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A network analysis of the heterogeneity and associated risk and protective factors of depression and anxiety among college students

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Background: Comorbidity of depression and anxiety is common among adolescents and can lead to adverse outcomes. However, there is limited understanding of the latent characteristics and mechanisms governing these disorders and their interactions. Moreover, few studies have examined the impacts of relevant risk and protective factors. **Methods:** This cross-sectional study involved 1,719 students. Mplus 8.0 software was used to conduct latent profile analysis to explore the potential categories of depression and anxiety comorbidities. R4.3.2 software was used to explore the network of core depression and anxiety symptoms, bridge these disorders, and evaluate the effects of risk and protective factors. **Results:** Three categories were established: “healthy” (57.8%), “mild depression-mild anxiety” (36.6%), and “moderately severe depression-moderate anxiety” (5.6%). “Depressed mood”, “nervousness”, and “difficulty relaxing” were core symptoms in both the depression-anxiety comorbidity network and the network of risk and protective factors. Stress perception and neuroticism serve as bridging nodes connecting some symptoms of depression and anxiety and are thus considered the most prominent risk factors. **Conclusions:** According to the core and bridging symptoms identified in this study, targeted intervention and treatment can be provided to groups with comorbid depression and anxiety, thereby reducing the risk of these comorbidities in adolescents.

Keywords Depression, Anxiety, Latent profile analysis, Network analysis

Abbreviations

LPA	Latent profile analysis
BIC	Bayesian information criterion
aBIC	Adjusted BIC
AIC	Akaike's information criterion
BLRT	Bootstrap likelihood ratio test
LMR	Lo–Mendell–Rubin
EI	Expected influence
CS	Correlation stability
BEI	Bridge expected influence

Depression and anxiety have long been widespread mental health problems among adolescents. An annual review of studies on the prevalence of mental disorders in children and adolescents globally revealed that the prevalence of anxiety disorders was 6.5%, and the prevalence of depressive disorders was 2.6%¹. The Systematic Global Burden of Disease Study conducted in 2019 showed that both depression and anxiety ranked among the top ten causes of burden-of-disease injuries in adolescents aged 10–24 years². A study shows that the overall

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prevalence of depression is 24.8%³, whereas the pooled prevalence of anxiety symptoms during the COVID-19 pandemic was 25.0% among Chinese college students⁴. Thus, it is urgent and necessary to pay more attention to adolescents' mental health. Studies have also shown that depression and anxiety lead to various adverse outcomes, such as interpersonal distress, impaired emotional perception and regulation, and academic and employment limitations^{5,6}. In addition, depression and anxiety are highly comorbid^{7,8}, and those with these comorbidities have symptoms of both depression and anxiety, often causing more harm than depression or anxiety alone. This can lead to more frequent anxiety attacks, more severe symptoms, and even an increased risk of suicide^{9,10}. Overall, the issue of depression and anxiety among teenagers is deeply concerning and requires further investigation. Price et al. found that a treatment regimen targeting both diagnoses may exhibit better efficacy than a treatment targeting only one of these disorders⁷. Therefore, it is valuable to further elucidate the mechanism governing the comorbidities of depression and anxiety to explore ways to identify them and effectively intervene in vulnerable populations.

Anxiety and depression are heterogeneous¹¹, meaning that individuals with similar diagnoses may have different symptoms. However, most studies have applied a variable-centered approach, which treats samples as homogeneous¹², ignores the inherent heterogeneity of individuals, and can interfere with the analysis of different subgroups of depression and anxiety comorbidities. This may hinder targeted identification and intervention. The present study adopts an individual-centered approach, which classifies individuals into subgroups based on their responses to each extraneous variable, thereby accounting for group heterogeneity¹³. The research methods commonly used in the individual-centered approach include mean segmentation, latent profile analysis (LPA), cluster analysis, and latent profile modeling. Recently, many researchers have used LPA to identify potential categories of depression and anxiety. For example, Lei et al. detected four categories in a sample of Japanese adults: "depression and anxiety", "depression and moderate anxiety", "mild anxiety", and "most healthy"¹⁴. Sun et al. proposed a three-profile model comprising a "healthy group", "anxiety group", and "depression-anxiety group"¹⁵. Latent profile analysis is an emerging statistical method for continuous variables that assigns individuals to distinct categories based on specific probabilities. Depression and anxiety are significant predictors of adolescent mental health¹⁶, and understanding their heterogeneity may facilitate early identification and intervention to help young populations deal with mental health problems early and promptly, thereby preventing further worsening of various important but easily overlooked symptoms.

Recently, networks have begun to emerge in psychology, psychiatry and other fields. This allows us to visualize comorbidities as a network of symptoms, thus providing a new perspective¹⁷. During diagnosis, mental disorder comorbidities are often considered separate and distinct disorders with no direct link between symptoms¹⁸. From the network perspective, mental disorders can be viewed as a network comprising interactions between the symptoms; specifically, symptoms are the nodes, and symptom-to-symptom interactions are the edges¹⁷. Network analysis evaluates the role of nodes in the entire network and their impacts on other nodes via indicators describing node characteristics. One study statistically evaluated a network model of depression and anxiety symptoms and classified the core symptoms as "depressed mood", "worry out of control", and "overly worried", and the bridge symptoms as "depressed mood", "restless", and "psychomotor disorder"¹⁹. Similarly, Garabiles et al.²⁰ identified three bridge symptoms of "fatigue", "depressed mood", and "anhedonia", and three core symptoms of "fatigue", "overly worried", and "depressed mood" while exploring comorbidities between anxiety and depression in Filipino migrant domestic workers. In these correlational networks of depression and anxiety, the indicators (i.e., core and bridging symptoms) represent potential targets for intervention, thus providing insights regarding the interactions and connections between symptoms^{21–23}. Therefore, network analysis can effectively supplement category models to describe individual psychological traits. This can facilitate the identification of core and bridging symptoms for comorbidities to elucidate the mechanisms underlying the comorbidity between these disorders. This would further allow the development of more effective intervention measures or the proposal of new therapies to prevent and treat these disorders.

