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Special Section on University Student Depression

Comorbid anxiety and depression psychopathology in university students: a network approach

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Abstract

Depression in university students is known to commonly co-occur with other mental disorders, especially anxiety. It is, however, not known how this comorbidity affects the psychopathology of depression in university students. Compared to commonly used methods, the clinical network approach provides a better framework for understanding comorbidity. Accordingly, regularized partial correlation network models were used in this study to (1) examine the severity structure of individual depressive symptoms by the level of comorbid anxiety, and (2) explore the gender differences among these symptoms in university students ($N = 919$; $M_{age} = 21$ years., $SD = 2.99$; 72% = Female). *Anhedonia*, *hopelessness*, *worthlessness*, *self-blame*, and *loneliness* were the most central symptoms of depression in this study. The Network Comparison Test revealed no statistically significant global structure and strength of the depressive symptom network by comorbid anxiety level and gender. Implications of the results and network framework with regard to developing alternative treatment options, and the optimization of clinical care and assessment of depression are discussed.

Keywords

Anxiety, comorbidity, depression, network structure, students

Depression is a growing public health concern in university students. Besides being linked with a variety of negative health outcomes (Bravo et al., 2017), it has also been implicated in poor academic attainment among university students (Ibrahim et al., 2013; January et al., 2018). Even though depression has adverse outcomes for university students, research efforts to understand symptom presentation, complexity, and relations (e.g., comorbidity) in this cohort are limited – negatively affecting treatment efforts. This is a significant gap in the literature, especially since depression is known to commonly co-occur with other mental disorders. For instance, depression

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and anxiety are highly prevalent, comorbid, and are known to share common diathesis in university students (Kotov et al., 2010; Perez-Rojas et al., 2017). Further, although depression and anxiety are independent conditions, research shows both of them to be related to similar mental health outcomes (An et al., 2019). Studies further show general anxiety to be a determinant for the future development of depression (Horn & Wuyek, 2010), while academic anxiety has been found to predict depression among university students (Cassady et al., 2019). In addition, depressed patients co-presenting with anxiety have been shown to have higher rates of suicidality than those presenting with depression only (An et al., 2019; Fava et al., 2006; Goes et al., 2012; Seo et al., 2011). However, while the above-cited studies suggest increased depression severity and poor prognosis because of comorbid anxiety, it remains unknown how anxiety influences the psychopathology of depression in university students.

A common method for studying the relationship between anxiety and depression, and the prevalence and gender differences in depression is to use the composite score of a depression measure. However, this established practice of operationalizing the severity of depression through symptom composite scores has increasingly been criticized (see Fried, 2015). For instance, no two individuals present with depression the same way, despite having the same composite score because of the heterogeneity of depressive symptoms (Fried & Nesse, 2015a; Olbert et al., 2014). The use of composite scores further complicates matters because it assumes depression instruments to be unidimensional, regardless of considerable evidence that commonly used measures of depression are multidimensional (e.g., Beck Depression Inventory-II; Makhubela & Mashegoane, 2016).

Psychological network theory overcomes the shortcomings of existing approaches and presents researchers with novel ways of understanding mental disorders. Clinical network theory considers mental disorders to be a network of dynamic self-reinforcing causal interactions between symptoms (Borsboom, 2008; Fried et al., 2017). This new psychopathology paradigm resulted in an analytic method called psychometric network models, capable of assessing network structures of between-groups and repeated-measure data. Network models examine the individual relationship between each symptom pair while at the same time holding all the other symptoms in the network constant and bringing spurious associations to zero (Epskamp & Fried, 2018; Mullarkey et al., 2018).

A symptom is said to be central to the network when it has strong connections with other symptoms (i.e., strength), when it has strong associations with most symptoms in the network (i.e., closeness), and when it is the shortest path between other symptoms (i.e., betweenness). There is a sizable literature that provides a comprehensive methodological treatment of this framework and its workings (see Borsboom, 2017; Borsboom & Cramer, 2013; Cramer et al., 2012; Cramer, Waldorp, et al., 2010), as such we will refrain from providing a detailed introduction of the paradigm and method – particularly because this is not a methodological article. It is clear though that important data about the possible causal interactions between specific symptoms and the centrality of some symptoms to the network are missed by exclusively restricting ourselves to common cause research (i.e., symptoms viewed as independent measures of a latent disorder).

The network approach to psychopathology gives researchers and clinicians tools to also identify symptoms that may have a role in maintaining and connecting psychopathology – symptoms that could be a useful focus for clinical attention (Armour et al., 2017; van Borkulo et al., 2015; van Rooijen et al., 2017). This has also been reflected by studies, with other mental disorders, that have shown symptom network structures to be associated with the prospective course and prognosis of the disorder (van Borkulo et al., 2015). Therefore, targeted clinical intervention aiming primarily on central symptoms should reduce the triggering of the associated symptoms and thus enable better treatment success and outcome (Ross et al., 2018). As shown before (e.g., St Quinton & Stain, 2020), focusing on the relationship between individual depression symptoms, rather than on composite depression scores, may be more informative about the maintenance of depression. Furthermore, network theory provides a useful framework for understanding comorbidity through the consideration of bridge symptoms among mental disorders (Fried et al., 2017). Bridge symptoms predict future vulnerability for developing comorbid conditions and provide an opportunity for mental health monitoring and prevention.

