

Anxiety and depressive symptoms among students in higher vocational colleges: application of latent profile analysis and network analysis

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Abstract

Background

Depression and anxiety commonly co-occur among students in higher vocational colleges. However, most previous studies have treated this population as homogeneous, overlooking the heterogeneity of anxiety-depression comorbidity. Consequently, the symptom interaction patterns across distinct subgroups remain poorly understood. This study aims to identify potential subgroups of anxiety-depression comorbidity among vocational college students, explore the core and bridging symptoms within the symptom networks that sustain these conditions in each subgroup, and compare differences in network structures across the subgroups.

Methods

A cross-sectional survey was conducted among 7,932 students from higher vocational colleges in Wenjiang District, Chengdu, China, between January and February 2022 using stratified random sampling. Anxiety and depressive symptoms were assessed using the Generalized Anxiety Disorder-7 (GAD-7) and the Patient Health Questionnaire-9 (PHQ-9). Latent Profile Analysis (LPA) was performed to identify heterogeneous subgroups of anxiety–depression comorbidity. Symptom networks were constructed for each subgroup, and Expected Influence (EI) and Bridge Expected Influence (BEI) were estimated to identify core and bridge symptoms. Network Comparison Tests (NCTs) were conducted to compare network structure and global strength across subgroups.

Results

LPA classified the study participants into three subgroups: the low comorbidity group (68.3%), the moderate comorbidity group (24.7%), and the high comorbidity group (7.0%). The most central bridging symptom in the low comorbidity group was PHQ6 (low self-esteem), while in both the moderate comorbidity and high comorbidity groups, GAD5 (restlessness) was the most prominent bridging symptom. Global strength differed significantly across all pairwise profile comparisons in the unadjusted analyses; however, these differences were no longer statistically significant after covariate adjustment. No significant differences in overall network structure were detected.

Conclusion

Developing personalized intervention plans targeting subgroup-specific bridging symptoms may improve the prognosis of comorbid depression and anxiety among vocational college students.

1 Introduction

As social competition and academic pressure continue to escalate, understanding the mental health burden among students in higher vocational colleges has become critically important. The World Health Organization (WHO) World Mental Health International College Student Project has identified anxiety and depressive disorders as among the most prevalent mental health disorders among college students worldwide[1]. A meta-analysis of 100,187 college students conducted by Li et al[2]. found prevalence rates of 39.0% for anxiety and 33.6% for depressive symptoms. Domestic research has further reported that anxiety and depression affect 27.3% and 33.4% of Chinese undergraduates, respectively, while the corresponding figures among higher vocational college students are substantially higher, at 51.6% and 37.6%- significantly surpassing those of the general population[3, 4]. Such elevated prevalence is linked not only to poorer sleep quality, greater academic pressure, and lower life satisfaction, but may also compromise emotion regulation and psychological resilience, ultimately impairing academic performance, interpersonal functioning, and quality of life[5, 6].

Numerous studies have shown that anxiety and depressive symptoms are among the most common mental health problems in students enrolled in higher vocational colleges, and that these two conditions frequently co-occur[3, 7]. Epidemiological evidence indicates that a substantial proportion of higher vocational college students experience clinically significant anxiety or depressive symptoms, with many presenting with both symptom domains simultaneously[8, 9]. Compared with students with a single psychological problem, those with co-occurring anxiety and depressive symptoms generally exhibit greater psychological distress, poorer academic performance, weaker social functioning, and a higher risk of self-harm and suicide[10–13]. The Tripartite Model posits that anxiety and depression share a common basis in negative affect, while differing in physiological hyperarousal and low positive affect, thereby providing an important theoretical framework for understanding their high comorbidity[14]. In addition, accumulating evidence suggests that anxiety and depression are not merely parallel conditions, but may interact and mutually reinforce one another through mechanisms such as cognitive bias, difficulties in emotion regulation, avoidance behaviors, and sleep disturbances, ultimately contributing to the persistence and exacerbation of symptoms[15]. Longitudinal studies have further demonstrated that anxiety symptoms significantly increase the risk of subsequent depressive symptoms, whereas depressive symptoms also predict higher levels of later anxiety, indicating a clear bidirectional relationship between the two[16]. For students in higher vocational colleges, academic pressure, employment competition, financial burden, and limited social support may further intensify the interaction between anxiety and depression, making psychological problems more likely to persist and worsen[17]. Given the strong comorbidity and mutual reinforcement between anxiety and depression, once one type of symptom emerges in higher vocational college students, the other is often more likely to occur as well[16]. As symptoms accumulate over time, students' emotion regulation capacity, learning efficiency, interpersonal functioning, and daily adaptation may all be adversely affected, thereby creating a vicious cycle of reciprocal influence and progressive deterioration[18].

As asserted by Fried and Nesse[19], there exists substantial variation in symptoms among individuals. Even when the overall levels of anxiety or depression are similar, individuals can display vastly different symptom patterns and outcomes. Therefore, despite consistent evidence showing that vocational college students experience a high prevalence of anxiety and depressive symptoms, as well as frequent co-occurrence of

these conditions, most existing studies have adopted a variable-centered approach that emphasizes population averages while implicitly assuming population homogeneity[20, 21]. Such approaches may obscure meaningful heterogeneity in symptom configurations and fail to identify distinct subgroups with unique clinical characteristics. Given the unique academic demands, career uncertainties, and social adaptation challenges faced by vocational college students, heterogeneous anxiety–depression symptom profiles are likely to exist within this population[22]. Identifying these latent subgroups is therefore essential for advancing precision mental health assessment and developing targeted intervention strategies. Although Latent Profile Analysis (LPA) has been increasingly applied to characterize anxiety–depression symptom patterns, evidence regarding the heterogeneity of comorbid symptom profiles among vocational college students remains limited.

Furthermore, the analytical approach associated with standardized tests, known as the latent variable models and factor analysis, treats symptoms as separate entities and is commonly used in diagnosing and measuring psychiatric and psychological disorders[23]. But this approach does not consider differences in the importance of symptoms and ignores interactions between symptoms[24]. The network theory of mental disorders suggests that mental illnesses develop and persist due to interactions between symptoms. Strong interactions can create a feedback loop that propels the illness forward[25]. Network analysis, a methodology derived from network science, enables the simultaneous consideration of multiple factors' interactions within a mathematical model[26, 27]. When applied to psychopathology research, it allows for the identification of core symptoms (nodes) and the interactions (edges) between symptoms[28]. Network analysis also provides the potential to delve deeper into the mechanisms of comorbidity between multiple psychiatric disorders[29]. For instance, the anxiety-depression symptom network enables the exploration of the relationship between anxiety and depression at the symptom level. Identifying bridging symptoms in the network can reveal which anxiety symptoms are most likely to influence depressive symptoms and vice versa, thereby determining which symptoms form the bridges between disorders[30]. Moreover, network analysis has clinical utility. Interventions targeting core symptoms may impact the entire network, and addressing bridging symptoms in a network of comorbidities may help disrupt the cycle between multiple psychiatric disorders or weaken their interconnections[24]. Although network analysis has been widely used to investigate anxiety and depressive symptoms in diverse populations, including adolescents, older adults with disabilities, and family caregivers of older adults, relatively little is known about how symptom-level associations vary across distinct anxiety–depression profiles among students in higher vocational colleges.[31–34].