Numerous studies investigating the causes of sadness and anxiety have demonstrated that both intrinsic traits and external factors may trigger fluctuations in mental health status^{24–26}. Therefore, it is necessary to understand the mechanism whereby relevant risk or protective factors influence depression and anxiety within the symptom network. However, most studies have focused on how one or a few risk factors impact depression and anxiety, while research on protective factors also lacks comprehensive assessments of multiple factors. Indeed, relevant studies have provided insights regarding the effects of social support²⁷, prosocial behavior²⁸, executive function¹⁵, emotional regulation²¹, COVID-19²⁹, childhood psychological abuse³⁰ and other factors on depression and anxiety. The present study focuses on three risk factors (stress perception, neuroticism, and interpersonal distress) and two protective factors (general self-efficacy and perceived social support). Stress perception refers to the extent to which an individual perceives stress in response to external stimuli. Referring to the transactional model of stress and coping, perceived stress directly influences an individual's selection of coping strategies, which can subsequently change their psychology and behavior³¹. The five-factor model of personality indicates that personality traits significantly influence mental health³². Neuroticism is characterized by an individual's heightened sensitivity to negative emotions, making them more prone to experiencing anxiety, depression, and other adverse emotional states³³. Friendly interpersonal relationships reflect an individual's capacity for effective interaction with others³⁴. Maslow's Hierarchy of Needs posits that individuals require emotional ties or relationships with others, and the absence of these connections may lead to distress³⁵. Based on Bandura's social learning theory³⁶ and foundational research on self-efficacy³⁷, self-efficacy refers to an individual's personal assessment of their capacity to effectively execute a behavior, which influences the individual's emotional condition and behavior, with self-factors mediating behavioral regulation. According to the buffering hypothesis³⁸, social support can buffer or mitigate the negative effects of stress on an individual's physical and mental health. Perceived social support refers to an individual's subjective assessment of the support and concern received from others, which might mitigate psychological stress responses³⁹. In summary, these

factors are anticipated to substantially enhance the comprehension of participants' overall psychological well-being and functioning. Their inclusion in the analysis facilitates a more holistic view of participants' experiences, along with the potential interactions and influences among these psychological elements.

Based on a thorough review of the relevant literature, we apply network analytical methods to study the interactions between multivariate variables and depression and anxiety symptoms. This study evaluates multiple protective factors and risk factors to explore their relationships with depression and anxiety in order to improve the accuracy of individual mental health status assessments.

This study aimed to explore various categories of depression and anxiety by analyzing participant profiles according to their questionnaire scores to distinguish depression and anxiety comorbidity risk groups. Herein, we also investigate the core and bridging symptoms of depression and anxiety using a network model. Finally, we examine the network relationships between depression and anxiety and the established risk and protective factors (i.e., stress perception, neuroticism, interpersonal distress, perceived social support, and general self-efficacy).

Materials and methods

Participants

The present study was conducted in October 2022 at a higher vocational college in Hebei Province, China. Prior to the commencement of the research, ethical approval was obtained from the Ethics Committee of North China University of Science and Technology (N0.2021037). Informed consent was obtained from all participants and the study procedures were carried out in accordance with the Declaration of Helsinki guidelines. The questionnaires were posted on Wenjuanxing, which is a professional online questionnaire, exam, assessment and polling platform. In the written informed consent at the beginning of the questionnaire, we informed them of the survey purpose, confidentiality principles, and their rights to withdraw freely, among other relevant matters. Ultimately, A total of 1,824 questionnaires were distributed, of which 1,719 were valid, corresponding to, an effective rate of 94.24%. Questionnaires were excluded as invalid if they were incomplete, if the checkbox options were all the same, or if the completion time was less than 300 s. The average age of the valid respondents was 18.23 ± 0.96 years; 559 were male; 1160 were female; all were first-year students.

Measurements

Depression and anxiety

The 9-item Patient Health Questionnaire (PHQ-9), developed in 1999 and derived from the Primary Care Evaluation of Mental Disorders (PRIME-MD)⁴⁰, was used to assess their degree of depression. The items were scored on a 4-point Likert scale. The total score range is 0–27, with 0–4 being no depression, 5–9 being mild depression, 10–14 being moderate depression, 15–19 being moderately severe depression, and 20–27 being severe depression. The internal consistency and reliability were evaluated based on Cronbach's alpha coefficient for the scale, which was 0.863⁴¹.

The 7-item Generalized Anxiety Disorder (GAD-7) scale, developed by Spitzer and colleagues, was used to assess each participant's anxiety level. The items were scored on a 4-point Likert scale. The total score range is 0–27, with 0–4 being no clinically significant anxiety, 5–9 being mild anxiety, 10–14 being moderate anxiety, and ≥ 15 being severe anxiety. The internal consistency and reliability were evaluated based on Cronbach's alpha coefficient for the scale, which was 0.903⁴².

Risk and protective factors

The Perceived Stress Scale-10 (PSS-10), developed by Cohen et al.⁴³ and translated and revised by Yang and Huang⁴⁴, measures an individual's perception of stress in terms of their stress tolerance and other related characteristics. This scale contains 10 items scored on a 5-point Likert scale, with questions 4, 5, 7, and 8 being reverse-scored. The total score range is 10–50. Otherwise, higher scores indicate more pronounced psychological stress higher scores indicate higher levels of perceived stress. The internal consistency and reliability were evaluated based on Cronbach's alpha coefficient for the scale, which was 0.816.

The Big Five Inventory-2 (BFI-2), developed by Soto and John⁴⁵ and later translated and revised by Zhang et al.⁴⁶, includes 60 entries and five dimensions (extroversion, agreeableness, openness, neuroticism, and conscientiousness). The Neuroticism subscale has 12 questions scored on a 5-point Likert scale. Entries 4, 9, 24, 29, 34, 39, 44, and 49 are reverse-scored. The total score range is 12–60. Otherwise, higher scores indicate a higher level of neuroticism. The internal consistency and reliability of the scale were evaluated based on Cronbach's alpha coefficient, which was 0.876.