Although a number of studies have to date used network analysis to explore depression as a possible system of causal interactions between symptoms (e.g., Bringmann et al., 2015; Mullarkey et al., 2018, 2019; van Borkulo et al., 2015), network studies concerning the relations between anxiety and depression symptoms (among university students and other populations) have generally been limited. To be sure, only two network studies have to date explored the association between anxiety and depression: one with older adults (An et al., 2019) and another with a psychiatric sample (Beard et al., 2016). However, An et al. (2019) found mixed results, in that, anxiety worsened the severity of depression symptoms but did not change the psychopathology of depression. On the other hand, Beard et al. (2016) found within-domain connections to be stronger than between-domain connections. While depression in university students and adults may differ in form and function (course), there are still some shared similarities (Arnett, 2000; Galambos et al., 2006). For instance, depression has been shown to have similar levels of comorbidity in both adults and the elderly, and university students (i.e., emerging adults) and adults (Rohde et al., 2013). It is not clear, though, if this is the case between university students and the elderly. Therefore, it is necessary to ascertain what sort of relationship does depression and comorbid anxiety have at a symptom level, by investigating whether comorbid anxiety has any role in the psychopathology and prognosis of depression in university students.

Specifically, we assessed the interaction of individual depressive symptoms by the level of comorbid anxiety and explored the gender differences among these symptoms in university students using network modelling. This was achieved by conducting network comparisons of depressive symptoms between (1) low- and high-anxiety students, and 2) male and female students. The second objective is important because depression is reported to be more widespread in women than in men (van de Velde et al., 2010). Studies of whether depression symptoms interrelate differently across gender groups remain scarce in university students, especially in South Africa. To gain a better understanding of gender differences in depression within university students, thoroughgoing information relating to the underlying symptom network structure and profile across gender is necessary.

Methods

Participants

This study analysed student data (N=919; M_{age}=21.26 years, SD=2.99, range 18–50 years; 72%=Female; 63%=Black; 2%=Coloured; 3%=Asian; 32%=White) from two South African universities across faculties of education, medical sciences, humanities, natural sciences and management sciences. Participants were all undergraduate students (38%=1st year; 26%=2nd year; 36%=3rd year).

Instruments

Hopkins Symptom Checklist. The Hopkins Symptom Checklist (HSCL-25; Mollica et al., 1987) consist of two subscales that measure depression (15 items) and anxiety symptoms (10 items) using a severity scale (1 [not at all] to 4 [extremely]). The measure has good psychometric evidence in past studies (Halvorsen & Kagee, 2010) and good reliability in the current study (i.e., total and subscales: $\alpha = .81– .89$). A cutoff score of 1.75 on the HSCL-10 (anxiety), usually recommended for symptomatic cases, was used to classify participants as having experienced high or low anxiety (see Mollica et al., 1987; Winokur et al., 1984).

Procedure

Participants were recruited from undergraduate lectures. All participants who volunteered to partake in the research provided informed written consent, and the data were collected in groups outside of official class time.

Ethical considerations

The research was approved by the Research Ethics Committee at the University of Limpopo.

Data analysis

Network estimation. The statistical analyses were conducted with R version 4.0.2. Regularized partial correlations (Epskamp & Fried, 2016) of the symptom pairs were computed to estimate the network structure of 15 items of the HSCL depression subscale applying the Extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selection Operator (EBICglasso) where each symptom is represented by a node and the strength of the interaction between symptoms by an edge (Epskamp et al., 2017). The network was visualized by applying the Fruchterman–Reingold algorithm wherein symptoms (i.e., nodes) with lesser strength and connections are located far from each other, whereas those with good strength and a high number of associations near each other. Edges are either blue or red in colour, indicating positive and negative partial correlations, correspondingly. Thicker edges/lines point to stronger associations between the symptoms.

Node strength and ExpectedInfluence were examined with R-package *ggraph* to identify the most central nodes in the depression symptoms network (wherein higher node strength indicates the centrality of a given symptom [node]; Fried et al., 2018; Opsahl et al., 2010). Node strength is presented as standardized Z score and offers information about the relative importance of a given node through its connection with other nodes, while ExpectedInfluence tells us how a particular node is connected to the sum of all edge weights (Robinaugh et al., 2014).

Predictability, or how much a particular symptom is predicted by the other symptoms within the network (Haslbeck & Fried, 2017), was examined with the R-package *mgm* (Haslbeck & Waldorp, 2018). Compared to node strength, predictability is an absolute metric (i.e., from 0 [cannot be predicted by other nodes] to 1 [perfect prediction by other nodes]) of how clinically significant the interconnections between the nodes are. The difference in the connections between depression symptoms (i.e., structural similarity of the two networks) across low- and high-anxiety participants and male and female students was statistically compared with the R-package *Network Comparison Test (NCT*; van Borkulo et al., 2016). Structural differences in the depression symptom network on account of comorbid anxiety were examined through the following steps: (1) a baseline network of depression in university students, (2) a depression symptom network with an anxiety node, and (3) NCT of depression network between low- vs high-anxiety students. The anxiety node was created with the aggregate HSCL-25 anxiety subscale score.

Network stability. Because the requisite sample size to obtain stable networks is not yet known, bootstrapping method was performed to evaluate the stability of the edge weights and node centrality measures. The correctness of edge weights was estimated with bootstrapped confidence intervals (CIs) and difference test for edge weights and node strength ($\alpha = .05$; 1000 bootstrap iterations; Epskamp et al., 2016). The correlation stability coefficient for strength and ExpectedInfluence centrality ranges between 0 and 1, with values $\geqslant .5$ considered to represent acceptable stability (Epskamp et al., 2018; Fried et al., 2018).

Topological overlap among symptoms. The goldbricker function in R-package networktools (Jones, 2018) was applied to examine nodes that might underlie a similar construct or process. Node pairs were considered to have topological overlap if $r > .50$ and conceptual overlap >75% (<25% of significantly divergent depended correlations; $p = .05$; Bernstein et al., 2019).