In recent years, accumulating evidence has shown that anxiety and depressive symptoms exhibit substantial heterogeneity in both symptom severity and symptom configuration[35]. Individuals with similar total scores may present markedly different symptom profiles and patterns of symptom interaction[35]. Consequently, constructing a symptom network based on the overall sample implicitly assumes population homogeneity, potentially obscuring subgroup-specific symptom associations[36]. When symptom interaction patterns differ across latent subgroups, the resulting pooled network may represent only an aggregate of heterogeneous subgroup networks, thereby limiting the accurate identification of central and bridge symptoms[37, 38]. To address this limitation, the present study integrates latent profile analysis (LPA) with network analysis to investigate anxiety-depression comorbidity among vocational college

students. Specifically, the study aims to (1) identify heterogeneous comorbidity profiles of anxiety and depression and (2) determine the bridge symptoms linking anxiety and depression across different comorbidity profiles.

2 Methods

2.1 Participants

This study recruited higher vocational college students from five institutions in Wenjiang District, Chengdu, between January and February 2022 using a stratified random sampling approach. A total of 8,628 questionnaires were distributed, and 7,932 valid responses were retained for analysis, yielding an effective response rate of 91.93%. All participants provided informed consent prior to enrollment, and the study was reviewed and approved by the Ethics Committee of Wenjiang District People's Hospital of Chengdu (Approval No: 2023008).

2.2 Measures

2.2.1 Anxiety

The Generalized Anxiety Disorder Scale-7 (GAD-7), developed by Spitzer et al.[39], was employed to evaluate the severity of anxiety symptoms. The scale comprises 7 items, each scored from 0 (not at all) to 3 (nearly every day), yielding a total score range of 0–21, with higher scores indicating greater anxiety severity. According to established cutoff points, scores of 0–4 indicate minimal anxiety, 5–9 mild anxiety, 10–14 moderate anxiety, and 15–21 severe anxiety[40]. In this study, the GAD-7 demonstrated excellent internal consistency, with a Cronbach's α of 0.966.

2.2.2 Depression

The Patient Health Questionnaire-9 (PHQ-9), developed by Spitzer et al.[41], was used to assess the severity of depressive symptoms. This instrument consists of 9 items, each rated on a 4-point scale from 0 (not at all) to 3 (nearly every day). The total score is calculated by summing all item scores, with higher scores indicating greater depression severity. Specifically, scores ranging from 5 to 9 may suggest mild depression, scores from 10 to 14 may indicate moderate depression, and scores from 15 to 27 may reflect severe depression[42]. In the present study, the Cronbach's α for the PHQ-9 was 0.948.

3 Data analysis

Latent profile analysis (LPA) was conducted using Mplus version 8.3 based on the item-level scores of the GAD-7 and PHQ-9 to identify subgroups with distinct anxiety–depression symptom profiles. Although the individual items were rated on four-point ordinal scales (0–3), they were treated as approximately continuous indicators in the LPA. Maximum likelihood estimation with robust standard errors (MLR) was used to reduce the influence of non-normality on parameter estimation. Indicator means were freely estimated across profiles, whereas item variances were constrained to be equal across profiles. Within-profile covariances among the indicators were fixed to zero, consistent with the assumption of local

independence. Models with one to five latent profiles were estimated sequentially. The optimal number of profiles was determined by considering statistical fit indices, classification accuracy, profile size, parsimony, and substantive interpretability. Model fit was evaluated using the Akaike information criterion (AIC), Bayesian information criterion (BIC), sample-size-adjusted Bayesian information criterion (aBIC), entropy, the bootstrapped likelihood ratio test (BLRT), and the Lo–Mendell–Rubin adjusted likelihood ratio test (LMR-LRT). Lower AIC, BIC, and aBIC values indicated better relative model fit, while entropy values closer to 1 indicated greater classification accuracy, with values above 0.80 generally considered acceptable. Significant BLRT and LMR-LRT results ($p < 0.05$) indicated that a k -profile model provided a better fit than the corresponding $(k - 1)$ -profile model[43]. Profile size was also considered when selecting the final model, with profiles comprising less than 5% of the sample regarded as potentially unstable or of limited substantive interpretability[44].

Second, symptom networks were constructed separately for each comorbidity subgroup using R 4.4.2 to identify central and bridge symptoms and to compare network characteristics across subgroups. Network visualization and estimation were performed using the qgraph package (v1.9.8) and the bootnet package (v1.5.6), respectively. The 16 items of the PHQ-9 and GAD-7 served as network nodes. Given the ordinal nature and non-normal distribution of the PHQ-9 and GAD-7 items, Spearman correlations were used to construct the association matrix for network estimation. A partial correlation network was then estimated within the Gaussian Graphical Model (GGM) framework, in which each edge represents the partial correlation between two nodes after statistically controlling for all remaining nodes. To enhance network sparsity and reduce false-positive edges, the graphical LASSO (least absolute shrinkage and selection operator) algorithm was applied to regularize the GGM, with the optimal regularization parameter selected by minimizing the Extended Bayesian Information Criterion (EBIC); the hyperparameter γ was set to 0.5. In the network plot, edge thickness reflects the magnitude of association strength, with green and red edges representing positive and negative partial correlations, respectively. To identify central and bridge symptoms within each network, the networktools package (v1.5.2) was used to compute Expected Influence (EI) and Bridge Expected Influence (BEI) for each node. EI is defined as the weighted sum of all edge weights connected to a given node, including negative connections, and reflects the node's overall influence within the network[45]. BEI specifically aggregates the edge weights connecting a given node to nodes belonging to different symptom communities, thereby quantifying its cross-community bridging role[29]. To evaluate edge-weight accuracy and centrality stability, 95% bootstrapped confidence intervals for edge weights were obtained using a nonparametric bootstrap procedure. The stability of Expected Influence (EI) and Bridge Expected Influence (BEI) was assessed using a case-dropping bootstrap procedure, and CS coefficients were calculated for both indices[27]. A CS coefficient of at least 0.25 is generally considered acceptable, whereas values above 0.50 are preferable; narrower 95% confidence intervals indicate greater estimation precision.

Finally, network comparison tests (NCTs) were conducted using the NetworkComparisonTest package (v2.2.2) with 2,500 permutations to compare network structure and global strength across the three symptom profiles. In addition to the unadjusted comparisons, covariate-adjusted analyses were performed controlling for household income, only-child status, parental education, daily online time, and physical activity, which were prespecified as potential sociodemographic and behavioral confounders. Within each

profile, each PHQ-9 and GAD-7 item was regressed on these covariates, and the resulting residuals were used to re-estimate the symptom networks using the same estimation procedure as in the primary analysis. NCTs were subsequently repeated on the adjusted networks. Where individual edge differences were examined, p values were corrected for multiple comparisons using the Holm method.

4 Results

4.1 Descriptive statistics

Table 1 presents the basic characteristics of vocational college students. After adjusting for covariates using analysis of covariance (ANCOVA), female vocational college students had significantly higher anxiety and depression scores than male students.

