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Adolescent anxiety and depression: perspectives of network analysis and longitudinal network analysis

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Abstract

Background Anxiety and depression often co-occur, exhibiting high comorbidity, with their trends evolving over time. However, the specific pathways through which comorbid symptoms of anxiety and depression evolve and interact remain unclear. To investigate these questions, this study employed Network Analysis (NA) and Longitudinal Network Analysis (LNA) to explore the central symptoms of anxiety and depression, as well as the temporal evolution of these central symptoms.

Methods The study focused on 606 high school students who were not in their final year in Shandong of China, with assessments conducted from March to September 2022. The bootnet package in R was used for establishing NA and LNA models, as well as for conducting accuracy analysis and node stability analysis.

Results The results of the NA indicated that adolescent highly susceptible to anxiety and depression. And uncontrollable worry was a common central symptom, while irritability emerged as a central bridging symptom across all three NAs. The LNA results revealed that suicidal ideation and worthlessness were key central symptoms in the LNA. Furthermore, worthlessness played a pivotal role in the developmental pathway of "suicidal ideation → worthlessness → anxiety and uncontrollable worry." A reduction in suicidal ideation was associated with decreased severity in other symptoms.

Conclusions The findings suggest that adolescent anxiety and depression are in a state of vulnerability, and that irritability, worthlessness, and suicidal ideation are potential targets for interventions to address adolescent anxiety and depression.

Keywords Anxiety, Depression, Network analysis, Longitudinal network analysis

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Background

Anxiety and depression are among the most common psychological disorders. According to the World Mental Health Report published by the World Health Organization, the global incidence of anxiety and depression increased by 25% following the COVID-19 pandemic [1]. Of particular concern is the worsening of anxiety and depression among adolescents, which has shown a significant increase [2], attracting considerable attention from researchers.

Numerous studies have demonstrated a high level of comorbidity between anxiety and depression [3–5], with a specific interconnection [6]. This comorbidity frequently manifests during adolescence [7]. Given the severity of anxiety and depression and their substantial impact on disability-adjusted life years among adolescents [8], it is imperative to further explore the relationship between symptoms of anxiety and depression and to identify these symptoms effectively in adolescents. Addressing the potential risks associated with comorbid anxiety and depression is of paramount importance.

The network approach to psychological constructs is based on network theory, which suggests that higher-level attributes such as disorders, traits, and abilities can emerge from lower-level processes where individual symptoms, attitudes, behaviors, beliefs, and skills interact with each other, forming dynamic systems that culminate in specific outcomes [9–12]. From this theoretical perspective, patterns of symptom-symptom interaction can be represented within a network structure, with symptoms depicted as nodes. Network analysis (NA) is a valuable tool for analyzing and visualizing the interconnected relationships among symptoms in psychological disorders by quantifying the relationships between nodes. This approach provides unique insights into the genesis, perpetuation, and progression of psychological conditions.

In studies involving the NA of anxiety and depression, the PHQ-9 and GAD-7 scales are widely used. Table 1 described the findings from related literature. Most studies used the PHQ-9 and GAD-7. Variations in results were noted due to differences in research subjects, focus of inquiry, and research backgrounds. However, the importance of symptoms such as uncontrollable worry, excessive worry, and motor function, as well as the high stability of the anxiety and depressive symptom network, has been widely validated. Additionally, studies conducted during the COVID-19 pandemic revealed unique characteristics, such as the increased significance of motor function symptoms due to the social context. Specific details are presented in Table 1.

Previous studies (as shown in Table 1) primarily used traditional NA methods to establish anxiety-depression networks. However, an NA model typically assumes that symptoms operate on the same time scale and that interactions between symptoms are pairwise and symmetrical. This approach does not allow for the inference of predictive relationships between central symptoms and other symptoms over time within a single network. Furthermore, in clinical practice, many symptoms exhibit multidimensionality and asymmetry, with interactions among symptoms unfolding over weeks or even months [12, 13]. Consequently, Borsboom and Cramer advocated for collecting longitudinal data to further elucidate the causal relationships between symptoms [14]. In the study of anxiety and depression, although some research has collected longitudinal data [15, 16], these studies only established multiple NAs, which might make it difficult to intuitively observe the changing relationships between symptoms.

To further elucidate the causal relationships between symptoms and explore temporal trends in networks and the mutual predictive relationships between symptoms, Longitudinal Network Analysis (LNA) was developed. LNA is particularly useful for understanding mental health problems from a temporal perspective, providing insights with clinical relevance [24–26]. The key characteristic of LNA is that the relationships among individual items are modeled over time as directed regression coefficients, reflecting the shared variance between a predictor variable at time T and an outcome variable at time T+1, controlling for all other predictors at time T [25]. This approach allows LNA to identify the behaviors, emotions, traits, or symptoms that are causally responsible for these auto-regressive and cross-lagged longitudinal relationships. In LNA, central symptoms are identified by their roles as "high-output centrality symptoms" (those that influence other symptoms) or "high-input centrality symptoms" (those influenced by other symptoms) [13]. By establishing regression relationships between symptoms at different time points, LNA effectively reveals predictive relationships among symptoms over time, allowing researchers to examine the stability of symptom networks and predict interactions across multiple time points.

Given the limitations of methods used in previous research, this study aims to employ both NA and LNA methods to investigate the relationships between anxiety and depression symptoms among high school students. By identifying central symptoms and examining their interplay, the current study might help identify effective intervention targets, providing theoretical guidance for preventing and addressing mental health issues related to anxiety and depression in adolescents.

