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Understanding the Co-occurrence of Depressive and Anxiety Symptoms Among 2021 Henan Flood Victims Through Panel Network Analysis: A 6-Month, Three-Wave Longitudinal Study

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ABSTRACT

Previous studies have mostly used cross-sectional network to analyze the co-occurrence of depression and anxiety, but this method cannot capture the temporal influences between symptoms. This study uses longitudinal data to explore the dynamic structure of the cooccurrence of depressive and anxiety symptoms among flood victims in Henan in 2021. Data were collected at 3-month intervals from July 20, 2021, to January 30, 2022, and the final sample included 279 disaster victims reporting on items measuring anxiety and depression. We employ the generalized vector autoregressive model approach to estimate network models. The contemporaneous network results show that, within the same measurement occasion, all connections between anxiety and depressive symptoms are positive, with the strongest connection observed between “Sleep” and “Appetite”. And “Nervous” is the most central symptom, while “Irritable” and “Motor” are the top two strongest bridge symptoms. The temporal network results indicate that depressive symptoms are more temporally causal and predictive, while the temporal associations between anxiety symptoms are rare. And depressive symptoms were found to predict anxiety symptoms. Additionally, “Suicide” and “Concentration” showed significant positive autocorrelations, indicating a self-sustaining capacity. “Anhedonia” has the highest in-strength centrality (incoming influence from prior time point), demonstrating the most downstream effect. In contrast, “Concentration” has an out-strength centrality (outgoing influence to the next time point) far exceeding that of other symptoms, suggesting it has the most outward influence. These patterns suggest testable, symptom-focused priorities for post-disaster care: early attention-focused strategies to curb downstream spread from concentration problems; behavioral activation for anhedonia; proactive safety planning and scheduled follow-ups for suicidal ideation; brief transdiagnostic modules targeting irritability and motor activation to reduce comorbidity; and integrated routines addressing the sleep–appetite dyad. Implications are observational and intended to inform hypothesis-driven trials and service planning.

1 | Introduction

Natural disasters have negative consequences and cause psychological distress to those who experience them (Framingham and Teasley 2012; Norris et al. 2002). Depression and the family of anxiety disorders are common in disaster contexts (Grineski et al. 2023; Park and Bae 2022) and frequently co-occur (Kar and Bastia 2006; Marthoenis et al. 2019; Pan et al. 2015). In the early days, Seligman and Ollendick (1998) proposed based on clinical diagnostic practice that due to the overlapping definitions of depression and anxiety, the illusion of their comorbidity may occur during diagnosis. The comorbidity of depression and anxiety refers to their frequent co-occurrence, where these disorders appear simultaneously in individuals. Previous studies have proposed three models from a theoretical perspective to explain the co-occurrence of depression and anxiety (Cummings et al. 2014), namely the Tripartite Model (Clark and Watson 1991), the Behavioral Inhibition/Activation System (BIS/BAS) Model (Johnson et al. 2003; Schofield et al. 2009a), and A Multiple Pathways Model (Cummings et al. 2014). Most previous studies have focused on shared causes of depression–anxiety co-occurrence, such as negative emotions and other transdiagnostic risk factors (Clark and Watson 1991; Cummings et al. 2014). As a result, the symptom-to-symptom relation between depression and anxiety has been underexamined—particularly in longitudinal designs and in disaster-affected cohorts—leaving an incomplete account of how their co-occurrence unfolds over time. This limits the ability to provide a more accurate basis for diagnosis and treatment.

Due to the limitations of traditional methods, the introduction of psychopathology network method in clinical psychology and psychiatry offers a new way to address the shortcomings of previous research. The psychopathology network method emphasizes the relations between symptoms and argues that mental disorders are caused by causal relations between symptoms (Borsboom and Cramer 2013; Cramer et al. 2010). In the network, symptoms are represented as nodes, and the relations between symptoms are represented as edges between nodes. (Borsboom 2017). Network analysis enables researchers to identify central symptoms, bridge symptoms, and edge patterns, providing new insights into how symptoms influence each other and cause the co-occurrence of disorders (Borsboom 2017; Borsboom and Cramer 2013). In recent years, the application of the psychopathology network method has become widespread, not only in studies of clinical populations (Beard et al. 2016; Kaiser et al. 2021; Mihić et al. 2024), but also in studies of disaster victims (Qi et al. 2021; Wang and Ma 2023; Yang et al. 2022) and other populations (Garabiles et al. 2019; Luo et al. 2024; Ren et al. 2021). Importantly, in the network-analytic literature on depression-anxiety co-occurrence, anxiety is most often operationalized at the level of generalized-anxiety symptoms—typically via the GAD-7—rather than across the broader anxiety-disorders spectrum. Representative network and dynamic-network studies explicitly assessed generalized anxiety symptoms with the GAD-7 alongside depressive symptoms, including large trauma-exposed or community cohorts and specialized subgroups (Bekhuis et al. 2016; Price et al. 2019; Wang et al. 2021; 2024; Yang and Ma 2025).

