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ORIGINAL RESEARCH

The Bidirectional Relationship Between Subjective Well-Being and Depression: A Cross-Sectional and Cross-Lagged Network Analysis

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Purpose: Network modeling has been suggested as an effective approach to uncover intricate relationships among emotional states and their underlying symptoms. This study aimed to explore the dynamic interactions between subjective well-being (SWB) and depressive symptoms over time, using cross-sectional and cross-lagged network analysis.

Methods: Data were drawn from three waves (2016, 2018, and 2020) of the China Family Panel Studies (CFPS), including 13,409 participants aged 16 and above. SWB was measured through indicators like life satisfaction and future confidence, while depressive symptoms were assessed using the CES-D8 scale. Symptom-level interactions were analyzed via cross-sectional network analysis at each wave, and cross-lagged panel network analysis was employed to examine the temporal dynamics and bidirectional relationships between SWB and depressive symptoms.

Results: The cross-sectional symptom network analysis showed that the number of non-zero edges at T1, T2, and T3 were 50, 44, and 49, respectively, with network densities of 0.90, 0.80, and 0.89. The core symptom "feeling sad" (D7) consistently had a significantly higher strength than other symptoms. The negative correlation between "life satisfaction" (Z2) and depressive symptoms was particularly evident at T3. The cross-lagged symptom network analysis revealed the key roles of "feeling lonely" (D5) and "feeling sad" (D7), as well as "feeling unhappy" (D4) and "not enjoying life" (D6) across different time periods, which may form a negative feedback loop. "Life satisfaction" (Z2) and "confidence in the future" (Z3) exhibited significant protective effects, forming a positive feedback loop that suppresses negative emotions through mutual reinforcement. Stability analysis showed that the network structure was stable, with a centrality stability coefficient of 0.75.

Conclusion: The study reveals a dynamic, bidirectional relationship between SWB and depressive symptoms. These results offer valuable insights for targeted interventions and public health initiatives aimed at improving mental well-being.

Keywords: subjective well-being, depression, symptom network analysis, cross-lagged network model

Introduction

Subjective well-being (SWB) refers to an individual's evaluation of life quality based on personal standards and experiences.[1] It is a key indicator of both life quality and mental health.[2] Higher levels of SWB are associated with positive emotional states, serving as a psychological resource and a protective mechanism against depression.[3] Depression refers to a mental health disorder affecting emotions, cognition, and behavior, with symptoms such as lack of motivation, loss of interest, and negative future outlooks.[4] While both SWB and depression are crucial to mental health,[5,6] their dynamic interaction remains underexplored. This study examines their bidirectional relationship using symptom network analysis to understand how they influence each other over time. The findings are essential for developing interventions to prevent depression and enhance well-being.

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Existing research indicates a significant negative correlation between SWB and depression.[7–9] For example, LI & Yu (2021) found a strong inverse relationship between SWB and depressive symptoms ($r = -0.30$, 95% CI [−0.35, −0.25]).[7] Similarly, Zeng et al (2023) found that subjective well-being significantly and negatively predicts depression ($\beta = -0.45$, $p < 0.001$).[8] However, there remains debate regarding the causal direction of this relationship, with two main perspectives emerging. The first perspective posits that low SWB may lead to depression.[10–13] SWB is positively correlated with physical and mental health and serves as a significant predictor of psychological well-being.[11] SWB influences various aspects of individuals' lives, including physical health, academic performance, and interpersonal relationships. Depression-prone individuals often exhibit lower levels of SWB than their non-depressed counterparts.[14] Enhancing positive psychological experiences can significantly alleviate depressive symptoms, increase SWB, and reduce depressive levels in clinical patients.[11] Higher SWB also provides individuals with positive resources, acting as a protective factor against depression.[3] Furthermore, a longitudinal study found that individuals with higher SWB are less likely to experience depressive symptoms following unemployment.[15] The second perspective suggests that depression is a critical antecedent of low SWB.[10,15–18] Depression is considered a key factor negatively impacting SWB.[19] As depressive symptoms diminish, SWB significantly improves.[20,21] Additionally, studies show that university students raised under "helicopter parenting" exhibit higher levels of depression and lower SWB.[22] Despite valuable insights from earlier studies, four key limitations remain.

First, there is insufficient research on causal mechanisms. Previous studies often employed unidirectional models to explore either how depression impacts SWB or how SWB affects depressive emotions. These studies generally assumed a unidirectional relationship without delving into the potential bidirectional causal mechanisms between the two. To address this limitation, this study utilizes cross-lagged network models to investigate the bidirectional causal relationship between SWB and depression, thereby uncovering the dynamic interactions between the two constructs.

Second, there are limitations in research perspectives. Most previous studies have examined the relationship between SWB and depression at a macro-variable level, focusing on their correlations or main effects while overlooking the potential complex interactions among specific symptoms. SWB and depression are not single constructs but are composed of multiple dimensions or symptoms (eg, core symptoms of depression include low mood, loss of interest, and sleep problems). These symptoms may function independently or interact with one another to impact overall psychological states differently. However, traditional research has treated SWB and depression as holistic variables, failing to investigate how specific symptoms change and exert influence under different circumstances. Neglecting symptom-level analysis risks overlooking which symptoms play key roles in the interaction between SWB and depression, leading to overly general interventions that may not address specific issues effectively. Additionally, interactions between different symptoms may hold critical causal clues; ignoring symptom-level studies could limit the depth and breadth of theoretical frameworks. This study employs cross-sectional symptom network analysis to identify the specific interactions between SWB and depression at the symptom level. It also incorporates cross-lagged network analysis to explore how these interactions evolve over time. By adopting this approach, the study uncovers the dynamic mechanisms between specific symptoms (low mood in depression or life satisfaction in SWB), addressing the limitations of previous research perspectives and providing a theoretical basis for developing precise symptom-level intervention strategies.

Third, there are limitations in analytical methods. Traditional studies often rely on correlation analysis, regression models, or structural equation modeling, which typically assume linear relationships between variables and primarily focus on direct effects between overall variables. These approaches often overlook the potential for nonlinear interactions and indirect effects among specific symptoms. For instance, a symptom of SWB, such as positive emotions, might indirectly influence overall psychological states through another symptom of depression, such as loss of interest. However, traditional methods struggle to capture such complex relationships. Additionally, the aggregate analysis of variables in traditional approaches may obscure critical mechanisms. Nonlinear and indirect effects may be overlooked, leading to a fragmented understanding of the relationship between SWB and depression. Furthermore, the roles of essential symptoms may remain unidentified. Some key symptoms might act as "mediators" or "bridges" within the network, but they remain unrecognized using conventional methods. This study incorporates cross-sectional symptom network analysis and cross-lagged network analysis to address these methodological limitations. Cross-sectional symptom network analysis is employed to reveal the static interactions between SWB and depressive symptoms at a single time point. Cross-lagged network analysis is used to explore causal relationships and evolutionary trajectories among symptoms over time. This approach captures complex nonlinear and indirect effects, effectively identifying which symptoms play pivotal roles in the relationship between SWB and depression. These insights provide more targeted theoretical guidance for clinical interventions.