Method and data description

Participants

Data on anxiety and depression were collected from non-graduating students of a high school in Shandong,

Table 1 Descriptive characteristics of relevant literature

Study	Sample	Focus of research	Designs	Measures	Central symptom	Bridge symptom	Edge
Kaiser et al. [15]	Clinical patient (N = 5614, N_{Femal} = 3570; M_{age} =42.24)	Performed at admission and discharge	Longitudinal	PHQ-9 & GAD-7	Sad mood, restlessness, trouble relaxing, too much worry and uncontrollable worry	Moving slowly/restless (Motor), trouble concentrating and trouble relaxing	Control worry – too much worry was decreased at discharge, and sad mood – too much worry increased
Beard et al. [16]	Clinical patient (N = 1029; M_{age}=42.24)	Performed at admission and discharge	Longitudinal	PHQ-9 & GAD-7	Sad mood and too much worry	/	Too much worry – unable to control worry and sad mood - anhedonia
Wang et al. [17]	Nonclinical public (N_{T1}=2540; M_{age} = 25.28; N_{T2} = 2543; $M_{age\ =}$ 22.03)	Comparison outbreak stage (T1) and after peak stage(T2) during COVID-19	Cross-sectional	PHQ-9 & GAD-7	Impaired motor skills, restlessness and inability to relax	Impaired motor skills, restlessness and inability to relax	/
Tao et al. [18]	College students with an inclination toward depressive disorders (N = 622; M_{age} = 19.10)	Comparison of two subgroups, which was divided by the presence or absence of suicidal ideation	Cross-sectional	PHQ-9 & GAD-7	Students with suicidal ideation: excessive worry and motor function; Students without suicidal ideation: excessive worry and uncontrollable worry	Students with suicidal ideation: excessive worry and motor function; Students without suicidal ideation: restlessness and motor function	Students with suicidal ideation: nervousness - uncontrollable worry; Students without suicidal ideation: uncontrollable worry - excessive worry
Tao et al. [19]	Nonclinical adolescents (N = 20,544, N_{Femal} = 10,743 ; M_{age} = 16.9)	Comparison of three age subgroups	Cross-sectional	PHQ-9 & GAD-7	Uncontrollable worry and energy	Restlessness, irritability and suicide (some differences among different age groups)	Uncontrollable worry-excessive worry(some differences among different age groups)
Bai et al. [20]	College students (N = 3062, N_{Femal} = 2,068; M_{age} = 19.80)	Depressive and anxiety symptoms network in college students in the late stage of the COVID-19 outbreak	Cross-sectional	PHQ-9 & GAD-7	Fatigue, excessive worry, trouble relaxing and uncontrollable worry	Motor; feeling afraid and restlessness	Nervousness - Uncontrollable worry
Garabiles et al. [21]	Nonclinical public (N = 355; M_{age} = 40.5)	Filipino domestic workers employed in Macao	Cross-sectional	PHQ-9 & GAD-7	Fatigue, worry too much and depressed mood	Fatigue, depressed mood and anhedonia	Concentration difficulties - psychomotor agitation/retardation
Marian et al. [22]	Undergraduate Romanian psychology students (N = 126, M_{age} = 22.11; 88.88% female)	Temporal interactions of anxiety and depression symptoms at the level of day-to-day experiences	Intensive	PHQ-9 & GAD-Q-IV	Sad mood and concentration difficulties	Sad mood	Sad mood - concentration difficulties
Bai et al. [23]	Chinese nursing students (N = 932, N_{Femal} = 702; M_{age} = 19.78)	Chinese nursing students during the COVID-19	Cross-sectional	PHQ-2 & GAD-7	Irritability, uncontrollable worry, trouble relaxing and depressed mood	Depressed mood, nervousness and anhedonia	/

Note: N = number; M = mean; PHQ = Patient health questionnaire; GAD = Generalized anxiety disorder

China, at three different time points: March (T1), June (T2), and September (T3) in 2022. During data collection, questionnaires were uniformly distributed through the school's class *WeChat* groups and sent to the parents' phones (students were prohibited from using phones). The class teachers distributed the online questionnaire links, explained the purpose of the survey, and obtained informed consent. A total of 1,968 adolescents participated in March, 2,563 in June, and 2,030 in September. Participants were also free to withdraw at any time. After data collection was completed, data cleaning was performed, and questionnaires that were not submitted within the data collection period (distribution day and the following two days) and those with excessively long or short completion times (2 min < completion time < 10 min) were deleted. Furthermore, the study

retained only those participants who completed all three assessments. Ultimately, 606 participants were included in the study (average age = 16.30 ± 0.69, with 229 males). The corresponding results are presented in Table 2.

Measures

The Generalized Anxiety Disorder-7 (GAD-7) is a self-rating scale for assessing anxiety and is a highly effective tool based on the American Diagnostic and Statistical Manual of Mental Disorders [27]. It has been widely used in anxiety-related research [16, 18, 21]. The scale consists of 7 items (e.g., "Feeling nervous, anxious, or on edge"), with respondents rating their experiences on a 4-point Likert scale ranging from 0 ("never") to 3 ("almost every day"). This study used the Chinese version of the GAD-7, which has demonstrated high reliability and validity among adolescents [28, 29]. The total score indicates the severity of anxiety symptoms. In this study, the internal consistency was consistently strong across all assessment waves (Cronbach's $\alpha = 0.93$, 0.92, and 0.93 at T1, T2, and T3).