Table 1
The characteristics of vocational college students

Project	Males(n = 3261)	Female(n = 4671)	F/t/χ ²	p
	n(%) / M(SD)	n(%) / M(SD)		
GAD	2.74(4.324)	3.04(4.356)	0.057	0.812
PHQ	4.03(5.402)	4.12(5.341)	0.166	0.918
GAD_A	2.74(4.324)	3.04(4.356)	15.802	< 0.001
PHQ_A	4.03(5.402)	4.12(5.341)	18.851	< 0.001
Economic status			42.478	< 0.001
High	124(3.8)	136(2.9)		
Medium	2276(69.8)	3566(76.3)		
Low	861(26.4)	969(20.7)		
Only child				
Yes	1065(32.7)	912(19.5)	177.03	< 0.001
No	2196(67.3)	3759(80.5)		
Father's educational level			41.274	< 0.001
Primary school and below	922(28.3)	1513(32.4)		
Middle School	1366(41.9)	2053(44)		
High school	769(23.6)	856(18.3)		
College degree or above	204(6.3)	249(5.3)		
Mother's educational level			29.537	< 0.001
Primary school and below	1298(39.8)	2100(45)		
Middle School	1286(39.4)	1784(38.2)		
High school	555(17)	660(14.1)		
College degree or above	122(3.7)	127(2.7)		
Average online time			2486.975	< 0.001
Note: GAD_A, PHQ_A = Adjusted by analysis of covariance.				

Project	Males(n = 3261)	Female(n = 4671)	<i>F/t/χ²</i>	<i>p</i>
	n(%) / M(SD)	n(%) / M(SD)		
1-2h	1539(47.2)	608(13)		
3-4h	1572(48.2)	1401(30)		
5-6h	114(3.5)	1736(37.2)		
> 6	36(1.1)	926(19.8)		
Achieving the standard for physical exercise			74.969	< 0.001
Yes	1271(39)	1385(29.7)		
No	1990(61)	3286(70.3)		
Note: GAD_A, PHQ_A = Adjusted by analysis of covariance.				

Specifically, regarding anxiety symptoms, female students scored significantly higher than male students on GAD1, GAD2, GAD3, GAD6, and GAD7 ($p < 0.05$); no significant gender differences were observed for GAD4 and GAD5. Regarding depressive symptoms, significant gender differences were observed for PHQ3 and PHQ5 ($p < 0.05$), and male students scored significantly higher than female students on PHQ8 ($p = 0.009$); differences on the remaining items were not significant. See Table 2.

Table 2
Descriptive statistics for PHQ-9 and GAD-7 items and sex differences

Project		Male(n = 3261)	Female(n = 4671)	t	p	Cohen's d
		M(SD)	M(SD)			
Anxiety	GAD1	0.42(0.683)	0.49(0.704)	-4.56	< 0.001	0.1
	GAD2	0.36(0.667)	0.41(0.690)	-2.84	0.005	0.07
	GAD3	0.46(0.528)	0.52(0.744)	-3.676	< 0.001	0.09
	GAD4	0.41(0.701)	0.43(0.705)	-1.528	0.127	
	GAD5	0.33(0.639)	0.33(0.625)	0.478	0.633	
	GAD6	0.39(0.685)	0.45(0.721)	-3.802	< 0.001	0.09
	GAD7	0.37(0.676)	0.41(0.689)	-2.492	0.013	0.06
Depression	PHQ1	0.48(0.741)	0.47(0.731)	0.665	0.506	
	PHQ2	0.50(0.733)	0.53(0.719)	-1.621	0.105	
	PHQ3	0.51(0.784)	0.57(0.800)	-3.534	< 0.001	0.08
	PHQ4	0.56(0.782)	0.56(0.767)	-0.344	0.731	
	PHQ5	0.48(0.774)	0.53(0.803)	-2.807	0.004	0.06
	PHQ6	0.49(0.752)	0.50(0.762)	-0.602	0.547	
	PHQ7	0.40(0.731)	0.42(0.731)	0.323	0.747	
	PHQ8	0.33(0.667)	0.31(0.647)	2.607	0.009	0.03
	PHQ9	0.24(0.567)	0.23(0.571)	0.666	0.505	

4.2 Latent Profile Analysis of Higher Vocational College Students

The item-level scores of the PHQ-9 and GAD-7 were used as indicators in the latent profile analysis (LPA), and solutions comprising one to five profiles were evaluated. The AIC, BIC, and aBIC decreased progressively as the number of profiles increased. For the two-profile solution, the BLRT was significant ($p < 0.001$), whereas the LMR-LRT was not ($p = 0.333$). Both the LMR-LRT and BLRT were significant for the three- and four-profile solutions (all $p < 0.001$). For the five-profile solution, the BLRT remained significant ($p < 0.001$), whereas the LMR-LRT was not ($p = 0.285$). Entropy values ranged from 0.960 to 0.984, with the three-profile solution yielding the highest value (0.984), indicating excellent classification accuracy. Although the four-profile solution provided improved statistical fit, inspection of the profile patterns showed that the additional profile primarily reflected a further subdivision of symptom severity rather than a substantively distinct symptom configuration. The five-profile solution further reduced the information criteria but produced a small subgroup comprising only 3.45% of the sample and was not supported by the

LMR-LRT. Given the excellent classification accuracy of the three-profile solution, its adequate profile sizes, greater parsimony, and clearer substantive interpretability for subsequent profile-specific network analyses, the three-profile solution was retained as the primary model. See Table 3.

Table 3
Latent profile solutions for depression and anxiety

LPA Models	AIC	BIC	aBIC	Entropy	LMRT(p)	BLRT(p)	Smallest profiles(%)
1-class	272659.738	272883.055	272781.365				
2-class	196309.796	196651.751	196496.038	0.982	0.333	< 0.001	25.700
3-class	165460.867	165921.459	165711.724	0.984	< 0.001	< 0.001	6.980
4-class	157820.272	158399.5	158135.743	0.96	< 0.001	< 0.001	5.700
5-class	151885.688	152583.554	152265.774	0.96	0.285	< 0.001	3.450

Based on the anxiety and depressive symptom scores, the three-class solution was characterized as follows. Low anxiety–depression symptom profile, comprising 5,416 participants (68.3%), was characterized by consistently low levels of anxiety and depressive symptoms across all assessed items and was therefore designated the low-symptom profile. Moderate anxiety–depression symptom profile included 1,962 participants (24.7%) and exhibited intermediate levels of anxiety and depressive symptoms, corresponding to the moderate-symptom profile. High anxiety–depression symptom profile comprised 554 participants (7.0%) and demonstrated the highest symptom levels across all assessed items, thus representing the high-symptom profile. Chi-square analysis indicated no significant difference in gender distribution across the three latent profiles ($\chi^2=4.539$, $p = 0.103$).

To characterize the symptom-severity patterns of the identified profiles, PHQ-9 and GAD-7 item scores were compared across the three groups. Mean scores for all items increased progressively from the low-symptom profile to the moderate- and high-symptom profiles, and the between-profile differences were statistically significant (all $p < 0.001$). These comparisons describe the severity gradient underlying the profile labels and should not be interpreted as independent validation of the three-profile solution, because the same items were used as indicators in the LPA. Detailed item scores are presented in Fig. 1 and Table 4.

