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The impact of primary mental healthcare on core symptoms of depression among underrepresented adolescents: a network analysis perspective

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Abstract

Background Depression has emerged as a leading contribution of the global mental health burden, particularly among underrepresented adolescents. Despite the World Health Organization's promotion of primary mental healthcare as a critical solution, its real-world effectiveness in low- and middle-income countries remains debated due to high costs and insufficient follow-up. This study aimed to explore the impact of primary mental healthcare on the core symptoms of adolescent depression using network analysis, while examining the influence of demographic factors such as gender, age, and family support, to identify more precise and targeted healthcare strategies, improving its effectiveness.

Methods A citywide, multi-center, longitudinal cohort study was conducted in Nanchong, Sichuan Province, China, involving 73,750 adolescents (34,606 girls and 39,144 boys) with median age of 14.00 years old. The Comprehensive Primary Healthcare for Adolescents Program (CPHG) involved two rounds of psychological screening and early intervention. Depressive symptoms were assessed using the Center for Epidemiological Studies Depression Scale (CES-D). Network analysis was employed to map the interrelations between depressive symptoms and evaluate the healthcare's impact.

Results The CPHG program significantly reduced CES-D median scores from 6.00 to 2.00 ($p < 0.001$). Network analysis revealed changes in the structure and centrality of depressive symptoms post-intervention, with specific symptoms such as sadness (C18) showing consistent reductions across subgroups. Gender disparities were evident, with female adolescents exhibiting stronger symptom interconnectivity. Junior high school students also demonstrated a more robust symptom network compared to senior high school students. Adolescents living in social welfare institutions exhibited higher global expected influence of depressive symptoms than those living with both parents.

Conclusions Primary mental healthcare effectively modifies the network structure of depressive symptoms in adolescents, with specific symptoms like sadness being critical targets. Gender and grade-level differences highlight

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the need for tailored mental healthcare strategies. The findings underscore the importance of addressing both core and peripheral symptoms to enhance treatment efficacy and reduce the severity and recurrence of depression among underrepresented adolescents.

Keywords Primary mental healthcare, Depression, Underrepresented adolescents, Network analysis

Introduction

Depression has emerged as one of the leading contributors of the global mental health burden, posing a significant threat to adolescents' psychological well-being [1–4]. According to the World Health Organization (WHO), depression is the primary cause of disability-adjusted life years (DALYs) in adolescents aged 10 to 19 [1]. Adolescence, a critical period marked by significant physical and mental development, is characterized by dynamic changes in physiology, brain function, and social relationships. These transitions amplify psychosocial vulnerabilities and elevate susceptibility to depression [5–8]. Currently, the global prevalence of adolescent depression is rising at a significant rate [2, 9].

The growing mental health crisis among adolescents requires strong policy support. In response, the WHO has advocated community-based mental healthcare—a strategy integrating prevention, early intervention, and treatment into primary health systems—as a cornerstone response [10, 11]. However, despite the decades of implementation, some studies indicate that the impact of primary mental healthcare has fallen short of expectations [12, 13]. This heterogeneity stems from three systemic barriers. First, persistent resource constraints on supply-side significantly hamper the effectiveness of primary mental healthcare. According to the WHO's Mental Health Atlas, the ratio of psychiatrists or mental health professionals to the population is as low as one per 100,000 individuals [14]. Furthermore, in many low- and middle-income countries, mental health expenditure constitutes less than 1% of the total health budget. This inadequate allocation of resources directly constrains the implementation of primary mental healthcare programs, significantly undermining their anticipated effectiveness [11, 15]. Second, demand-side challenges, such as limited awareness of depression as a treatable condition, as well as stigma and social exclusion associated with reduced help-seeking behavior, have also contributed to the suboptimal effectiveness of primary mental healthcare [16]. Patel emphasizes that in low- and middle-income countries, social exclusion and stigma not only reduce patients' willingness to seek treatment but also weaken their family and community support systems, further undermining the sustained effectiveness of primary mental healthcare [17, 18]. Third, the variations in the effectiveness of primary mental healthcare can be largely attributed to symptom heterogeneity in treatment responses. For instance, while some symptoms, such as sleep problems, may improve, others, such as hopelessness, may worsen within the same patient, resulting in no observable change in overall depressive levels [19, 20]. Therefore, it is of significant interest to evaluate the real-world effectiveness of primary mental healthcare and to explore the mechanisms underlying these heterogeneous treatment responses [11, 21].

Heterogeneity in the real-world effectiveness of primary mental healthcare may reflect distinct depression symptom profiles moderated by demographic characteristics [22]. Demographic differences, including gender [23], grade level [24], and parenting style [25], may lead to distinct structural characteristics of depressive symptom networks. Fried et al. [26] found that in females, the depressive symptom network demonstrates stronger connections between affective symptoms (e.g., sadness and hopelessness) and somatic symptoms (e.g., fatigue and sleep disturbances). In contrast, in males, cognitive symptoms (e.g., self-criticism and feelings of worthlessness) tend to occupy a more central role within the network [27].

Furthermore, research indicates that the network centrality of depressive symptoms in adolescents may vary with advancing grade levels [24]. Parental and family factors also emerge as critical determinants of mental health outcomes among adolescents. A substantial body of evidence highlights the protective role of supportive family environments in reducing the risk of mental health disorders and improving the efficacy of therapeutic interventions [28, 29]. Adolescents who perceive strong familial support are more likely to utilize mental health services and adhere to treatment plans, leading to more favorable outcomes. Conversely, adolescents from dysfunctional or unsupportive family environments often encounter significant barriers to accessing and benefiting from mental healthcare. This study aims to examine the interplay of gender, age, and family support in shaping the effectiveness of primary mental healthcare for adolescents. Applying a comprehensive analytical framework, this study seeks to clarify the differential impacts of these factors and offer evidence-based recommendations to improve mental health service delivery for this vulnerable population.