The 9-item Patient Health Questionnaire for Depression (PHQ-9) is a highly effective self-rating scale based on the American Diagnostic and Statistical Manual of Mental Disorders [30]. It has been widely used in depression-related research [16, 18, 21]. The scale consists of 9 items (e.g., "I feel sad or empty"), with items 1 through 9 representing different symptoms. Respondents rate each item on a 4-point Likert scale ranging from 0 ("not at all") to 3 ("nearly every day"). This study used the Chinese version of the PHQ-9, which has demonstrated high reliability and validity among adolescents [28, 29]. The total score is used to gauge the severity of depressive symptoms. In this study, the internal consistency was consistently strong across all assessment waves (Cronbach's $\alpha = 0.89$, 0.91, and 0.90 at T1, T2, and T3, respectively).

Data analysis

Before conducting the NA and LNA analyses, this study employed Multi-group Confirmatory Factor Analysis (MGCFA) to assess the measurement invariance of the PHQ-9 and GAD-7 across different time points (T1, T2, and T3) [31, 32]. This analysis involved progressively adding constraints to compare the fit of the configural invariance, metric invariance, scalar invariance, and strict invariance models. The primary fit indices used were χ^2, CFI, TLI, RMSEA, and SRMR. All data analyses were performed using the lavaan package in R version 4.2.2.

Table 2 Descriptive statistics

Time	T1			T2			T3		
	M ± sd	Skewness	Kurtosis	M ± sd	Skewness	Kurtosis	M ± sd	Skewness	Kurtosis
GAD-7									
A1: Anxiety	0.59 ± 0.67	1.17	1.95	0.5 ± 0.62	1.21	1.87	0.59 ± 0.67	1.02	1.24
A2: Uncontrollable worry	0.46 ± 0.64	1.38	2.02	0.39 ± 0.61	1.59	2.85	0.41 ± 0.62	1.61	3.09
A3: Generalized worry	0.54 ± 0.67	1.16	1.36	0.49 ± 0.65	1.34	2.18	0.48 ± 0.65	1.39	2.21
A4: Trouble relaxing	0.53 ± 0.68	1.37	2.13	0.45 ± 0.61	1.39	2.42	0.44 ± 0.64	1.52	2.54
A5: Restlessness	0.34 ± 0.59	1.95	4.35	0.34 ± 0.59	1.93	4.39	0.32 ± 0.57	1.96	4.33
A6: Irritability	0.52 ± 0.69	1.40	2.17	0.5 ± 0.68	1.35	1.88	0.52 ± 0.72	1.53	2.50
A7: Fear of awful events	0.38 ± 0.61	1.75	3.47	0.37 ± 0.63	1.88	3.92	0.34 ± 0.59	1.91	4.35
Below 4 points(n)	412			414			423		
5–9 points(n)	162			163			152		
10–14 points(n)	20			24			22		
15–21 points(n)	12			5			9		
PHQ-9									
D1: Anhedonia	0.45 ± 0.62	1.31	1.76	0.53 ± 0.72	1.51	2.45	0.51 ± 0.68	1.37	2.06
D2: Depressed mood	0.45 ± 0.6	1.25	1.88	0.44 ± 0.63	1.48	2.55	0.45 ± 0.61	1.30	1.86
D3: Sleep problems	0.52 ± 0.69	1.43	2.27	0.62 ± 0.78	1.28	1.40	0.59 ± 0.77	1.25	1.13
D4: Low energy	0.7 ± 0.74	0.93	0.74	0.65 ± 0.78	1.25	1.41	0.64 ± 0.73	1.09	1.16
D5: Appetite problems	0.5 ± 0.67	1.43	2.35	0.59 ± 0.76	1.29	1.36	0.54 ± 0.68	1.13	1.06
D6: Worthlessness	0.44 ± 0.67	1.65	2.74	0.48 ± 0.7	1.58	2.48	0.46 ± 0.71	1.70	2.88
D7: Trouble concentrating	0.42 ± 0.62	1.45	2.15	0.42 ± 0.66	1.78	3.59	0.43 ± 0.64	1.48	2.06
D8: Psychomotor problems	0.36 ± 0.61	1.90	4.15	0.33 ± 0.61	2.10	4.85	0.35 ± 0.63	1.98	3.99
D9: Suicidal ideation	0.18 ± 0.52	3.42	12.61	0.18 ± 0.51	3.38	12.59	0.15 ± 0.42	3.35	13.35
Below 4 points(n)	372			377			367		
5–9 points(n)	178			163			168		
10–14 points(n)	41			43			53		
15–21 points(n)	12			10			14		
Above 19 points(n)	3			13			4		

NA was conducted using the bootnet package in R 4.2.2, incorporating accuracy and stability analyses along with centrality difference tests. Expected Influence (EI), defined as the sum of all edges extending from a given node, was used to measure central symptoms because there were negative edges in the network [33]. The Networktools package was used to calculate bridge centrality in the network, allowing for the identification of central bridge nodes, which play a critical role in communication between communities [34]. Similarly, bridge central symptoms were assessed using Bridge Expected Influence.

The NetworkComparisonTest package was used to compare the results of NA across different time points. The Network Invariance Test was employed to assess whether there were significant differences between two network models, and the Global Strength Invariance Test was used to compare differences in global expected influence between them [35, 36].