Most existing studies estimate networks of the co-occurrence of depression and anxiety based on cross-sectional data, identifying central symptoms, bridge symptoms and edge patterns in different populations. For example, first, in clinical settings, a psychiatric partial-hospital program sample showed "Sad Mood" and "Worry" among the most central symptoms (Beard et al. 2016). In a large psychiatric inpatient sample, psychomotor agitation/retardation was the strongest bridge between depression and anxiety, while "Sad Mood" and the inability to control worry were most central (Kaiser et al. 2021). Second, in disaster victim populations, depressive symptom "Sad Mood" is identified as the most central symptom and "Energy", "Sad Mood", "Suicide" are bridge symptoms among adolescents who have experienced the COVID-19 pandemic (Cai et al. 2022). And for flood disaster victims, depressive symptom "Anhedonia" is identified as a central symptom (Wang and Ma 2023). Additionally, among doctors who experienced the COVID-19 disaster, the connection between "Restless" and "Afraid" was the strongest edge in the anxiety subnetwork, and the connection between "Concentration" and "Motor" was the strongest edge in the depression subnetwork (Jin et al. 2022). Third, in other populations, such as Filipino domestic workers, the centrality index of depressive symptom "Energy" is the highest (Garabiles et al. 2019). For Chinese female nursing students, "Sad Mood" and "Irritable" have been identified as bridge symptoms (Ren et al. 2021). Moreover, for college freshmen, finding that the connection between "Nervous" and "Control Worry" was the strongest edge (Luo et al. 2024). Beyond population factors, cross-study differences may also reflect sampling variability and estimation uncertainty—for example, finite-sample fluctuations in edge weights and centrality indices, variation in item content, and distinct modeling choices.

In addition, there have been longitudinal studies focused on the co-occurrence of depression and anxiety, though their number is relatively limited. Some studies have employed two-wave longitudinal design. For instance, after two surveys of adolescents 6 months apart, finding that anxiety symptoms generally predicted depressive symptoms. And after controlling for sex and age, "Relax" showed strong predictive power for other symptoms in the network (Zhang et al. 2024). Additionally, research have used ecological momentary assessments to explore the bridge states of the co-occurrence of depression and anxiety, finding that "Sad Mood" served as the strongest bridge psychological state in both the co-occurrence group and the anxiety group (Groen et al. 2020). Currently, longitudinal studies on the co-occurrence of depression and anxiety in disaster victim populations have yet to receive significant attention.

The above research findings indicate that central symptoms, bridge symptoms, edge patterns, and the temporal influences between symptoms are inconsistent in the co-occurrence of depression and anxiety. This may be caused by different trauma types (Ferreira et al. 2022) and the subjects′ occupations, age, past experiences, etc. (Wang and Ma 2023). Additionally, differences in research methods, such as cross-sectional and longitudinal studies, varying intervals in longitudinal studies (Collins and Graham 2002), may also contribute to differing results. The variability in research findings indicates a need for further studies to explore the co-occurrence of depression and anxiety across different populations, under varying conditions, and employing diverse research methods.

Previous research on the co-occurrence of depression and anxiety in disaster victim populations have largely relied on cross-sectional data, which limits the ability to reveal causal relations between symptoms (Fisher et al. 2017; McNally 2016). Network analysis method aims to elucidate the causal processes between symptoms that lead to the development of disorders (Borsboom 2017; Borsboom and Cramer 2013; Fried and Cramer 2017; McNally 2016). Since cross-sectional network data is collected at a single time point, the resulting network is often undirected, with edges indicating correlations between symptoms but not representing causal (Fisher et al. 2017; McNally 2016). To more accurately discern causal relations, future research could utilize longitudinal data to explore the dynamic structure of the co-occurrence of depression and anxiety (Epskamp 2020; Fried and Cramer 2017). Beyond establishing temporal ordering, dynamic network models for longitudinal data explicitly target within-subject processes. In graphical vector autoregressive frameworks, subject-specific means and random effects are modeled so that stable between-subject differences (e.g., trait negative affect or demographic composition) are attenuated. This reduces artifactual between-sample contrasts and focuses inference on within-subject dynamics. The within-subject component comprises two parts: a temporal (lagged) process across waves and a contemporaneous (within-occasion) residual process. Within this framework, the temporal network measures the lagged relations of symptoms from one measurement time point to the next in a directed network, thereby meeting the minimum requirement for causal relations in terms of temporal precedence (Fisher et al. 2017; Fried and Cramer 2017; Granger 1969). The temporal network can calculate the degree to which a symptom is predicted by other symptoms in the previous measurement time point, as well as the extent to which a symptom predicts other symptoms in the next measurement time point (Epskamp 2020; Gou and Ma 2023). The contemporaneous network represents the associations between symptoms within the same measurement occasion (Epskamp 2020; Gou and Ma 2023). Estimating temporal and contemporaneous networks of depressive and anxiety symptoms can deepen our understanding of the underlying mechanisms driving their co-occurrence. Cross-sectional analyses remain valuable for delineating the symptom landscape at a single occasion, prioritizing candidate central and bridge symptoms, and informing screening or measurement. However, because cross-sectional designs conflate between-subject variation with within-subject co-variation, they cannot adjudicate directionality and may overstate between-group contrasts.

We employ a network approach to investigate the dynamic structure of the co-occurrence of depressive and anxiety symptoms among victims of the 2021 Henan flood by estimating contemporaneous and temporal networks (with anxiety indexed as generalized anxiety symptoms via the GAD-7). We use three-wave survey data conducted during a 6-month period, with a 3-month interval between each survey. First, we use this data to estimate a contemporaneous network of depressive and anxiety symptoms to explore symptom relations within the same measurement occasion and identify central symptoms, bridge symptoms, and edge patterns. Second, we also estimate a temporal network, exploring time dependent relations and causal pathways between depressive and anxiety symptoms

The present analysis draws on the three-wave Henan flood panel. Prior publications from this cohort examined (a) cross-sectional symptom networks at Wave 1 during the disaster, including depressive, anxiety, and acute stress symptoms and their links with instant flood exposure (Wang and Ma 2023), and (b) the dynamic structure of post-traumatic growth items over three waves using a graphical vector autoregressive approach (Gou and Ma 2023). In contrast, the current study focuses on depressive and anxiety symptoms only and estimates both contemporaneous and temporal networks across all three waves to elucidate time-ordered co-occurrence among symptoms—a question not addressed previously.