Fourth, there is a lack of focus on temporal dynamics. Most existing research relies on cross-sectional data,[23] which can describe static associations between SWB and depression but fail to capture the dynamic evolution of symptom interactions over time. For example, a symptom of SWB, such as life satisfaction, may initially have a significant influence on a depressive symptom, such as low mood, but this relationship might change over time. Additionally, the causal direction of symptom relationships may reverse or weaken across temporal dimensions. The absence of temporal dynamic analysis can lead to several issues: the inability to clarify causal directions among symptoms, difficulty identifying key time points of change, and the potential for shifts in symptom interaction patterns at different time points, making it challenging to design dynamic intervention strategies based on cross-sectional analysis. To address these gaps, this study employs cross-lagged network analysis, which uses multi-wave data to trace causal chains among symptoms and their changes over time. This approach identifies which symptoms play critical roles at specific time points, providing a foundation for timely and targeted interventions. By incorporating temporal dynamics, the study not only enhances the theoretical depth of existing research but also lays the groundwork for time-sensitive intervention strategies focused on symptom dynamics.

To address these gaps, this study incorporates cross-sectional symptom network analysis as a core method to explore the relationship between SWB and depression at a micro level. By examining the specific interactions between symptoms, we aim to identify how individual symptoms of SWB and depression influence one another. Additionally, the study uses cross-lagged symptom network analysis as a key approach to uncover the causal directions between symptoms, enabling a deeper understanding of how the relationship between SWB and depression evolves over time. Combining both static and dynamic methods, the study aims to establish a comprehensive framework for understanding how SWB and depression influence each other through specific symptoms and their temporal interactions.

Subjects and Methods

Data Source

The data were drawn from the China Family Panel Studies (CFPS) database, covering 25 provinces in mainland China and implemented by the Institute of Social Science Survey at Peking University.[24] This study utilized self-reported data on subjective well-being and depression from three waves of CFPS, conducted in 2016 (T1), 2018 (T2), and 2020 (T3). Relevant items were extracted from each wave and merged based on individual IDs. The following criteria were used to select the sample: (1) individuals aged 16 years and above with complete data on subjective well-being and depression assessments across T1, T2, and T3; (2) exclusion of cases with missing values for study variables. A total of 13,409 valid cases were obtained, including 6,652 males and 6,757 females.

Variable Measurement

Subjective Well-Being (SWB)

SWB was measured using the approach proposed by Li et al.[25] While multi-item SWB scales have been developed in prior research, the SWB scale provided in the CFPS adult questionnaire has been validated as a reliable measure of overall SWB[26] and is widely utilized in secondary data studies on SWB.[27] Accordingly, this study measured SWB using three items from the CFPS adult questionnaire: "life satisfaction", "perceived social status" and "Confidence in the future". This scale has been widely proven to have reliability and validity.[25–27] In the current study, the Cronbach's α coefficients at T1, T2, and T3 were 0.764, 0.747, and 0.767, respectively.

Depression

The Center for Epidemiologic Studies Depression Scale Short Form (CES-D8) was used to measure depressive symptoms. This scale consists of 8 items scored on a 4-point Likert scale (1 = rarely or none of the time, 4 = most of the time). Previous CFPS-based studies have frequently utilized this scale to assess depressive symptoms,[28,29] and it has demonstrated good applicability in China.[30] Respondents were asked about the frequency of the following feelings or behaviors over the past week: (1) "I felt depressed", (2) "I felt everything I did was an effort", (3) "My sleep was restless", (4) "I felt happy", (5) "I felt lonely", (6) "I enjoyed life", (7) "I felt sad", and (8) "I felt life was not worth living". In this study, the items "I felt happy" and "I enjoyed life" were reverse-coded. This scale has been widely proven to have reliability and validity.[28–34] In the current study, the Cronbach's α coefficients at T1, T2, and T3 were 0.779, 0.765, and 0.771, respectively.

Control Variables

Considering that individual SWB can be influenced by other factors, this study incorporates demographic control variables based on previous literature. These demographic characteristics include gender and household registration.

Results

Correlation Analysis

Correlation analyses were conducted using SPSS (Windows version 22.0). Cross-lagged network estimation was performed using R (version 4.1.2), with the glmnet package for regularized regression estimation and the qgraph package for network visualization. Cross-lagged networks were constructed for T1 — T2 and T2 — T3 to explore the predictive pathways of symptom networks across the three waves of data collected in 2016, 2018, and 2020. The cross-lagged network analysis followed the methodological guidelines proposed by Rhemtulla et al.[35]

The descriptive statistics and additional analyses are presented in Table 1. Pearson correlation analysis revealed significant positive correlations between SWB at T1, T2, and T3 ($r = 0.340–0.435$, $p < 0.001$) and between depression levels at T1, T2, and T3 ($r = 0.420–0.491$, $p < 0.001$). At the same time points, SWB and depression were significantly negatively correlated ($r = −0.191$ to $−0.301$, $p < 0.001$), indicating a high degree of stability in the relationship between the two variables. Additionally, structural SWB and depression showed significant negative correlations between T1 — T2 and T2 — T3 ($r = −0.224$ to $−0.283$, $p < 0.001$), suggesting a lagged association consistent with the assumptions of a cross-lagged design.

Cross-Sectional Network Analysis

Cross-sectional network analysis was conducted using the qgraph package in R.[36–38] Core symptoms were evaluated using centrality metrics, including closeness and strength. Closeness reflects the average distance from one node to all other nodes in the network, calculated as the reciprocal of the sum of the shortest path distances to all other nodes. Strength centrality represents the absolute sum of the connection weights between a given node and all other nodes.[38–41]

In Figure 1A–C correspond to the symptom networks of subjective well-being (SWB) and depression at T1, T2, and T3, respectively. In terms of network structure, out of the possible 55 edges, the numbers of non-zero edges were 50, 44, and 49 for T1, T2, and T3, respectively. The average edge weights were 0.067, 0.077, and 0.071, and the network densities were 0.90, 0.80, and 0.89, respectively. Correlations included both positive and negative relationships. Overall, the eight dimensions of depression were positively correlated, as were the three dimensions of SWB. However, "life

Table 1 Correlation Analysis

	Mean	Standard Deviation	SWB (T1)	SWB (T2)	SWB (T3)	Depression (T1)	Depression (T2)	Depression (T3)
SWB (T1)	3.4686	0.8014	1	0.340**	0.386**	−0.301**	−0.224**	−0.198**
SWB (T2)	3.2938	0.9427	0.340**	1	0.435**	−0.129**	−0.191**	−0.136**
SWB (T3)	3.778	0.7536	0.386**	0.435**	1	−0.191**	−0.220**	−0.283**
Depression (T1)	1.6388	0.49149	−0.301**	−0.129**	−0.191**	1	0.491**	0.420**
Depression (T2)	1.6955	0.49126	−0.224**	−0.191**	−0.220**	0.491**	1	0.488**
Depression (T3)	1.7072	0.51512	−0.198**	−0.136**	−0.283**	0.420**	0.488**	1

Notes: Statistically significant values, ** $p<0.01$.
Abbreviation: SWB, Subjective Well-Being.