The Interpersonal Comprehensive Diagnostic Scale (ICDS) was developed by Zheng et al.⁴⁷ and used to assess individuals' distress during interpersonal interactions on a 28-item scale that includes four dimensions (interpersonal conversation, interpersonal communication, dealing with people, and dissimilarity). A 2-point scale is used and the total score range is 0–28, where a higher total score indicates a higher level of interpersonal distress. The internal consistency and reliability of the scale were evaluated based on Cronbach's alpha coefficient, which was 0.899.

The General Self-Efficacy Scale (GSES) was initially compiled by Schwarzer et al.⁴⁸ and later translated and revised by Wang et al.⁴⁹ to assess individuals' general self-efficacy. The scale contains 10 questions scored using a 4-level Likert method. The total score is calculated by adding the scores of the 10 questions and dividing by 10. The total score range is 1–4. The higher the score, the greater the individual's general self-efficacy. The internal consistency and reliability of the scale were evaluated based on Cronbach's alpha coefficient, which was 0.883.

The Perceived Social Support Scale (PSSS) was compiled by Blumenthal et al.⁵⁰ and later translated and revised by Jiang⁵¹, which reflects the degree of social support individuals feel. The scale includes 12 questions encompassing three sub-dimensions (family, friends, and other support) scored using a 7-level Likert method.

The total score range is 12–84. The higher the total score, the higher the level of perceived social support. The internal consistency and reliability of this scale were evaluated based on Cronbach’s α coefficient, which was 0.939.

Statistical analysis

Common method bias tests, descriptive statistical analysis, correlation analysis, and multivariate logistic regression were performed using SPSS 23.0 software.

Mplus 8.0 software was used to perform LPA of depression-anxiety comorbidities to determine the latent categories and distribution. We started with one category and gradually increased the number of categories for LPA until we attained the optimal model. Six metrics (i.e., AIC, BIC, aBIC, LMR, BLRT, and Entropy) were combined to determine the best-fitting model for the potential classes^{52–55}. The values of AIC, BIC, and aBIC were used for model comparisons, where the smaller the value, the better the model fit. The values of LMR and BLRT reached the significance level of $p < 0.05$, which indicated that adding one more profile significantly improved the model fit. Entropy reflected the classification accuracy of the model, and Entropy ≥ 0.8 suggested that the classification accuracy was greater than 90%⁵⁶.

Multiple network model construction and computations were carried out using R 4.3.2 software employing a partial correlation coefficient based on the introduction of a penalty factor, i.e., the Image Least Absolute Value Convergence and Selection Algorithm (GLASSO)⁵⁷ to increase specificity and efficiency⁵⁸. Green lines connecting nodes indicate positive correlations, whereas red lines indicate negative correlations. Edge weights are denoted by the thickness of the line, such that more correlated edges are thicker. Next, the four centrality metrics of the GLASSO network were calculated to evaluate the importance of each node in the network⁵⁹. We also calculated the Bridge Expected Impact (BEI) to identify the bridge symptoms in the network⁶⁰.

Correlation stability (CS) coefficients were calculated using the bootnet package to assess the stability of the centrality and bridging centrality indices. The CS coefficients were computed by running a 727-case discard subset bootstrap indicating what proportion of participants could be discarded from the analysis to ensure that the correlation between the original and new centrality indices would be no less than 0.7⁶¹.

Results and analysis

Common method bias test

Considering that all of the data for this study came from the questionnaires, Harman’s one-factor method was used to test for possible common method bias. The results showed that 15 factors had eigenvalues greater than 1. The first factor explained 24.6% of the variance, which is less than the 40% threshold proposed by Podsakoff et al.⁶². It is therefore reasonable to infer that the study did not have significant common method bias and meets the statistical requirements.

Descriptive statistics

Table 1 presents the descriptive statistics and correlation coefficients for stress perception, neuroticism, general self-efficacy, perceived social support, interpersonal distress, and anxiety and depression. The results showed that perceived social support and general self-efficacy were significantly and negatively correlated with depression and anxiety, whereas interpersonal distress, neuroticism, and stress perception were significantly and positively correlated with depression and anxiety.

Latent profiles of depression and anxiety symptoms

Model optimization

In this study, five potential profile models were selected for fitting analysis, and the fitting indices are shown in Table 2. The values of AIC, BIC, and aBIC decreased as the number of classes increased and were lower and similar when they were divided into 3, 4, and 5 categories. The smaller the AIC, BIC, and aBIC values, the better the model fits. In contrast, the larger the Entropy value, the better the model fit, and in general, the closer the Entropy value is to 1, the more accurate the classification. LMR and BLRT were significant, indicating that the addition of a profile significantly improved the model fit. The Entropy value was the highest when divided into 5 categories, followed by 3 categories and finally 4 categories, and the LMR and BLRT values of several groups were significant. However, the probabilities corresponding to 4 and 5 categories were less than 5%, and the proportion of categories needed to be higher, which was of no practical significance. On the basis of these simulations, the

Variable	M	SD	1	2	3	4	5	6	7
1 = Stress Perception	25.040	6.007	1						
2 = Neuroticism	34.740	7.614	0.688***	1					
3 = General Self-Efficacy	2.666	0.407	-0.411***	-0.493***	1				
4 = Perceived Social support	62.150	12.348	-0.389***	-0.398***	0.296***	1			
5 = Interpersonal Distress	8.890	6.064	0.550***	0.582***	-0.430***	-0.400***	1		
6 = Anxiety	3.670	3.823	0.627***	0.618***	-0.336***	-0.366***	0.588***	1	
7 = Depression	5.130	4.311	0.618***	0.585***	-0.346***	-0.410***	0.573***	0.808***	1

Table 1. Descriptive statistics and correlation analysis of each variable. *** $P < 0.001$.