2 | Methods

2.1 | Participants and Procedure

The data for the current study were collected between July 20, 2021, and January 30, 2022. Participants were recruited through Credamo (https://www.credamo.com/), an online reward-based crowdsourcing platform similar to Amazon's Mechanical Turk. The assessment of disaster victims was conducted at three time points: 0 months (Wave 1), 3 months (Wave 2), and 6 months (Wave 3) following the Henan floods. Wave 1 took place between July 20 and August 6, 2021, when citizens of Henan were still experiencing the effects of the floods. At baseline, 937 respondents completed the survey on Credamo. Of these, 223 (23.8%) were excluded per pre-specified quality/eligibility criteria (failed the attention check or responded "not applicable" to the flood-exposure screener), and one gender-minority participant (0.1%) was excluded due to an extremely small cell ($n = 1$), to avoid identifiability risk and unstable subgroup estimates. This yielded a valid Wave 1 cohort of 713 who were invited to follow-ups. Wave 2 (October 30–November 5, 2021) yielded 410 valid responses and Wave 3 (January 28–30, 2022) yielded 279, corresponding to 42.5% attrition from Wave 1 to Wave 2, (303/713), 32.0% from Wave 2 to Wave 3 (131/410), and an overall retention of 39.1% from the valid Wave 1 cohort (279/713). We quantified attrition patterns and compared baseline characteristics between dropouts and three-wave completers. There were no significant differences in educational background ($\chi^2 = 5.015$, $p = 0.414$), marital status ($\chi^2 = 7.656$, $p = 0.105$), or annual family income ($\chi^2 = 9.634$, $p = 0.210$). By contrast, dropouts were significantly younger and were more likely to be men (age: $W_{\text{Mann–Whitney}} = 52{,}020$, $p = 0.001$; sex: $\chi^2 = 8.538$, $p = 0.014$). Little's test for Missing Completely at Random (MCAR) applied to the depressive and anxiety symptom items across the three waves did not reject the MCAR null ($\chi^2 = 19.200$, $p = 0.259$). Given the study's focus on comparable three-time-point trajectories and model-implied estimates, our primary analyses used three-wave completers ($N = 279$) to maintain a balanced panel. While MCAR was not rejected statistically, the observed age/sex differences indicate that missingness is at least related to observed covariates; thus, our inference acknowledges a MAR-consistent attrition pattern. only participants who completed all three waves were included ($N = 279$). Of these participants, 43.37% were male, 46.95% were married, and the average age was 28.17 years.

2.2 | Measures

2.2.1 | The 9-Item Patient Health Questionnaire (PHQ-9)

The PHQ-9 measures the frequency of depressive symptoms as defined by the DSM-5 over the past 2 weeks (Kroenke and Spitzer 2002). This study uses the Chinese version of the PHQ-9 to measure the severity of individual depression (Liu et al. 2016; Xiong et al. 2015). The PHQ-9 consists of 9 items, each representing a specific symptom of depression, as shown in Table S1. The scoring for each item ranges from 0 (not at all) to 3 (nearly every day). The total score of the items, ranging from 0 to 27, reflects the severity of an individual's depression (Garabiles et al. 2019; Wang and Ma 2023). A cutoff of seven exhibits an equal sensitivity and specificity rate of 86% (W. Wang et al. 2014). The Cronbach's alpha of PHQ-9 in the three-wave were 0.878, 0.880, and 0.883, respectively.

2.2.2 | The 7-item Generalized Anxiety Disorder (GAD-7)

The GAD-7 is used to assess symptoms of Generalized Anxiety Disorder (GAD) in the past 2 weeks according to DSM-5 criteria (Spitzer et al. 2006). This study uses the Chinese version of the GAD-7 to assess the level of anxiety in individuals (Gong et al. 2021; Tong et al. 2016), as shown in Table S1. The GAD-7 has 7 items, each scoring from 0 to 3, indicating "not at all", "several days", "more than half the days", and "nearly every day". The total score ranges from 0 to 21, reflects the severity of an individual's anxiety. A cutoff score of 10 has been established for this scale, demonstrating a sensitivity of 86.20% and specificity of 95.50% (Spitzer et al. 2006). The Cronbach's alpha of GAD-7 in the three-wave were 0.899, 0.897, and 0.902, respectively.

2.3 | Statistical Analysis

2.3.1 | Descriptive Analysis

Descriptive analysis was used to outline the basic characteristics of the participants. In addition, to assess changes in the total scores and scores for each depressive and anxiety item across the three-wave, we conducted within-subjects ANOVA and used partial η^2 as the effect size. The cutoff scores of partial η^2 are 0.01 for small effect size, 0.06 for medium effect size, and 0.14 for large effect size (Lakens 2013).

2.3.2 | Network Analysis

Using the Gaussian graphical model (GGM) to describe the dynamic relation between depressive and anxiety symptoms. In the GGM, all variables are represented as nodes, and the partial correlations between variables are represented as edges (Bernal et al. 2022; Epskamp et al. 2018). Our data covers information from three time points, utilizing the generalized vector autoregressive model (GVAR) to estimate two different networks within-subject, the temporal network and the contemporaneous network. Both networks are estimated using the fixed effects method, controlling for confounding factors that remain unchanged over time in individuals, allowing the model to more accurately estimate the relation between variables (Abrigo and Love 2016).

In addition, this study uses maximum likelihood estimation and proceeds in three steps. First, we estimate a baseline model that includes all possible paths. Then, we prune the paths that are not significant in the baseline model, with a significance threshold of $\alpha = 0.05$. Finally, a stepwise model enhancement strategy is used to gradually add the paths with the highest modification indices to the model based on the pruned model until there is no significant improvement in the Bayesian Information Criterion (BIC). Model fit was evaluated using the BIC, the Comparative Fit Index (CFI), the Tucker–Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA).