Results

Descriptive statistics

The mean HSCL-25 (depression) scale score for the entire sample was 1.74 ($SD = 0.46$; 1.0–3.8; clinical cutoff score $\geqslant 1.75$), while female university students ($M = 1.795$; $SD = 0.47$) reported more depressive symptoms and had higher mean sum scores compared with their male peers ($M = 1.589$, $SD = 0.41$). Female students had significantly higher item mean scores on all items than male students, with the exception of the following items: Dep20, Dep21, Dep23, Dep24, and Dep25 (Table 4). High-anxiety students had higher mean scores on all depression items than low-anxiety students (Table 3). All HSCL-25 depression symptoms had significant and positive correlations with all other symptoms (in the total sample and across subgroups).

Conceptually overlapping symptoms

The results suggested that less than 25% of correlations are significantly different for the following node pair: Dep22 (*Worry*) and Dep19 (*Loneliness*) indicating that these redundant symptoms cannot be included together in the network (0.153; Fried et al., 2017). Accordingly, only Dep 19 was included in the network analyses.

Network stability

The bootstrapped CIs for the edge weights indicate that the network structures were accurately estimated (see Figures 1 to 4). Correlation-stability (CS)-coefficients for centrality stability (i.e., 0.67–0.75; 0.45–0.52) were within acceptable levels/ recommended cutoff point for both ExpectedInfluence and Strength, respectively (Epskamp et al., 2018; Fried et al., 2018).

Baseline network of depression in university students

Figure 5 presents the baseline network structure of the depressive symptoms. The network had 70% non-zero edges. The strongest edges were *suicidal thoughts–feeling trapped*, *anhedonia–everything being an effort*, and *sleep–appetite*. The predictability of symptoms, node strength centrality, and ExpectedInfluence are presented in Table 1. The mean predictability for the network was 21%. *Loneliness* (24%), *anhedonia* (29%), and *self-blame* (26%) had the highest predictability, whereas *anhedonia, hopelessness*, and *worthlessness* had the highest ExpectedInfluence in the

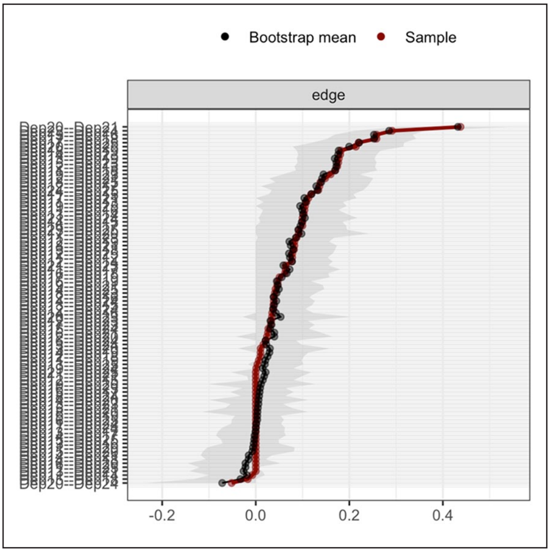

Figure 1. Baseline network (edge stability).
The grey area represents the bootstrapped confidence intervals.

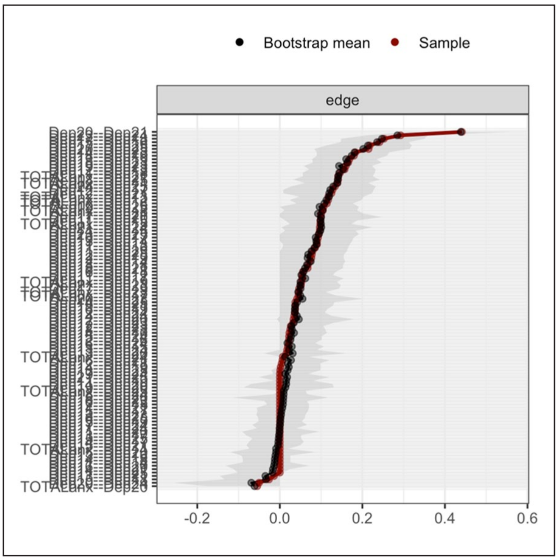

Figure 2. Baseline network with anxiety (edge stability).
The grey area represents the bootstrapped confidence intervals.

network. According to standardized node strength, *anhedonia, hopelessness*, and *worthlessness* were also the most central symptoms in the group. Although, most of the edges were positively associated, three edges were negatively associated (i.e., *energy–sex*; *appetite–sadness*; *suicidal thoughts–everything being an effort*). These negative interconnections are inconsistent with the pairwise correlation matrix of the items (i.e., all relations were positive), and are thus generally considered to be artificial in the network literature (Pfeiffer et al., 2019).

