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Relationship between time perspective and depressive symptoms in young people working in high-altitude environments

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Abstract

Background Depression rates are significantly higher in high-altitude regions, making it important to understand its underlying mechanisms. Time perspective, which refers to how individuals perceive their past, present, and future, is closely linked to depression in low-altitude areas. However, its relationship with depression in high-altitude regions remains unclear.

Methods A cross-sectional survey was conducted with 4942 young male workers from high-altitude regions. The association between time perspectives and depressive symptoms were examined by univariate and multivariate analyses. Network analysis was employed to identify central symptoms and their interactions, and to compare the differences between individuals with and without depression.

Results The study identified that elevated past negative (PN), reduced past positive (PP), increased present fatalistic (PF) and present hedonistic (PH) orientations, and lower future (F) were significant risk factors for depressive symptoms in plateau populations. In the network structure of the depression group, PN, PF, PH, SDS18 "emptiness", and SDS13 "psychomotor agitation" were key elements influencing depressive symptoms and the strongest edge was F-PP. Significant differences were detected between the depressive and non-depressive groups, with the depressive group demonstrating significantly greater global strength invariance and a more robust network invariance.

Conclusions Abnormal time perspectives, especially PN, PF and PH were strongly associated with depression in high-altitude environments, and the strong connection between F-PP provides a potential intervention target. Future research should further explore the causal relationship.

Keywords Depression, Time perspective, High-altitude environment, Network analysis

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Introduction

Depression has become a significant contributor to the global burden of disease nowadays [1], with the lifetime prevalence of 6.9% among adults in China. The pathogenesis of depression is multifactorial and involves biochemical, genetic, individua, familial, social and environmental components [2]. Living in high-altitude areas is considered a risk factor for depression [3].

High-altitude areas, defined as regions located 2,500 m or above sea level [4], are associated with higher rates of depression and depressive symptoms than lowland regions [5]. Studies reported a 17.9% prevalence of depressive symptoms among high-altitude residents, with a particularly high rate of 28.7% in Chinese high-altitude regions [6]. However, existing researches about depression in high-altitude areas have focused mainly on physiological factors [7], leaving psychological factors less explored. With the increase in the number of people traveling to or working in high-altitude regions, investigating the pathogenesis of depressive symptoms in high-altitude environments and exploring potential treatment strategies are highly important.

The unique conditions of high-altitude environments often put individuals at risk for both mental and physical adaptation issues, such as decreased memory capacity [8], increasing time interval perception [9] and feelings of isolation [10]. This complexity makes it difficult to fully grasp the psychological factors that contribute to high-altitude depression.

Time perspective is an important psychological concept that reflects how people perceive and make sense of their past, present, and future [11], and it plays a significant role in shaping behaviors and decision-making. As a key factor in the development and progression of various psychiatric disorders [12–14], the abnormal time perspective has a strong connection to depression [15–17]. While the causality of this relationship need further exploration, studies have shown that an abnormal time perspective can be both a consequence of depression and contributes to its onset by reinforcing negative emotions [18]. However, how this relationship plays out in high-altitude environments remains unclear. Given the complexity of depression and its wide range of symptoms, a more comprehensive approach is needed to explore these connections beyond traditional models.

Traditional psychiatric epidemiology conceptualizes mental disease as a set of symptoms of equal weight, but this view overlooks the dynamic relationships between symptoms [19]. In contrast, network analysis views illness as a system of interacting symptoms, allowing researchers to identify core symptoms and their connections [20]. This approach has been successfully applied to explore the relationships between depression and various psychological factors (e.g., personality traits [21]), as well as other mental factors such as anxiety [22] and posttraumatic stress disorder [23]. However, it remains underexplored in the context of high-altitude depression. By mapping these associations, network analysis can provide new insights into the complex relationship between time perspectives and depression. Additionally, this method addresses limitations of traditional models by capturing the dynamic relationships between symptoms and cognitive factors [24, 25].

This study aims to employ network analysis to uncover the specific links between time perspective and depressive symptoms in high-altitude populations, and to compare how these factors interact differently in individuals with and without depression. By examining the time perspective-depressive symptom network in high-altitude environments, this study could provide a new framework for understanding the underlying mechanisms behind high-altitude depression and to provide a theoretical foundation for more targeted interventions.

