central symptoms in the change over time network, even though centrality estimates were obtained in completely independent samples. These findings were robust to residualizing out standard deviation from the strength centrality estimates in the cross-sectional sample given the modest,

negative association between strength centrality and standard deviation in that sample ($r = 0.73$, 95% CI: 0.35, 0.82; See Supplemental Materials Section S4). Therefore, the ability of cross-sectional centrality to predict change over time centrality out of sample was not due to the variability of items in the cross-sectional sample.

Self-dislike (1), *anhedonia* (2), and *sadness* (3) had the highest median centrality rankings across the 1,000 bootstrap replicates of cross-sectional networks. The symptoms with the highest median centrality rankings in the 1,000 bootstrap replicates of the change over time networks were largely consistent with the cross-sectional network— *self-dislike* (2, no symptom was ranked 1), *sadness* (3), and *effort to work* (3). *Anhedonia* (8) had a lower median centrality rank in the change over time network bootstrap replicates compared to the cross-sectional networks. *Appetite* (12/13) and *negative body image* (12/13) consistently had the lowest centrality rankings in the bootstrap replicates of the cross-sectional and change over time networks.

We then calculated the correlations between 1,000 bootstrap replicates of cross-sectional endorsement rates for each symptom in Sample 1 and 1,000 bootstrap replicates of change over time strength centrality in Sample 2. These metrics were not strongly associated, $r = 0.11$ (95% CI: -0.27, 0.36). This weak association implies that cross-sectional endorsement of symptoms does not significantly predict change over time strength centrality out of sample. In other words, commonly endorsed symptoms in Sample 1 do not identify the most central symptoms in the change over time network in Sample 2. Further, this confidence interval did not overlap with cross-sectional strength centrality confidence interval, meaning cross-sectional strength centrality predicts change over time centrality significantly better than cross-sectional endorsement rate.

Cross-Sectional Network Comparisons Across Gender

We found no differences in global network connectivity across genders at timepoint 1 (global strength difference = 0.01; females global strength = 5.29, males global strength = 5.30; $p = 0.97$). We also found no differences between genders on any individual edges ($p = 0.93$).

Discussion

Our network analysis of college student depression found that the most central symptoms in cross-sectional and symptom change networks were *self-dislike* and *sadness*. *Self-dislike*, *sadness*, and *pessimism* were hypothesized to be central symptoms in this population, meaning two of the three hypothesized symptoms were indeed central while one was not. A network comparison analysis in the cross-sectional sample ($N = 10,005$) also revealed many network structural differences between males and females, including the hypothesized stronger association between *negative body image* and *self-dislike* among females. However, this gender difference (or any other gender differences) were not observed at the first time point in the symptom change sample ($N = 700$). A network comparison analysis in the cross-sectional sample also did not find evidence for any global or structural differences between college students above and below the clinical cut-off for self-reported depression. Finally, cross-sectional symptom strength centrality was robustly associated with symptom centrality strength in a symptom change network in an independent sample. In contrast, symptom endorsement in the cross-sectional network was not associated with centrality strength in the symptom change network.

The central symptoms identified in this study were a mixture of central symptoms found in adolescents (Mullarkey et al., 2018) and adults (Beard et al., 2016). This unique combination of central symptoms lends support to depressive symptoms in emerging adulthood overlapping with symptoms in adulthood and adolescence while still being a distinct developmental period

for depression (Galambos et. al., 2006). Future studies could compare the network structures across adolescents, emerging adults, and adults to test this hypothesis more directly.

The current study, along with prior evidence from adolescents and adults, indicates that certain depression symptoms may be more important for depression than others. Importantly, in the current study, central symptoms measured cross-sectionally identified symptoms that are central to symptom change, albeit symptom change was measured over a relatively short period of time (7.6 weeks on average, although the range was 2 to 52 weeks). This is consistent with prior research documenting that more central depression symptoms predict whether participants will have a major depressive episode in the following six years (Boschloo et al., 2016) better than non-central symptoms. In contrast, other work suggests that cross-sectional centrality does not predict strength in individual person-level depression symptom networks over time (Bos et al., 2017), although the sample size was relatively small ($N = 104$) and centrality stability was not assessed. Given these mixed findings, much more work, particularly in large, well-powered samples, is needed to conclusively determine whether cross-sectional networks can identify symptoms that are important to symptom change.