Table 4
Differences in depression-anxiety dimensions across latent profiles (M ± SD)

Item	C1(n = 5416)	C2(n = 1962)	C3(n = 554)	F	P	η^2	Post hoc tests (Bonferroni)
	M(SD)	M(SD)	M(SD)				
GAD1	0.10(0.309)	0.98(0.457)	2.08(0.672)	9008.78	< 0.001	0.69	C1 < C2 < C3
GAD2	0.04(0.196)	0.88(0.04)	2.09(0.688)	11438.573	< 0.001	0.74	C1 < C2 < C3
GAD3	0.12(0.336)	1.05(0.485)	2.22(0.629)	9280.383	< 0.001	0.7	C1 < C2 < C3
GAD4	0.06(0.235)	0.95(0.523)	2.12(0.646)	10623.663	< 0.001	0.73	C1 < C2 < C3
GAD5	0.03(0.166)	0.74(0.541)	1.85(0.776)	7891.787	< 0.001	0.67	C1 < C2 < C3
GAD6	0.06(0.245)	0.93(0.491)	1.85(0.776)	11354.406	< 0.001	0.74	C1 < C2 < C3
GAD7	0.07(0.257)	0.86(0.556)	1.99(0.784)	7322.104	< 0.001	0.65	C1 < C2 < C3
PHQ1	0.14(0.394)	0.98(0.655)	1.92(0.779)	4449.282	< 0.001	0.53	C1 < C2 < C3
PHQ2	0.17(0.404)	1.05(0.565)	1.97(0.738)	5151.797	< 0.001	0.57	C1 < C2 < C3
PHQ3	0.21(0.478)	1.05(0.723)	2.03(0.824)	3540.415	< 0.001	0.47	C1 < C2 < C3
PHQ4	0.21(0.454)	1.09(0.639)	2.09(0.750)	4466.706	< 0.001	0.53	C1 < C2 < C3
PHQ5	0.19(0.493)	0.97(0.765)	1.94(0.862)	2887.708	< 0.001	0.42	C1 < C2 < C3
PHQ6	0.14(0.391)	1.03(0.666)	2.01(0.799)	4840.003	< 0.001	0.55	C1 < C2 < C3
PHQ7	0.10(0.351)	0.89(0.684)	1.93(0.868)	4447.131	< 0.001	0.53	C1 < C2 < C3
PHQ8	0.05(0.224)	0.70(0.634)	1.78(0.920)	4877.446	< 0.001	0.55	C1 < C2 < C3
PHQ9	0.20(0.139)	0.48(0.584)	1.49(0.994)	3758.867	< 0.001	0.49	C1 < C2 < C3

4.3 Network Analysis of Vocational College Students

4.3.1 Network Estimation and Accuracy

Figures 2A-C present the estimated anxiety–depression symptom networks for the low, moderate, and high comorbidity profiles, respectively. Each network comprised 16 nodes and 120 possible edges. Of these, 86 edges (71.67%) were retained in the low comorbidity network, including 78 positive and 8 negative edges; 63 edges (52.50%) were retained in the moderate comorbidity network, including 55 positive and 8 negative edges; and 77 edges (64.17%) were retained in the high comorbidity network, including 75 positive and 2 negative edges. The strongest edge in the low comorbidity network was observed between PHQ1 (loss of interest) and PHQ2 (depressed mood) (weight = 0.294). In the moderate comorbidity network, the strongest edge connected PHQ8 (psychomotor agitation or retardation) and PHQ9 (suicidal ideation or self-harm) (weight = 0.286). In the high comorbidity network, the strongest edge was identified between GAD3 (excessive worry) and GAD4 (difficulty relaxing) (weight = 0.288).

The CS coefficients for EI were 0.750, 0.750, and 0.516 for the low-, moderate-, and high-symptom profile networks, respectively. The corresponding CS coefficients for BEI were 0.672, 0.750, and 0.361. These results indicated good stability of the EI estimates across all three networks. The BEI estimates showed good stability in the low- and moderate-symptom profile networks, whereas stability was acceptable but comparatively lower in the high-symptom profile network. Therefore, bridge centrality findings for the high-symptom profile should be interpreted with caution (Supplementary Fig. 1). Moreover, the bootstrap CIs for edge weights were relatively narrow in all three networks, demonstrating good precision of the estimated edge weights (Supplementary Fig. 2).

4.3.2 Centrality indicators

Figure 3 and Table 5 summarize the Expected Influence (EI) estimates for all symptoms across the three comorbidity profiles. In the low comorbidity profile, PHQ4 (lack of energy; EI = 1.119) and PHQ2 (depressed mood; EI = 0.997) were the most central symptoms. In the moderate comorbidity profile, PHQ8 (psychomotor agitation or retardation; EI = 0.973) and PHQ4 (lack of energy; EI = 0.867) exhibited the highest centrality. In the high comorbidity profile, GAD3 (excessive worry; EI = 1.070), GAD4 (difficulty relaxing; EI = 1.036), and PHQ2 (depressed mood; EI = 1.012) ranked highest in EI. Descriptively, the symptoms with the highest EI values differed across the three profiles.

Table 5
Expected influence of low comorbid, moderate comorbid, and high comorbid

Item	C1 low comorbid (n = 5416)	C2 moderate comorbid (n = 1962)	C3 high comorbid (n = 554)
GAD1	0.45	-1.16	-0.2
GAD2	-1.2	0.6	0.27
GAD3	1.06	-0.2	1.72
GAD4	-0.68	-0.37	1.41
GAD5	-1.88	0.94	-0.62
GAD6	-0.58	-0.94	-0.1
GAD7	-0.35	-1.41	-1.43
PHQ1	0.56	0.44	-0.61
PHQ2	1.31	0.78	1.2
PHQ3	0.23	-0.52	-1.47
PHQ4	2.02	1.41	1.13
PHQ5	-0.57	-1.08	-0.5
PHQ6	0.62	-0.53	-0.24
PHQ7	-0.19	-0.14	0.61
PHQ8	0.06	2.19	0.06
PHQ9	-0.89	-0.02	-1.23

Figure 4 and Table 6 summarize the Bridge Expected Influence (BEI) values for bridge symptoms across the three comorbidity profiles. In the low comorbidity profile, PHQ6 (low self-esteem; BEI = 0.210), PHQ2 (depressed mood; BEI = 0.180), and GAD1 (nervousness or anxiety; BEI = 0.183) emerged as the primary bridge symptoms. In the moderate comorbidity profile, PHQ8 (psychomotor agitation or retardation; BEI = 0.167), GAD5 (restlessness; BEI = 0.185), and PHQ9 (suicidal ideation or self-harm; BEI = 0.144) were identified as key bridge symptoms. In the high comorbidity profile, GAD5 (restlessness; BEI = 0.295), GAD1 (nervousness or anxiety; BEI = 0.203), and PHQ8 (psychomotor agitation or retardation; BEI = 0.197) exhibited the highest BEI values.