Method

Settings and subjects

A cross-sectional survey was conducted in the Hetian area of Xinjiang and the Ali area of Tibet (altitude range from 3100 ~ 4260 m) between February and June 2023 via a snowball convenience sampling method for convenience. The inclusion criteria for participants were as follows: (1) were adults aged 18 years or older, (2) had worked in high-altitude areas for at least one month, and (3) were able to read and write fluently in Chinese. No specific exclusion criteria were applied in the study.

The survey was administered through *Questionnaire Star*, a widely used WeChat-based platform, where participants completed the survey by scanning a QR code. To ensure data completeness, the system was configured to require participants to answer all questions before submission; however, they retained the option to withdraw at any time. All individuals who provided demographic information completed the survey in its entirety, and took no less than five minutes to do so were included in the final analysis.

Measures

The sociodemographic information collected from the participants included age, sex, marital status, educational level, parents' marital status, and whether they were only children.

Depression was assessed via the Self-rating Depression Scale (SDS) developed by Zung in 1965 [26]. The scale employs a scoring method ranging from 1 ("a little of the time") to 4 ("most of the time"), with 10 items scoring positively and 10 items scoring negatively. The total raw score is multiplied by 1.25 to obtain the standard score, and higher scores indicate deeper levels of depression. Scores of 50–60 indicate mild depression, scores of 61–70 indicate moderate depression, and scores of ≥ 70 indicate severe depression.

Time perspective was assessed using the Zimbardo Time Perspective Inventory (ZTPI) [27]. This scale consists of 56 items, and is rated on a five-point Likert scale from 1 (very uncharacteristic of me) to 5 (very characteristic of me). The ZTPI measures five dimensions of time perspective (TP): Past Negative (PN) and Past Positive (PP), which measure how individuals view their past—either negatively or positively. Present Hedonistic (PH) reflects one's lifestyle driven by impulsiveness or risk-taking, with a focus on immediate pleasure. Present Fatalistic (PF) reflects a belief that individuals cannot control their fate, whereas Future (F) measures the degree of planning and preparation for future events.

Statistical analysis

Single-factor and multifactor analyses were conducted via SPSS version 22.0. The normality distribution of continuous variables was assessed via the single-sample Kolmogorov–Smirnov test. Demographic variables were compared between depressed patients and nondepressed patients via the Mann–Whitney U test for continuous variables and the chi–square test for categorical variables, as appropriate. A significance level of $P < 0.05$ (two-tailed) was set for statistical significance.

Network estimation

Network structural analysis was performed via R software (version 4.3.1). For a network with 25 nodes, which requires estimating 300 parameters ($25 \times 24/2$), our sample size meets the requirement of ≥ 500 and is sufficient for data analysis [28]. The edges in the network were shrunk with the graphic least absolute shrinkage and selection operator (LASSO) in combination with the extended Bayesian information criterion (EBIC). Network estimation was implemented via the "bootnet" package in R and visualized via the "qgraph" package. In the network, nodes represented the individual dimensions of time perspective or depressive symptoms, whereas edges represented correlations between symptoms. Thicker edges denote stronger associations between two nodes, with green indicating positive correlations and red indicating negative correlations.

Centrality indices

The expected influence (EI), predictability, and bridge Expected influence (bridge EI) indices were calculated to assess the network properties of each node, using the "*qgraph*", "*mgm*", and "*networktools*" packages. Compared to traditional centrality measures like strength, EI is more suitable for networks that include both positive and negative connections. Bridge EI is particularly useful for identifying nodes that act as bridges between different communities within the network. Nodes with higher EI values are considered to be more influential within the network, while those with higher bridge EI values are seen as playing a key role in linking separate communities. Predictability, on the other hand, reflects the shared variance between a node and its neighboring nodes.

Network stability and network comparison test

The "*bootnet*" package were used to assess the accuracy and stability of the network model. Stability was evaluated by the correlation stability coefficient (CS), where a value greater than 0.25 indicated acceptable stability, and values above 0.5 were preferable [28]. Nonparametric bootstrapping with a 95% confidence interval (CI) of edge weights was used to assess the accuracy of the network, with a narrower CI indicating a more reliable network. Bootstrapped difference tests were conducted to compare the weights of edge pairs. To further clarify the impact of time perspective on depression occurrence, the "*NetworkComparisonTest*" package was used to test global strength invariance and network invariance between depressed and non-depressed groups.