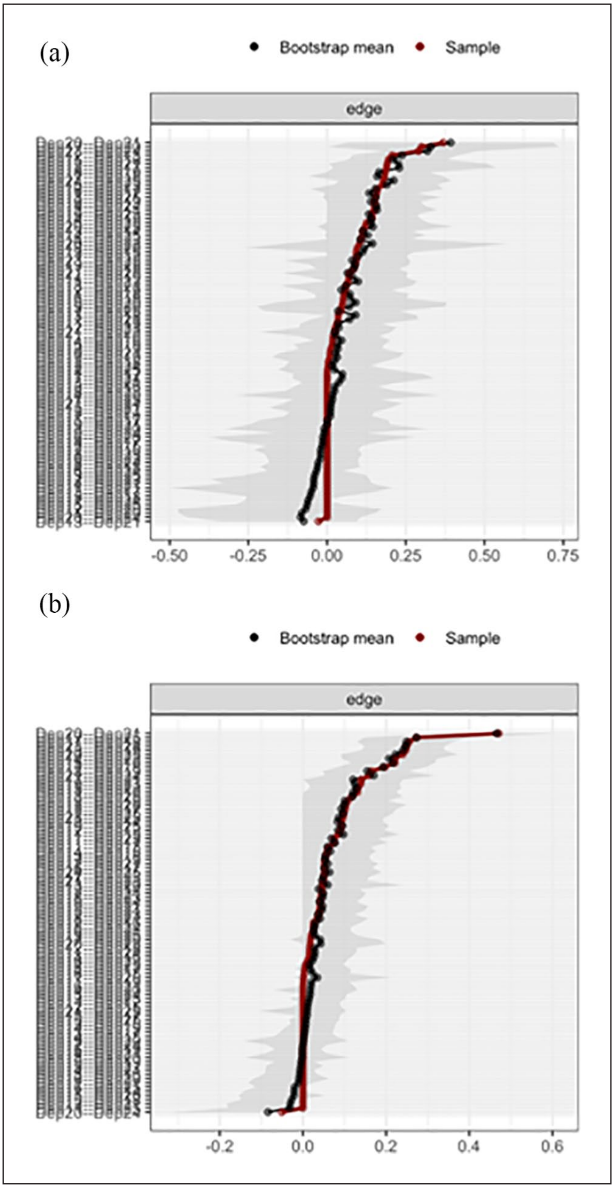

Figure 3. (a) Low-anxiety network (edge stability). (b) High-anxiety network (edge stability).
The grey area represents the bootstrapped confidence intervals.

Depression symptom network with the addition of an anxiety node

According to the network structure, the anxiety node is positioned in the periphery and had positive interrelations with all the depression symptoms apart from *suicidal thoughts* (see Figure 6). Notably, the anxiety node had strong edges with *self-blame, energy*, and *sleep*. The network had 71% non-zero edges. The strongest edges were *suicidal thoughts–feeling trapped*, *anhedonia–everything being an effort*, and *hopelessness–sadness*. The predictability of symptoms, node strength centrality, and ExpectedInfluence are presented in Table 2. According to strength,

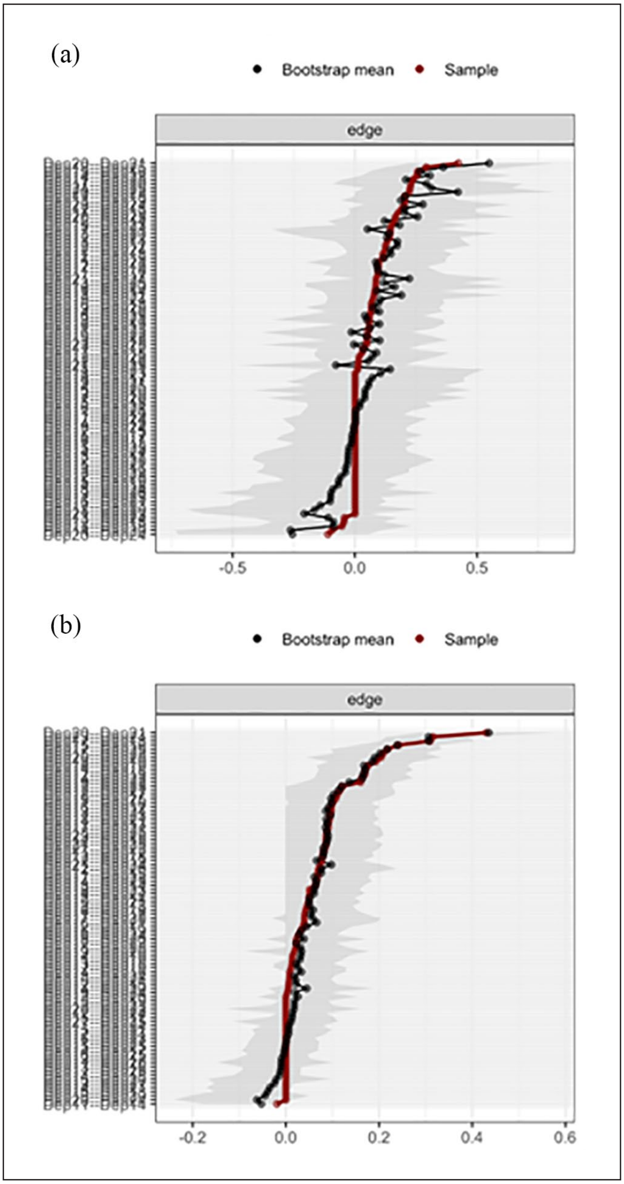

Figure 4. (a) Male network (edge stability). (b) Female network (edge stability).
The grey area represents the bootstrapped confidence intervals.

anhedonia and *hopelessness* were the most central depression symptoms. The mean predictability for the network was 29%. *Sadness* (39%), *anhedonia* (38%), and *hopelessness* (37%) had the highest predictability, whereas *anhedonia, sadness*, and *hopelessness* had the highest ExpectedInfluence in the network. Most of the edges were positively associated, while edges *appetite–sadness* and *suicidal thoughts–everything being an effort* were negatively associated.

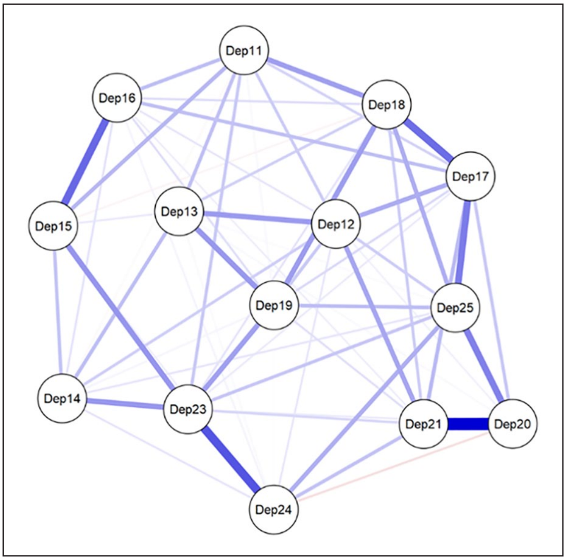

Figure 5. Estimated depression network without anxiety node.
Blue lines = positive partial correlations; red = negative partial correlations; thickness of line = stronger associations between the symptoms.