Given the high interdependence and mutual influence of depressive symptoms [20] as well as the demands for symptom-level precise intervention measures, a network approach to analyzing intervention effects is particularly advantageous. Unlike conventional scale-summary approaches, network analysis maps how interventions take effect through symptom-to-symptom pathways [30]. Recent studies employing network analysis have uncovered complex relationships among core symptoms of depression, demonstrating how mental healthcare can modify these networks and potentially inform more effective treatment strategies [31, 32]. A recent longitudinal network analysis on adolescent anxiety and depression revealed that core symptoms like worthlessness and suicidal ideation exhibit bidirectional temporal influences, suggesting that interventions targeting these central nodes could disrupt symptom cascades [33]. This aligns with the theoretical framework of our study, which posits that primary mental healthcare may modify network connectivity through symptom-specific pathways.

Despite the widespread implementation of primary mental healthcare services, persistent resource limitations—particularly chronic underinvestment in low-income areas—have constrained their effectiveness. Given these constrained resources, it becomes imperative to adopt a more targeted focus on specific core symptomatic manifestations. This necessitates implementing symptom-level network analysis among underrepresented adolescents to uncover complex symptom interactions, thereby informing the development of precision healthcare strategies. This study aims to address this gap by utilizing network analysis to investigate the complex relationships between core symptoms of depression and the effects of primary mental healthcare. By focusing on the unique challenges faced by adolescents, such as gender disparities, age, and family support, this study aims to enhance understanding of how these factors shape treatment outcomes. Ultimately, the study aims to offer insights that could inform more effective and sustainable mental healthcare strategies for adolescents.

Methods

Healthcare procedure

The healthcare was conducted in Nanchong, Sichuan Province, China, as a citywide, multi-center, population-based longitudinal cohort study. The primary objective was to assess the real-world effects of the Comprehensive Primary Healthcare for Adolescents Program (CPHG) on mitigating the risk of depression in adolescents [34]. Nanchong, a city with a mid-to-low economic profile in western China, was selected as the study site to represent the typical challenges faced by economically disadvantaged regions. The CPHG program [34] established 385 healthcare service centers and social welfare institutions across Nanchong to provide comprehensive primary mental healthcare for middle and high school students. The program established a system on controlling the risk of depression as well as suicidal ideation, which mainly involved psychological healthcare practice, psychological healthcare education, psychological healthcare training, and psychological healthcare management [34]. Psychological healthcare practice was designed as a "2 +2" pattern with two rounds of psychological screening and two rounds of early psychological care. Psychological healthcare education refers to a series of scientific popularization efforts targeting parents of primary and middle school students, teachers, personnel involved in work related to minors, and volunteers, which includes both online and offline methods. Psychological healthcare training refers to the instructional program focusing on knowledge and skill development for full-time (or part-time) teachers of psychological healthcare within primary and middle schools. This training encompasses fundamental counseling techniques, psychological crisis intervention, identification and management of severe mental disorders, diagnostic interview techniques, design and implementation of group counseling, school reintegration-related issues, ethics and legal regulations, as well as group counseling and case supervision. Psychological healthcare management includes the establishment of integrated information platforms, coordinated management platforms, and comprehensive service platforms to ensure unimpeded data and information flow across all teams, thereby enhancing collaborative efforts among working groups.

Specifically, the "2 +2" psychological healthcare practice is the core procedure of CPHG. All enrolled children and adolescents were initially screened for depressive symptoms by the Center for Epidemiological Studies-Depression Scale (CES-D) [35] as part of the first round of psychological screening. The second round of psychological screening focused on individuals identified as at risks for depressive symptoms during the first round. Following the two rounds of screening, individuals identified with severe depression received two rounds of specific psychological care (the latter "2" in the "2 +2" workflow). In the subsequent psychological healthcare phase, children and adolescents identified with depression underwent the first round of psychological care, which was administered by qualified psychological healthcare specialists. A subset of these children and adolescents was referred to government-sponsored mental health center for clinical medical treatments based on specialist recommendations, constituting the second round of the latter "2".

Study design and participants

Participants were selected from the CPHG program based on the following inclusion criteria: [1] adolescents aged 12—18 years, (2) enrolled in participating schools or social welfare institutions, and (3) providing informed consent, The study utilized a large-scale, multicenter cohort (n= 249,772) [34] to examine the effects of the entire CPHG system on depression among underrepresented children, in which the exposure factor was whether participant was included in this system. For this analysis, data from the first and second rounds of screening were used for statistical analysis. Based on the exclusion criteria—including (1) current psychiatric diagnosis requiring immediate clinical intervention, (2) cognitive impairment, (3) inability to participate in activities, or (4) with incomplete demographic information—we excluded several groups of participants, resulting a final matched dataset comprised 73,750 adolescents (34,606 girls and 39,144 boys). The median age was 14.00 years (interquartile range [IQR]: 3.00 years).

Measure

Demographic information was collected as part of the mental health screening process. Depressive symptoms were assessed using the Chinese version of the Center for Epidemiologic Studies Depression Scale (CES-D) [35]. The CES-D is a brief self-report scale developed to measure depressive symptoms in the general population [36]. The scale comprises 20 items, each rated on a 4-point scale ranging from "0" (rarely or none of the time) to "3" (most or all of the time), with four items (4, 8, 12, and 16) reverse-scored. Total scores range from 0 to 60, with higher scores indicating greater depressive symptom severity [35]. The CES-D has demonstrated good reliability and validity among both adolescents and children [37–39]. In the present study, the CES-D demonstrated excellent internal consistency, with a Cronbach's α coefficient of 0.95, and showed good construct validity.

Statistical analyses

Descriptive statistics

For descriptive statistics, the median, interquartile range (IQR), kurtosis, and skewness were calculated for the CES-D. Given the non-normal distribution of the data, the Wilcoxon signed-rank test was employed to assess whether a significant overall change in depression scores occurred following the intervention. Demographic characteristics and descriptive statistics were performed using IBM SPSS Statistics 25.0 [40].