Results

Prevalence and correlates

This study included a total of 4942 male participants (Table 1). The mean age of the subjects was 24.86 years ($SD = 4.423$). All participants had completed at least 9 years of compulsory education, with 3450 individuals (69.8%) having received higher education. Among the participants, 1032 (20.88%) were married, 432 (8.7%) came from single-parent families, and 1286 (26%) were the only children in their families.

In this population, the prevalence of depressive symptoms (SDS score ≥ 50) was 17.16% ($n = 848$), with 282 participants showing moderate to severe depression (SDS score ≥ 60). As shown in Table 1, the depressed subgroup tended to be older ($p = 0.002$), married ($p < 0.001$), and more likely to be only children ($p = 0.019$) than the non-depressed subgroup. Additionally, a greater proportion of individuals in the depressed group had not received higher education ($p = 0.017$), while coming from a single-parent family did not have a significant effect ($p = 0.187$). Significant differences were observed in the time perspective dimensions (PN, PP, F, PH, and PF) between the depressed and non-depressed groups ($p < 0.001$) (Table 2). Individuals who paid more attention to their past negative experiences and less attention to their positive ones lacked future planning, sought immediate

Table 1 Sociodemographic and categorical characteristics of participants with and without depression

Variables	Total (*N* = 4942)		Without Depression (*N* = 4094)		With Depression (*N* = 848)		Univariable analysis		
	n	%	*n*	%	*n*	%	x^2	*df*	*p*
Married	1031	20.86	819	20.00	212	25	10.617	1	***< 0.001***
Higher education and above	3450	69.80	2887	70.52	563	66.39	5.675	1	***0.017***
Single child	1286	26	1041	25.43	245	28.89	4.379	1	***0.036***
Single parent	432	8.70	348	8.50	84	9.91	1.739	1	*0.187*

Table 2 Group differences in continuous variables

Variables	Total (*N* = 4942)	Without depression (*N* = 4094)	With depression (*N* = 848)	*Z*	*p*
	Mean ± SD	Mean ± SD	Mean ± SD		
AGE	24.86 ± 4.42	24.75 ± 4.31	25.41 ± 4.90	-3.050	***0.002***
PN	2.44 ± 0.68	2.38 ± 0.63	2.75 ± 0.82	-14.736	***< 0.001***
PP	3.56 ± 0.55	3.62 ± 0.50	3.26 ± 0.67	-14.610	***< 0.001***
F	3.28 ± 0.43	3.34 ± 0.39	2.97 ± 0.47	-21.333	***< 0.001***
PH	2.60 ± 0.53	2.59 ± 0.49	2.64 ± 0.70	-4.759	***< 0.001***
PF	2.54 ± 0.61	2.49 ± 0.56	2.79 ± 0.78	-13.926	***< 0.001***

pleasure, and felt a lack of control in the present were more likely to exhibit symptoms of depression.

Network structure of the depression group

Figure 1 displays the Network model for the depressed group, while the network stability results are showed in Figure S1. The CS coefficient of EI is 0.75, indicating that the network is highly stable. The five nodes with the highest EI and bridge EIs in the network of depressed group are the same: PN (Past negative), PF (present fatalistic), PH (Present hedonistic), SDS18 "Emptiness", and SDS13 "Psychomotor agitation". This suggests that these five nodes have the most significant influence in the network and act as crucial links between time perspective and depressive symptoms. In contrast, nodes like SDS7 "Weight loss", SDS2 "Diurnal variation", and SDS8 "Constipation" have minimal influence within the network. The average predictability for the 25 nodes is 49.9%, meaning that, on average, nearly 50% of the variance for each node can be explained by its neighboring nodes in this model. More descriptive information can be found in Table S1.

The top 10 edges with the highest weights in the network include F-PP, PN-PF, SDS13 "Psychomotor agitation" -SDS15 "Irritability", SDS11 "Confusion" -SDS12 "Psychomotor retardation", PH-PF, SDS17 "Personal devaluation"-SDS18 "Emptiness", PH-PN, PH-PP, SDS3 "Crying spells"-SDS19 "Suicidal rumination", and SDS9 "Tachycardia"-SDS10 "Fatigue". The 95% confidence interval results for the bootstrap testing of estimated edge weights further validate the significance of these 10 edges in the network, as they demonstrate statistically significant differences from the majority of other edges (Figure S1).