Model	AIC	BIC	aBIC	LMR	BLRT	Entropy	Probability
1	57035.861	57210.245	57108.585				
2	48215.842	48482.868	48327.200	0.0000	0.0000	0.938	0.693/0.307
3	44873.127	45232.794	45023.119	0.0000	0.0000	0.942	0.578/0.366/0.056
4	43712.783	44165.092	43901.410	0.0334	0.0000	0.902	0.442/0.302/0.212/0.044
5	42162.650	42707.600	42389.911	0.0017	0.0000	0.957	0.517/0.043/0.204/0.198/0.038

Table 2. Latent profile models for depression and anxiety.

class	1	2	3
1	0.978	0.022	0.000
2	0.037	0.960	0.003
3	0.000	0.008	0.992

Table 3. Average attributions for each latent class.

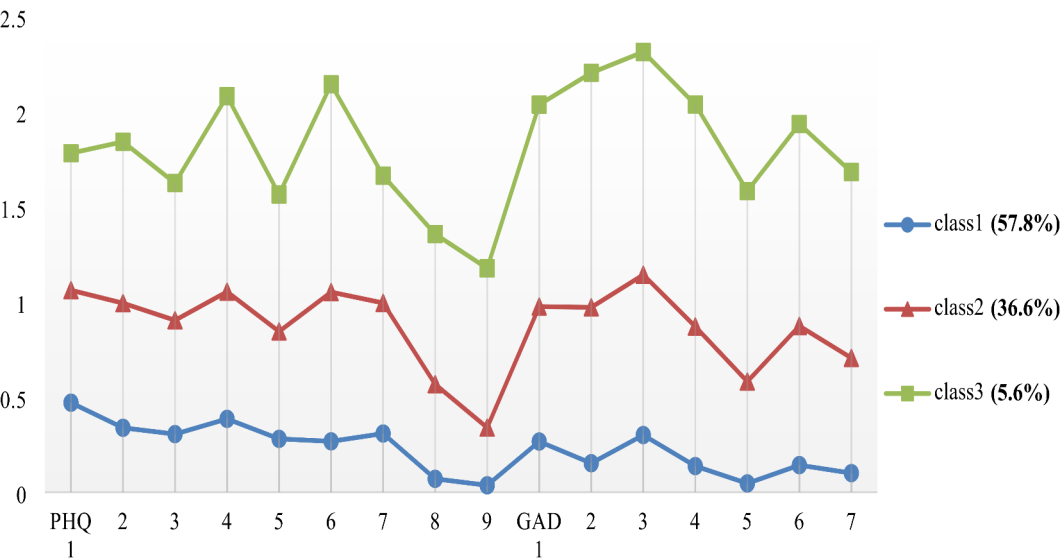


Fig. 1. Estimated conditional mean for each latent class.

models were divided into three optimal types. Table 3 shows that the average attribution probability for different potential categories is between 96 and 99%, indicating that the results of these three types of models are credible.

Naming latent classes

The scores of the three potential classes in terms of the 16 dimensions of depression and anxiety are shown in Fig. 1. The average scores of depression and anxiety in class 1 were 2.44 and 1.12, respectively, and this class exhibited almost no symptoms of depression or anxiety. The class 2 scores in each dimension were significantly higher than those of class 1. Class 2 comprised 36.6% of the participants, whose average scores of depression and anxiety were 7.86 and 6.16, respectively. The scores of class 3 in each dimension were significantly higher than those of the other two categories. Class 3 comprised 5.6% of the participants, and the average scores of depression and anxiety were 15.53 and 13.8, respectively. According the PHQ-9 and GAD-7 scoring criteria (Fig. 1), class 1, 2, and 3 were named “healthy”, “mild depression-mild anxiety”, and “moderately severe depression-moderate anxiety”, respectively. In this study, class 2 and class 3 were considered risk groups for depression and anxiety comorbidity.

Network analysis

Symptoms of depression and anxiety

A network analysis was performed for the risk groups for depression and anxiety comorbidities. The weights of the edges and the positive and negative correlations between the nodes are illustrated in Fig. 2, where GAD2 (“worry out of control”) and GAD3 (“overly worried”) are most closely connected to anxiety items, and PHQ4 (“fatigue”) is most closely connected with PHQ1 (“anhedonia”) among depression items. The strongest