2.3.3 | Node Centrality Analysis

Based on the network estimation results, we calculate the node centrality index using the centrality function in the *qgraph* package. In the contemporaneous network, the strength of a node is the absolute sum of the weights of the edges connected to it (Borsboom et al. 2021; Epskamp et al. 2018). The bridge strength of a node is the absolute sum of the weights of all edges between the node and nodes in different communities (Jones et al. 2021). In the temporal network, the in-strength of a node is the sum of the absolute weights converging on that node., indicating the potential of the node to be predicted or influenced by other nodes at the previous time point. The out-strength of a node is calculated by summing the absolute weights emanating from that node, indicating the potential of the node to predict or influence other nodes at the next measurement time point (Epskamp et al. 2018).

2.3.4 | Sample Size Determination

In line with current recommendations, we documented sample-size adequacy using an RMSEA-based a priori power analysis implemented in the *semPower* package (Moshagen and Bader 2023). For our fitted baseline model (df = 680), we targeted the ability to detect minimally important misfit of RMSEA = 0.05 at $\alpha = 0.05$ with 80% power, which indicated a required sample of $N = 59$. Our analytic sample ($N = 279$) exceeds this target.

2.3.5 | Network Stability

Currently, assessing network stability in panel network analysis is not always required, as panel network estimation typically includes more parameters than cross-sectional estimation (Jordan et al. 2020). However, to provide a reference for robustness, we followed previous recommendations (Zhang and Ma 2024) and applied a case-drop bootstrap approach to reestimate the baseline model (Epskamp et al. 2018). Specifically, the case-drop bootstrap was conducted 200 times, with 25% of the participants randomly excluded from the total sample for each re-estimation. At each replication, we dropped whole subjects—that is, all waves for approximately 25% of participants—without replacement, then re-estimated the same panel GVAR specification (lag-1, identical node set and constraints) using maximum likelihood (ML) with a fixed random seed for reproducibility. For each refit, we stored the directed temporal coefficient matrix (β) and the within-occasion residual covariance (Ω_ζ, within). As a summary index of stability, we vectorized the baseline β and Ω_ζ, within matrices and computed Pearson correlations with the corresponding bootstrap means across the 200 replications.

The main analytical code for the current study is uploaded to the online repository of the Center for Open Science (https://osf.io/y2z7w).

3 | Results

3.1 | Descriptive Results

Table S2 presents the descriptive statistics of the variables across three-wave, while Figure 1 provides a visual representation of these descriptive statistics. First, using 7 points as the cutoff on the PHQ-9, the results show that all participants scored above this threshold across the three waves, indicating elevated depressive symptom levels. Then, using 10 points as the cutoff on the GAD-7, 85.66%, 74.19%, and 68.46% of participants scored above this threshold at Waves 1–3, respectively, indicating elevated generalized anxiety symptom levels. These thresholds reflect screening cutoffs on self-report measures and do not constitute clinical diagnoses. The one-way within-subjects ANOVA showed that there were no significant differences in the total scores and scores for each item of depression across the three-wave ($p > 0.05$), and the partial η^2 did not reach the threshold for small effect size (partial $\eta^2 < 0.01$). However, the total scores and scores for each item of anxiety were significantly different ($p < 0.001$), and partial η^2 reached the threshold for small effect size (partial $\eta^2 > 0.01$). These results indicate that the scores of depressive symptoms remain stable over time at the within-subject level, while the scores of anxiety symptoms change. Detailed results of the one-way within-subjects ANOVA and post hoc analysis are provided in Tables S3 and S4.

3.2 | Results for Network Estimation

To examine the co-occurrence of depressive and anxiety symptoms, we estimated contemporaneous and temporal (lagged) network models. Following a standard three-stage network estimation workflow, the final model showed acceptable fit (BIC = 25,332.58; CFI = 0.92; TLI = 0.91; RMSEA = 0.032). Case-dropping bootstrap diagnostics indicated excellent correspondence between bootstrap and original estimates for the contemporaneous network ($r = 1.000$, $p < 0.001$) and modest but significant correspondence for the temporal network ($r = 0.217$, $p < 0.001$). These correlations are comparable to those reported in prior dynamic network analyses (Zhang and Ma 2024, 2025), supporting the stability of our network results.

3.2.1 | Contemporaneous Network

After controlling for individual fixed effects, we estimated the contemporaneous network of the three-wave surveys, as shown in Figure 2a. First, at the same measurement occasion, the connections between depressive and anxiety symptoms are all positive. For example, positive connections are found between "Anhedonia" and "Energy", "Sleep" and "Concentration", as well as "Control Worry" and "Worry A Lot".

Second, the weight of the edge in the network represents the strength of the connection between symptoms. In the entire contemporaneous network, the connection between "Sleep" and "Appetite" is the strongest edge. The strongest edge in the anxiety symptom subnetwork is the connection between "Control Worry" and "Relax". The connection strength between "Anhedonia" and "Energy", "Motor" and "Restless", "Control Worry" and "Worry A Lot" are also stronger than the connection between other symptoms. Additionally, the strong cross-community connections between "Motor" and "Irritable" as well as between "Motor" and "Restless" indicate that these edges serve as important channels for the co-occurrence of depression and anxiety. The scores of edge weights in the contemporaneous network can be found in Table S5.

Third, the centrality index of each node represents its special position and role in the network. Figure 3 shows that the top three symptoms with the highest strength centrality in the contemporaneous network are "Nervous", "Energy", and "Restless". The three symptoms with the highest bridge strength centrality are "Irritable", "Motor", "Anhedonia", indicating that these symptoms play a connecting role in the co-occurrence of depression and anxiety. In addition, "Appetite", "Guilty", and "Suicide", which are not connected to anxiety symptoms, are unique to depression, while "Afraid" is unique to anxiety. The scores of strength centrality and bridge strength centrality of all nodes in the contemporaneous network can be found in Table S7.