Network comparison

To further explore the influence of time perspective on depressive symptoms, we compared the networks constructed from the depressed and non-depressed groups. The network comparison test revealed significant differences in network invariance (M = 0.174, $p = 0.023$) and global strength invariance (Dep: 11.590 vs. Without Dep: 10.312; S = 1.278, $p < 0.01$) (Figure S3). Figure 2 displays the network structure and its attributes for the depressed and non-depressed subgroups.

After 1000 bootstrap tests on network nodes (Table S2), SDS symptoms, except for SDS1, SDS2, SDS3, SDS13, and SDS14, showed significant differences in EI values ($p < 0.05$). Specifically, SDS19 "Suicidal rumination" presented an increased EI value in the depressed network. With respect to the TPs, with the exception of the PN, the other TPs had significantly higher EIs in the depressed network.

Discussion

This study is the first to employ network analysis to explore the complex relationships between time perspectives and the manifestation of depression in high-altitude

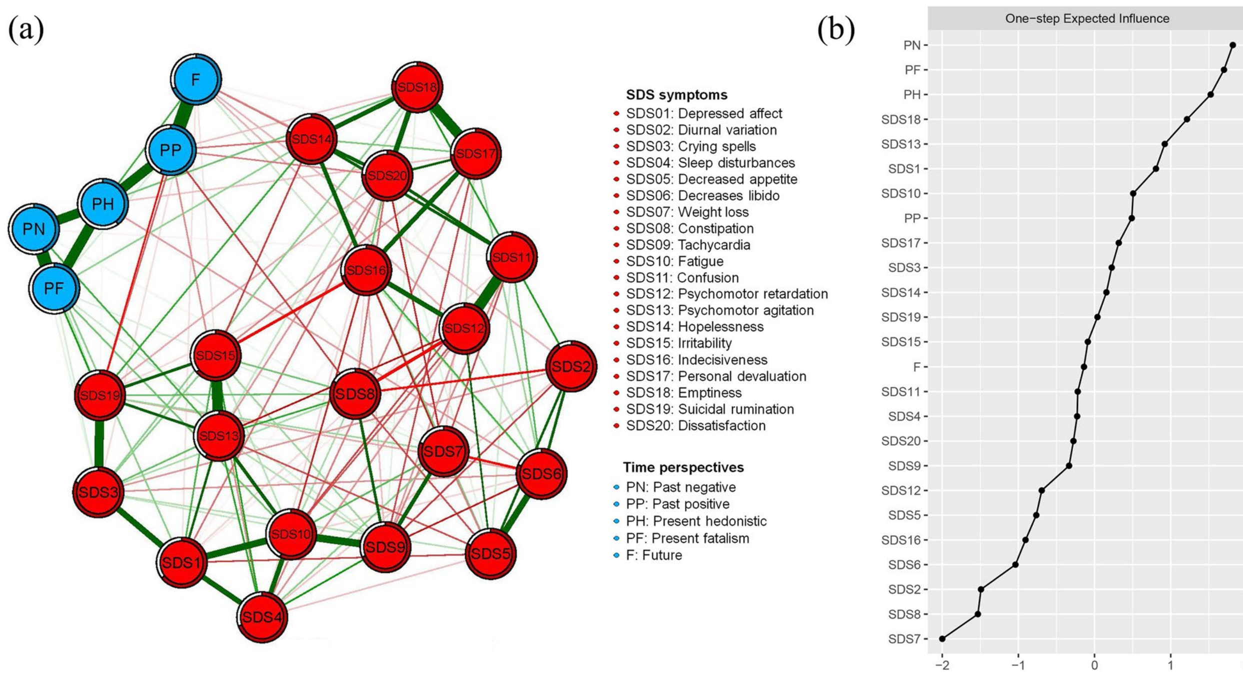

Fig. 1 Network structure and bridge Expected Influence of depressive symptoms and time perspectives in depressed subgroup. **a** Network structure comprised by depressive symptoms and time perspectives in the depressed subgroup. Depressive symptoms are represented by red nodes, while time perspective variables are indicated by blue nodes; The ring area surrounding each node reflects the variable's predictability within the network. Correlations between variables are depicted through edges, with edge color denoting correlation direction (green for positive, red for negative associations), and edge thickness corresponding to correlation strength (thicker edges indicate stronger correlations). **b** Standardized bridge EI(1-step) values for each variable in this network