Table 6
Bridge expected influence (1-step) of low comorbid, moderate comorbid, and high comorbid

Item	C1 low comorbid (n = 5416)	C2 moderate comorbid (n = 1962)	C3 high comorbid (n = 554)
GAD1	1.26	0.33	1.11
GAD2	-1.31	0.12	-0.84
GAD3	0.82	-1.48	-1.28
GAD4	0.28	-0.47	-0.31
GAD5	0.09	2.06	2.42
GAD6	-0.27	-0.22	0.35
GAD7	0.54	0.13	0.32
PHQ1	-0.99	-0.75	-1.33
PHQ2	1.23	0.1	0.74
PHQ3	0.2	-0.47	-0.24
PHQ4	-0.04	-0.89	-0.13
PHQ5	-0.01	-0.57	0.12
PHQ6	1.66	-0.72	-0.88
PHQ7	-0.73	-0.47	-0.99
PHQ8	-0.66	1.81	1.03
PHQ9	-2.08	1.5	-0.09

4.3.3 Network comparison

Pairwise network comparison tests were conducted to compare the anxiety–depression networks across the three comorbidity profiles. Holm-adjusted p values were used to account for the three pairwise comparisons. The network structure invariance test provided no evidence of structural differences between the low and moderate profiles ($M = 0.137$, $p = 0.312$), the low and high profiles ($M = 0.145$, $p = 0.942$), or the moderate and high profiles ($M = 0.173$, $p = 0.312$). In contrast, global strength differed significantly between the low and moderate profiles ($S = 0.528$, $p = 0.008$), the low and high profiles ($S = 0.824$, $p = 0.012$), and the moderate and high profiles ($S = 1.352$, $p = 0.003$). Global strength was highest in the high profile (6.818), followed by the low (5.994) and moderate (5.466) profiles. No individual edge differences remained significant after correction for multiple edge comparisons.

After adjustment for economic status, only-child status, paternal and maternal educational levels, average daily Internet use, and meeting physical activity recommendations, no evidence of network structure

differences was found between the low and moderate profiles ($M = 0.133, p = 0.321$), the low and high profiles ($M = 0.145, p = 0.915$), or the moderate and high profiles ($M = 0.172, p = 0.321$). Differences in global strength were also nonsignificant between the low and moderate profiles ($S = 0.311, p = 0.729$), the low and high profiles ($S = 0.961, p = 0.204$), and the moderate and high profiles ($S = 1.272, p = 0.117$). The corresponding adjusted global strength values were 5.851, 5.540, and 6.812 for the low, moderate, and high profiles, respectively. No individual edge differences survived correction for multiple comparisons.

5 Discussion

This study systematically investigated the heterogeneity of anxiety–depression comorbidity patterns among vocational college students. By integrating latent profile analysis with network analysis, participants were classified into three distinct latent subgroups: low comorbidity, moderate comorbidity, and high comorbidity. For each subgroup, the study further identified the central symptoms that maintain the symptom network, as well as the bridge symptoms that connect the anxiety and depression symptom clusters.

5.1 Latent Profile Analysis

This study identified distinct latent profiles of anxiety-depression comorbidity among vocational college students. The three-profile model demonstrated satisfactory fit across all model-fit indices, and significant differences in anxiety and depression scores were observed among the profiles, indicating substantial heterogeneity in comorbidity severity within this population. The identified profiles primarily reflected quantitative differences in symptom severity rather than qualitative differences in symptom configuration, suggesting that severity-based stratified interventions may be particularly applicable in clinical and educational settings. Specifically, participants were classified into three latent profiles: low comorbidity (68.3%), moderate comorbidity (24.7%), and high comorbidity (7.0%). Students in the low-comorbidity profile exhibited the lowest levels of depressive and anxiety symptoms, indicating that most vocational college students maintain relatively good mental health. The moderate-comorbidity profile was characterized by intermediate symptom severity, suggesting a need for continued monitoring of psychological status, although symptoms generally remained within a manageable range. In contrast, the high-comorbidity profile demonstrated the most severe clinical manifestations, with significantly higher depression and anxiety scores than those observed in the other two profiles. This subgroup therefore represents a high-risk population requiring timely psychological assessment and targeted intervention. Overall, these findings highlight the importance of developing differentiated intervention strategies tailored to the severity characteristics of each latent subgroup.

This study found no significant differences in gender distribution across the three anxiety–depression comorbidity profiles ($\chi^2 = 4.539, p = 0.103$), a finding that differs from previous evidence suggesting that females are generally more susceptible to internalizing disorders[47, 48]. This pattern indicates that gender did not distinguish comorbidity profile membership in the present sample, suggesting that male and female vocational college students may be at comparable risk for anxiety–depression comorbidity. However, given the limited sample size within individual subgroups, this study was unable to examine whether gender

moderates the structure of the anxiety–depression symptom network. Future studies with larger samples are therefore warranted to investigate the potential influence of gender on network structure, including the identification of central and bridge symptoms, as well as the mechanisms underlying anxiety–depression comorbidity among vocational college students.

5.2 Network Analysis of Anxiety–Depression Comorbidity Across Latent Subgroups of Vocational College Students

In the low-comorbidity subgroup, PHQ4 (lack of energy) and PHQ2 (depressed mood) exhibited the highest expected influence, suggesting that these symptoms may play a central role in maintaining the relatively mild anxiety–depression comorbidity network. In the moderate-comorbidity subgroup, PHQ8 (psychomotor retardation or agitation) and PHQ4 (lack of energy) emerged as the most influential nodes, indicating that depressive psychomotor symptoms become more prominent as symptom severity increases. In the high-comorbidity subgroup, GAD3 (excessive worry), GAD4 (difficulty relaxing), and PHQ2 (depressed mood) demonstrated the greatest expected influence, suggesting that pervasive worry, together with persistent depressed mood, may represent key mechanisms underlying severe anxiety–depression comorbidity. The symptoms with the highest EI values differed descriptively across the three profiles. However, because no significant between-profile differences in overall network structure were detected by the NCT, these variations in centrality rankings should be interpreted cautiously and should not be regarded as evidence of distinct network structures.[48, 49].

The bridge symptoms identified across the three latent subgroups showed both common and subgroup-specific characteristics. In the low-comorbidity subgroup, PHQ6 (low self-esteem) and PHQ2 (depressed mood) emerged as the primary bridge symptoms. In the moderate-comorbidity subgroup, the most prominent bridge symptoms were GAD5 (restlessness), PHQ8 (psychomotor retardation or agitation), and PHQ9 (thoughts of self-harm or suicide). In the high-comorbidity subgroup, GAD5 (restlessness), GAD1 (nervousness or anxiety), and PHQ8 (psychomotor retardation or agitation) exhibited the highest bridge centrality. The highest-ranking bridge symptoms were not identical across the three profiles, suggesting potentially profile-specific patterns that require confirmation in future studies.

This study identified GAD5 (restlessness) as a shared bridge symptom in both the moderate- and high-comorbidity subgroups, suggesting that restlessness may play a particularly important role in linking anxiety and depressive symptoms as comorbidity severity increases. The bridging role of GAD5 (restlessness) in anxiety–depression comorbidity has been consistently reported in previous studies. For example, Wang et al.[50] identified GAD5 (restlessness) as a key bridge symptom connecting anxiety and depression among first-year college students, while Luo et al.[51] similarly reported GAD5 as one of the most influential bridge symptoms in patients with depression. Furthermore, a systematic review by Cai et al.[49], which synthesized evidence from 33 studies involving 78,721 participants, found that GAD5 (restlessness) was among the most consistently identified bridge symptoms across diverse populations. Collectively, these findings suggest that the bridging role of GAD5 (restlessness) is robust across different populations and research settings. From the perspective of stress theory, vocational college students are exposed to multiple chronic stressors, including academic demands, employment-related pressures, and

developmental role transitions[52]. Sustained exposure to these stressors may contribute to persistent physiological and psychological hyperarousal[53]. As a behavioral manifestation of this heightened arousal state, restlessness may facilitate interactions between anxiety and depressive symptoms, thereby strengthening their co-occurrence and reinforcing the anxiety–depression comorbidity network[54]. Consequently, targeting restlessness may represent a promising strategy for disrupting symptom transmission between anxiety and depression and mitigating the maintenance of comorbidity.