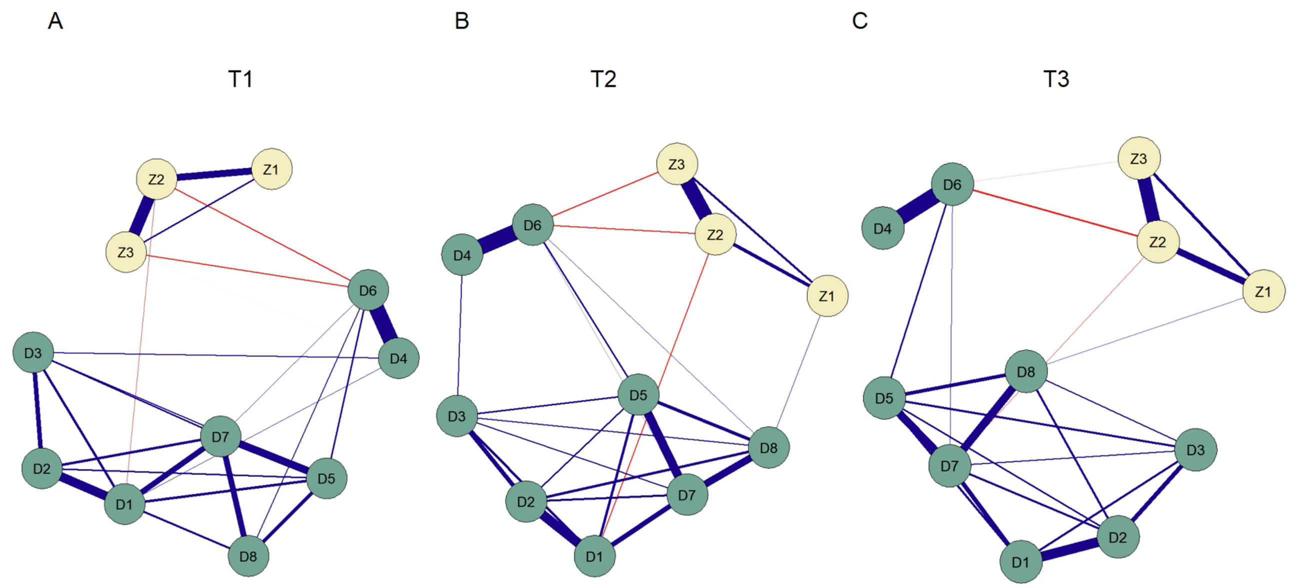

Figure 1 Cross-Sectional Network Analysis at T1 (**A**), T2 (**B**), and T3 (**C**).
Notes: Z1=Perceived social status; Z2= Life satisfaction; Z3=Confidence in the future; D1=Feeling down; D2=Everything feels like an effort; D3= Restless sleep; D4=Feeling unhappy; D5=Feeling lonely; D6=Not enjoying life; D7=Feeling sad; D8=Feeling life is not worth living.

satisfaction" (Z2) and "future confidence" (Z3) from the SWB dimensions were negatively correlated with "not enjoying life" (D6) from the depression dimensions.

Some connections were present in all networks, such as the link between "feeling sad" (D7) and "feeling life is not worth living" (D8). A few connections appeared only in specific networks, such as the association between "feeling sad" (D7) and "life satisfaction" (Z2) at T3. Based on strength estimates (see Figure 2), the strength of "feeling sad" (D7) was significantly higher than most other symptoms over time, making it a stable central symptom. "Feeling sad" (D7) was consistently associated with depressive symptoms such as "feeling down" (D1), "feeling lonely" (D5), and "feeling life is not worth living" (D8) across all networks. However, its connection with "life satisfaction" (Z2) was specific to T3. "Life satisfaction" (Z2) was negatively associated with "feeling down" (D1) at T1 and T2, and with "feeling sad" (D7) at T3. The strength centrality coefficient (CS) for D7 was 0.75 at T1, T2, and T3, exceeding the threshold of 0.5, indicating stability. The overall network strength was 6.70, 6.75, and 6.97 at T1, T2, and T3, respectively. The strength of "feeling down" (D1) significantly decreased from T1 to T3, while the strength of "feeling lonely" (D5), "feeling sad" (D7), and "future confidence" (Z3) significantly increased during the same period.

Cross-Lagged Network Analysis

Cross-lagged panel network analysis, developed by Rhemtulla et al,[35] is a method for using longitudinal panel data to infer the predictive directions of variables within a network. This approach controls for the autoregressive effects of each variable while considering both within-timepoint (undirected) and between-timepoint (directed) associations. It estimates the influence of a variable at one time point on all other variables at the subsequent time point. We calculated unstandardized coefficients for within-timepoint and between-timepoint relationships and regularized autoregressive coefficients. The least absolute shrinkage and selection operator (LASSO) was employed for regularization to cautiously identify network edges and reduce the number of false positives.

To enable visual comparisons of different networks, we used the average Layout function in the qgraph package to create consistent layouts for the nodes across cross-lagged networks. In other words, identical nodes across different networks were fixed at the same positions. The minimum edge weight in the networks was set to 0.05. In the symptom network diagrams, nodes represent symptoms, and arrows denote the directions of cross-lagged effects. Green arrows indicate positive predictions, red arrows indicate negative predictions, and the thickness of the lines reflects the strength