Given the 3-month spacing between waves, contemporaneous edges are interpreted as within-occasion partial associations (conditional on prior-wave terms and subject effects) that likely reflect short-timescale co-activation within the 2-week recall window of the PHQ-9 and GAD-7. Such couplings may not persist across 3 months, which helps explain the sparser temporal links.

3.2.2 | Temporal Network

The results of the temporal network provide a basis for understanding the temporal dynamics of the relation between depressive and anxiety symptoms, as shown in Figure 2b. First, compared to the contemporaneous network, the connections within the temporal network are also positive but are much

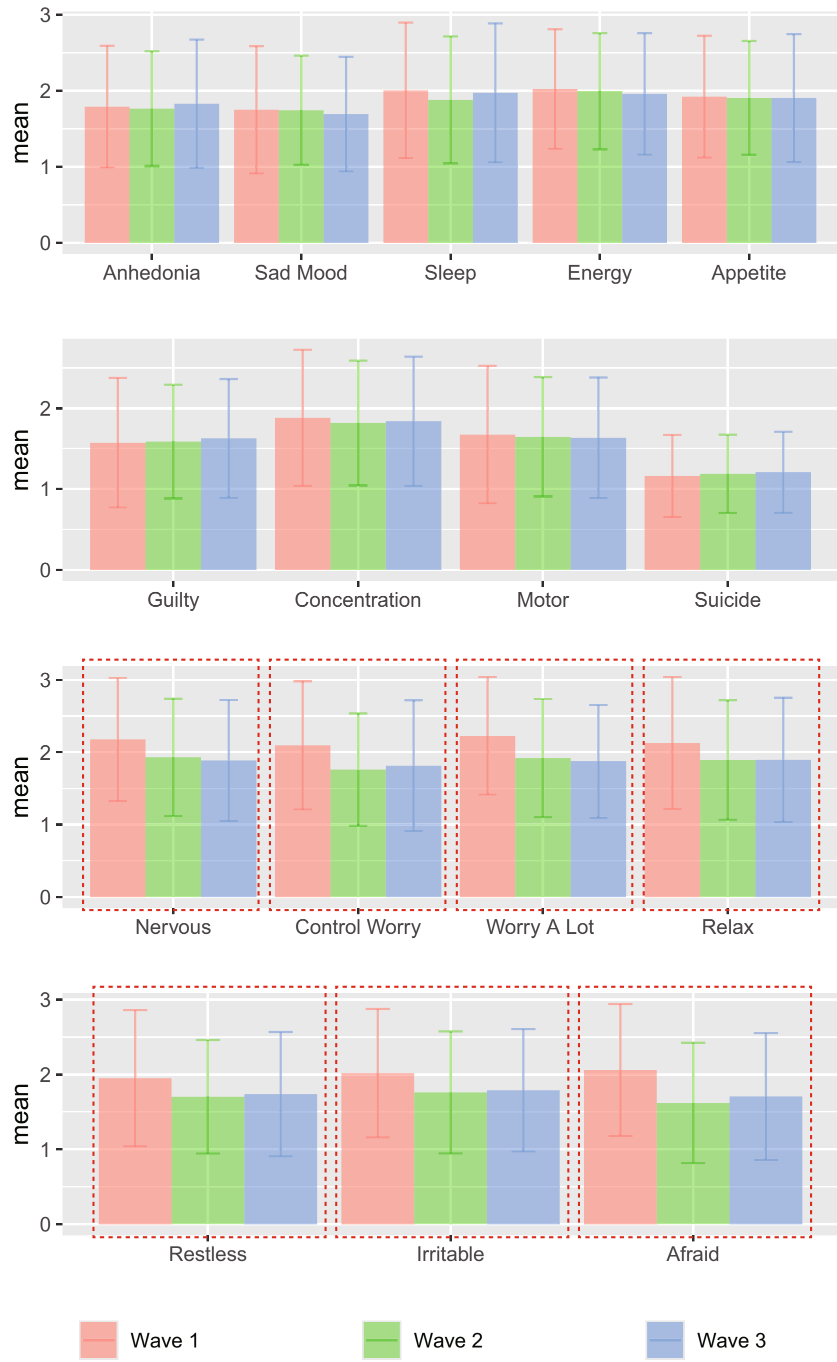

FIGURE 1 | Descriptive results of depressive and anxiety symptoms across three waves. Error bar amplitude matches mean ± SD. Results highlighted by a red dotted frame denote differences among four waves that were statistically significant.

sparser. For instance, there are positive connections between "Concentration" and "Anhedonia", "Concentration" and "Sad Mood", as well as "Appetite" and "Restless". Moreover, within this sparse network, the connections are primarily concentrated among depressive symptoms, with only one connection among anxiety symptoms, which is between "Worry A Lot" and "Nervous". This suggests that for flood disaster victims, anxiety symptoms may interact more at the same measurement occasion, but have little temporal association. In contrast, depressive symptoms exhibit both forms of influence.

Second, the edge weights in the temporal network provide further evidence for the strong temporal correlation between depressive symptoms. Specifically, the top strongest three edges in the temporal network are all within depressive symptoms: "Suicide" connected to itself, "Concentration" and "Anhedonia", as well as "Concentration" and "Motor". The scores of all edge weights in the temporal network can be found in Table S6.