Network estimation

To investigate the underlying mechanisms of depression and identify potential targets for healthcare, network analysis was used to map the interrelationships between individual depressive symptoms [30]. All network analyses were performed using R scripts [41] in RStudio (Version 4.2.2) [42]. The network was estimated using a Gaussian Graphical Model (GGM) approach, implemented with the Least Absolute Shrinkage and Selection Operator (LASSO) regularization to enhance network sparsity. The Extended Bayesian Information Criterion (EBIC) was applied to select the optimal set of factors for each node [43, 44]. GGM estimates conditional independence relationships via partial correlations, differentiating direct symptom interactions from indirect effects mediated by shared variables (e.g., spurious correlations arising from third symptoms). This ensures that only clinically meaningful connections are retained. LASSO regularization further enhances robustness by imposing sparsity constraints on the precision matrix, effectively filtering out unstable or weak edges and preventing overfitting, particularly in high-dimensional data with limited samples. The integration of GGM and LASSO balances sensitivity to true symptom associations with specificity against spurious links, aligning with methodological standards in psychopathological and biomedical network analyses [43, 45].

The symptom network consists of nodes (representing individual depressive symptoms) and edges (representing partial correlations between symptom pairs) [30]. After connecting each node to several other nodes, the network is automatically constructed, displaying the strength of direct relationships between nodes. In the network graph, nodes that are more frequently and strongly associated with other nodes are positioned at the center, and the strength of associations between nodes is indicated by edge thickness [46].

Network centrality

In the analysis of network centralities, Expected Influence (EI) was selected over Strength due to its sensitivity to the directionality of edges (i.e., positive vs. negative weights), which aligns with theoretical assumptions of causal interactions in psychopathological networks. Unlike Strength, which aggregates absolute edge weights and may overestimate the importance of nodes with inhibitory connections, EI accounts for the net influence of a node by summing signed edge weights, measuring a node's overall impact in a network by summing the weights of its connections to other nodes, considering both positive and negative effects, thereby better reflecting its potential to activate or suppress other nodes in the network [47]. The higher EI values indicate greater centrality within the network [48]. This analysis was performed using the "qgraph" [46] package, and the results are visualized as standardized scores (z-scores).

Centrality stability tests

According to the recommendations of Bringmann et al. [49], we assessed the robustness of the network solution by estimating the accuracy of edge weights and the stability of centrality indices using the R package "bootnet" [50]. We employed non-parametric bootstrapping to calculate 95% confidence intervals for the accuracy of edge weights. Wider confidence intervals indicate lower precision in edge estimates, whereas narrower intervals suggest higher network reliability. Further, we conducted case-dropping subset bootstrapping (1,000 samples) to calculate correlation stability coefficient (CS-C), which evaluates the stability of centrality indices. If the centrality indices of a node do not change significantly after removing a subset of samples from the dataset, the network structure is considered stable [50]. The CS-C should not fall below a certain threshold (i.e., 0.25) to ensure stability.

Time-variant and subgroup analyses

After confirming the network's stability, we performed time-variant and subgroup analyses to examine intervention effects and demographic variations. We focused on changes in the expected influence of the depression symptom network before and after the primary mental healthcare as well as the subgroup differences. Using the "NetworkComparisonTest" (NCT) [51] package in R, we applied a permutation test with 1,000 iterations to assess differences. We built and compared symptom networks through 1,000 bootstrap resamples to derive the null distribution of network differences, maintaining a significance level of 0.05 (corrected by false discovery rate (FDR) correction).

The NCT evaluates within-participant differences across intervention in three main areas: (1) global expected influence, which is the total of nodes' direct or potential indirect effects in the network, (2) structural invariance, which looks at significant changes in relationships between variables and nodes, and (3) edge and centrality invariance, which focuses on changes of specific edges or nodes centrality indices. However, as for subgroup network comparisons, we mainly concentrated on (1) global expected influence and (2) structural invariance.

Result

Sample characteristics

All demographic variables and descriptive statistics are presented in Table 1. The sample comprised 46,027 (62.4%) junior high school students, and 27,723 (37.6%) senior high school students. In terms of family support, 25,712 live with both parents, 23,743 live with one parent, 23,600 live with other relatives, and 695 live in a social welfare institute. Results of CHPG showed significant effects of practicing this system on preventing depression among individuals; the CES-D median score decreased from 6.00 to 2.00 ($p < 0.001$) compared to the first round.

Table 1 Demographic characteristics and descriptive statistics of the participants

Variables	N (73,750)	%	Median	IQR
Age	73,750		14.00	3.00
Gender				
Female	34,606	46.9		
Male	39,144	53.1		
Grade				
Junior students	46,027	62.4		
Senior students	27,723	37.6		
CES-D				
First round			6.00	14.00
Second round			2.00	8.00
Living status with parents				
Living with both parents	25,712	34.9		
Living with one parent	23,743	32.2		
Living with other relatives	23,600	32.0		
Living in the social welfare institute	695	0.9		

N number of valid samples, *IQR* interquartile range, *CES-D* Center for Epidemiologic Studies Depression Scale

Network analysis

Network estimation and visualization

The network of depressive symptoms following two rounds across primary mental healthcare is displayed in Fig. 1, with detailed edge weights provided in Supplementary Table 1S and 2S. Centrality indices, including strength, betweenness, closeness, and expected influence were calculated for the symptom networks at both time points, and comparisons of these values is illustrated in Fig. 2. In alignment with previous research, which emphasizes the reliability of symptom rankings based on centrality measures, our analysis primarily focuses on symptom expected influence as the indicator of the symptom's global importance within the network. Accordingly, interpretations of network structure and changes over time are centered on these centrality measures.