LNA was established by referring to the code of Odenthal and colleagues [24]. In the network model, symptoms are represented as nodes, and the direction of the effect is depicted by edge arrows. Positive predictions are shown with green arrows, while negative predictions are shown with red arrows, with the thickness of the arrows indicating the strength of the association. Given that the autoregressive path is typically the strongest path in the network, it was visually de-emphasized to focus on the cross-lag effects, which were most relevant to the study's objectives [37]. In this study, the autoregressive pathway was deliberately set to zero to highlight cross-lag effects and enhance the clarity of the prediction path. The R code to reproduce the current results is openly available on the OSF (https://osf.io/bwdmc/?view_only=74416a90817e42f09f91cd442f14b1de).

Specific data analysis included the following steps: First, the autoregressive path was calculated, representing the regression coefficient of a node from one time point to the next, while controlling for all other nodes. Second, the longitudinal path was computed, predicting one node at one time point from another node at a subsequent time point, taking into account the autoregressive effect and all other nodes. Regression coefficients were calculated using the least absolute shrinkage and selection operator (LASSO) method, with a tuning parameter of 0.5 to minimize the likelihood of spurious edges [38, 39]. Longitudinal network models from T1 to T2 and T2 to T3 were derived using the glmnet package [12, 40]. The visualization of the two cross-lagged network models was achieved using the averagelayout function in the qgraph package [41].

In quantifying the centrality of nodes in cross-lag network analysis, two key centrality metrics are typically used: out-expected influence (out-EI) and in-expected influence (in-EI). Out-EI represents the sum of all outgoing edges from a node, indicating the degree to which a node predicts other nodes in the network. In-EI represents the sum of all incoming edges to a node, indicating the extent to which a node is predicted by other nodes in the network. Nodes with high out-EI can predict a substantial number of other nodes, suggesting that their activation may trigger additional nodes in the network. This metric is especially valued in clinical studies [42].

Stability and accuracy analyses were conducted using the bootnet package [39]. Edge accuracy was calculated from the 95% confidence interval (CI) of the bootstrap weight of the edge, with 1,000 bootstrapped samples. The stability of node centrality in the model was assessed using a subsetting bootstrap approach, where a certain proportion of samples is removed, and the network's centrality is recalculated. If the centrality of the network constructed after excluding most samples correlates highly with the centrality of the original network, the model is considered stable. The Centrality Stability coefficient (CS) served as a reference index, with CS values below 0.25 considered unacceptable. The edge weight difference test and centrality difference test were employed to assess differences in edge weights and centrality metrics, respectively [39].

Results

Multi-group Confirmatory Factor Analysis

First, this study conducted MGCFA on three measurements of PHQ-9 and GAD-7 to assess their measurement invariance across different time points. By gradually adding constraints, the fit of the Configural Invariance model, Metric Invariance model, Scalar Invariance model, and Strict Invariance model was compared, as detailed in Table 3. The results showed that although the model fit indices slightly decreased with each added

Table 3 Model fit of various invariance models for the PHQ-9 and GAD-7 by time

	χ^2	df	CFI	TLI	RMSEA	SRMR
Configural Invariance	1362.49	309	0.94	0.94	0.08	0.04
Metric Invariance	1420.26	337	0.94	0.94	0.07	0.05
Scalar Invariance	1490.17	365	0.94	0.94	0.07	0.05
Strict Invariance	1561.33	397	0.94	0.94	0.07	0.06

Note: χ2=Chi-square; df=Degrees of freedom; CFI=Comparative Fit Index; TLI=Tuker-Lewis Index; RMSEA=Root Mean Square Error of Approximations; SRMR=Standardized root mean squared residual

constraint, these decreases were minimal. Overall, the factor structure, factor loadings, item intercepts, and measurement error variances of the questionnaires remained consistent across different time points. This indicates that the questionnaires possess good measurement invariance.

Network Analysis

Network comparison

Figure 1 illustrated the NA results at three different time points. The number of non-zero edges in different NAs is relatively consistent (n_{T1}=39, n_{T2}=40, n_{T3}=38). And edge weights of the three NAs are highly correlated ($r_{T1\&T2}$ = 0.609, p<0.001, $CI_{95\%}$ = [0.526, 0.680], $r_{T2\&T3}$ = 0.634, p<0.001, $CI_{95\%}$ = [0.555, 0.702], $r_{T1\&T3}$ = 0.650, p<0.001, $CI_{95\%}$ = [0.573, 0.716]). Similarly, the EI of symptoms in the three network models is highly significantly correlated ($r_{T1\&T2}$ = 0.690, p=0.003, $CI_{95\%}$ = [0.295, 0.883], $r_{T2\&T3}$= 0.593, p=0.015, $CI_{95\%}$ = [0.138, 0.841], $r_{T1\&T3}$= 0.546, p=0.028, $CI_{95\%}$ = [0.069, 0.820]).