Third, the centrality of symptoms in the temporal network indicates the ability to predict and be predicted. Figure 3 shows that the top three symptoms with the highest in-strength are "Anhedonia", "Motor", and "Appetite", indicating that these symptoms are more likely to be predicted by other symptoms from the previous measurement time point. The top three symptoms with the highest out-strength are "Concentration",

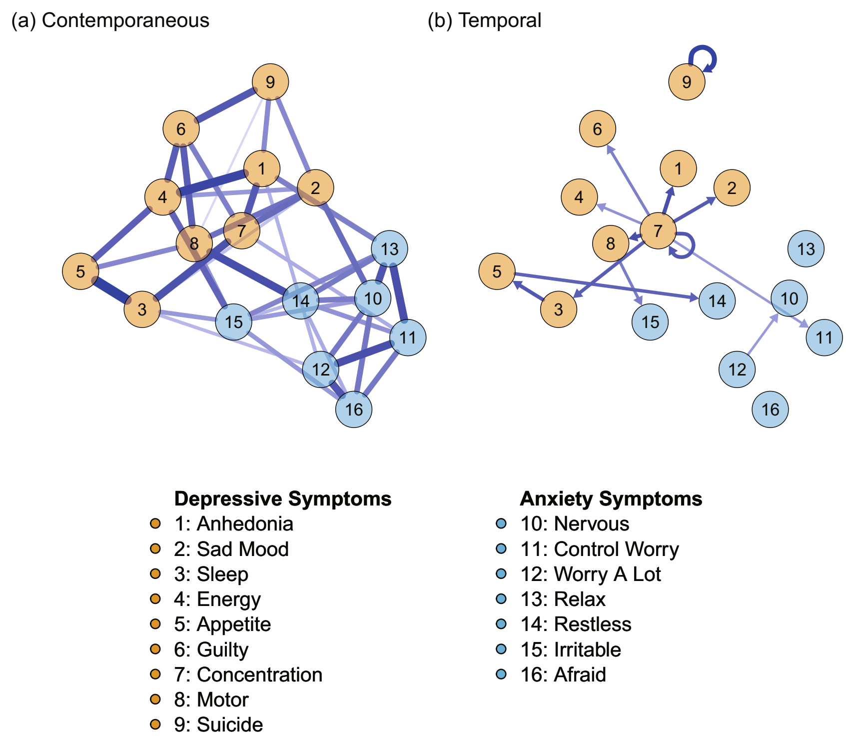

FIGURE 2 | Results of panel network analysis. Blue edges denote positive associations between two nodes.

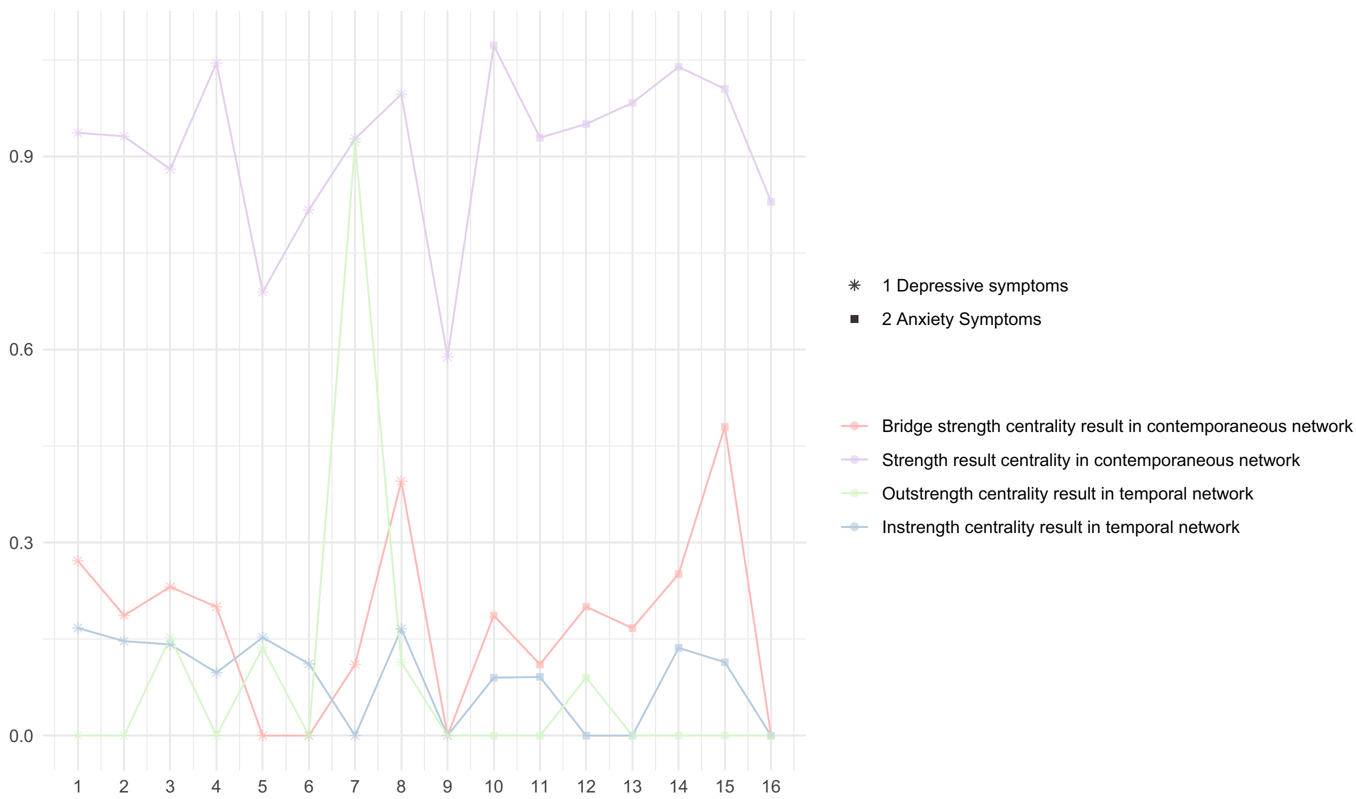

FIGURE 3 | Node strength of panel network analysis. Numbers of each node could be identified as follows: 1 Anhedonia, 2 Sad Mood, 3 Sleep, 4 Energy, 5 Appetite, 6 Guilty, 7 Concentration, 8 Motor, 9 Suicide, 10 Nervous, 11 Control Worry, 12 Worry A Lot, 13 Relax, 14 Restless, 15 Irritable, 16 Afraid.