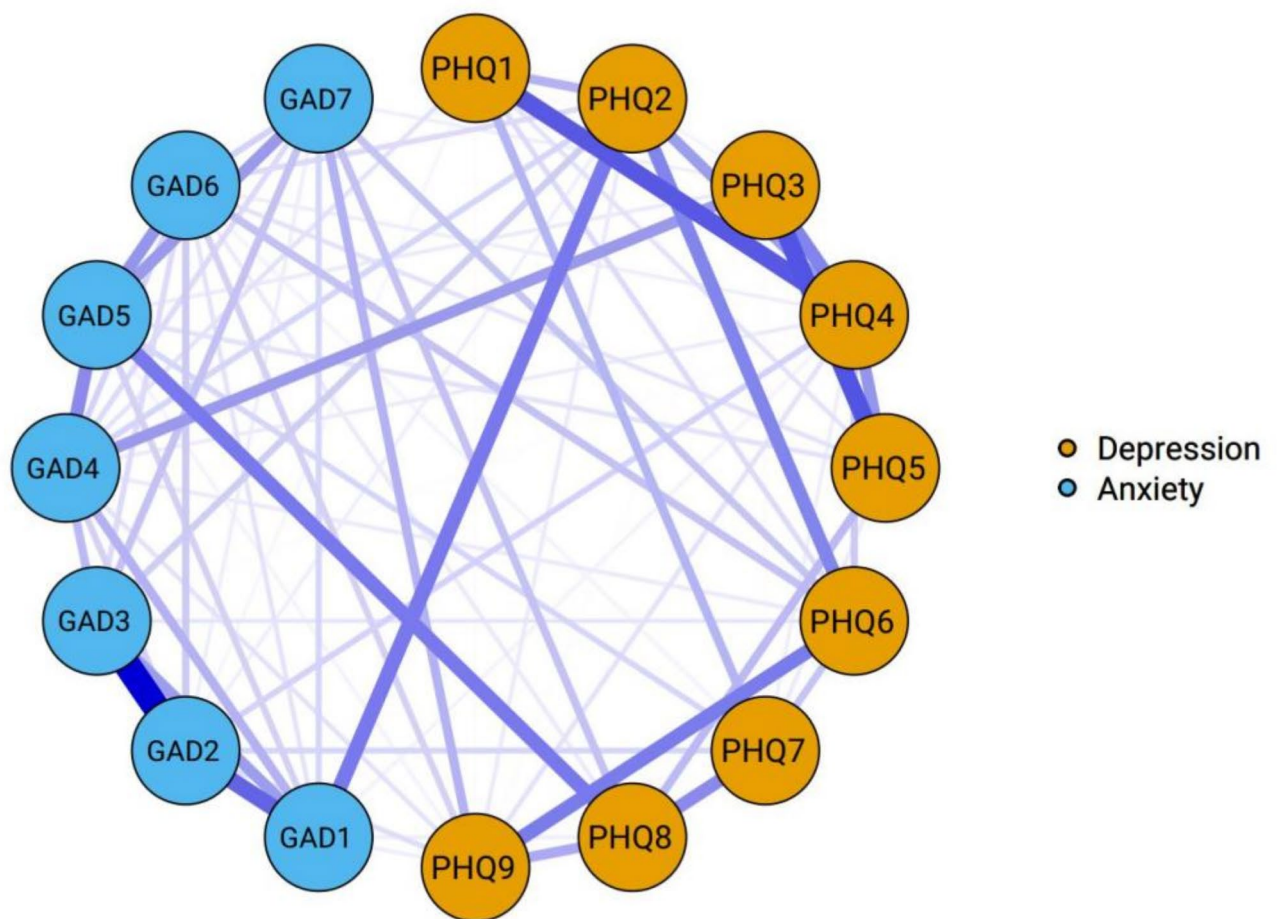


Fig. 2. Depression and anxiety symptoms network.

connection is between GAD1 (“nervousness”) and PHQ2 (“depressed mood”). Overall, depressive symptoms and anxiety symptoms are closely related, and each symptom affects at least one other.

The centrality results (Fig. 3a) indicate that PHQ2 (“depressed mood”) had the highest EI value among the depression items and had high closeness and strength, highlighting it as a core symptom of depression; it also had the most significant impact on each node in the depression network. Among the anxiety items, GAD4 (“difficulty relaxing”) has the highest EI value, followed by GAD1 (“nervousness”), which also had higher closeness and strength. Similarly, these can be regarded as the core symptoms of anxiety because they had the most significant impacts on each node in the anxiety network. Figure 3b shows that PHQ2 (“depressed mood”) had the highest BEI value and was the most prominent bridging symptom among the depression items. Figure 2 highlights the strong relationship between PHQ2 (“depressed mood”) and many symptoms of anxiety, including GAD1 (“nervousness”), GAD3 (“overly worried”), GAD4 (“difficulty relaxing”), and GAD6 (“irritable”), followed by PHQ8 (“psychomotor disorder”), which is also a bridging symptom. The most prominent bridging symptom of anxiety was GAD4 (“difficulty relaxing”). Figure 2 indicates that GAD4 (“difficulty relaxing”) had high weights corresponding to its edges with PHQ2 (“depressed mood”), PHQ3 (“sleep disturbance”), PHQ4 (“fatigue”), and PHQ9 (“suicidal ideation”), followed by GAD5 (“restless”). Indeed, most of the depression and anxiety nodes had high BEI values, meaning they can be considered as bridging symptoms that support the comorbidity network of depression and anxiety. The CS-C was presented in Figure S1, which suggests the stability of centrality indicators and bridge expected. The narrow 95% confidence interval for the edges supports the conclusion that the network exhibits high accuracy (Figure S2).

Risk and protective factors

Based on the network of depression and anxiety comorbidity, the incorporation of risk and protective factors for network analysis (Fig. 4) revealed that all factors were connected, with neuroticism and stress perception having the strongest correlations with depression and anxiety. Notably, there was a strong positive correlation between stress perception and neuroticism. GAD1 (“nervousness”) and GAD4 (“difficulty relaxing”) represented the EI maxima among anxiety symptoms, whereas PHQ2 (“depressed mood”) exhibited the EI maximum among depression symptoms (Fig. 5a); these factors had the strongest impacts on their respective communities, consistent with the results from the network analysis of depression and anxiety symptoms. Besides, GAD1,