Results from the network invariance test indicate non-significant differences between NA_{T1} and NA_{T2} (*Test statistic M*=0.255, p=0.25), between NA_{T1} and NA_{T3} (*Test statistic M*=0.187, p=0.82), and between NA_{T2} and NA_{T3} (*Test statistic M=0.304*, p=0.05). The global strength test results demonstrate that the overall EI of the three networks remains stable. Specifically, there are no significant differences in global strength between NA_{T1} and NA_{T2} ($Global\ strength_{NAT1}$ = 5.89, $Global\ strength_{NAT2}$ = 5.91, *Test statistic S*=0.019, p=0.95), NA_{T1} and NA_{T3} ($Global\ strength_{NAT1}$ = 5.89, $Global\ strength_{NAT3}$ = 5.77, *Test statistic S*=0.120, p=0.82), and NA_{T2} and NA_{T3} ($Global\ strength_{NAT2}$ = 5.91, $Global\ strength_{NAT3}$ = 5.77, *Test statistic S*=0.140, p=0.79).

Symptom centrality

Due to the presence of negative correlations in NA in this study, the EI centrality indicator is primarily referenced, with the other two indicators used as supplementary references. The results of the centrality analysis are depicted in Fig. 2, along with the outcomes of the EI centrality difference test (Appendix fig S1). The specific symptom centrality results are as follows: in NA_{T1}, A2 has the highest EI, followed by A5 and D6. In NA_{T2}, A2, D8, and D6 show the highest EI. In NA_{T3}, D6 has the highest EI, with A3, A2, and A6 following closely.

As depicted in Fig. 2, the Bridge Expected Influence analysis reveals that the EI of bridges in A6 and D2 in NA_{T1} is significantly higher than in some other symptoms. In NA_{T2}, A6 and D2 exhibit higher bridge EI compared to other symptoms. Among NA_{T3}, A6 and D6 have the higher bridge EI.

Edges weight

The five strongest edges in the three network models differ. In NA_{T1}, the five strongest edges are A1 and A2 (β=0.333), D2 and D1 (β=0.266), A5 and A6 (β=0.255), D9 and D8 (β=0.238), and D9 and D6 (β=0.212). In NA_{T2}, the five strongest edges are D7 and D8 (β=0.305), D9 and D6 (β=0.280), A1 and A2 (β=0.258), A2 and A3 (β=0.245), and D3 and D4 (β=0.233). For NA_{T3}, the five strongest edges are D3 and D4 (β=0.339), A4 and A5 (β=0.328), A2 and A3 (β=0.290), D3 and D5 (β=0.284), and D1 and D7 (β=0.243). The results of the edge weight difference test are illustrated in Appendix fig S2.

Accuracy and stability

The bootstrap confidence interval results for the edge weights indicate that all three network models are moderately accurate. There is considerable overlap between the $CI_{95\%}$ of the edge weights, although some of the strongest edges do not overlap with the confidence intervals, as illustrated in Appendix fig S3. The bootstrap results for node stability indicate that the EI of nodes and the EI stability of bridge nodes for the three network models are acceptable, as displayed in Appendix fig S4.