"Sleep", and "Appetite", suggesting that these symptoms have a significant potential to predict other symptoms in the next measurement time point. It is worth noting that the out-strength of "Concentration" is much higher than that of other symptoms, indicating that "Concentration" plays a key role in predicting changes in other symptoms in the next measurement time point. The scores of in-strength centrality and out-strength centrality of all nodes in the temporal network can be found in Table S7.

Fourth, the temporal network result also shows the causal relation between symptoms. For example, "Suicide" predicts an increase in itself in the next measurement time point, "Concentration" predicts the increase in "Anhedonia" in the next measurement time point, and "Concentration" predicts the increase in "Motor" in the next measurement time point.

4 | Discussion

To the best of our knowledge, this study is one of the few studies that investigated the dynamic structure of co-occurrence of depressive and anxiety symptoms in flood victims. We estimated the contemporaneous network to explore the relation of depressive and anxiety symptoms at the same measurement occasion and identified the strongest edges, highest central symptoms and bridge symptoms. By estimating the temporal network, it was found that the temporal associations within depressive symptoms and within anxiety symptoms showed significant differences, and depressive symptoms were found to predict anxiety symptoms. Notably, the positive autocorrelation of some depressive symptoms suggests a self-sustaining ability after 3 months. Moreover, by calculating out-strength and in-strength, the symptoms with the most outward influence and the most downstream effect were identified.

4.1 | The Internal Structure of the Co-occurrence at the Within-Subjects Contemporaneous Level

The results of the contemporaneous network found some strongly connected edges. First, the connection between "Sleep" and "Appetite" is the strongest edges. Some studies have explained this connection from a pathophysiological perspective, believing that lack of sleep can downregulate the satiety hormone leptin and upregulate the appetite-stimulating hormone ghrelin, thereby increasing hunger and food intake. In addition, the connection strength between "Anhedonia" and "Energy", "Control Worry" and "Relax" are significantly stronger than other edges in the network, and they are all positively correlated. This shows that the negative consequences of natural disasters cause mental health problems in victims (Framingham and Teasley 2012). The more the victims feel anhedonia, the less energy they feel. Similarly, the less they can effectively control their worries, the harder it is to relax and relieve anxiety. This forms a vicious relation that aggravates the level of depression and anxiety in victims.

The results of the node strength centrality index at the same measurement occasion show that "Nervous" is the most central symptom. This is inconsistent with previous studies that found that "Sad Mood" (Beard et al. 2016; Cai et al. 2022), "Energy" (Garabiles et al. 2019), and "Restless" (Luo et al. 2024) are the most central symptoms in the co-occurrence network of depression and anxiety. As mentioned at the beginning of this article, the reasons for the inconsistent results may be due to factors such as differences in research methods, types of traumatic events, and research subjects. For example, some studies have mentioned that the network structure of symptoms will be affected by the type of traumatic events, with different types of trauma leading to variations in the PTSD symptom network (Benfer et al. 2018; Ferreira et al. 2022). The traumatic event in this study is the flood disaster. The possible reason why the victims feel nervous is the series of negative consequences caused by the flood disaster, such as the destruction of homes, threats to life, loss of property and uncertainty about the future (Foa 2006; Goldmann and Galea 2014). In addition, "Energy", "Restless" and "Irritable" are also high central symptoms in the network. One explanation path is that the series of negative consequences caused by the flood disaster lead to sleep disorders in victims, making them prone to lack of energy and irritability (Kim and Lee 2021; Lavie 2001). As central symptoms, it indicates a higher possibility of activating other symptoms and increasing the overall level of functional impairment (Ding et al. 2024). Therefore, identifying these central symptoms and giving priority to them during intervention may be crucial to treatment. Beyond population context, time-scale and item-set differences may also contribute: our contemporaneous graph indexes same-occasion partial associations within the PHQ-9 and GAD-7 2-week recall, whereas some prior reports used different anxiety measures or purely cross-sectional designs; sampling variability and estimation choices can further shift the rank ordering of central nodes. In a post-flood setting, hyperarousal-linked "Nervous" may transiently dominate cross-domain coupling, consistent with heightened BIS activation.

The bridge strength of nodes in the contemporaneous network indicates that the bridge of the co-occurrence of depression and anxiety involved many nodes. Among these, "Irritable" and "Motor" are the top two strongest bridge symptoms in the co-occurrence of depression and anxiety, which enriches previous research findings (Jin et al. 2022; Kaiser et al. 2021; Ren et al. 2021). This means that these two symptoms play an important role in connecting depression and anxiety and lead to their high co-occurrence rate (Ding et al. 2024; Fried 2015). For example, the negative consequences caused by flood disaster may make victims feel irritable (Kar and Bastia 2006), thereby triggering depression-related symptoms such as lack of energy and "Motor". In addition, the important role of "Motor" as a physical symptom in bridging depression and anxiety is supported. For example, depressive symptoms such as fatigue and psychomotor changes are associated with reduced heart rate variability-a characteristic that is more pronounced in patients with major depressive disorder and anxiety disorder compared to the general population (de Jonge et al. 2007; Kemp et al. 2012). Moreover, a study on physical activity in patients with depression, anxiety, or concurrent diagnoses showed that patients with concurrent disorders were more active than those with depression or anxiety alone (Helgadóttir et al. 2015).