In contrast, PHQ6 (low self-esteem) emerged as the primary bridge symptom in the low-comorbidity subgroup. This finding is consistent with that reported by Zhao et al.[55], who identified PHQ6 (low self-esteem) as a key bridge symptom linking anxiety and depression among patients with heart failure, suggesting that its bridging role may be relatively robust across different populations and clinical contexts. As a core cognitive feature of depression, low self-esteem may facilitate the co-activation of anxiety and depressive symptoms even at relatively low levels of comorbidity, suggesting that negative self-appraisal may represent a shared cognitive vulnerability underlying anxiety–depression comorbidity[56, 57]. Among vocational college students, academic demands, uncertainty regarding future employment, and reduced confidence in personal competence may contribute to persistent negative self-evaluation, thereby increasing vulnerability to both anxiety and depressive symptoms[58–60]. From a network perspective, these cognitive symptoms may serve as early pathways through which anxiety and depression become interconnected. Accordingly, interventions targeting individuals in the early stages of anxiety–depression comorbidity may benefit from focusing on maladaptive cognitive symptoms, particularly low self-esteem, to weaken the connections between anxiety and depression and potentially prevent progression to more severe comorbidity[61, 62].

The unadjusted network comparison revealed a non-monotonic pattern of global strength across the three comorbidity profiles, with the highest global strength observed in the high-comorbidity profile, followed by the low- and moderate-comorbidity profiles. Although all three pairwise differences were statistically significant in the unadjusted analyses, these differences were attenuated and no longer significant after adjustment for household income, only-child status, parental educational attainment, time spent online, and physical activity. In addition, no significant differences in overall network structure or individual edge weights were detected after correction for multiple comparisons in either the unadjusted or adjusted analyses. These findings suggest that the three profiles differed more clearly in symptom severity than in the organization of symptom-to-symptom associations. Thus, greater comorbidity severity was not accompanied by a demonstrably distinct network structure. Similar patterns have been reported in previous network studies, in which group differences in symptom severity or unadjusted global connectivity were reduced after demographic and clinical characteristics were balanced, whereas the broader organization of symptom associations remained relatively stable. Accordingly, the numerical ordering of global strength in the unadjusted networks should be interpreted cautiously and does not provide robust evidence that symptoms were more strongly interconnected in one profile than in another. The attenuation of global strength differences after covariate adjustment indicates that the unadjusted comparisons may have partly reflected differences in the sociodemographic and behavioral composition of the three profiles. However, because the adjustment was based on observational data, these covariates should not be interpreted as causal explanations for the observed attenuation. Overall, the findings are consistent with a broadly shared

anxiety–depression network architecture across the three comorbidity profiles, despite marked differences in symptom severity. Therefore, identifying symptoms that are consistently central or that bridge anxiety and depression across profiles may provide a more defensible basis for intervention than developing profile-specific strategies based solely on differences in global network strength.

5.3 Implications for Practice

The findings of this study have several important implications for the prevention and management of anxiety–depression comorbidity among vocational college students. First, by adopting a person-centered analytical approach, this study identified three distinct comorbidity profiles, highlighting the heterogeneity of symptom severity within this population. Considering that vocational college students commonly experience substantial academic and career-related stress, limited psychological resources, and restricted access to professional mental health services, stratified mental health management based on subgroup-specific symptom profiles may facilitate more efficient allocation of limited intervention resources and improve the precision of preventive and therapeutic strategies. Second, the identification of subgroup-specific bridge symptoms provides potential targets for precision interventions. In the low-comorbidity subgroup, PHQ6 (low self-esteem) emerged as the primary bridge symptom connecting the anxiety and depression symptom clusters. Negative self-evaluation is common among vocational college students facing academic challenges and uncertainty about future employment and may contribute to the co-occurrence of anxiety and depressive symptoms. Accordingly, early cognitive interventions that target maladaptive self-evaluation, such as cognitive restructuring and other cognitive–behavioral strategies, may help weaken the connections between anxiety and depression and potentially reduce progression to more severe comorbidity[66]. In both the moderate-comorbidity and high-comorbidity subgroups, GAD5 (restlessness) was identified as the predominant bridge symptom. Persistent restlessness may reflect sustained physiological and psychological hyperarousal associated with chronic stressors, including academic demands, employment-related concerns, and developmental transitions[53]. Therefore, interventions for these subgroups may benefit from prioritizing strategies aimed at reducing hyperarousal, such as relaxation training, mindfulness-based stress reduction, and other evidence-based stress management approaches. By alleviating restlessness and related symptoms, these interventions may reduce the transmission of symptom activation between anxiety and depression, thereby contributing to the disruption of the comorbidity network and improving overall psychological well-being[49].

5.4 Limitations and Future Directions

Several limitations should be acknowledged. First, the cross-sectional design precludes causal or temporal inferences regarding the relationships among anxiety and depressive symptoms and their network structure. Second, although the overall sample was large, the high-comorbidity subgroup was relatively small, and subgroup-specific edge estimates and network comparisons should therefore be interpreted with caution. Third, although the three-profile solution was retained on the basis of classification accuracy, profile size, parsimony, and substantive interpretability, alternative profile specifications may yield different subgroup-specific network structures. Accordingly, node-level findings, particularly central and bridge symptoms, require cautious interpretation and independent replication. Finally, participants were recruited

from vocational colleges within Sichuan Province, which may limit the generalizability of the findings to students in other regions.

6 Conclusions

This study identified significant heterogeneity in anxiety–depression comorbidity patterns among higher vocational college students by integrating latent profile analysis and network analysis. Three distinct subgroups were identified, including low, moderate, and high comorbidity profiles, indicating that students with similar overall symptom levels may exhibit different symptom interaction patterns. Furthermore, subgroup-specific network analyses revealed that low self-esteem was a key bridge symptom in the low-comorbidity group, whereas restlessness emerged as a prominent bridge symptom in both the moderate- and high-comorbidity groups. These findings highlight that anxiety and depressive symptoms are interconnected through distinct mechanisms across different levels of comorbidity severity. Targeting subgroup-specific bridge symptoms may provide potential directions for early identification and personalized psychological interventions. Overall, this study emphasizes the importance of adopting a person-centered and symptom-oriented framework to improve the precision of mental health assessment and intervention strategies among higher vocational college students.

Abbreviations

- AIC
Akaike information criterion
- ANCOVA
analysis of covariance
- aBIC
sample-size-adjusted Bayesian information criterion
- BEI
Bridge Expected Influence
- BIC
Bayesian information criterion
- BLRT
bootstrapped likelihood ratio test
- CI
confidence interval
- CS
correlation stability
- EBIC
Extended Bayesian Information Criterion
- EI
Expected Influence
- GAD-7
Generalized Anxiety Disorder Scale-7

GGM
Gaussian Graphical Model
LASSO
least absolute shrinkage and selection operator
LMR-LRT
Lo–Mendell–Rubin adjusted likelihood ratio test
LPA
latent profile analysis
MLR
maximum likelihood estimation with robust standard errors
NCT
Network Comparison Test
PHQ-9
Patient Health Questionnaire-9
SD
standard deviation
WHO
World Health Organization.