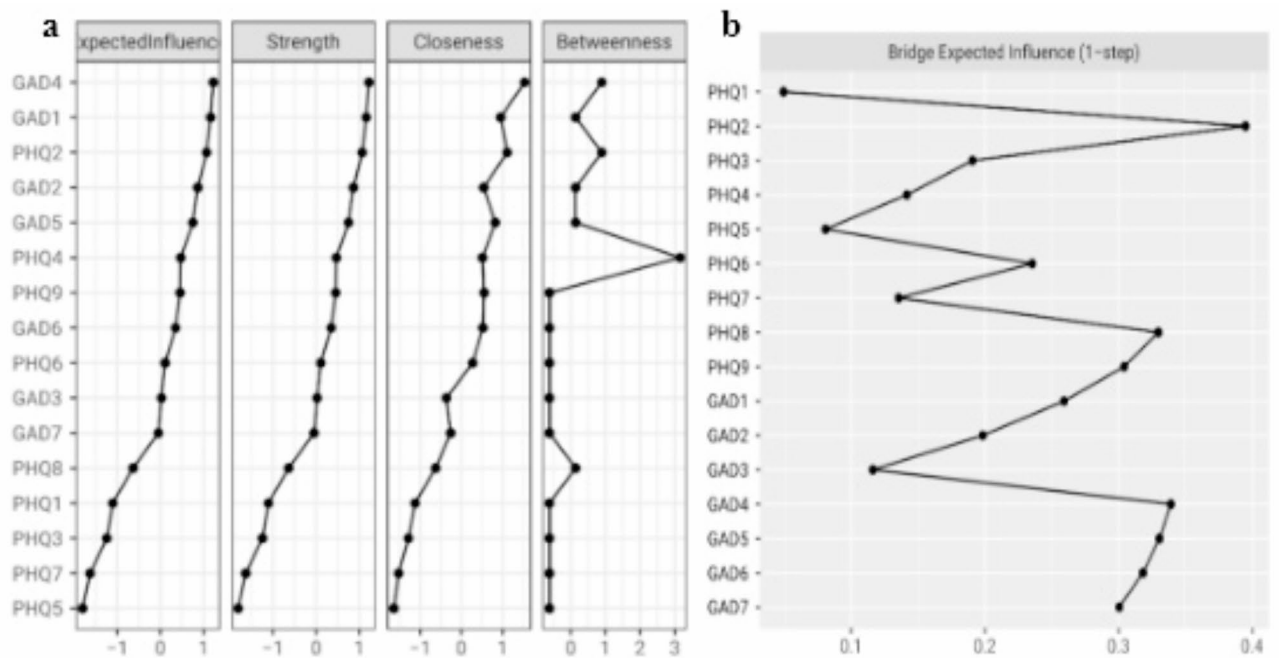


Fig. 3. Centrality index(a) and Bridge Expected Influence(b) for depression and anxiety symptoms network.

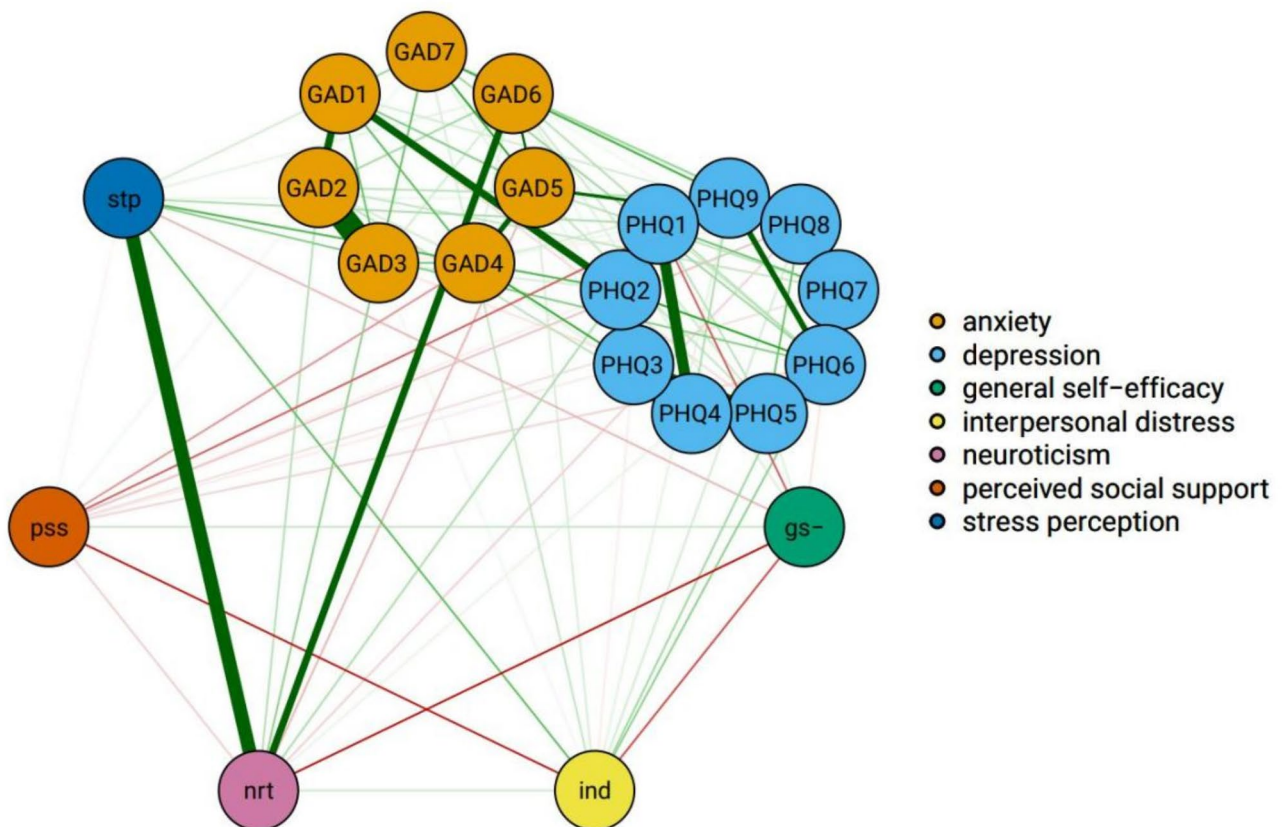


Fig. 4. Risk and protective factors with anxiety and depression comorbidity network.