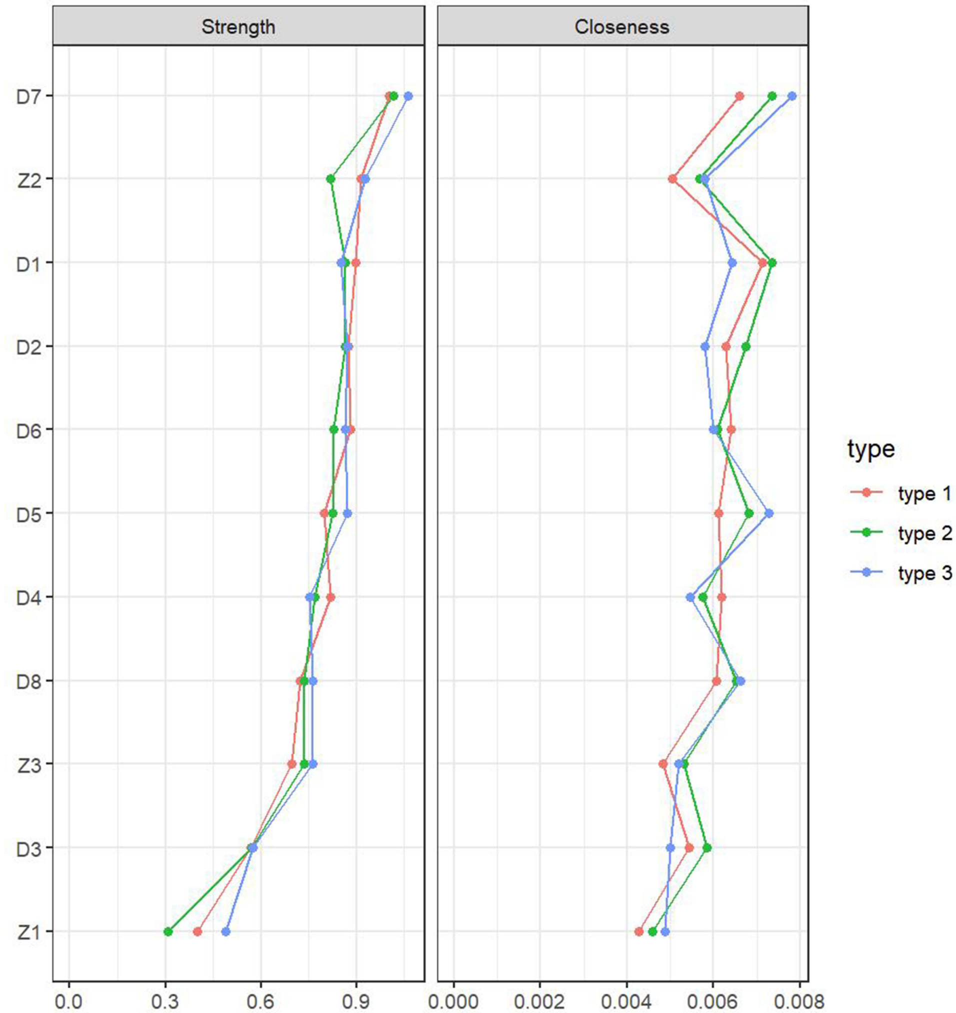

Figure 2 Strength and Closeness of Symptoms in Cross-Sectional Networks at T1, T2, and T3.
Notes: Z1=Perceived social status; Z2= Life satisfaction; Z3=Confidence in the future; D1=Feeling down; D2=Everything feels like an effort; D3= Restless sleep; D4=Feeling unhappy; D5=Feeling lonely; D6=Not enjoying life; D7=Feeling sad; D8=Feeling life is not worth living.

of the associations. Since autoregressive paths are the strongest in the network, they were visually suppressed to highlight cross-lagged paths, which are the primary focus of this type of study.[42] Accordingly, autoregressive paths were set to zero in the main figures to emphasize the cross-lagged effects most relevant to the study objectives.

Network Estimation

The cross-lagged network estimated from T1 — T2 is shown in Figures 3A and 4A. Green arrows represent positive predictions, while red arrows indicate negative predictions. Results reveal that during the T1 — T2 phase, most symptoms exhibit strong autoregressive effects. Among them, "feeling life is not worth living" (D8) emerges as the most predictive symptom in the network, positively influencing symptoms such as "everything feels like an effort" (D2), "not enjoying life" (D6), "feeling lonely" (D5), and "feeling sad" (D7), while negatively affecting "confidence in the future" (Z3). The network also shows some indirect symptom effects, such as "feeling life is not worth living" (D8) influencing "not enjoying life" (D6), which in turn affects "feeling unhappy" (D4). Additionally, circular feedback loops appear within the network, for instance: "feeling life is not worth living" (D8) → "feeling sad" (D7) → "feeling lonely" (D5) → "feeling life is not worth living" (D8). The T2 — T3 cross-lagged network is illustrated in Figures 3B and 4B. Green arrows again represent positive predictions, while red arrows indicate negative predictions. During this phase, strong autoregressive effects persist across most symptoms. "Feeling life is not worth living" (D8) remains the most

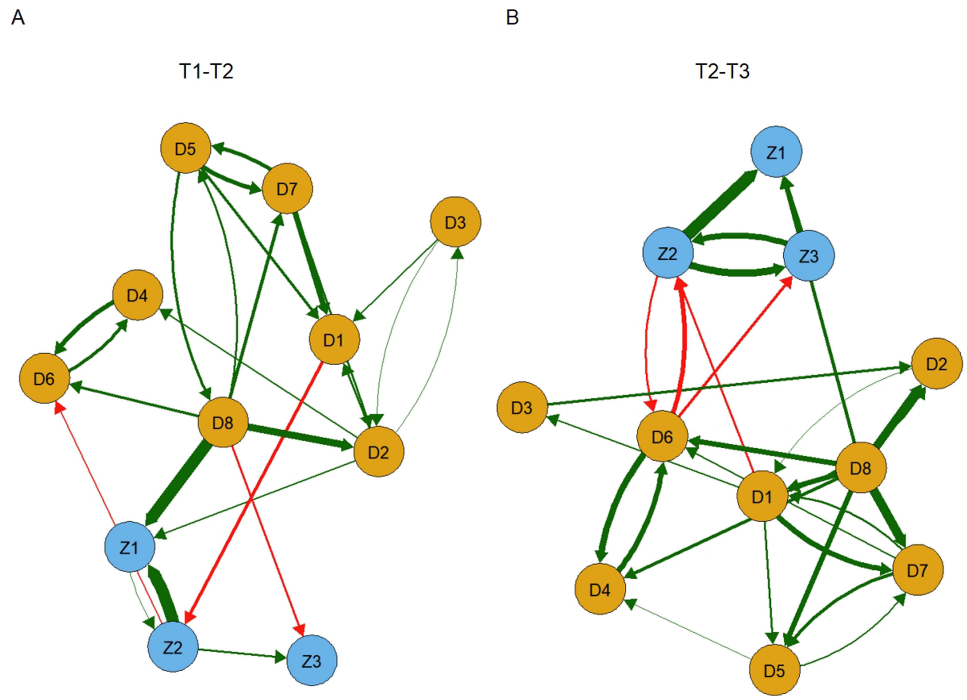

Figure 3 Cross-Lagged Networks Analysis of Subjective Well-Being and Depression from T1 — T2 (**A**) and T2 — T3 (**B**) (Autoregressive Paths Hidden).
Notes: Z1=Perceived social status; Z2= Life satisfaction; Z3=Confidence in the future; D1=Feeling down; D2=Everything feels like an effort; D3= Restless sleep; D4=Feeling unhappy; D5=Feeling lonely; D6=Not enjoying life; D7=Feeling sad; D8=Feeling life is not worth living.

predictive symptom, influencing variables such as "perceived social status" (Z1), "feeling down" (D1), "everything feels like an effort" (D2), "not enjoying life" (D6), "feeling lonely" (D5), and "feeling sad" (D7). Indirect effects also appear in this phase, such as "feeling life is not worth living" (D8) influencing "feeling down" (D1), which subsequently impacts "feeling lonely" (D5). For a complete representation including autoregressive paths for all variables, refer to the full network diagrams provided in Figure S1.