Declarations

Ethics approval and consent to participate

This study was approved by the Ethics Committee of Wenjiang District People's Hospital of Chengdu (Approval No. 2023008). Written informed consent was obtained from all participants prior to participation. The study was conducted in accordance with the Declaration of Helsinki. The privacy and confidentiality of all participants were strictly protected throughout the study.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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Author Contribution

Shujie Meng: Writing - original draft, Writing - review & editing, Conceptualization, Methodology, Formal analysis. Zhaoying Jin: Writing - review & editing, Methodology. Xia Wang: Writing - original draft, Writing - review & editing, Formal analysis, Methodology. Hongyan Chen: Writing - review & editing, Data curation, Investigation, Resources. Feiran Qiu: Writing - review & editing, Formal analysis. Xiaoya Du: Writing - review & editing, Investigation. Jingjing Xiong: Writing - review & editing, Investigation. Ru Gao: Writing – Review & Editing & Final Approval

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Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author upon reasonable request.

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Figures

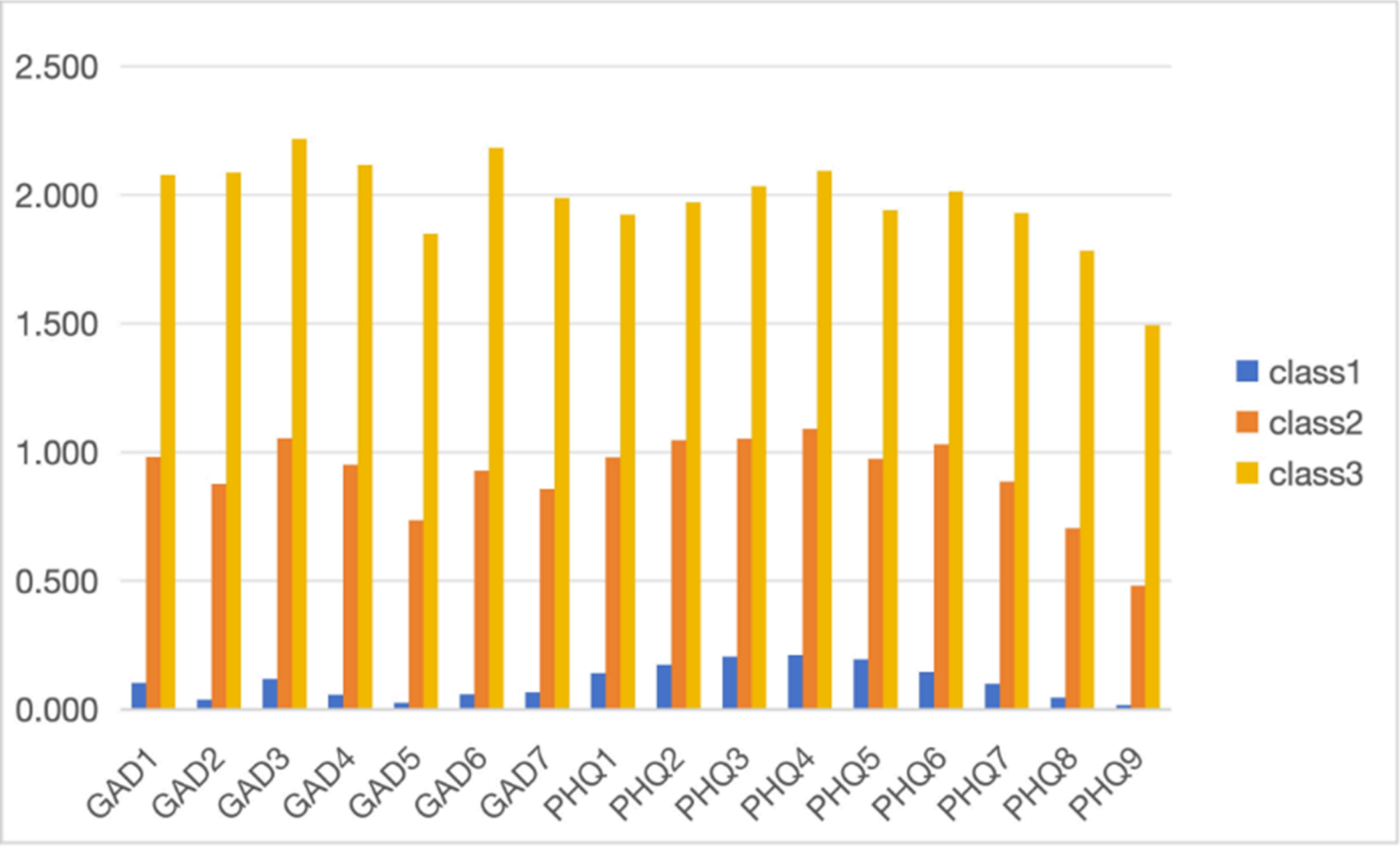


Figure 1

Symptoms profiles in the 3-class model.

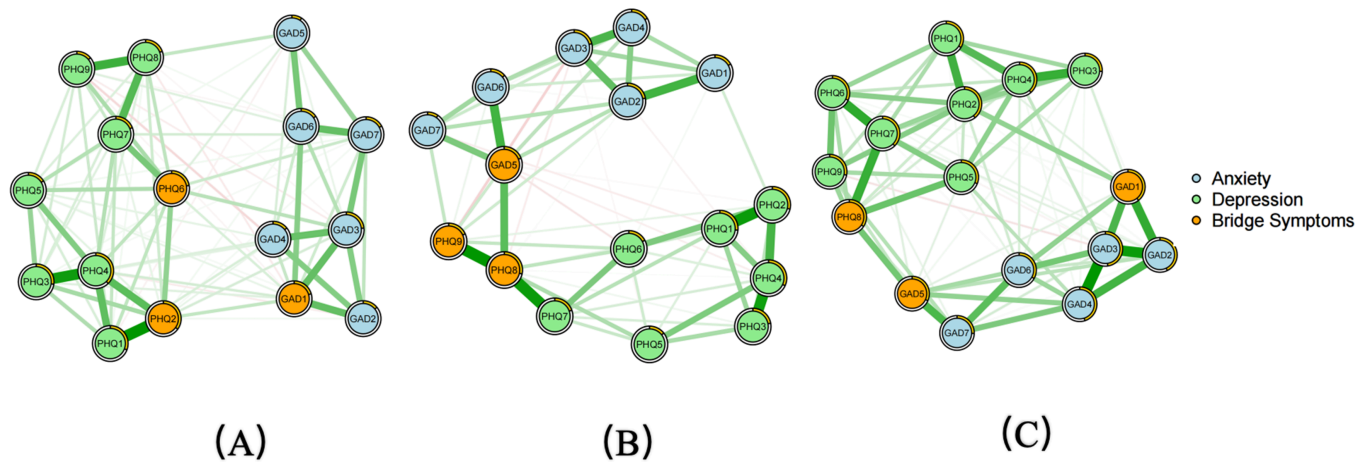


Figure 2

Network structures of anxiety and depressive symptoms across the three latent profiles

(A) Class 1; (B) Class 2; and (C) Class 3. Nodes represent individual symptoms of the GAD-7 and PHQ-9. Blue nodes represent anxiety symptoms, green nodes represent depressive symptoms, and orange nodes indicate bridge symptoms identified by a standardized one-step Bridge Expected Influence (BEI) value > 1. Edges represent regularized partial correlations between symptoms after controlling for all other symptoms in the network. Green edges indicate positive associations and red edges indicate negative associations; thicker and more saturated edges represent stronger associations.