Network structure and edge weight

In the first round, the symptom network contained 145 non-zero edges out of 190 possible connections (Supplementary Table 1S). Notable connections included the association between C8 (Hopeful) and C9 (Feeling like a failure) with the strongest edge weight, followed by the

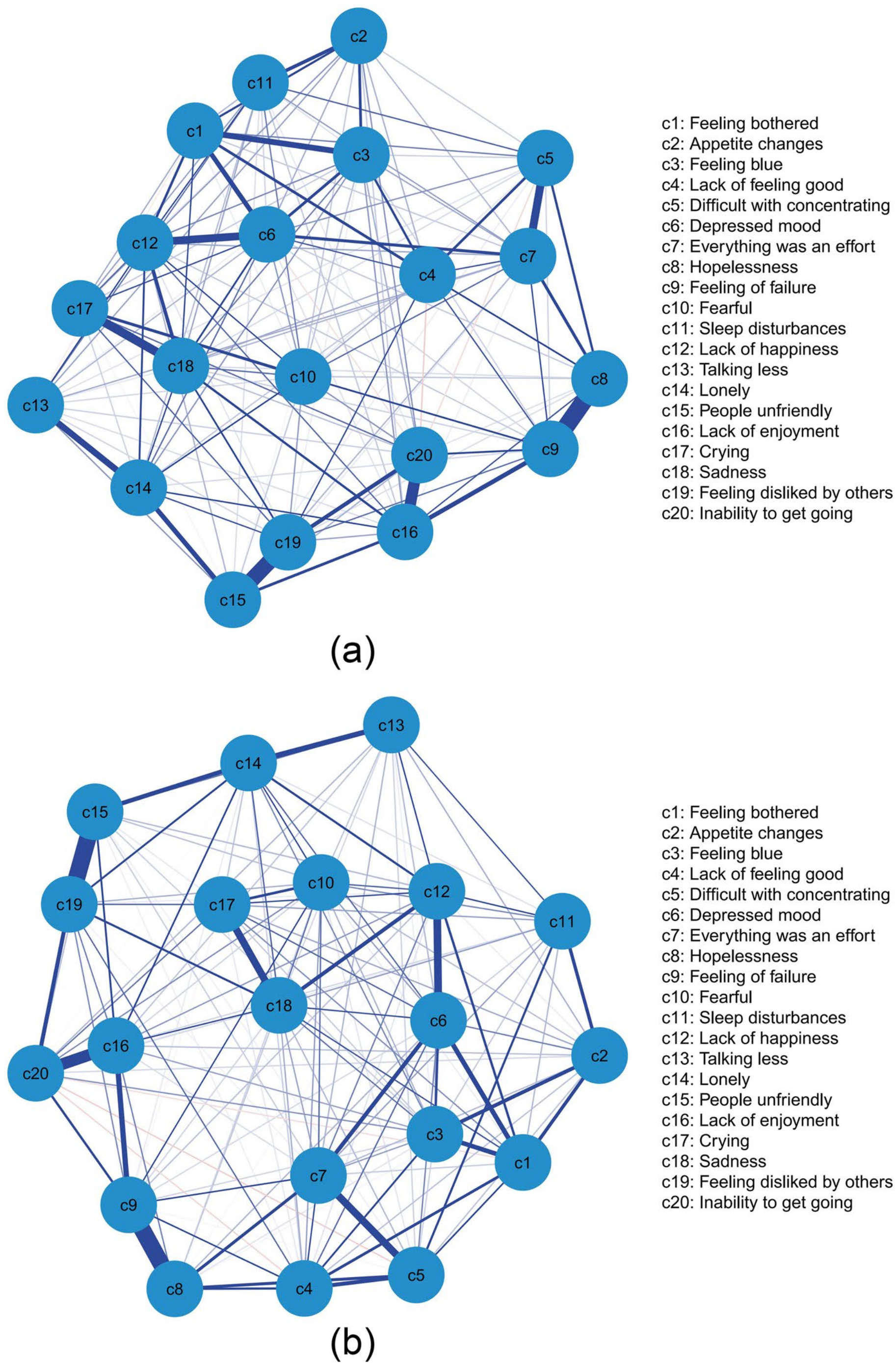

Fig. 1 Estimated network model for adolescent depressive symptoms (N = 73,750). Note: (**a**) the first round; **b** the second round. Red edges represent negative connections

connection between C15 (People unfriendly) and C19 (Feeling disliked by others) as well as the edge between C16 (Life is interesting) and C20 (Inability to get going) in weights. The network expanded slightly with structural changes (M = 0.037, p = 0.002) in the second round, of which 150 edges out of 190 possible connections were non-zero (Supplementary Table 2S). The strongest association in this round was between C15 (People unfriendly) and C19 (Feeling disliked by others). This was followed by the connections between C8 (Hopelessness)

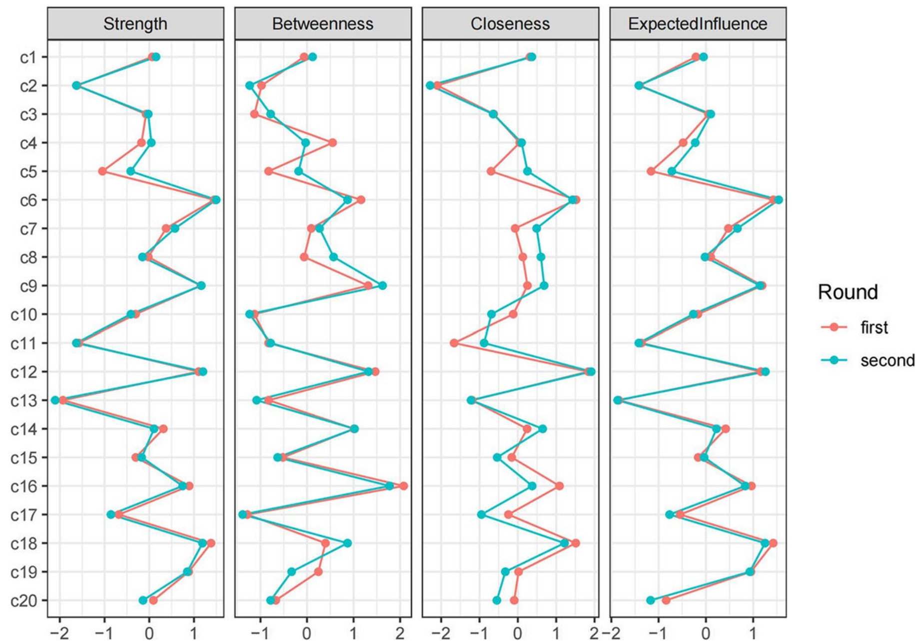

Fig. 2 Centrality indices of depressive symptoms, shown as standardized values z-scores. Note: The red line indicates the first-round intervention of CPHG and the green line indicates the second round

and C9 (Feeling like a failure) and between C16 (Lack of enjoyment) and C20 (Inability to get going).