During the T1 – T2 phase, "feeling life is not worth living" (D8) emerged as a critical node with a strong negative impact. It not only influenced other negative emotions, such as "feeling down" (D1) and "feeling lonely" (D5), but also exhibited high centrality, indicating its role as a core factor in triggering depressive emotions. "Perceived social status" (Z1), representing positive emotions related to social standing, also played a significant role during this phase, particularly in mitigating negative emotions, acting as a buffering factor. In the T2 – T3 phase, key changes in network nodes were observed. The importance of "feeling life is not worth living" (D8) diminished compared to the T1 – T2 phase. Although it remained a significant negative emotion node, its influence on other emotions weakened. This may reflect an improvement in individuals' ability to cope with extreme negative emotions over time or an increased influence of positive emotions. "Life satisfaction" (Z2) showed higher centrality during the T2–T3 phase, particularly within the feedback mechanisms of positive emotions. Its role extended beyond alleviating negative emotions, becoming more critical in enhancing overall emotional health. The increased influence of "life satisfaction" (Z2) suggests that, over time, individuals' perceptions of life satisfaction became more impactful on their overall emotional state. "Feeling down" (D1) remained an important negative emotion node in both phases, but its influence strengthened during the T2 – T3 phase. This may be linked to stronger interactions with other negative emotion nodes, indicating that "feeling down" may more readily trigger or exacerbate other negative emotions over time.

During the T1 – T2 phase, connections among negative emotion nodes were relatively dense, forming numerous negative feedback loops. For instance, "feeling life is not worth living" (D8) had a strong influence on other negative emotions, triggering a cascade of reactions that exacerbated the overall emotional state. In contrast, during the T2 – T3 phase, connections among positive emotion nodes became tighter. For example, the interaction between "life satisfaction" (Z2) and "confidence in the future" (Z3) became more prominent. This strengthening of positive connections likely

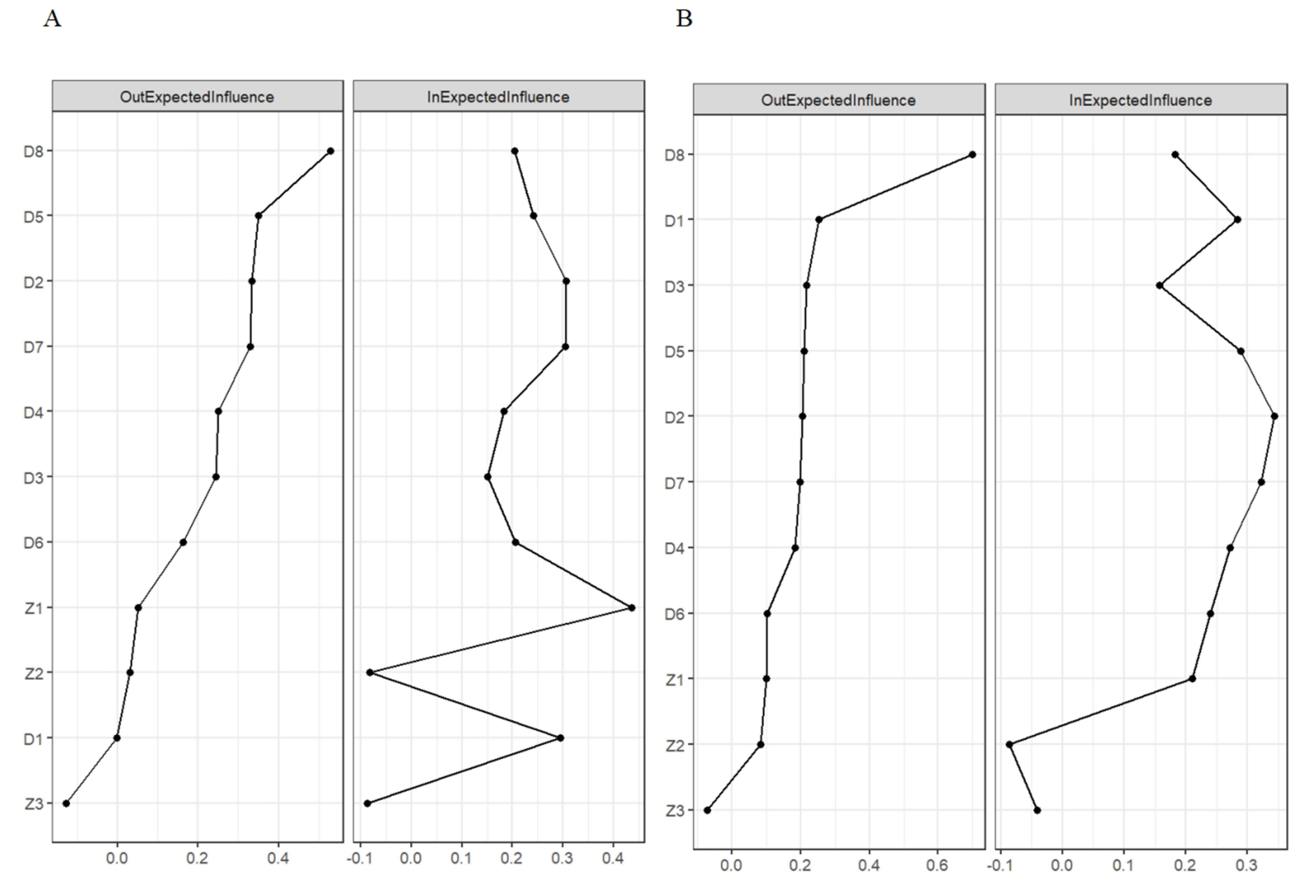

Figure 4 Out-EI and In-EI of Symptoms in the Cross-Lagged Networks of Subjective Well-Being and Depression from T1 — T2 (**A**) and T2 — T3 (**B**).
Notes: Z1=Perceived social status; Z2= Life satisfaction; Z3=Confidence in the future; D1=Feeling down; D2=Everything feels like an effort; D3= Restless sleep; D4=Feeling unhappy; D5=Feeling lonely; D6=Not enjoying life; D7=Feeling sad; D8=Feeling life is not worth living.

contributed to mitigating the impact of negative emotions and breaking the cycles of negative feedback. Additionally, the connections between negative emotions weakened during this phase, suggesting that individuals' emotional regulation abilities may have improved over time, reducing the self-perpetuating mechanisms of negative emotions.

During the T1 – T2 phase, "confidence in the future" (Z3), while a positive emotion node, exhibited low centrality and had limited influence on the overall emotional network. However, in the T2 – T3 phase, the importance of Z3 increased significantly, particularly in its interaction with "life satisfaction" (Z2). Its positive impact on the overall emotional network became more pronounced. This suggests that confidence in the future plays a progressively crucial role in maintaining emotional well-being over longer periods, highlighting its growing importance for sustaining emotional health.

During the T1 – T2 phase, the emotional network structure was relatively simple, with stronger connections among negative emotions. This indicates a cumulative effect and mutual reinforcement among negative emotions. In contrast, during the T2 – T3 phase, the complexity of the emotional network increased, with interactions between positive and negative emotions becoming more intricate. This shift may reflect an enhanced adaptability in individuals' emotional regulation mechanisms when coping with persistent emotional states.

During the T1 – T2 phase, the lagged effects of negative emotions were more pronounced. For instance, "feeling down" (D1) had a significant impact on other negative emotion nodes, indicating that negative emotions tended to spread more easily within the emotional network.In contrast, during the T2 – T3 phase, the lagged effects of positive emotions became more prominent over time. For example, "life satisfaction" (Z2) had an increasing influence on other emotion nodes during this phase, highlighting the growing role of subjective well-being in regulating the emotional network.