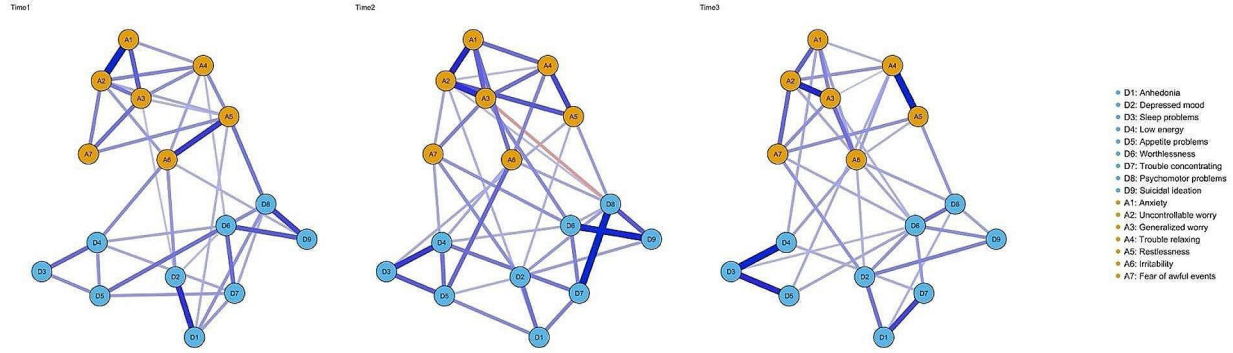

Fig. 1 Network Analysis of Different Time Point

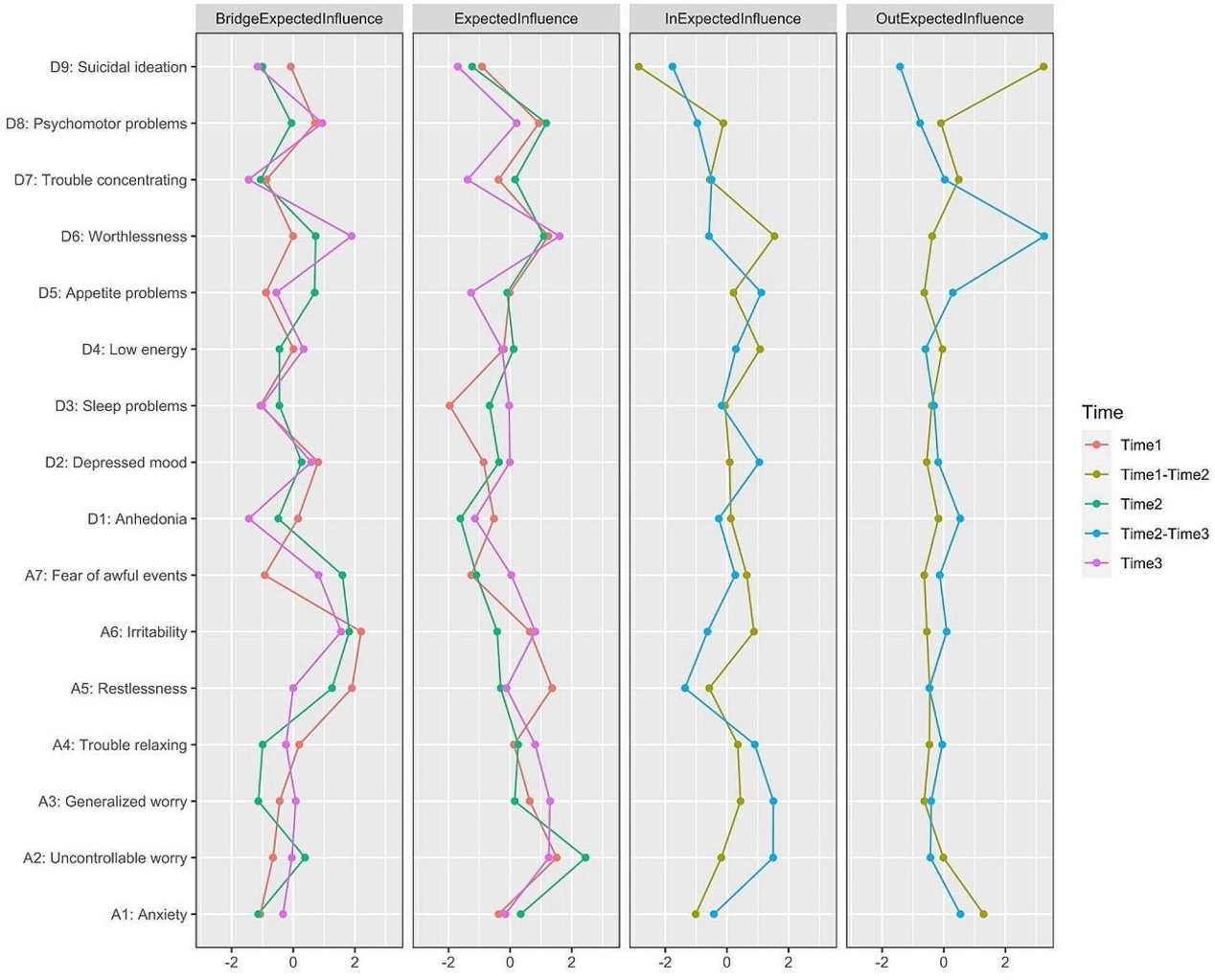

Fig. 2 Centrality Measures of NA and LNA

Longitudinal Network Analysis

Network comparison

The two cross-lagging network models are illustrated in Fig. 3. There are variations in the number of non-zero edges in different cross-lag network models (n_{T1-T2} = 132, n_{T2-T3} = 117). A significant negative correlation was observed between the edges of the cross-lagging network model (r = -0.155, p=0.016, $CI_{95\%}$ = [-0.276, -0.029]). The correlation for out-EI was not significant (r = -0.380, p=0.146, $CI_{95\%}$ = [-0.737, 0.142]), and the overall correlation for in-EI was not significant (r=0.493, p=0.052, $CI_{95\%}$ = [-0.003, 0.795]).

Symptom centrality

The results of the centrality analysis for LNA are displayed in Fig. 2, specifically in the out-EI and in-EI. Combined with the results of the centrality difference test (Appendix fig S5 & Appendix fig S6), it is evident that nodes with high out-EI and in-EI in the LNA exhibit temporal specificity. Notably, the in-EI of D6, D4, and A6 is the strongest, and the out-EI of D9 is the strongest in LNA_{T1-T2}. In LNA_{T2-T3}, A2, A4, and D2 have the strongest in-EI, while D6 has the strongest out-EI. Additionally, this study identified that D9 emitted a positive effect in LNA_{T1-T2}, while a negative effect in LNA_{T2-T3}.

Edges weight

The five strongest edges in the analysis of the two LNAs are not identical, and the results of the edge weight difference test are presented in Appendix fig S7. In LNA_{T1-T2}, the strongest edge is from D9 → D6 (β=0.376), the second strongest is from D9 → D2 (β=0.300), the third strongest is from D9 → D8 (β=0.282), the fourth strongest is from D9 → A3 (β=0.197), and the fifth strongest is from D9 → A7 (β=0.196). In LNA_{T2-T3}, the strongest edge is from D6 → A1 (β=0.250), the second strongest is from D5 → D3 (β=0.211), the third strongest is from D6 → D2 (β=0.206), the fourth strongest is from