Network centrality

Regarding node expected influence, there was no obvious shift in the centrality ranking of symptoms between the two rounds of primary mental healthcare. However, the bootstrap difference test confirmed that the changes in global expected influence and node expected influence between the two-time points were statistically significant. Specifically, the global expected influence slightly expanded (S =0.077, $p <$ 0.001) after intervention, indicating that the symptoms affected each other more closely. Among the nodes, C2 (Appetite changes), C4 (Lack of feeling good), C5 (Difficult with concentrating), C7 (Everything was an effort), C11 (Sleep disturbances), and C15 (People unfriendly) increased obvious in expected influence after intervention, whereas C14 (Lonely), C16 (Lack of enjoyment), and C18 (Sadness) decreased (Fig. 2. See Supplementary Table 3S for details). These results reinforced the relevance of these central symptoms in the progression or alleviation of depression, among which emotional related symptoms (C14, C16, and C18) played important roles in weakening the symptom connections along with the intervention period. Additionally, the nodes C2 (Appetite changes), C11 (Sleep disturbance), C13 (Taking less), and C20 (Inability to get going) stayed peripheral. This indicated that although there were some changes for centralities, these nodes demonstrated less importance within the networks across intervention. Among them, C20 (Inability to get going) only decreased on expected influence, suggesting that it may contributed to global weakening of the network rather than affected its local part.

Network stability and accuracy

Applying case-dropping bootstrap methods (n= 1,000), the stability analysis of the network demonstrated that the centrality indices (i.e., strength, betweenness, closeness, and expected influence) exhibited exceptionally high stability, with a correlation stability (CS) coefficient of 0.75. This indicated that the centrality measures remained highly consistent even when up to 75% of the sample data was removed (Fig. 3).

We used the non-parametric bootstrapping (n= 1,000) method to calculate the edge weight accuracy. Figure 4 demonstrated the close alignment of the bootstrapping mean with the original sample, which indicated high accuracy across healthcare.

Subgroup analysis

We performed network comparison tests to examine differences in global expected influence across gender, grade level, and parenting style subgroups before and after the healthcare. Gender-based analyses revealed significant differences on network structure across time (Time1: M= 0.060, $p <$ 0.001; Time2: M= 0.067, $p <$ 0.001). Notably, the global expected influence of depressive symptoms