During the T1 – T2 phase, the influence of positive emotions was relatively limited, with minimal suppressive effects on negative emotions. However, in the T2 – T3 phase, the feedback mechanisms of positive emotions, such as "life satisfaction" (Z2) and "confidence in the future" (Z3), became more active. This indicates an enhanced role of positive emotions in counteracting negative emotions. This shift suggests that individuals may develop more effective emotional coping mechanisms over time, particularly as positive emotions play an increasingly significant role in mitigating negative emotional states.

During the T1 – T2 phase, the bidirectional relationship between SWB and depressive emotions was more unidirectional, with depressive emotions predominantly eroding SWB. In contrast, during the T2 – T3 phase, the bidirectional influence became more balanced, with improvements in SWB exerting a stronger buffering effect on depressive emotions. This change suggests that individuals' emotional regulation abilities may have strengthened over time, enhancing their capacity to mitigate the impact of depressive emotions.

During the T1 – T2 phase, feedback loops were predominantly concentrated among negative emotions, forming multiple negative feedback cycles. For instance, "feeling life is not worth living" (D8) strongly reinforced other negative emotions through feedback loops, leading to the self-perpetuation and further intensification of negative emotional states. This structure heightened the vulnerability of individuals' emotional states, making them more prone to sustained low mood. In the T2 – T3 phase, more positive feedback loops emerged, particularly among positive emotion nodes. For example, the interaction between "life satisfaction" (Z2) and "confidence in the future" (Z3) strengthened, creating a positive spiral that improved emotional states when individuals faced negative emotions. Concurrently, the negative feedback loops among negative emotions weakened, suggesting that individuals' emotional regulation mechanisms had matured during this period, effectively curbing the escalation of negative emotions.

By comparing the emotional network complexities in the T1 – T2 and T2 – T3 phases, the temporal evolution of the emotional network becomes evident. The T1 – T2 emotional network was relatively simple, predominantly dominated by negative emotions, with fewer feedback loops and interactions. This simplicity contributed to a less stable overall emotional state. In contrast, the T2 – T3 emotional network exhibited greater complexity. The strengthening of positive emotions and the diversification of interactions contributed to a more stable network. Additionally, the increased richness of feedback loops, particularly among positive emotions, enhanced the overall robustness of the emotional state during this phase.

Centrality Estimation

The centrality of symptoms in the cross-lagged networks is shown in Figure 4. Cross-lagged network analysis across the two time periods revealed time-specific patterns for symptoms with high out-expected influence (out-EI). During the T1 – T2 phase, "feeling life is not worth living" (D8) exhibited the highest out-EI, followed by "feeling lonely" (D5). In contrast, "perceived social status" (Z1) and "feeling down" (D1) had the highest in-expected influence (in-EI). During the T2 – T3 phase, "feeling life is not worth living" (D8) and "feeling down" (D1) had the highest out-EI, while "everything feels like an effort" (D2), "feeling sad" (D7), and "feeling lonely" (D5) showed the highest in-EI.

Stability Analysis

Two stability analyses were performed using the bootnet package in R.[36] First, the accuracy of edge weights was evaluated by constructing 95% confidence intervals (CIs) through bootstrapping (1,000 bootstrapped samples). Minimal overlap between these CIs indicated high accuracy. Second, a subsetting bootstrap procedure was conducted to assess the stability of centrality estimates. This involved removing a proportion of the sample and re-estimating the network. If the order of centrality estimates in the subset networks remained highly correlated with the original network, the centrality estimates were considered stable Additionally, the centrality stability coefficient (CS-coefficient), a recognized metric for stability, was calculated. A CS-coefficient greater than 0.5 indicates high stability, while values above 0.25 are acceptable Results of the T1 – T2 cross-lagged network stability analysis demonstrated very high stability for all expected influence measures, including bridge expected influence, in-expected influence, and out-expected influence. All these metrics achieved CS-coefficients of 0.75, the highest possible level of stability, indicating a robust network structure. Finally, differences in out-expected influence (out-EI) and in-expected influence (in-EI) among symptoms were evaluated using centrality difference tests.[32]

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Discussion

This study first used cross-sectional symptom network analysis at three time points (T1, T2, T3) and compared the results across these time points to explore the complex relationship between depressive symptoms and various dimensions of SWB. We then applied cross-lagged network models to analyze the dynamic interactions between T1-T2 and T2-T3, providing an in-depth exploration of the interactions between SWB and depressive emotions. These findings offer a new perspective on the temporal evolution of emotions and support clinical interventions and mental health management.

First, the cross-sectional symptom network analysis showed that although network density and strength varied across T1, T2, and T3, the influence of core symptoms remained stable For example, "feeling sad" (D7) was consistently a core symptom, with its influence significantly higher than that of other symptoms. This is consistent with the findings of Zeng et al (2023), who concluded that SWB serves as a protective factor for mental health.[8] In the cross-sectional symptom network analysis at T3, a significant cross-dimensional association between "life satisfaction" (Z2) and "feeling sad" (D7) was observed, suggesting that certain dimensions of SWB may play an important role in regulating depressive symptoms. The study by Li & Yu (2021) also found a significant negative correlation between SWB and depressive symptoms ($r = -0.30$, 95% CI [−0.35, −0.25]), further supporting the conclusions of our study.[7]

Second, the cross-lagged network analysis in this study revealed several key phenomena: First, negative feedback loops were found between "feeling lonely" (D5) and "feeling sad" (D7), as well as between "feeling unhappy" (D4) and "not enjoying life" (D6), which could further activate extreme negative emotions. This suggests that emotional regulation strategies should incorporate multidimensional interventions, rather than focusing solely on a single symptom. Second, "life satisfaction" (Z2) and "confidence in the future" (Z3) exhibited significant protective effects over the long term. These factors not only suppressed negative emotions but also enhanced an individual's psychological resilience through emotional interaction mechanisms. This finding is consistent with the meta-analysis by Burns et al (2011), which found a significant negative correlation between positive emotions in SWB and depressive emotions ($r = -0.333$, $p < 0.01$).[16]

Theoretical Implications

First, this study expands the theoretical framework of the relationship between SWB and depression. Previous research mostly assumes a unidirectional relationship between the two, without exploring the potential bidirectional causal mechanisms. SWB and depressive emotions are not merely inversely related.[7–12] By combining advanced cross-sectional symptom network analysis and cross-lagged network models, this study reveals a more complex bidirectional causal relationship between them, providing a new theoretical perspective.

Second, this study emphasizes the temporal dynamics of emotional states. Traditional emotion research primarily relies on cross-sectional data, with limited exploration of how emotions change over time.[10,16,17,22,23] By utilizing longitudinal data and cross-lagged network models, this study reveals the reciprocal influence and evolving dynamics of SWB and depressive emotions, enriching the temporal dimension in emotional theories.

Third, this study offers a new perspective on emotion analysis methods, advancing the paradigm of emotional research. Traditional studies often treat SWB and depression as holistic variables.[3,12] However, subjective well-being and depression are not singular concepts; they consist of multiple dimensions or symptoms. This study, Through symptom network analysis and cross-lagged symptom network analysis, this study reveals SWB and depressive emotions as interconnected systems, uncovering the complex associations among symptoms and how these relationships evolve over time.