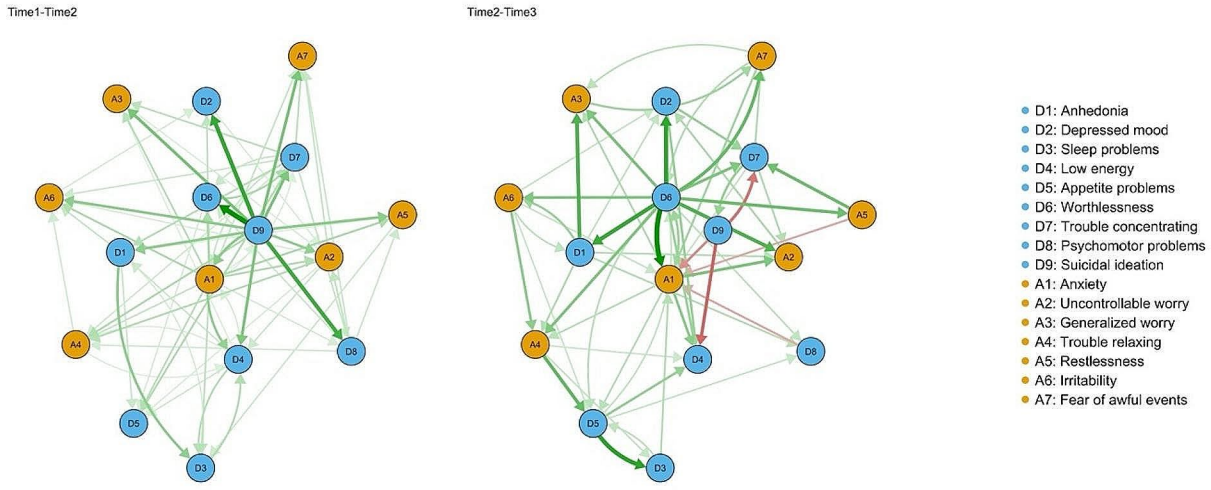

Fig. 3 Longitudinal Network Analysis of Different Time Point

D6 → D1 (β=0.197), and the fifth strongest is from D1 → A3 (β=0.176).

Accuracy and stability

The results of the edge-weighted bootstrap confidence interval indicate that both LNA are moderately accurate. There is substantial overlap between the $CI_{95\%}$ of the edge weights, although some of the strongest edges do not overlap with the confidence interval, as depicted in Appendix fig S8. The bootstrap results for node stability demonstrate that the edge, out-EI, and in-EI stability are acceptable in both networks, as illustrated in Appendix fig S9.

Discussion

This study has shed light on the symptoms and relationships of anxiety and depression in adolescents across multiple time points. The NA results revealed the stability of the network structure and the central symptoms of anxiety and depression in adolescents over time. LNA further identified potential therapeutic targets by analyzing the pathways of symptom development. All network models demonstrated acceptable accuracy and stability, providing valuable insights into the understanding and characterization of anxiety and depression in adolescents.

In all three symptom centrality results of NA, uncontrollable worry consistently exhibited high EI. This symptom has been consistently identified as significant in both clinical and non-clinical studies on anxiety and depression [18–20]. There may be several reasons for this symptom's prominence. Borkovec and Lyonfields suggested that concerns and thoughts about potential adverse events or risks could contribute to its emergence. High school adolescents often face considerable uncertainty, especially regarding their educational future, which aligns with Borkovec and Lyonfields' definition [43]. Additionally, NA results showed that the strong association between uncontrollable worry and anxiety symptoms (T1) might evolve into a strong association between uncontrollable worry and generalized vocabulary symptoms (T3), consistent with the results of Chinese adolescents and college students [18, 19]. This suggests that uncontrollable worry could play a significant role in anxiety and depression among adolescents.

The NA results for symptom bridge centrality revealed that irritability from the GAD-7 emerged as the key symptom with the highest bridge EI among the three network analyses. This finding contrasts with the results of Marian and colleagues [22], who conducted a 21-day intensive tracking study of anxiety and depression in university students, identifying "sad mood" and "concentration difficulties" as significant bridge symptoms. The discrepancy could be due to the fact that our study assessed participants every three months, while Marian et al. [22]. examined anxiety and depression on a daily basis, underscoring the impact of different measurement methods on the network model of anxiety and depression symptoms. Furthermore, this difference might also be due to variations in the study populations, suggesting that future research could explore these differences in more depth.

Irritability is one of the most common presenting problems in child and adolescent psychiatric practice [44, 45]. It refers to a heightened propensity for anger compared to peers [46]. Neuroscientific and behavioral studies have shown that irritability is associated with dysfunction in circuits involving the frontal-striatal-lens-amygdala [46, 47]. Irritability is also recognized as a predominant symptom of depressive disorder in children and adolescents [48]. From a clinical perspective, bridge symptoms

are considered transdiagnostic indicators of comorbid conditions and serve as crucial targets for specific interventions [15]. The results of the present study support this view. In summary, the importance of irritability as a symptom in anxiety and depression highlights the emotional characteristics of adolescents at this stage of development. This observation warrants ongoing attention from educators and school-based mental health professionals.

From a holistic network perspective, most central symptoms in the NA at the three time points do not align with the high-weighted edges. This study suggests that the central symptoms within the anxiety and depression network among adolescents might in a state of high activation and low connectivity, and they remain relatively stable over time [13]. According to Borsboom [10], high activation and low connectivity represent a condition that falls outside the traditional spectrum of both mental health and mental disorders. This indicates that adolescents might in a delicate state of mental health, making them highly vulnerable to anxiety and depression [49]. Individuals in this state exhibit symptoms that are strongly influenced by external events, but these symptoms tend to diminish once those events are removed [13]. When adolescents encounter external stressors, such as the uncontrollable worry symptoms observed in the T2 network of this study, they are likely in a state of high activation and high connectivity. At T2, the participants in this study were going through their final exam period, with exam-related stress may contribute to their state of psychological sub-health [50]. Kumar and colleagues also found that exam stress was associated with a higher prevalence of anxiety, which tended to decrease once the exams were over [51].