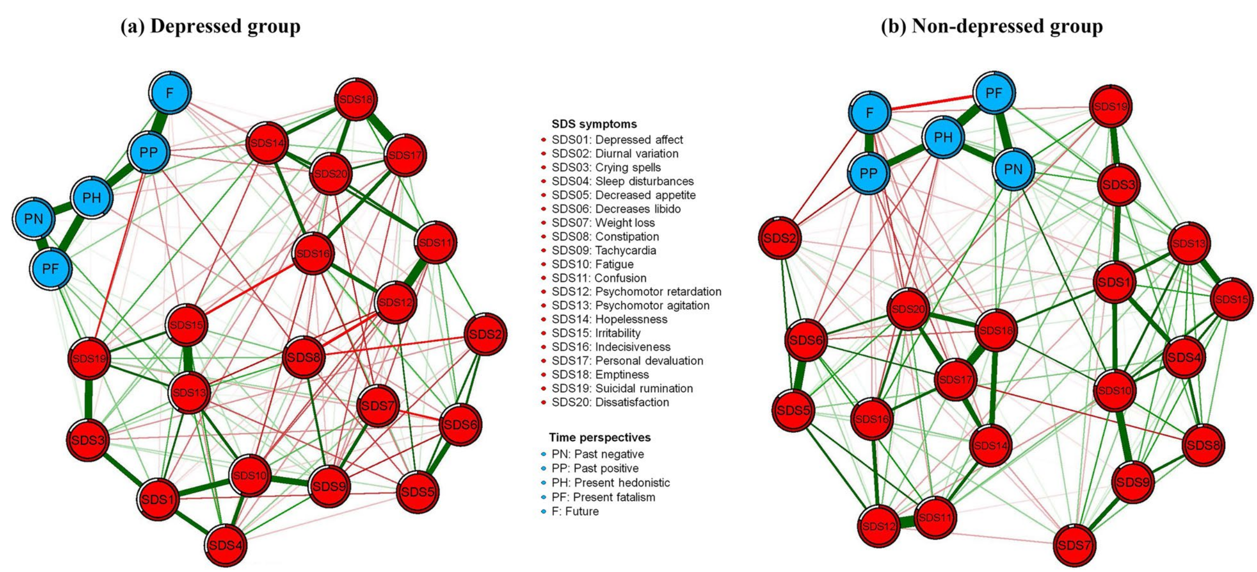

Fig. 2 Network structure of depression and non-depression group. **a** Network structure comprised by depressive symptoms and time perspectives of the depressed group. **b** Network structure comprised by depressed symptoms and time perspectives of the non-depressed group

populations. The results indicate that the prevalence of depressive symptoms in this population was 17.16%, which is lower than previous studies conducted in plateau regions [6] but comparable to levels observed in low-altitude areas [29]. This disparity may relate to sample characteristics: the study population consists of short-term plateau workers whose income is higher than that of similar positions in lowland areas. Additionally, improvements in living conditions on the plateau in recent years (e.g., increased availability of oxygen supply facilities) have reduced environmental stressors [5]. In contrast, the psychosocial stress faced by lowland populations has been continuously rising [30]. These factors may contribute to the convergence of prevalence rates.

The study found that abnormal time perspectives are significant risk factors for depression among high-altitude workers. Specifically, the findings that excessive focus on a negative past, lack of positive past, insufficient future planning, and fatalistic present perspective were all significantly associated with depression, are consistent with research conducted in lowland populations [11, 15, 16]. However, there was a notable difference in the manifestation of present-hedonistic orientation. In lowland populations with depression, a decline in hedonic capacity is commonly observed [18], whereas among plateau workers with depression in our study, PH scores were paradoxically higher. This may be attributed to the unique characteristics of the plateau environment: on one hand, the impairment of response inhibition due to hypoxia [31] may predispose this population to seek immediate rewards, thereby increasing their tendency for impulsive behavior. On the other hand, the monotonous living environment lead to a lack of social activities [32], which may prompt individuals to choose limited forms of entertainment [33], such as gaming, alcohol consumption, or card playing, as immediate forms of stimulation to alleviate psychological discomfort. This impulsive behavior pattern interacts with the risk-taking tendency associated with PH traits [13, 34], thereby constituting a distinct risk pathway for depression among plateau populations.