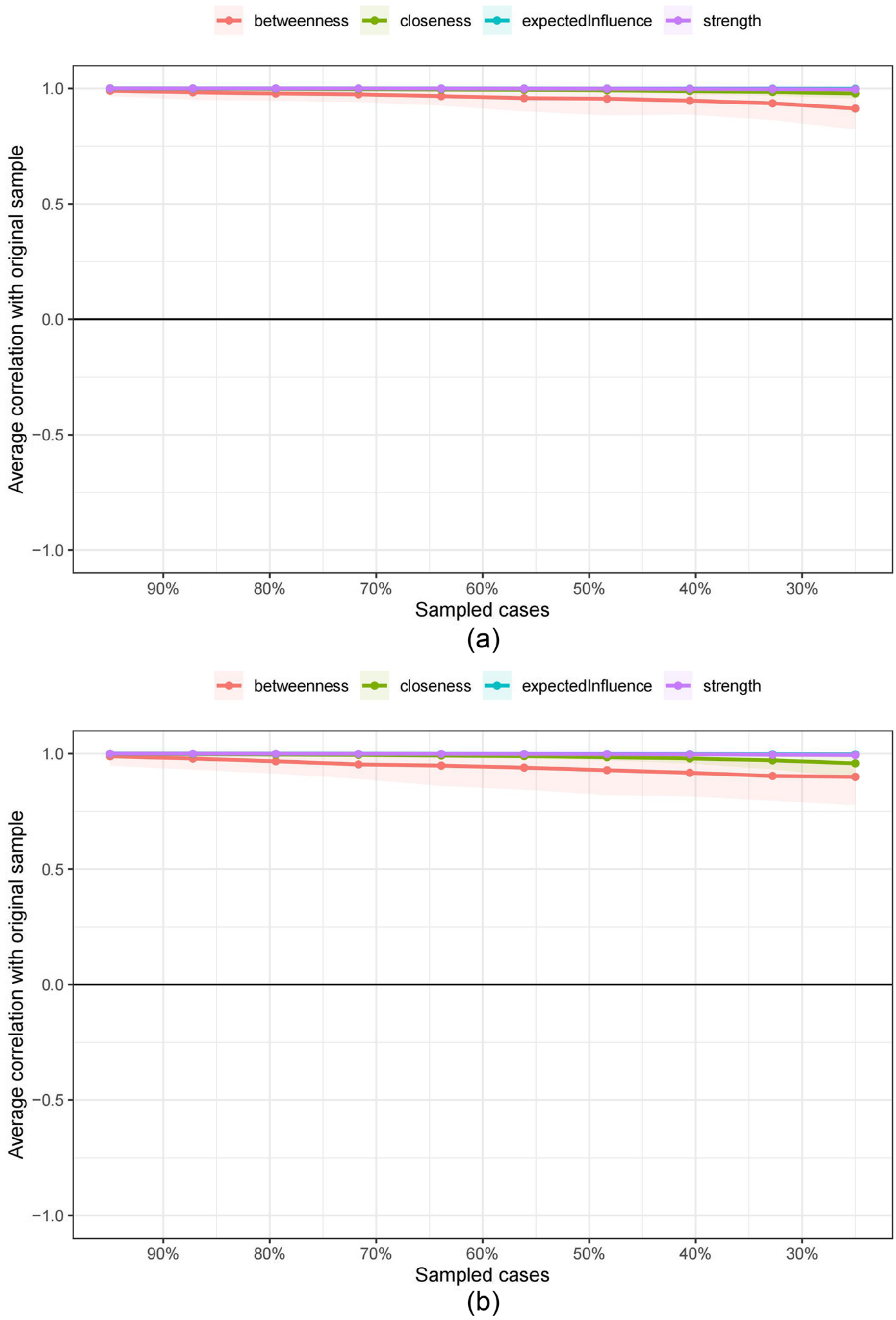

Fig. 3 Average correlations with the original sample. Note: (**a**) the first round; **b** the second round. The X-axis represents the percentage of the original sample used in each subset. The Y-axis depicts the average correlation between centrality indices in the original network and those in the re-estimated networks after excluding the corresponding percentage of cases

was significantly higher in girls compared to boys at both time points (Time1: S= 0.090, $p<$ 0.001; Time2: S= 0.076, $p<$ 0.001), suggesting stronger interconnectivity of depressive symptoms in female adolescents before and after mental healthcare.

Subsequently, we examined the grade-level differences in depressive symptom networks. Significant variations emerged between high and low grades both before (M =0.052, $p=$ 0.003) and after (M =0.092, $p<$ 0.001) primary healthcare. The global expected influence was

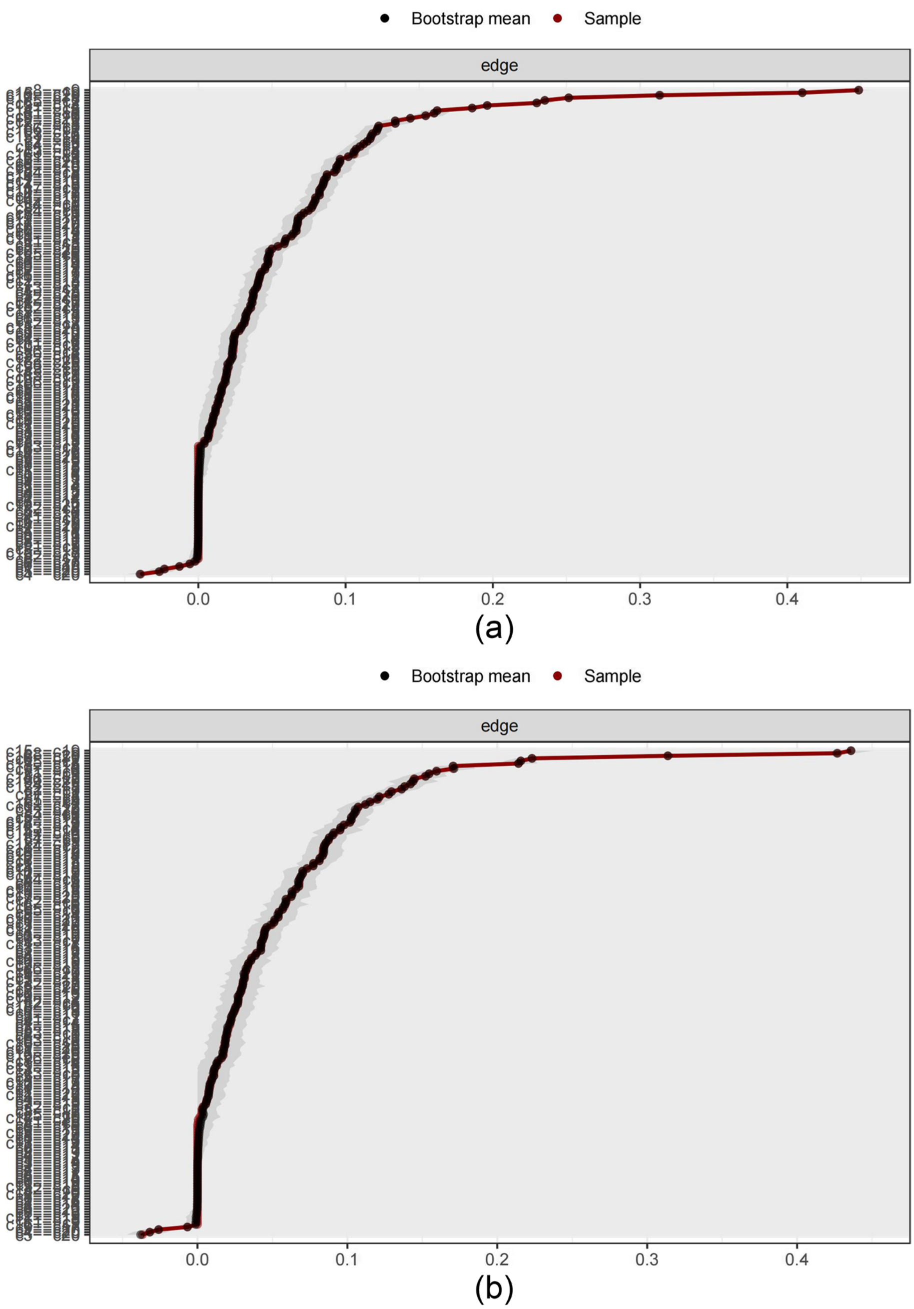

Fig. 4 Bootstrap means of the edge weights. Note: (**a**) the first round; **b** the second round

higher in the junior high school group than in the senior high school group across the two time points (Time1: S = 0.041, p = 0.005; Time2: S = 0.043, p = 0.004).

We next examined the depressive symptom networks for adolescents under different living statuses with parents. Network variance was only found between those living with both parents and living in the social welfare institute. There was significant difference (M = 0.252, p = 0.049) on network structure after healthcare, while no structural difference (M = 0.178, p = 0.326) was found before intervention. Notably, adolescents living with both parents demonstrated lower global expected influence than those living in the social welfare institute before and after intervention (Time1: S = 0.200, p = 0.017; Time2: S = 0.180, p = 0.043). These results indicate that adolescents living in the social welfare institute exhibit stronger depressive symptoms connections than those who live in normal environment.