Practical Implications

The findings of this study have significant implications for mental health interventions, personalized psychotherapy, and public health policies.

First, enhancing SWB as a strategy for preventing and addressing depression: Our study demonstrates that improving SWB can effectively alleviate depressive symptoms. Therefore, mental health interventions should not solely focus on reducing depressive symptoms but also consider how to enhance individuals' SWB. For example, psychological therapy can promote positive emotional experiences, such as increasing life satisfaction and confidence in the future, to reduce depression levels.

Second, scientific basis for personalized psychotherapy: Through emotional network analysis, we found that the emotional symptom structures vary among individuals. For instance, core depressive symptoms such as “loneliness” or “feeling down” may play different roles in different individuals, indicating their varying significance. Thus, mental health professionals can design precise intervention strategies based on individualized symptom networks, thereby improving treatment outcomes.

Third, scientific basis for public health policies: This study reveals that SWB is not only a personal emotional experience but also serves as a societal protective factor that significantly reduces the incidence of depression. As such, public health policies should focus on enhancing overall societal SWB to mitigate the widespread occurrence of depression. For example, improving social welfare, increasing employment opportunities, and strengthening community support may contribute to higher life satisfaction among community members, thereby reducing the prevalence of depression.

Limitations and Future Research

First, cultural applicability: The research data primarily originate from a specific cultural and social context, which may impose certain cultural limitations on the study’s conclusions. Therefore, future research should be conducted in diverse cultural environments to enhance the external validity of the findings.

Second, identification of long-term trends: The time span of this study is limited. Future research could adopt longer-term longitudinal study designs to capture the long-term evolutionary trends of emotional networks.

Third, data collection methods: This study mainly relies on self-reported data, which may be subject to social desirability bias and recall bias. Future research could incorporate physiological indicators and behavioral observations to provide more objective data support. Additionally, future studies may utilize mobile devices and wearable sensors for real-time emotion monitoring, which will help collect more precise emotional data and analyze the dynamic changes within emotional networks.

Conclusion

This study aimed to explore the bidirectional relationship between SWB and depressive symptoms using cross-sectional and cross-lagged network analyses. By employing data across three time points (2016, 2018, and 2020), we sought to uncover the dynamic interactions between these two emotional constructs over time. The results revealed intricate emotional networks, with depressive symptoms such as “feeling sad” (D7) emerging as central nodes in the depression network. In contrast, “life satisfaction “(Z2) and “Confidence in the future” (Z3) played pivotal roles within the SWB network.

Notably, the study shows that positive emotions, particularly “life satisfaction” (Z2) and “Confidence in the future” (Z3) form a positive feedback loop, with their buffering effect on depression strengthening over time, effectively alleviating depressive symptoms. These findings highlight the importance of enhancing SWB as a preventive strategy for depression management. By identifying the critical roles of specific symptoms and their temporal dynamics, the study offers insights for developing targeted interventions, early detection strategies, and public health policies aimed at improving mental well-being.

In sum, the results underscore the need to foster positive emotional resources, as they disrupt negative feedback loops and promote resilience against depression. These findings are crucial for shaping mental health initiatives that prioritize both the prevention of depressive symptoms and the enhancement of subjective well-being.

Data Sharing Statement

All the datasets can be accessed at the Peking University Open Research Data after being authorized.

Ethics Approval and Informed Consent

This study and its protocols have received approval from the Guangxi Science & Technology Normal University Medical Ethics Committee (Approval number: 2025–001). All methods were carried out in accordance with the guidelines of the Declaration of Helsinki and were approved by the aforementioned ethics committee. All participants were informed about the survey and provided their consent.

Author Contributions

All authors made substantial contributions to conception and design, acquisition of data, or analysis and interpretation of data; took part in drafting the article or revising it critically for important intellectual content; agreed to submit to the current journal; gave final approval of the version to be published; and agree to be accountable for all aspects of the work.

Disclosure

The authors report no conflicts of interest in this work.