Table 1. Item descriptions, distribution of the symptom scores, Stren, ExpInf, and Pred.

Item label	Description	*M*	*SD*	Skew	Stren	ExpInf	Pred
Dep 11	Energy	2.02	0.812	0.586	−0.654	0.728	0.149
Dep 12	Self-blame	1.91	0.861	0.714	0.277	0.917	0.256
Dep 13	Crying	1.82	1.017	0.924	−1.028	0.712	0.132
Dep 14	Sex	1.61	0.908	1.430	−1.485	0.578	0.206
Dep 15	Appetite	1.66	0.789	1.054	−0.770	0.699	0.181
Dep 16	Sleep	1.92	1.009	1.392	−0.978	0.693	0.193
Dep 17	Hopelessness	1.37	0.690	2.087	1.197	1.064	0.192
Dep 18	Feel blue/sadness	1.62	0.725	1.023	0.642	1.008	0.200
Dep 19	Loneliness	1.94	0.937	0.791	0.061	0.868	0.238
Dep 20	Suicide thoughts	1.14	0.553	8.359	−0.039	0.760	0.203
Dep 21	Feeling trapped	1.40	0.674	1.825	0.866	1.017	0.206
Dep 23	Anhedonia	1.73	0.752	0.902	1.847	1.192	0.288
Dep 24	Everything being an effort	2.06	0.966	0.661	−0.881	0.615	0.202
Dep 25	Worthlessness	1.41	0.735	1.903	0.946	1.026	0.152

Skew: skewness; Stren: strength; ExpInf: ExpectedInfluence; Pred: predictability.

NCT of depression network between low- and high-anxiety students

Depression symptom networks for high-anxiety ($n=470$) and low-anxiety ($n=444$) students are presented in Figure 7. The test for network connectivity difference suggests no statistical difference between the networks for high- and low-anxiety students (global strength difference = 0.10; high

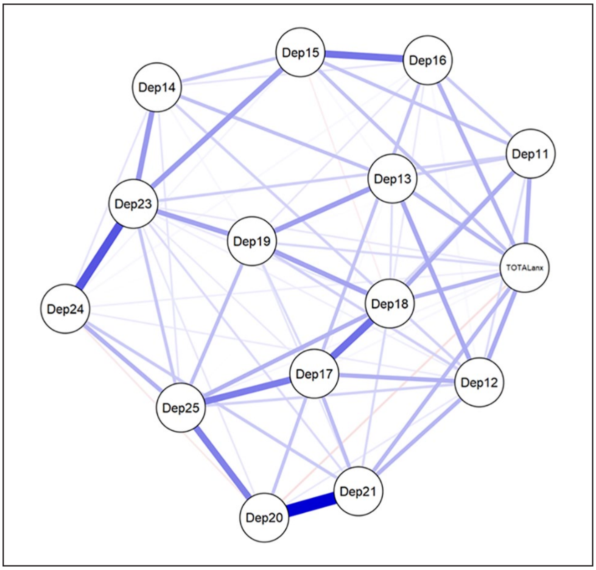

Figure 6. Estimated depression network with anxiety node.
Blue lines = positive partial correlations; red = negative partial correlations; thickness of line = stronger associations between the symptoms.

Table 2. Item descriptions, distribution of the symptom scores, Stren, ExpInf, and Pred for the network with anxiety node.

Item label	Description	*M*	*SD*	Skew	Stren	ExpInf	Pred
Dep 11	Energy	2.02	0.812	0.586	−0.781	0.690	0.258
Dep 12	Self-blame	1.91	0.861	0.714	0.226	0.917	0.336
Dep 13	Crying	1.82	1.017	0.924	−1.052	0.653	0.244
Dep 14	Sex	1.61	0.908	1.430	−1.660	0.463	0.133
Dep 15	Appetite	1.66	0.789	1.054	−0.731	0.618	0.209
Dep 16	Sleep	1.92	1.009	1.392	−1.007	0.626	0.222
Dep 17	Hopelessness	1.37	0.690	2.087	1.031	0.928	0.367
Dep 18	Feel blue/sadness	1.62	0.725	1.023	0.642	0.962	0.390
Dep 19	Loneliness	1.94	0.937	0.791	−0.054	0.882	0.337
Dep 20	Suicide thoughts	1.14	0.553	8.359	0.153	0.411	0.166
Dep 21	Feeling trapped	1.40	0.674	1.825	0.856	0.904	0.333
Dep 23	Anhedonia	1.73	0.752	0.902	1.634	1.093	0.382
Dep 24	Everything being an effort	2.06	0.966	0.661	−1.121	0.605	0.220
Dep 25	Worthlessness	1.41	0.735	1.903	0.807	0.864	0.325
TotalAnx	Anxiety	1.740	0.490	1.065	1.056	1.156	0.406

Skew: skewness; Stren: strength; ExpInf: ExpectedInfluence; Pred: predictability.

symptom = 5.56; low symptom = 5.46; p = .683). The networks also did not vary significantly in structure (maximum difference = 0.20; p = .118).