Additionally, we tested the within-participant changes of each subgroup followed by the primary healthcare. Participants living in the social welfare institute showed significant (S $=0.134$, $p= 0.043$) elevation on global expected influence of the depressive symptoms network after healthcare. Moreover, other subgroups (i.e., female, male, senior students, junior students, living with both parents, living with one parent, and living with other relatives) also demonstrated significant while more similar increase on expected influence (S: 0.057–0.089, $p= 0.001$) aligning with the total. Specifically, the node C18 (Sadness), which is the core emotional symptom of depression, decreased in expected influence after intervention across the participants classified as "female" ($p= 0.011$), "junior students" ($p= 0.011$), "living with one parent" ($p= 0.010$), and "living with both parents" ($p= 0.040$). This result indicated that C18 (Sadness) might be regarded as a key useful target in interventions among these subgroups.

Discussion

This study employed network analysis to examine the impact of primary mental healthcare on the core symptoms of adolescent depression. By focusing on gender, grade, and parenting style, we sought to provide a deeper understanding of how these demographic factors influence treatment outcomes and assess the overall efficacy and specific targets of primary mental healthcare. The results offer several important insights into the relationships between depressive symptoms and the effects of primary healthcare, which could inform future mental healthcare strategies.

Effectiveness of primary mental healthcare

Our network analysis reveals that primary mental healthcare significantly expands the depressive symptom network structure and enhance the between-symptom connection strength in adolescents, with reduced influences of certain symptoms (e.g., "Sadness" and "Lack of enjoyment"). This suggests the interventions may not sufficiently address depressive symptoms as an interconnected system, but rather target individual symptoms in isolation. However, the observed shift in centrality of the symptoms like C14 (Lonely), C16 (Lack of enjoyment), and C18 (Sadness) after intervention highlights the potential amendable targets in reducing the interconnectedness of specific depressive symptoms. Among these, C18 (Sadness) demonstrates stable changes by intervention across different subgroups, reveal that it is critical in controlling the expanding of depressive symptoms network, thereby mitigating the severity and recurrence of depression. These results align with existing research emphasizing the evolving nature of depression during adolescence, where emotional regulation and self-perception become increasingly central as individuals mature [52, 53]. The finding is also supported by recent studies indicating that reducing symptom connectivity can interpret treatment outcomes [54, 55]. Specifically, C18 (Sadness) emerges as a pivotal hub in the depressive symptom network, exerting bidirectional influences on emotional regulation and social functioning. Persistent sadness disrupts the dynamic equilibrium of brain networks—particularly the default mode network (DMN) and attention networks—by amplifying self-referential mentation while impairing goal-directed attention to external stimuli [56]. This neural imbalance exacerbates emotional dysregulation and social functioning problems [57]. Research demonstrates that cognitive reappraisal (a kind of emotional regulation manner) and social support seeking mitigates sadness, which also indicates the hidden mechanism of the influence of sadness [58]. However, the persistence of peripheral but indirectly affective symptoms such as C2 (Appetite changes), C11 (Sleep disturbance), and C13 (Talking less) which may even increase the severity of depressive network indicates that while interventions effectively diminish the impact of some symptoms, less prominent symptoms may necessitate additional, targeted treatment approaches. This suggests a need for comprehensive strategies that address both critical and peripheral symptoms to enhance overall treatment efficacy.

Gender disparities

Two significant findings from this study are that (1) "sadness" may be a critical symptom for weakening of the network among girls rather than boys, and that [2] the consistently higher average network expected influence of depressive symptoms in girls compared to boys, both before and after mental healthcare. This more robust interconnectivity of symptoms among female adolescents aligns with previous studies, which have demonstrated that girls are more likely to experience emotional co-activation [59, 60]. The observed gender disparities in symptom interconnectivity, with girls exhibiting stronger networks of depressive symptoms compared to boys, can be contextualized within broader psychosocial and developmental frameworks. During adolescence, girls often experience more pronounced emotional co-activation, which may be attributed to several factors. First, from a developmental perspective, girls tend to mature earlier than boys both physiologically and emotionally, which can lead to heightened sensitivity and reactivity to stressors [61]. This early maturation may result in a greater propensity for emotional co-activation and symptom interconnectivity. Second, socialization processes play a crucial role. Girls are often socialized to be more emotionally expressive, whereas boys are typically encouraged to suppress their emotions [62]. This gendered socialization can lead to a stronger interconnectedness of emotional symptoms in girls, as they are more likely to ruminate and co-activate multiple emotional states. These results suggest that primary mental healthcare for girls may need to address not only the core symptom of depression but also the heightened emotional reactivity that tends to sustain symptom networks. Meanwhile, research indicates that hormonal and social factors may contribute to this increased emotional reactivity in girls, necessitating tailored intervention strategies [63]. Therefore, future research should focus on gender-specific adaptations to mental healthcare to improve treatment efficacy for female adolescents. Such adaptations could include techniques to enhance emotional regulation and resilience, effectively reducing symptom interconnectivity [64, 65].

Age and grade-level differences

Our analysis also reveals significant differences in the global expected influence of depressive symptoms between junior and senior high school students. The symptom network is more robust in the junior high group across the two rounds of care, which aligns with a similar previous study that junior grade students, especially those at the first grade demonstrate high level of depression [66]. This may attribute to the difficult adjustment of new environment from primary school to middle school [66]. Research suggests that as adolescents entering new environment may encounter unfamiliar interpersonal relationship and poor social support, potentially exacerbating stress and emotional challenges [67, 68]. These pressures can intensify the interconnectedness of depressive symptoms, highlighting the need for age-specific interventions that address these unique stressors. Understanding these age-related shifts is crucial for tailoring interventions to the specific needs of adolescents at different developmental stages, ensuring that mental healthcare strategies are both relevant and practical.