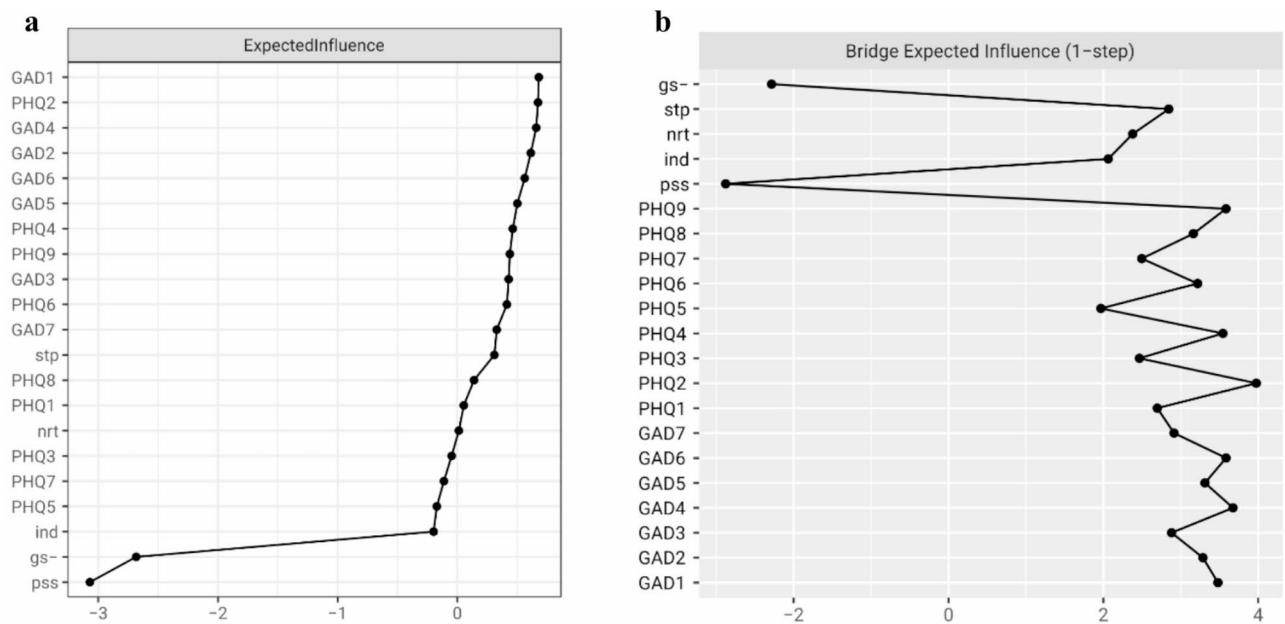


Fig. 5. Expected Influence(a) and Bridge Expected Influence(b) for risk and protective factors with anxiety and depression comorbidity network.

GAD4 and PHQ2 are also the most central factors in the entire network. Stress perception has the highest EI value and BEI value among the factors influencing depression and anxiety comorbidity, suggesting that the influence on depression-anxiety comorbidity is more significant than any other factors and it has the strongest bridging effect (Fig. 5b). Overall, it had a substantial positive correlation with depression and anxiety, followed by neuroticism, which also played a strong bridging role. Meanwhile, interpersonal distress also played a bridging role, although both its bridging role and correlation with depression and anxiety were weaker. The BEI values of perceived social support and general self-efficacy were both extremely low and negative, suggesting that their associations with other nodes were negatively correlated, and there was a positive correlation between the two. The network had excellent stability and accuracy. The CS-C of both nodes and bridge expected influence is 0.749 (Figure S3). The narrow 95% confidence interval for the edges supports the conclusion that the network exhibits high accuracy (Figure S4).

Discussion

Heterogeneity of depression and anxiety

In this study, LPA of students from a vocational college in Hebei Province, China, indicated that their depression and anxiety symptom scores had prominent categorical characteristics, allowing them to be divided into three categories: “healthy” (class 1), “mild depression-mild anxiety” (class 2), and “moderately severe depression-moderate anxiety” (class 3). The fitting indices showed that the models fit well, further indicating that there were differences among these categories in terms of the depression and anxiety symptoms in college students. These results reflect the heterogeneity of depression and anxiety in these representative groups. Participants in the “healthy” group had few symptoms of depression and anxiety, consistent with previous studies⁶³. Importantly, the present study did not identify a single depression or anxiety class. We inferred that depression and anxiety generally occur together, which is in line with the findings of Choi et al.⁹ and Yu et al.⁸. One study explained this result in terms of cultural context; specifically, Asians may be afraid of being labeled as “weak in character”, so they tend to emphasize somatic and anxiety symptoms while reporting depressed mood⁶⁴.

Correlations between depression and anxiety symptoms

The network analysis of depression and anxiety symptoms revealed strong connections between the various symptoms, yet not all symptoms had equal importance. The core and bridging symptoms of depression and anxiety comorbidity include PHQ2 (“depressed mood”) and GAD4 (“difficulty relaxing”). GAD1 (“nervousness”) is also a core symptom. These results are consistent with previous reports^{65–67}, which proposed that core symptoms play a crucial role in maintaining the symptom network; as a result, targeting these core symptoms for intervention and treatment can help restore mental health levels. University students face complex issues involving academics, employment, and interpersonal and romantic relationships. As society continues to advance, the pressures to address these issues can easily lead to the emergence of depression and anxiety symptoms. In particular, “difficulty relaxing” signifies mental tension, “nervousness” represents anxiety about impending disasters, and “depressed mood” indicates a low psychological state. The high centrality of the impact of high expectations suggests that reducing these symptoms could disrupt the depression and anxiety symptom network, leading to the highest potential benefits in terms of alleviating anxiety and depression⁶⁸. Specific measures can be

implemented to alleviate the three core symptoms: “difficulty relaxing” can be relieved by visiting green parks⁶⁹ and adopting intelligent stress relief systems⁷⁰; “nervousness” can be managed through restorative exercise⁷¹, relaxation breaks⁷², or cryotherapy (i.e., applying ice packs to the back of the neck to reduce tension)⁷³; and “depressed mood” can be addressed through emotional therapy⁷⁴ and therapeutic alliances⁷⁵.

Impacts of protective and risk factors

The network of risk and protective factors with anxiety and depression comorbidities showed that stress perception and neuroticism were the risk factors with the highest bridging performances. For example, the “nervousness” symptoms of generalized anxiety disorder and the “depressed mood” symptoms of depressive disorders are directly related to the first step (refer to Fig. 2); however, they are related through stress perception in the second step (refer to Fig. 4). On this basis, stress perception can be considered a common cause of depression and anxiety. It is also reasonable to conclude that stress perception is reinforced by an association between these two symptoms⁷⁶. This concept is consistent with previous findings showing that neuroticism and stress perception are strongly and positively correlated with depression and anxiety and thought to be the bridge supporting depression and anxiety comorbidity^{71,77,78}.