The symptom centrality results from the LNA revealed a shift in the central symptoms involved in the development of anxiety and depression, specifically from suicidal ideation to worthlessness, then to anxiety and uncontrollable worry. This finding aligns with the viewpoint of Borsboom and Cramer [14], which suggests that symptoms do not stem from a single underlying cause but actively reinforce (or inhibit) each other, ultimately contributing to the emergence of generalized psychopathological condition [10]. Sowislo and Orth posited that individuals with low self-esteem, characterized by feelings of worthlessness, are more likely to experience anxiety and depression [52]. Rhodes suggested that a positive sense of self-worth could reduce adolescents' vulnerability to the adverse effects of stressors on their mental health [53]. The placement of worthlessness within this sequence aligns with the findings of Van den Bergh et al. [54], underscoring the pivotal role of worthlessness in the development of anxiety and depression.

The result was also consistent with the study by Tao and colleagues which focused on suicidal ideation as a grouping indicator [18], showing a strong association between suicidal ideation and guilt (PHQ6) and nervousness (GAD1). The current result may enhance the understanding of this issue, providing insights into the longitudinal development of symptoms. This indicated that suicidal ideation symptoms may predict the emergence of other symptoms, and the decrease in suicidal ideation also triggered the recovery of other symptoms. The results of the current study suggested that, suicidal ideation in anxiety and depression of adolescents should be considered a significant signal of severe anxiety and depression, and a central target for intervening in anxiety and depression [55]. In future studies, more variables could be added to investigate the impact of suicidal ideation on symptoms of anxiety and depression.

Given the central role of key symptoms in previously reported networks, our findings could guide the customization and evaluation of interventions aimed at reducing the risk of concurrent anxiety and depression in adolescents. It should be stressed that adolescents are in a sensitive state, with a heightened risk of experiencing anxiety and depression. Furthermore, suicidal ideation among adolescents could be recognized as a critical warning signal for these conditions. Symptoms like feelings of worthlessness, uncontrollable worry, and irritability may serve as focal points for interventions addressing anxiety and depression. Lastly, it is crucial and urgent to nurture and strengthen adolescents' psychological resilience and emotional regulation skills.

Certain limitations in this study must be acknowledged. Firstly, the generalizability of current results must be considered. Fried and colleagues compared multiple depression scales and pointed out significant content differences among them, covering 52 different depression symptoms [56, 57]. Similarly, there are analogous issues with anxiety measurement scales [58]. The PHQ-9 and GAD-7 used in this study include only 16 items in total, which may limit the comprehensiveness of the current findings [59]. Future research may attempt to cover a wider range of symptoms, or optimize the network structure using different operationalizations, as suggested by Adamkovič and colleagues [60]. Secondly, this study relied on self-report measures from participants, which can introduce biases or concealment. Additionally, data collection relied on an online platform, which may limit the accuracy of the study's results. Future research could utilize more robust assessment methods. Thirdly, the study's sample was relatively concentrated, potentially limiting its representativeness. Finally, the findings in this study are data-driven and not grounded in a specific theoretical framework. Future research could consider

developing theories of anxiety and depression from a symptomatic perspective.

Conclusion

Drawing insights from both NA and LNA, it is clear that the anxiety and depression network in adolescents exhibits a certain degree of temporal stability, yet also shows signs of partial susceptibility. Within these networks, uncontrollable worry consistently appears as the central symptom, while irritability might play a central role in the comorbidity of anxiety and depression among adolescents. Furthermore, worthlessness and suicidal ideation might be identified as potential therapeutic targets for addressing anxiety and depression in adolescents.

Abbreviations

CS	Centrality Stability coefficient
X^2	Chi-square
CFI	Comparative Fit Index
CI	Confidence Interval
df	Degrees of freedom
GAD-7	Generalized Anxiety Disorder-7
In-EI	In-expected Influence
LNA	Longitudinal Network Analysis
MGCFA	Multi-group Confirmatory Factor Analysis
NA	Network Analysis
out-EI	Out-expected Influence
PHQ-9	Patient Health Questionnaire
RMSEA	Root Mean Square Error of Approximations
SRMR	Standardized Root Mean Squared Residual
TLI	Tuker-Lewis Index

Supplementary Information

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Supplementary Material 1

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Author contributions

L.D.Y. designed the study protocol. Y.M.S. conducted conducted data collection. L.D.Y., Z.X.Y. and C.J.J. conducted data management, cleaning. L.D.Y. wrote the first draft of the paper. Y.H.B. and Z.X.Y. substantially revised the manuscript.

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Data availability

The R code to reproduce the current results is openly available on the OSF .https://osf.io/bwdmc/?view_only=74416a90817e42f09f91cd442f14b1de.

Declarations

Ethics approval and consent to participate

Informed consent was obtained from all participants, while parents' permission was also obtained for those less than 18 years of age. The procedures were carried out in accordance with the Declaration of Helsinki. Ethical approval for this study was also obtained from the ethics committee of Tianjin Normal University.

Consent for publication

Not applicable.

Competing interests

All authors declare that they have no conflicts of interest with this study. However, outside the scope of the present paper, the authors report the following…Dongyu Liu, Xinyu Zhang and Jingjing Cui note that they are postgraduate students at Tianjin Normal University.Meishuo Yu note that she is a postgraduate student at Capital Normal University.Dr. Haibo Yang notes that he is a paid full-time faculty member at Tianjin Normal University.

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