Influence of family support

The results of our subgroup analysis based on parenting style provide further insight into the role of family support in adolescent mental health. The significantly lower network global expected influence observed in both-parents children compared to children living in social welfare across the intervention suggests that absence of parenting may lead to severe depression, which agrees with previous studies [69–72]. Meanwhile, the global expected influence of depressive network for children living in social welfare increases slightly after intervention, there is no changes on any of the symptom's expected influence. The attenuated intervention response observed among adolescents in social welfare institutions may stem from multifaceted psychosocial vulnerabilities. First, institutionalized adolescents or children frequently experience diminished social support networks compared to family-reared peers [73]. Second, chronic resource and support shortage result in cumulative stress burdens [74]. Third, transient caregiver-student relationships in institutional settings undermine the therapeutic alliance critical for intervention success [74]. This calls for more focused and systematical healthcare measures for institutionalized adolescents or children. However, although the global expected influence for parenting style subgroups like "living with one parent" and "living with both parents" increases obviously, the symptom "Sadness" plays an important role in reduce the network connectivity, which agrees with previous study indicating that sadness is among a causal chain of feelings and emotions triggered by a stress life event [75], while there is no direct evidence that intervention on sadness can mitigate the depressive symptoms. These groups' adverse total changes underscore the importance of advancing family-centered approaches into mental healthcare strategies, especially focusing on specific key symptoms that directly linked with distress emotion itself. This highlights the need for more comprehensive mental health policies that incorporate family-centered approaches, particularly for adolescents in high-risk family situations. Additionally, more innovative and effective intervention approaches need to be considered for children with no parents.

Implications for mental healthcare strategies

The network analysis conducted in this study provides a unique perspective on how primary mental healthcare affects the relationships between depressive symptoms over time. By identifying the core symptoms that remain central to adolescent depression networks, our results offer valuable insights for designing more targeted and effective interventions. Specifically, the core role of sadness and its hidden mechanisms among the depressive symptom network call for more precise healthcare or clinical intervention targets on emotion regulation and social support. Moreover, the demographic disparities observed across gender, age, and family support underscore the importance of personalized care strategies that address the unique challenges faced by different subgroups of adolescents. For girls, interventions should prioritize emotion-focused approaches targeting heightened symptom interconnectivity. Junior high students transitioning to new environments require school-based programs that strengthen peer support networks and adaptive coping skills during critical adjustment periods. Adolescents in social welfare institutions need systemic, trauma-informed care with consistent caregiver relationships to address chronic stressors and fragmented support systems.

In conclusion, this study underscores the significant contributions of network analysis in elucidating the complex interplay of depressive symptoms among adolescents undergoing primary mental healthcare. Our findings offer a nuanced understanding of how these interventions can be optimized for greater efficacy by pinpointing core emotional symptoms and highlighting demographic disparities. The potential value of this research lies in its ability to inform the development of more direct, precise and personalized treatment strategies.

Limitation

While this study provides valuable insights into the impact of primary mental healthcare on adolescent depression, several limitations should be acknowledged. First, the absence of a standard randomized controlled trial (RCT) because of ethical constraints and the lacking of considering other potential confounding variables (e.g., left-behind children, only-child status, and socioeconomic status, etc.) limit our ability to establish causality, which may affect the internal validity of the findings. Future research with RCT designs focused on specific population would strengthen the evidence. Second, we lacked clear metrics to assess the quality of care provided. Including such measures in future studies would better understand intervention effectiveness. Third, our sample was drawn from a provincial population, which may limit the broader applicability of our findings. Further research in diverse regions is needed to confirm these results. Lastly, when conducting subgroup analyses, analyzing the interaction effects of grouping variables can make the network analysis highly complex and reduce the interpretability of the results. Therefore, we analyzed the effects of each grouping variable separately. Thus, when examining the effect of one variable, the potential confounding effects from other variables cannot be controlled well. Future research should develop more appropriate network analysis methods to enable multivariate analysis and improve the interpretability of results.

Conclusion

This study utilized network analysis to explore the impact of primary mental healthcare on core symptoms of depression among adolescents. By examining the relationships between depressive symptoms and considering vital demographic factors such as gender, age, and family support, we gained valuable insights into the effectiveness of these interventions. Our findings revealed significant changes in the structure of symptom networks, highlighting the dynamic response of core depressive symptoms to mental healthcare. Gender disparities were evident, with girls exhibiting more robust symptom interconnectivity than boys, while age-related differences indicated that lower grade demonstrated stronger symptom connectivity. The influence of family support emerged as a critical factor in sustaining the care benefits, particularly for vulnerable adolescents. Additionally, targeted intervention on sadness directly may be the key to reduce the severity of the symptom network for specific subgroups of children. Future research should focus on broadening the geographic and socio-economic scope, integrating and precise healthcare measures, and utilizing more rigorous study designs to validate these findings further.

Supplementary Information

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Supplementary Material 1.

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Authors' contributions
Qianyu Zhang and Li Ran contribute equally to this study: Data handling; Formal analysis; Methodology; Original draft; Revision; Editing. Wei Li: Data curation; Visualization; Methodology. Xuerong Liu: Data curation; Formal analysis; Revision. Jie Gong: Revision; Validation. Xianyong An: Data curation; Validation. Zhengzhi Feng: Validation. Zhiyi Chen: Conceptualization; Funding acquisition. Jingxuan Zhang: Conceptualization; Funding acquisition; Critical review; Editing; Supervision.

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Data availability
The datasets used and/or analyzed during the current study are available from the corresponding authors on reasonable request.

Declarations

Ethics approval and consent to participate
This study is not a randomized controlled trial (clinical trial number: not applicable), but an observed design along with necessary primary healthcare measures, which was conducted in accordance with the Declaration of Helsinki. The study has been officially approved by the Internal Review Board (IRB) of Nanchong Psychosomatic Hospital (No. NCPP 2022002). Informed consent was obtained from all participants and their legal guardian online.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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