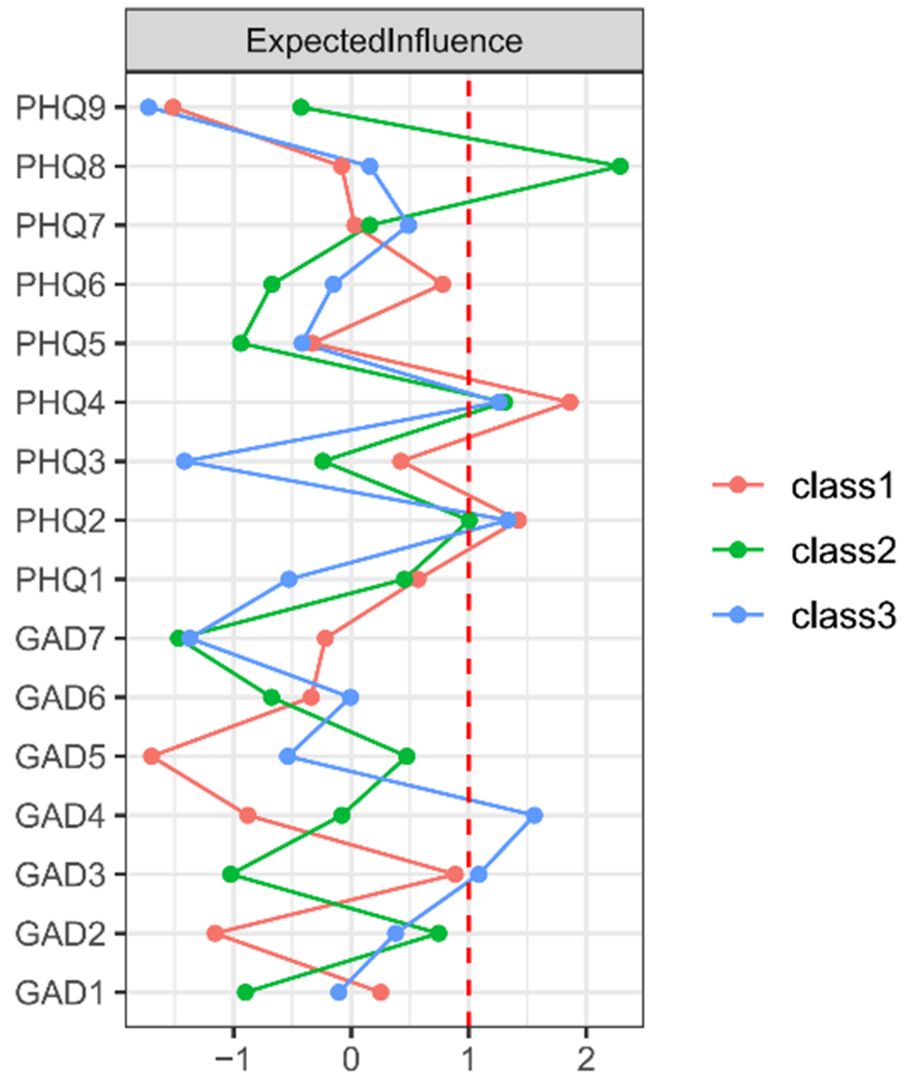


Figure 3

Expected Influence centrality of anxiety and depressive symptoms across the three latent profiles.

Expected Influence (EI) reflects the overall influence of each symptom within the symptom network while retaining the sign of its connections. Higher standardized EI values indicate greater overall influence within the network. Red, green, and blue lines represent Class 1, Class 2, and Class 3, respectively. The red dashed line indicates a standardized EI value of 1.

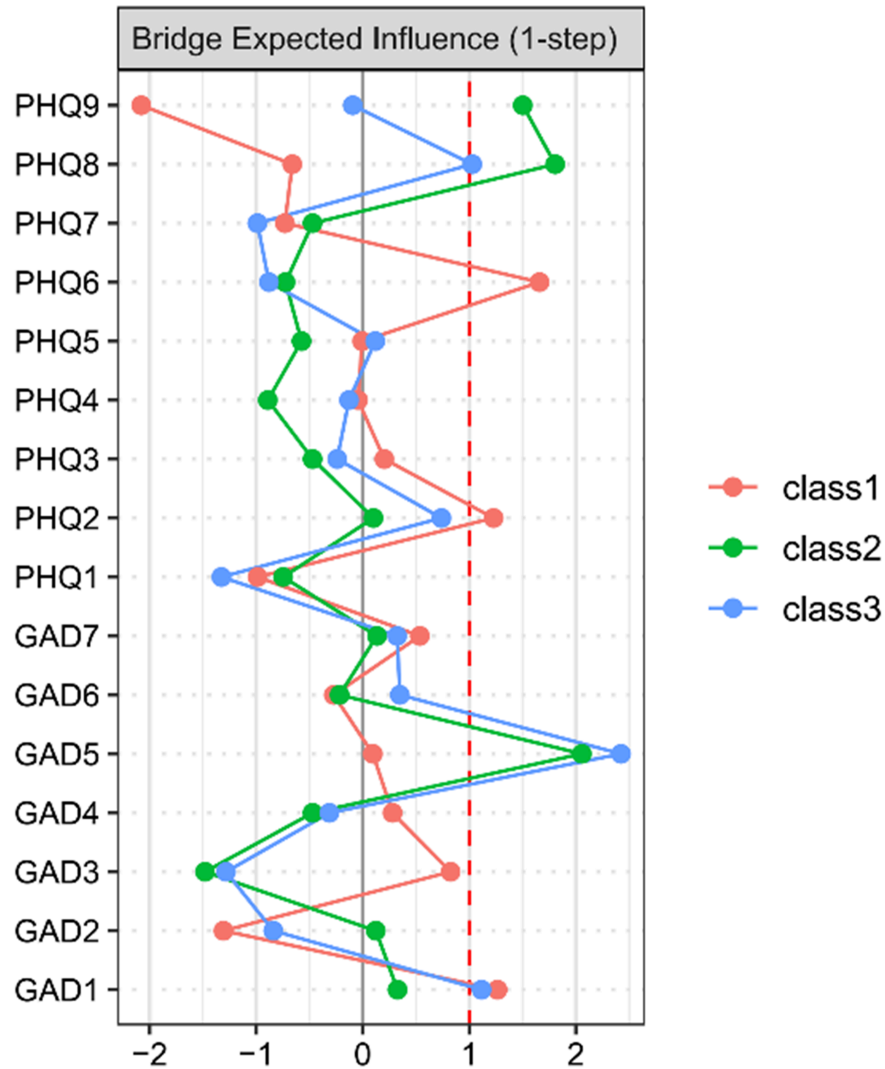


Figure 4

Bridge Expected Influence of anxiety and depressive symptoms across the three latent profiles.

Bridge Expected Influence (BEI) quantifies the extent to which a symptom is connected to symptoms belonging to the other symptom community (anxiety vs. depression), while retaining the sign of the associations. Higher standardized BEI values indicate a stronger potential role in linking the anxiety and depression communities. Red, green, and blue lines represent Class 1, Class 2, and Class 3, respectively. The red dashed line represents a standardized BEI value of 1; symptoms with standardized BEI >1 were identified as bridge symptoms.

Supplementary Files

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