In addition to facilitating associations between symptoms, a risk factor can influence comorbidities between two disorders because it has several associations with multiple symptoms of both mental health problems⁷⁹. In the present study, stress perception was shown to be strongly associated with the “fatigue” and “self-abasement” symptoms of depression, as well as with the “difficulty relaxing” symptom of anxiety. These relationships may be interpreted as stress perception leading to “fatigue”, “self-abasement”, and “difficulty relaxing”, thus highlighting the direct link between these symptoms and the comorbid disorders. Alternatively, it is equally reasonable to have a stronger stress perception due to more severe symptoms of depression and anxiety. Previous studies have shown that depression and anxiety symptoms may contribute to stress perception problems and vice versa; however, there is limited knowledge regarding which specific symptom(s) play the central role in this phenomenon. Neuroticism showed similar results to stress perception. The “irritable” symptom of anxiety and the “depressed mood” and “sleep disturbance” symptoms of depression are related through neuroticism and have a high positive correlation with the “irritable” symptom. This result is consistent with a previous report⁸⁰ and may be interpreted as high levels of neuroticism may cause a person to experience depressed mood and sleep disturbances, making them understandably irritable. It is worth exploring the positive correlation between neuroticism and stress perception and how the two may interact with one another to affect the comorbid network of anxiety and depression. Previous studies have shown that neuroticism is associated with higher perceived stress, regardless of whether COVID-19-related stressors are present⁸¹. Meanwhile, the network diagram of risk and protective factors and anxiety and depression indicated that interpersonal distress is another risk factor that plays a bridging role. However, the impact is not significant and relies on other factors⁸².

The results of this study also indicate that perceived social support and general self-efficacy are protective factors of depression and anxiety. In other words, these factors are inversely associated with some symptoms of depression and anxiety. These findings suggest that perceiving social support or having a strong sense of self-efficacy may reduce the severity of symptoms. Notably, support from family and loved ones appears to be the key to addressing negative psychopathological symptoms^{76,77}. Perceived social support was positively correlated with general self-efficacy, which may directly enhance its protective effect. This provides insights regarding the potential utility of using well-being traits to detect and prevent mental health issues. The link between social support and mental health problems, as well as the role of social support as a key protective factor in depression and anxiety, has been documented previously^{76,83,84}.

The findings of this study also have several clinical implications. The “depressed mood”, “difficulty relaxing”, and “nervousness” symptoms are the most important because they contribute to the development and continuation of comorbid depression and anxiety, as demonstrated in previous studies^{85–87}. Therefore, targeting these core symptoms, thereby inhibiting interactions between disorders may be a valuable strategy for treating depression and anxiety comorbidities. Similarly, the results suggest that stress perception problems and neuroticism can lead to the simultaneous occurrence of depression and anxiety. Therefore, experiencing these factors may increase the risk of depression and anxiety comorbidities in adolescents. Early intervention for adolescents to prevent stress perception problems and high risk of neuroticism may reduce the incidence of such comorbidities^{79,82}.

This study categorized a current sample of college students into three latent profile models through a person-centered and depression- and anxiety-symptom-based approach and subsequently constructed the “depression-anxiety symptom network” and the “influencing factors related to comorbid depression and anxiety” in the non-healthy groups. We studied the core symptoms, bridging symptoms, and factors influencing comorbidity of depression and anxiety. The results provide support for future research and guidance for interventions to treat depression and anxiety in adolescents. This study also offers a novel perspective on prevention and intervention in adolescents who are at risk of depression and anxiety or have already developed depression and anxiety comorbidities. The core and bridging symptoms identified in this study are valuable targets for formulating new treatment options and improving available interventions. Our inclusion of numerous influencing factors of depression and anxiety comorbidities expands the scope of previous studies, which can help to better understand these comorbidities to reduce their occurrence.

Inevitably, there are some limitations to this study. First, this study assessed students at one specific university, so the results should be interpreted and generalized (e.g., to the entire adolescent population) with caution. The symptom network structure may be affected by different sample populations, and therefore, future studies should increase the sample size and variability to obtain a more comprehensive and stable network structure, which could provide even more reliable conclusions. Second, the data used in this study were cross-sectional. They cannot determine the directionality of the margins, and therefore, it is impossible to determine causal

relationships between symptoms. Similarly, it cannot reveal dynamic changes between individual symptoms, so longitudinal data is needed for future studies. Third, the network structure is specific to the questionnaires used in this study, which means that different assessment questionnaires may result in different network structures. Moreover, the network analysis was affected by the number of included nodes and calculation methods, and thus, the results should be interpreted cautiously before implementation in clinical practice. Finally, because depression and anxiety symptoms were assessed according to self-reported scales, the effect of recall bias on the outcomes could not be avoided. Therefore, future studies could use more objective indicators or combine various types of reporting questionnaires to provide more comprehensive and objective information.

Data availability

The data from this study is available from the corresponding authors upon reasonable request.

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Author contributions

C.J.N.: Funding acquisition, Project administration, Writing-review & editing; Y.Y.J.: Conceptualization, Formal analysis, Writing-original draft; Y.H.L.: Conceptualization, Writing-original draft; X.D.W.: Visualization, Methodology, Software; Y.P.: Investigation, Supervision; H.Y.Z., Z.S.C., X.R.L., Z.W.L., X.Y.Y. & X.Z.: Writing-review & editing. All authors reviewed the manuscript.

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Declarations

Competing interests

The authors declare no competing interests.

Ethics approval and consent to participate

Informed consent was obtained from all participants and the study procedures were carried out in accordance with the Declaration of Helsinki guidelines. Ethical approval was obtained from the Ethics Committee of North China University Of Science And Technology (N0.2021037).

Additional information

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