If central symptoms are indeed better predictors of key outcomes, creating a centrality weighted sum score of depression symptoms may better capture depressive phenomenology. Current sum score measures of depression do not adequately integrate the potential differential importance of symptoms (Cramer et al., 2016), while current network approaches may not adequately account for the mean level of the symptoms in the network. Taking a formative sum score approach, or an approach where the indicators (e.g. symptoms) are presumed to cause any latent factor rather than the other way around (Fried et al., 2016), would allow us to weight the contribution of symptoms to the sum score based on their network centrality. This type of

formative sum score has already been utilized (Boschloo et al., 2016) and may allow us to better represent the phenomenology of depression than using either method in isolation (Bringmann & Eronen, 2018).

Further, treatments that target more central symptoms may produce a cascading deactivation of other symptoms over time. On the other hand, central symptoms may be more difficult to deactivate or be at greater risk of reactivation given their inherently stronger connections to other symptoms in the network (Borsboom, 2017). Determining to what extent current treatments for college students effectively target these central symptoms could help answer these empirical questions. If current interventions do not effectively target central symptoms, or do so inefficiently, focusing on developing brief, novel interventions for symptoms that are central across developmental periods (e.g. self-dislike, sadness) may help improve depression outcomes. Future work that constructs networks on the individual level may allow us to determine ideal symptoms to target in a personalized manner (Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017; Piccirillo & Rodebaugh, 2019).

Notably, a number of gender differences were observed in the cross-sectional network, such as a stronger association between self-dislike and body image for women compared to men. However, no gender differences were replicated at the first time point of the symptom change network. The lack of replication for these gender differences across networks might be in part due to sample size. The symptom change network sample was substantially smaller than the cross-sectional network sample (*Ns* were 700 vs. 10,005, respectively), even though the symptom change network sample is approximately four times larger than the average sample size of most clinical science studies (Reardon, Smack, Herzhoff, & Tackett, 2018). Given this pattern of results, we are hesitant to interpret the gender differences observed in the cross-sectional

network until additional large-scale replication studies have been completed. The gender difference for the association between self-dislike and body image may be most promising given it was observed previously (Mullarkey et al., 2018), but given the lack of replication in our current study, gender differences in the symptom networks may be somewhat small and variable.

There are limitations to the current analyses. The data from the current study is correlational, so no conclusions can be drawn about causality from this data (Dablander & Hinne, 2019). Also, this data was collected in a non-selected sample, meaning it may not generalize well to more clinically severe patients. However, nearly 20% of our sample met criteria for likely depression based on self-report and our analyses along with previous work (Santos, Fried, Asafu-Adjei, & Ruiz, 2017) do not find affirmative evidence for network structure differing based on clinical status.

We also used the short form of the Beck Depression Inventory, which is a relatively brief assessment of depression. We selected the BDI-SF because it is a frequently used depression scale (Beck et al., 1988; Knight, 1984) and is highly correlated with the long form of the BDI (Beck et al., 1974; Reynolds & Gould, 1981). However, it is important to keep in mind that the measurement of depression (and associated network analyses) may be somewhat instrument specific. For instance, Fried et al. (2017) document that among the most frequently used depression scales, only six symptoms (12%) are common to all instruments. Until there is greater consistency in the measurement of depression, depression symptom networks need to be examined with other symptom scales before we can be confident that the results observed here will generalize to other depression questionnaires.

Nevertheless, the current study identifies self-hate and sadness as among the most important symptoms of depression in college students. Strength centrality in a cross-sectional

network was also strongly associated with strength centrality in a symptom change network across two independent samples of college students. This suggests that cross-sectional centrality may be a useful indicator of which symptoms are important for predicting symptom change. A better understanding of depression during this crucial stage of development could help improve quality of life, academic achievement, and future economic outcomes for students. Some symptoms may be more important than others in relation to each of these domains, and network analysis provides a framework that can guide us toward these potentially more important symptoms. Combining network analysis with other symptom level approaches to depression may help us better understand and potentially treat this increasingly severe (Xiao et al., 2017) and prevalent (Center for Collegiate Mental Health, 2017) disorder.