The two groups had 67% and 61% non-zero edges, respectively. The strongest edges were *suicidal thoughts–feeling trapped* and *appetite–hopelessness* in the high-anxiety group, and

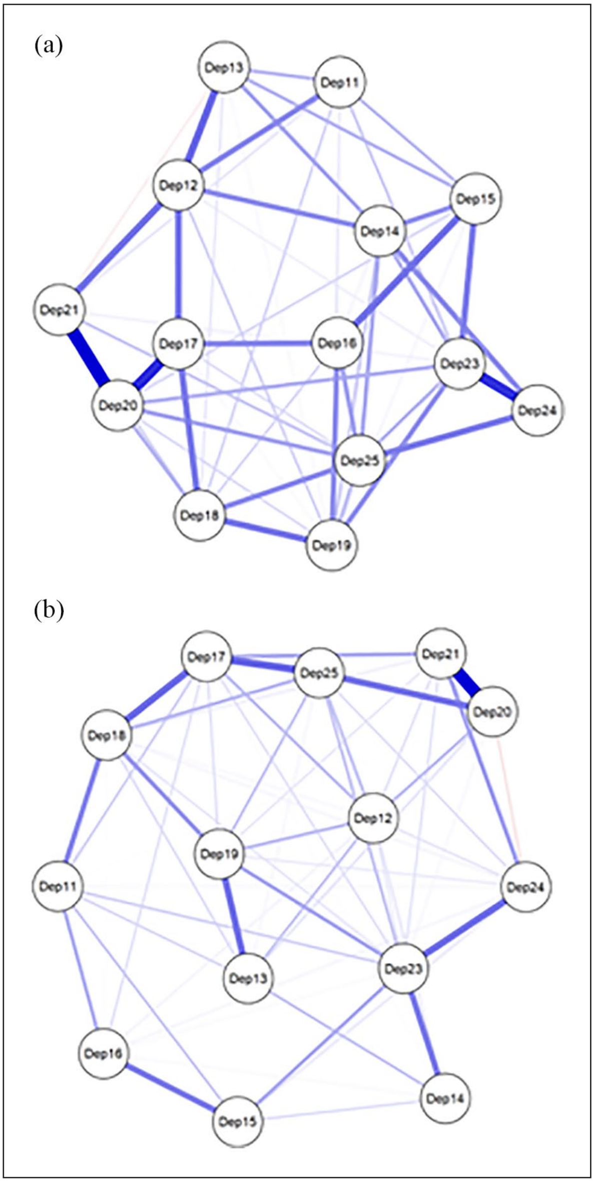

Figure 7. Estimated depression network for low and high anxiety separately. (a) Low-anxiety network. (b) High-anxiety network.
Blue lines = positive partial correlations; red = negative partial correlations; thickness of line = stronger associations between the symptoms.

suicidal thoughts–feeling trapped and *hopelessness–suicidal thoughts* in the low-anxiety group. The predictability of symptoms, node strength centrality, and ExpectedInfluence are presented in Table 3. The mean predictability for the high-anxiety group was 27%, while that of the low-anxiety group was 21%. *Feeling trapped* (37%), *worthlessness* (36%), and *hopelessness* (36%) had the highest predictability in the high-anxiety group, whereas *anhedonia* (29%), *self-blame*

Table 3. Item descriptions, descriptive statistics and group differences for the two anxiety groups.

Item label	Description	Low anxiety						High anxiety					
		M	*SD*	Skew	Stren	ExpInf	Pred	*M*	*SD*	Skew	Stren	ExpInf	Pred
Dep 11	Energy	1.73	0.682	0.561	−1.672	0.514	0.152	2.29	0.833	0.450	−0.644	0.624	0.182
Dep 12	Self-blame	1.59	0.679	0.974	0.983	0.880	0.256	2.21	0.908	0.369	−0.279	0.764	0.267
Dep 13	Crying	1.49	0.806	1.561	−1.436	0.488	0.134	2.13	1.095	0.466	−0.777	0.579	0.232
Dep 14	Sex	1.51	0.888	1.706	0.273	0.760	0.205	1.70	0.917	1.224	−1.557	0.392	0.111
Dep 15	Appetite	1.45	0.647	1.346	−0.375	0.694	0.181	1.86	0.856	0.757	−1.134	0.490	0.133
Dep 16	Sleep	1.59	0.787	1.163	−0.543	0.727	0.191	2.22	1.016	0.321	−1.375	0.457	0.121
Dep 17	Hopelessness	1.15	0.412	2.963	0.369	0.684	0.192	1.57	0.828	1.470	1.083	0.935	0.362
Dep 18	Feel blue/ sadness	1.33	0.534	1.329	−0.008	0.736	0.202	1.89	0.778	0.667	0.583	0.898	0.341
Dep 19	Loneliness	1.64	0.768	1.159	−0.062	0.788	0.239	2.22	0.994	0.443	0.469	0.891	0.335
Dep 20	Suicide thoughts	1.06	0.270	5.756	1.590	0.674	0.219	1.20	0.558	3.289	0.752	0.640	0.284
Dep 21	Feeling trapped	1.19	0.464	2.895	−0.192	0.691	0.202	1.60	0.773	1.266	0.745	0.882	0.372
Dep 23	Anhedonia	1.49	0.631	1.157	1.252	0.964	0.287	1.97	0.783	0.676	1.545	1.089	0.350
Dep 24	Everything being an effort	1.82	0.928	1.023	−1.180	0.563	0.205	2.28	0.949	0.425	−0.373	0.607	0.219
Dep 25	Worthlessness	1.22	0.568	3.153	1.000	0.619	0.154	1.60	0.822	1.315	0.961	0.919	0.363

Skew: skewness; Stren: strength; ExpInf: ExpectedInfluence; Pred: predictability.

(26%), and *loneliness* (24%) had the highest predictability in low-anxiety group. According to strength centrality, *loss of interest* and *hopelessness* were central symptoms in the high-anxiety group, while *suicidal thoughts* and *worthlessness* were the most central symptoms in the low-anxiety group. *Anhedonia* and *hopelessness* had the highest ExpectedInfluence in the high-anxiety network, while *anhedonia* and *suicidal thoughts* had the highest ExpectedInfluence in the low-anxiety network.