Network analysis revealed that in the depression symptom-time perspective network, PN and PF had the highest and second-highest EI and bridge EI values, respectively. The high centrality of PN supports the depressive cognition theory, which suggest sthat negative views of past experiences can worsen emotion decline through rumination, creating a vicious cycle of symptoms [35]. The prominent role of PF indicates that the belief in an "uncontrollable fate" in high-altitude environments may intensify depression. [16]. The PH node, which ranked third in the network, aligns with findings from previous analyses showing that individuals with plateau depression tend to have higher PH values. As the nodes with the highest bridge EI values, PN, PF, and PH are crucial in transmitting and evolving depressive symptoms. With these results, one can speculate that psychological therapies, such as cognitive-behavioral therapy, can help individuals with depression by breaking the negative cycle associated with high PN, reducing the pessimistic fatalistic thinking linked to PF, and addressing the impulsive behaviors connected to high PH. Through reshaping their time perspective, these interventions may improve emotional regulation and effectively alleviate depressive symptoms.

Notably, the F-PP (future planning-positive past) edge formed the strongest connection in the network, suggesting that positive past cognition may promote future orientation by enhancing psychological resilience, and the clarity of future goals may, in turn, positively regulate the evaluation of past experiences [36, 37], also offering potential targets for cognitive-behavioral interventions.

Among the depressive symptoms, SDS18 "Emptiness" and SDS13 "Psychomotor agitation") which are ranked fourth and fifth, respectively, are identified as key elements. Feelings of emptiness may stem from the social isolation and monotony of high-altitude environments, where limited social interaction and a lack of variety in daily life can intensify these feelings [38–41]. In this study, participants are living in the socially barren and monotonous plateau environments, are so they are more likely to experience a stronger sense of emptiness [42]. Since deep sense of emptiness may increase their dependence on addictive behaviors, such as excessive mobile gaming and alcohol consumption [33], this phenomena may serve as another explanation of their elevated PH values. Additionally, the high centrality of psychomotor agitation suggests that plateau depression may often involve comorbid anxiety, which aligns with previous findings on the overlap between depression and anxiety symptom networks [40]. The identification of these core symptoms provides important indicators for early screening.

Network comparison revealed that the global connectivity strength of the depressed group was significantly higher than that in the non-depressed group, with clear structural differences between the two. Specifically, the influence of the SDS19 "suicidal ideation" node was markedly stronger in the depressed group. Furthermore, with the exception of PN, the EI values of all other time perspective dimensions were significantly higher in the depressed group. This suggests that a dynamic reinforcement of the interaction between abnormal time perspectives and symptoms, reinforcing each other in the depressive state. This finding supports the bidirectional hypothesis that "abnormal time perspective is both a consequence and a maintaining factor of depression". However, the causal direction of this relationship requires further validation through longitudinal studies.

Limitations

The limitations of this study include: 1) the cross-sectional design makes it difficult to reveal the longitudinal dynamic relationships and causal links between nodes; 2) the sample being limited to males, although the literature suggests minimal gender differences in depression symptom networks, further validation in female populations is required; 3) although all participants were from plateau regions, the inconsistency in sampling areas may lead to sample heterogeneity; 4) the use of self-reported scales may introduce subjective bias, and categorizing depression subgroups based solely on scale scores is simplistic. Future research should adopt more comprehensive diagnostic methods.

Abbreviations

TP	Time perspective
PN	Past negative
PP	Past positive
PF	Present fatalistic
PH	Present hedonistic
EI	Expected influence
SD	Standard deviation
SDS	Self-rating depression scale

Supplementary Information

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Supplementary Material 1.

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Clinical trial number

Not applicable.

Authors' contributions

M.N., F.Z.Z. and W.Y.J. designed and conceptualized the study. M.N., Z.L.L.and Z.M.Y. conducted the data curation and data management. M.N. wrote the draft of the paper. F.Z.Z. and W.Y. J. supervised the whole study and revised the manuscript.

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Data availability

Data are available from corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Informed consent are obtained from all participants in this study, and the procedures are complies with the Declaration of Helsinki. This research was approved by the Ethics Committee of the Army Medical University (No. IEC-C-[B013]-02-J.02).

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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