MCM developed the study concept. All authors contributed to the study design. Testing and data collection were performed by TTW under the supervision of CGB. MCM and JS performed the data analysis and interpretation under the supervision of CGB. MCM drafted the paper, and RAS, TTW, JS, and CGB provided critical revisions. All authors approved the final version of the paper for submission.

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Table 1. Mean, standard deviation, minimum, maximum, skewness, kurtosis, and frequency of the BDI-SF Symptoms
(*N* = 10,005)

Symptoms	BDI-SF #	Mean	St.Dev	Min	Max	Skewness	Kurtosis	% Absence ("0")	% Presence ("1-3")
Sadness	1	0.34	0.56	0	3	1.64	3.01	37.11	62.89
Pessimism	2	0.27	0.52	0	3	2.04	4.49	66.67	33.33
Failure	3	0.16	0.45	0	3	3.09	10.25	35.03	64.97
Anhedonia	4	0.31	0.58	0	3	2.07	4.86	39.85	60.15
Guilt	5	0.21	0.48	0	3	2.52	6.91	63.74	36.26
Self-Hatred	6	0.31	0.53	0	3	1.67	3.08	62.98	37.02
Crying	7	0.28	0.66	0	3	2.77	7.69	36.92	63.08
Social Loss	8	0.30	0.53	0	3	1.66	2.32	73.47	26.53
Indecision	9	0.30	0.59	0	3	1.97	3.31	72.62	27.38
Body Image	10	0.38	0.71	0	3	2.08	4.12	52.97	47.03
Effort to Work	11	0.36	0.57	0	3	1.44	1.41	74.69	25.31
Fatigue	12	0.50	0.60	0	3	0.93	0.59	59.77	40.23
Appetite	13	0.28	0.56	0	3	2.04	4.14	61.10	38.90

Supplemental Material

Section S1. Item Informativeness

First, we checked the level of item informativeness (i.e., standard deviation of the item) (Table 1). All BDI-SF items were informative (i.e. within 2.5 standard deviations of the mean level of informativeness, 0.57 ± 0.07). Therefore, no items were excluded from the network analysis.

Section S2. Centrality Robustness Analyses

We investigated the stability in the order of the symptoms across the three centrality indices considered. Strength ($CS\text{-coefficient} = 0.75$) and closeness ($CS\text{-coefficient} = 0.672$) showed excellent levels of stability, while the level of stability for betweenness was less than optimal ($CS\text{-coefficient} = 0.367$). That is, for example, when dropping approximately 75% of the observations, the order of the symptoms in terms of strength still correlated at least 0.7 with the original order.

Section S3. Strongest Edges Analysis

Accuracy analysis revealed that the strongest edges (e.g., *self dislike-failure*, *anhedonia-social loss*, *indecision-effort to work*, *sadness-crying*, *pessimism-failure*, *guilt-self dislike*, *effort to work-fatigue*, *fatigue-appetite*, *self dislike-negative body image*, *sadness-pessimism*, *sadness-anhedonia*, *failure-guilt*, *self-deprecation-self-blame*, *pessimism-anhedonia*) were statistically different from 50% or more of the other non-zero edges (Figure S4). Therefore, 14 out of the 68 edges were stronger than at least 50% of the other edges (20.6% of edges). Further, 56 out of 68 edges are significantly stronger than

at least one other edge; therefore 82.4% of edges are statistically stronger than at least one other edge. We report these metrics for descriptive purposes, as the only current field standard is checking whether there are non-overlapping confidence intervals between at least some edges (doi: 0.3758/s13428-017-0862-1).

Section S4. Centrality Does Not Correlate with Symptom Mean But Does Negatively Correlate with Standard Deviation

It is notable that the bootstrapped correlations (which are more appropriate than Spearman correlations given that centrality is a statistic rather than an observation) between symptom endorsement and symptoms strength ($r = 0.15$, 95% CI: 0.00, 0.26) was not significant while the correlation between symptom standard deviation and symptom strength ($r = -0.37$, 95% CI: -0.68, 0.39) was significant and negative. However, previous concerns were primarily that centrality would correlate positively with centrality (e.g., PMID: 27880771) making them essentially redundant metrics. If anything we observe the opposite here. We also re-ran our primary analyses using cross-sectional centrality to predict change over time centrality while controlling for the standard deviation of each symptom in the cross-sectional network. We still observed a statistically significant result of similar magnitude ($r = 0.73$, 95% CI: 0.35, 0.82).