NCT of depression network across male and females students

Depression symptom networks for male ($n=259$) and female ($n=654$) students are presented in Figure 8. The test for network connectivity difference suggests no statistical difference between the networks for male and female students (global strength difference = 0.16; male symptom = 5.83; female symptom = 5.99; $p=.591$). The networks also did not vary significantly in structure (maximum difference = 0.22; $p=.107$).

The two groups had 61% and 71% non-zero edges, respectively. The strongest edges were *suicidal thoughts–feeling trapped* and *sadness–worthlessness* in the male group, and *suicidal thoughts–feeling trapped* and *anhedonia–everything being an effort* in the female group. The predictability of symptoms, node strength centrality, and ExpectedInfluence are presented in Table 4. The mean predictability for the male group was 29%, while that of the female group was 30%. *Feeling trapped* (45%), *hopelessness* (39%), and *worthlessness* (37%) had the highest predictability in the male group, whereas *anhedonia* (42%), *sadness* (42%), and *hopelessness* (37%) had the highest predictability in the female group. According to strength centrality, *suicidal*

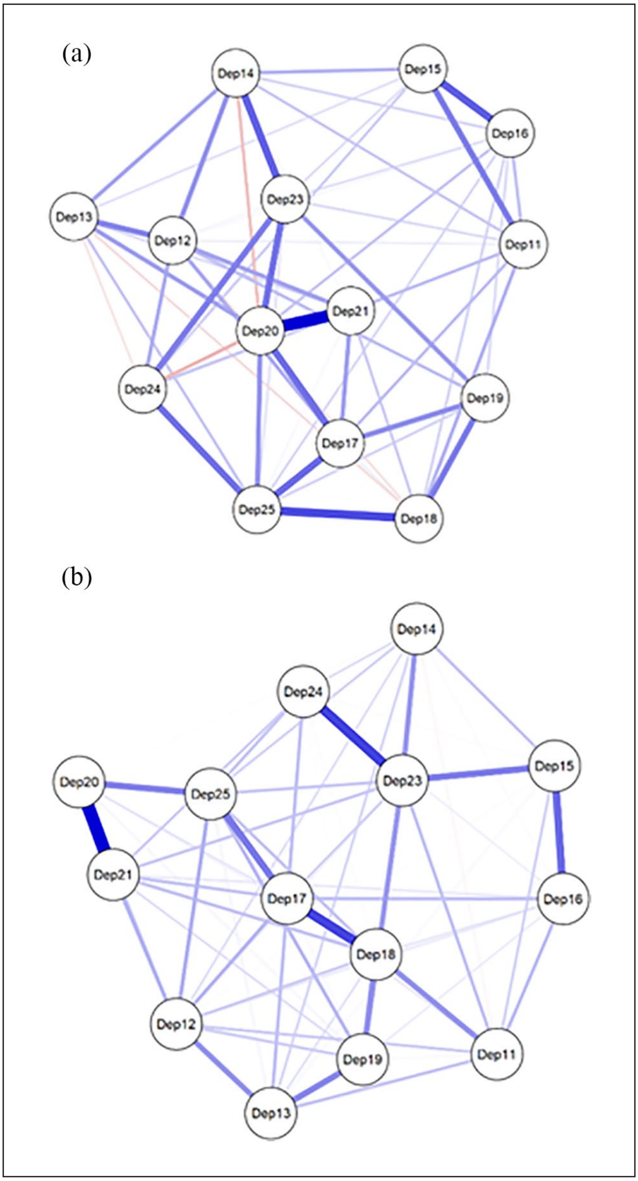

Figure 8. Estimated depression network for male and female separately. (a) Male network. (b) Female network.

Blue lines = positive partial correlations; red = negative partial correlations; thickness of line = stronger associations between the symptoms

thoughts and *worthlessness* were central symptoms in the male group, while *anhedonia* and *sadness* were the most central symptoms in the female group. *Worthlessness* and *feeling trapped* had the highest ExpectedInfluence in the male network, while *anhedonia* and *sadness* had the highest ExpectedInfluence in the female network.

Table 4. Item descriptions, descriptive statistics and group differences for the two gender groups.

Item label	Description	Male						Female					
		M	*SD*	Skew	Stren	ExpInf	Pred	*M*	*SD*	Skew	Stren	ExpInf	Pred
Dep 11	Energy	1.82	0.771	.677	−0.809	0.761	0.253	2.10	0.815	0.559	−0.753	0.761	0.230
Dep 12	Self-blame	1.79	0.789	0.826	0.042	0.843	0.324	1.96	0.884	0.658	0.478	0.843	0.363
Dep 13	Crying	1.21	0.519	2.564	−0.905	0.506	0.162	2.06	1.065	0.553	−0.679	0.506	0.263
Dep 14	Sex	1.44	0.713	1.620	−0.134	0.611	0.193	1.68	0.966	1.309	−1.487	0.611	0.119
Dep 15	Appetite	1.54	0.715	1.207	−0.944	0.656	0.213	1.71	0.811	0.988	−0.971	0.656	0.196
Dep 16	Sleep	1.72	0.857	0.950	−0.920	0.711	0.237	1.99	0.992	0.617	−0.999	0.711	0.198
Dep 17	Hopelessness	1.27	0.599	2.635	0.439	0.964	0.393	1.40	0.720	1.924	0.716	0.964	0.367
Dep 18	Feel blue/ sadness	1.43	0.601	1.310	−0.296	0.670	0.254	1.69	0.756	0.900	1.192	0.670	0.421
Dep 19	Loneliness	1.75	0.895	1.119	−0.925	0.742	0.274	2.01	0.943	0.684	0.092	0.742	0.372
Dep 20	Suicide thoughts	1.11	0.441	4.619	2.551	0.751	0.344	1.13	0.449	4.007	−0.216	0.751	0.241
Dep 21	Feeling trapped	1.39	0.685	1.989	0.537	1.079	0.448	1.40	0.670	1.760	0.672	1.079	0.349
Dep 23	Anhedonia	1.69	0.744	1.024	0.535	0.994	0.335	1.75	0.755	0.858	1.986	0.994	0.423
Dep 24	Everything being an effort	2.08	0.966	0.620	−0.364	0.541	0.187	2.05	0.966	0.679	−0.793	0.541	0.261
Dep25	Worthlessness	1.38	0.699	1.981	1.192	0.992	0.372	1.43	0.748	1.874	0.761	0.992	0.326