References

1. Diener E, Suh EM, Lucas RE, Smith HL. Subjective well-being: three decades of progress. *Psychol Bull*. 1999;125:276–302. doi:10.1037/0033-2909.125.2.276
2. Oswald AJ, Wu S. Objective confirmation of subjective measures of human well-being: evidence from the U.S.A. *Science*. 2010;327:576–579. doi:10.1126/science.1180606
3. Moreno RL, Godoy-Izquierdo D, Vazquez Perez ML. Multidimensional psychosocial profiles in the elderly and happiness: a cluster-based identification. *Aging Mental Health*. 2014;18(4):489–503. doi:10.1080/13607863.2013.856861
4. Smith K. Mental health: a world of depression. *Nature*. 2014;515:180–181. doi:10.1038/515180a
5. Beck AT, Weishaar ME. Cognitive therapy. In: Corsini RI, Wedding D, editors. *Current Psychotherapies*. 7th ed. Belmont, CA: Thomson Brooks/Cole; 2000:241–272.
6. Wichers M, Jacobs N, Derom C, Thiery E, van Os J. Depression: too much negative affect or too little positive affect? *Twin Res Hum Genet*. 2007;10(S1):19–20. doi:10.1375/twin.10.supp.19
7. Li Y, Yu JF. Influence of health behaviors on depressive tendencies in special education teachers: the chain mediation of evaluative support and subjective well-being. *Chin Special Educ*. 2021;4:27–33.
8. Zeng ZH, Peng LY, Zhan L, et al. The impact of childhood abuse on depressive symptoms in college students: the mediating role of subjective well-being and the moderating role of genes. *Psychol Dev Educ*. 2023;39(02):276–285. doi:10.16187/j.cnki.issn1001-4918.2023.02.14
9. Greger HK, Myhre AK, Klöckner CA, Jozefiak T. Childhood maltreatment, psychopathology, and well-being: the mediator role of global self-esteem, attachment difficulties, and substance use. *Child Abuse Negl*. 2017;70:122–133. doi:10.1016/j.chiabu.2017.06.012
10. Alonso Debreczeni F, Bailey PE. A systematic review and meta-analysis of subjective age and the association with cognition, subjective well-being, and depression. *J Gerontol B Psychol Sci Soc Sci*. 2021;76(3):471–482. doi:10.1093/geronb/gbaa069
11. Capistrant BD, Friedemann-Sánchez G, Novak LK, Zuijdwijk C, Ogle GD, Pendsey S. Mental health and well-being among type 1 diabetes caregivers in India: evidence from the IDREAM study. *Diabet Res Clin Pract*. 2017;134:168–177. doi:10.1016/j.diabres.2017.10.009
12. Kim H, Moon H, Yoo JP. How do time use and social relationships affect the life satisfaction trajectory of Korean adolescents? *Int J Environ Res Public Health*. 2020;17(5):1–12. doi:10.3390/ijerph17051532
13. Liu AL, Ou XC. The effect of childhood unhappiness on depression in college students: a moderated chain mediation model. *Chinese J Clin Psychol*. 2023;31(04):1013–1018+949. doi:10.16128/j.cnki.1005-3611.2023.04.049
14. Zhang LY. The influence of depression and social support on subjective well-being among normal college students. *Chinese J Health Psychol*. 2006;5:595–597. doi:10.13342/j.cnki.cjhp.2006.05.050
15. Liu B, Zou M, Bao H, et al. Mental health and meaning in life in Chinese military personnel: a cross-lagged analysis. *BMC Psychol*. 2024;12:426. doi:10.1186/s40359-024-01932-1
16. Burns RA, Anstey KJ, Windsor TD. Subjective well-being mediates the effects of resilience and mastery on depression and anxiety in a large community sample of young and middle-aged adults. *Aust N Z J Psychiatry*. 2011;45(3):240–248. doi:10.3109/00048674.2010.529604
17. Malone C, Wachholtz A. The relationship of anxiety and depression to subjective well-being in a mainland Chinese sample. *J Relig Health*. 2018;57:266–278. doi:10.1007/s10943-017-0447-4
18. Fervaha G, Agid O, Takeuchi H, Foussias G, Lee J, Remington G. Clinical and functional outcomes in people with schizophrenia with a high sense of well-being. *J Nerv Ment Dis*. 2015;203(3):187–193. doi:10.1097/NMD.0000000000000266
19. Yan BB, Zheng X, Zhang XG. Mechanism of the influence of social support on subjective well-being among college students: the mediating roles of self-control and depression. *Psychol Sci*. 2011;34(02):471–475. doi:10.16719/j.cnki.1671-6981.2011.02.009
20. Wang J, Liu SM, Zhang PC, Wu HY, Chi XL. The effect of positive psychological interventions on the emotions and subjective well-being of college students with depressive symptoms. *Chin Special Educ*. 2016;11:44–50.
21. Zhang XM, Li WQ, Liu YY. Analysis of the status and influencing factors of subjective well-being among the elderly in communities. *Population J*. 2017;39(03):88–96. doi:10.16405/j.cnki.1004-129X.2017.03.008
22. Shi ZF, Chen HH, Zhang YH, et al. The impact of helicopter parenting on subjective well-being among college students: the chain mediation of self-control and depression. *Res Psychol Behav*. 2024;22(01):116–122.
23. Ventura-León J, Caycho-Rodríguez T, Talledo-Sánchez K, Casiano-Valdivieso K. Depression, COVID-19 anxiety, subjective well-being, and academic performance in university students with COVID-19-infected relatives: a network analysis. *Front Psychol*. 2022;13:837606. doi:10.3389/fpsyg.2022.837606
24. Xie Y, Hu JW, Zhang CN. China Family Panel Studies: concepts and practices. *Society*. 2014;34(02):1–32. doi:10.15992/j.cnki.31-1123/c.2014.02.003
25. Li QR, Li CX, Yang YY, Chang NF. The heterogeneous impact of entrepreneurship on short-term and long-term happiness. *Manag J*. 2021;9:1335–1343.
26. Ryan RM, Deci EL. On happiness and human potentials: a review of research on hedonic and eudaimonic well-being. *Annu Rev Psychol*. 2001;52(1):141–166. doi:10.1146/annurev.psych.52.1.141

27. Zhou Y, Zou M, Woods SA, Wu CH. The restorative effect of work after unemployment: an intraindividual analysis of subjective well-being recovery through reemployment. *J Appl Psychol*. 2019;104(9):1195. doi:10.1037/apl0000393
28. Liao YG, Lian R. Latent transition analysis of depressive symptoms in adults: a four-year follow-up study. *Chinese J Clin Psychol*. 2020;28 (03):518–522. doi:10.16128/j.cnki.1005-3611.2020.03.018
29. Zhao XH, Ruan HQ. Socioeconomic gradients of depressive symptoms in Chinese adults: evidence from the China Family Panel Studies (2014 and 2016). *Beijing Soc Sci*. 2019;8:34–47. doi:10.13262/j.bjsshkxy.bjshkx.190804
30. Zhang J, Wu ZY, Fang G, Li J, Han BX, Chen ZY. Establishing national urban norms for the CES-D scale in China. *Chinese Ment Health J*. 2010;2:139–143.
31. Zhang Y. The relationship between corruption perception and depression: a multiple mediation model. *Psychol Res Behav Manag*. 2022;15:1943–1954. doi:10.2147/PRBM.S370045
32. Zhao H, Shi H, Ren Z, et al. The mediating role of extra-family social relationship between personality and depressive symptoms among Chinese adults. *Int J Public Health*. 2022;67:1604797. doi:10.3389/ijph.2022.1604797
33. Zhou T, Cheng G, Wu X, et al. The associations between sleep duration, academic pressure, and depressive symptoms among Chinese adolescents: results from China family panel studies. *Int J Environ Res Public Health*. 2021;18(11):6134. doi:10.3390/ijerph18116134
34. Missinne S, Vandeviver C, Van de Velde S, Bracke P. Measurement equivalence of the CES-D 8 depression-scale among the ageing population in eleven European countries. *Soc Sci Res*. 2014;46:38–47. doi:10.1016/j.ssresearch.2014.02.006
35. Wysocki A, Rhemtulla M, van Bork R, Cramer A. Cross-lagged network models. *Multivariate Behav Res*. 2021;56:288–302. doi:10.31234/osf.io/vjr8z
36. Epskamp S, Cramer AOJ, Waldorp LJ, Schmittmann VD, Borsboom D. qgraph: network visualizations of relationships in psychometric data. *J Stat Softw*. 2012;48(4):1–18. doi:10.18637/jss.v048.i04
37. Huang SS, Lai XX, Xue Y, Zhang C, Wang Y. A network analysis of problematic smartphone use symptoms in a student sample. *J Behav Addict*. 2021;9(4):1032–1043. doi:10.1556/2006.2020.00098
38. van Borkulo C, Boschloo L, Borsboom D, Penninx BW, Waldorp LJ, Schoevers RA. Association of symptom network structure with the course of depression. *JAMA Psychiatry*. 2015;72(12):1219–1226. doi:10.1001/jamapsychiatry.2015.2079
39. Borsboom D, Cramer AOJ. Network analysis: an integrative approach to the structure of psychopathology. *Ann Rev Clin Psychol*. 2013;9 (1):91–121. doi:10.1146/annurev-clinpsy-050212-185608
40. Cai YQ, Dong SY, Yuan S, Hu CP. Network analysis models for relationships between variables and their applications. *Adv Psychol Sci*. 2020;28 (1):178–190. doi:10.3724/SP.J.1042.2020.00178
41. Mullarkey MC, Marchetti I, Beevers CG. Using network analysis to identify central symptoms of adolescent depression. *J Clin Child Adolesc Psychol*. 2019;48(4):656–668. doi:10.1080/15374416.2018.1437735
42. Funkhouser CJ, Chacko AA, Correa KA, Kaiser AJ, Shankman SA. Unique longitudinal relationships between symptoms of psychopathology in youth: a cross-lagged panel network analysis in the ABCD study. *J Child Psychol Psychiatr*. 2021;62(2):184–194. doi:10.1111/jcpp.13320