Section S5. Suggestive Differences in Network Structure Between Sexes

The edges that were suggestively stronger in females than males were *guilt-social loss* (Female: 0.31, Male: 0.15; $p = 0.02$) and *self dislike-indecision* (Female: 0.09, Male: 0.00; $p = 0.03$). The edges that were suggestively stronger in males than females were

sadness-indecision (Male: 0.01, Female: -0.03; $p = 0.046$), *pessimism-negative body image* (Male: 0.02, Female: -0.01; $p = 0.03$), *crying-effort to work* (Male: 0.01, Female: -0.05; $p = 0.045$), *anhedonia-fatigue* (Male: 0.12, Female: 0.06; $p = 0.03$), *pessimism-appetite* (Male: 0.05, Female: -0.01; $p = 0.02$), and *fatigue-appetite* (Male: 0.25, Female: 0.17; $p = 0.03$).

Section S6. Sample Size Sensitivity Tests for Network Comparison Between Sexes

As different sample sizes can lead to loss of power when comparing networks, we conducted a sensitivity test where we subsampled the female network down to an equivalent number of participants as the male network 5 times and re-did our network comparisons (Fried et al., 2018). The results from the main text converged with the results for the sensitivity analyses. The results reported in the paper all remained significant in 2 out of the 5 tests. In 2 of the tests *pessimism – social loss* was only stronger in males at a marginally significant level ($p = .06$ and $p = .07$) after correcting for multiple comparisons. In one test *pessimism – social loss* was non-significantly different between males and females ($p = 0.16$) after correcting for multiple comparisons. Also, in one of the 5 tests *negative body image – self dislike* was marginally stronger in females compared to males ($p = .06$) after correcting for multiple comparisons.

Section S7. Sample Size Sensitivity Tests for Network Comparison Between Clinical Cut Point Status Groups

As different sample sizes can lead to loss of power when comparing networks, we conducted a sensitivity test where we subsampled the below clinical cut point status

network down to an equivalent number of participants as the above the clinical cut point status network 5 times and re-did our network comparisons (Fried et al., 2018). The results from the main text converged with the results for the sensitivity analyses. No $p < .005$ differences between networks were observed in 3 out of the 5 network comparisons. In two network comparisons the *negative body image – self dislike* link appeared to be stronger in the group above the clinical cut point than below the clinical cut point ($p < .001$ in both cases). In one network comparison, *pessimism – failure* appeared to be stronger in the group above the clinical cut point than below the clinical cut point ($p < .001$).

Table S1. Mean, standard deviation, t-test of CDI Symptoms by gender

Symptoms	BDI	Mean Female	St.Dev Female	Mean Male	St.Dev Male	t-test	Adjusted <i>p</i>
Sadness	1	0.39	0.58	0.27	0.52	10.14	<0.001
Pessimism	2	0.27	0.52	0.27	0.53	-0.45	1.000
Failure	3	0.15	0.44	0.18	0.47	-2.40	0.21
Anhedonia	4	0.31	0.58	0.33	0.59	-1.29	1.000
Guilt	5	0.22	0.50	0.19	0.46	2.49	0.16
Self-Hatred	6	0.32	0.53	0.30	0.52	1.25	1.000
Crying	7	0.33	0.65	0.66	0.67	9.24	<0.001
Social Loss	8	0.30	0.53	0.30	0.55	0.45	1.000
Indecision	9	0.33	0.62	0.24	0.53	7.54	<0.001
Body Image	10	0.44	0.74	0.28	0.62	11.67	<0.001
Effort to Work	11	0.37	0.57	0.33	0.57	3.73	0.002
Fatigue	12	0.55	0.61	0.41	0.58	10.86	<0.001
Appetite	13	0.30	0.57	0.25	0.52	3.84	0.002

Note. *p* value was adjusted after Bonferroni correction.