Skew: skewness; Stren: strength; ExpInf: ExpectedInfluence; Pred: predictability.

Discussion

This is the first network study to examine how comorbid anxiety affects the course and symptomatology of depression in university students – going further to compare how depressive symptoms interrelate differently among male and female university students.

Centrality of depression symptomatology

In the current study, *anhedonia*, *hopelessness*, *worthlessness*, *self-blame*, and *loneliness* were among the most central depressive symptoms in the network. This result implies that these symptoms, compared to other depression symptoms, may play a key role in depression in university students. Within network theory, symptoms are considered central because they share causal connections with other symptoms. Within cross-sectional analysis, central symptoms are estimated as undirected edges rendering these symptoms, especially relevant as target for clinical intervention in the treatment of depression (Fried et al., 2018). For instance, research shows that central depression symptoms predict whether participants will experience a major depressive episode in the following 6 years better than non-central symptoms (Boschloo et al., 2016). Our results are consistent with previous network studies with university students (*self-dislike*; Mullarkey et al., 2018), general population adolescents (*self-dislike*, *pessimism*, and *loneliness*; Mullarkey et al., 2019), and clinical population adults (*anhedonia*; Bringmann et al., 2015).

Comorbid anxiety and depression symptomatology

According to the results, anxiety does not alter the strength or structure of the depression network. For instance, adding anxiety to the baseline network did not have any significant influence on depressive symptoms in the network. The strongest edges and symptom centrality remained somewhat the same. This finding suggests that comorbid anxiety had a peripheral effect on depression in that its presence did not increase the interaction between depressive symptoms in university students. This result is supported by the NCT that also showed no statistically significant structural and global strength difference between networks of low- and high-anxiety students. This outcome is similar to that of other studies that found comorbid anxiety to not affect/change the overall psychopathology of depression (An et al., 2019; Beard et al., 2016).

Symptom-level group differences

While our results are consistent with other studies on depression (Salk et al., 2017) with respect to the differential endorsement of depression symptoms and mean (item and composite) scores across gender, there were no significant gender differences in the depression networks. This result is in keeping with most depression measurement invariance studies that have reported negligible differences across gender in students (Makhubela & Debusho, 2016) and other network research with students, adolescents and adults (e.g., Mullarkey et al., 2019). These results imply that the gender differences in the prevalence of depression in university students do not seem to be explained by differences in the depressive symptom severity and architecture (i.e., processes of depression) but by differences in external factors (e.g., socio-demographic) that give rise to depression. Indeed, multi-country research shows that temperament, cognitive styles, biological factors, socio-economic, and family-related factors (household and family support) explain the association between gender and depression (Salk et al., 2017; Tiedt, 2013; van de Velde et al., 2010). Future research should compare depression network structures across the above-cited factors to examine this hypothesis more directly.

Conclusion

In conclusion, the results suggest that *anhedonia*, *hopelessness*, *worthlessness*, *self-blame*, and *loneliness* might be more prominent and exert more influence over other symptoms in depressed South African university students (regardless of gender) and should accordingly be considered in clinical assessment and care. The findings of this study have implications for depression treatment and assessment in university students. First, if we are to accept central symptoms as good predictors of psychopathology outcome (course, prognosis, and aetiology; Borsboom, 2017), then the current approach of using aggregate depression measure scores falls short when it comes to accounting for the differential importance of individual symptoms (Cramer et al., 2016; Mullarkey et al., 2018). Using weighted sum scores based on symptom centrality, as recommended in the network literature, may be a better option for operationalizing the phenomenology of depression (Boschloo et al., 2016; Bringmann & Eronen, 2018; Fried et al., 2016). Second, our findings offer clinicians the much needed data to design targeted short-term evidence-based interventions for depression, suitable for resource-limited student counselling environments and primary health care contexts in middle- and low-income countries like South Africa. Simplified interventions are less resource intensive and yet have similar efficacy as traditional individual therapies (Cuijpers et al., 2019). Abridged forms of therapy like behavioural activation (independent of cognitive behavioural therapy) that focus explicitly on symptoms like anhedonia (central symptom in the current study) show that it is indeed possible to tailor-make interventions while simultaneously increasing the chances for treatment success (Fried et al., 2018). It goes without mention that, in clinical practice, the viability of central symptoms as targets for intervention should generally be interpreted with care and considered together with the entire clinical picture.

There are limitations to the present study. The cross-sectional data used in the study make it difficult to draw too many conclusions from the centrality results concerning clinical intervention targets and causality. Only longitudinal data can provide definitive information with regard to these aspects. The relatively small sample of the study – especially the male sample – suggests that large-scale replication studies are necessary to ascertain the generalizability of the network findings, particularly the gender difference results. Because the sample was largely self-selected, these results may not generalize to clinical patients or participants receiving counselling – although network structures do not differ according to clinical status (Mullarkey et al., 2018; Santos et al., 2017). Future studies should also replicate these findings with other depression measures (i.e., given that network results tend to be instrument specific) or clinical interviews.

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