4.2 | The Internal Structure of the Co-occurrence at the Within-Subjects Temporal Level

Temporal network results show that depressive symptoms are more temporally causal and predictive, while anxiety symptoms are less temporally dependent. First, there are dense directed connections among depressive symptoms, indicating that some depressive symptoms can predict changes in other depressive symptoms at the next time point. For example, inability to concentrate increased "Anhedonia" and "Sleep" after 3 months. In addition, it is worth mentioning that the positive autocorrelation of "Suicide" is significant and has the strongest weight, indicating that suicidal thoughts have a strong self-sustaining ability across 3 months. The possible reason is that natural disasters cause the death of family members or huge economic losses, etc., which have a huge psychological impact on the victims, causing them to have suicidal thoughts (Jafari et al. 2020) and continue them. For anxiety symptoms, only "Worry A Lot" increased "Nervous" after 3 months. All in all, depressive symptoms tend to be more persistent due to having more temporal influence transmission between them. Anxiety symptoms are relatively independent in time, and it is possible that temporal changes are driven by external factors, which probably indicates that anxiety is superficially developed and might be easier to cure from specific symptom levels (Salari et al. 2020; Santomauro et al. 2021). Finally, the relative sparsity of anxiety-to-anxiety lagged edges likely reflects short-lived worry–arousal linkages that dissipate within days to weeks; under a 3-month lag, such influences register primarily as contemporaneous clustering rather than durable temporal paths.

In addition, depressive symptoms predict anxiety symptoms, namely "Concentration" predicts "Control Worry", "Appetite" predicts "Restless", and "Motor" predicts "Irritable". The goal of studying the temporal patterns of depression and anxiety is to solve the problem of "which comes first" (Long et al. 2018). Studies have explored this in adolescent population. For example, Research have used cross-lagged network analysis to find that more anxiety symptoms predict depressive symptoms (Zhang et al. 2024). Research have also used dynamic latent change score models to find that anxiety symptoms can predict the subsequent increase in depressive symptoms over time (Kouros et al. 2013). These are inconsistent with the findings of this study, and the reason for the difference may be the different research subjects. For adolescents, academic pressure may cause them to grow anxieties about the criticism of others, worries about the future. When these worries and anxieties are useless, they will further produce symptoms related to depression, such as sleep problems (Wang and Fan 2023). For disaster victims, when faced with the huge impact of the disaster, they often experience emotional disorders first, and show early depressive symptoms such as inability to concentrate and decreased appetite. As the direct impact of the disaster gradually subsides, the individual's feeling of being unable to cope with the current situation may gradually evolve into worry and restless about the uncertainty of the future, and the anxiety level may rise accordingly (Norris et al. 2002).

Furthermore, the centrality index in the temporal network indicates that the "Concentration" has an out-strength far exceeding that of other symptoms, which demonstrates its substantial outward influence. The outward influence of "Concentration" is on oneself, other depressive symptoms, and the anxiety symptom "Control Worry". This can be explained by the process model of emotion regulation, in which attention plays an important role in regulating self-emotion (Gross 1998). Due to lack of concentration, victims may have difficulty effectively regulating their emotions during the disaster and post-disaster recovery, which can easily trigger negative emotional reactions, such as sleep disturbances and anxiety. Although previous studies have explored the relation between "Concentration" and other depressive and anxiety symptoms, they only revealed the static relationship at a measurement time point (Jin et al. 2022; Kaiser et al. 2021). This study reveals that "Concentration" has the ability to activate other symptoms and self-maintain over time, enhancing the understanding of the relation at a nuanced level. In addition, "Anhedonia" has the highest in-strength, indicating that "Anhedonia" has the most downstream effect and is more easily affected by other symptoms.

4.3 | Theoretical Implications

The contemporaneous network showed uniformly positive cross-domain edges between depressive and anxiety symptoms, consistent with the Tripartite Model's shared negative affect component as a common substrate linking both syndromes (Clark and Watson 1991). The prominence of "Nervous" in strength centrality and the bridging roles of "Irritable" and "Motor" align with anxiety-specific hyperarousal and heightened BIS responsivity, which can propagate arousal across symptom clusters during disaster-related stress. In parallel, the strong coupling between "Sleep" and "Appetite" reflects a vegetative and energy-loss cluster aligned with low positive affect—depression-specific in the Tripartite Model—and reduced BAS engagement (Schofield et al. 2009b). Importantly, the temporal paths from depressive to anxiety symptoms are consistent with accounts in which diminished approach tendencies and reduced positive affect, together with energy dysregulation and lower BAS, set the stage for subsequent anxious apprehension that is BIS dominant, rather than the reverse. Although cross-lagged coefficients are modest, as is typical in three-wave panels, the pattern coheres with these models and helps explain why depressive processes in this context appear more temporally generative than anxiety-focused dynamics.

Several environmental and contextual processes may account for why depressive processes exert a sustained, anxiety-promoting influence among disaster victims. First, loss and demoralization diminish positive affect—a core feature of depression in the Tripartite Model (Clarke et al. 2000)—while shared negative affect and anticipatory worry become more salient over time. Second, allostatic overload and disruption of daily rhythms after displacement often present initially as vegetative disturbances and psychomotor change, with later hyperarousal contributing to anxiety (Liu et al. 2022). Third, stress sensitization and kindling imply that accumulating secondary stressors and reminders progressively lower thresholds for anxious apprehension (Lachowicz et al. 2025). Fourth, conservation-of-resources dynamics suggest that early material losses promote withdrawal and reduced activity, whereas sustained threat to remaining resources heightens vigilance and worry (Hobfoll 1989). Fifth, prolonged uncertainty and perceived uncontrollability during rebuilding and compensation can shift cognition from rumination toward prospective worry (Zhang and Ma 2025). Finally, contextual modifiers—including the timing and clarity of aid and relocation (Liu et al. 2023), the resumption of work and school (Liu et al. 2022; Liu et al. 2025), fluctuations in social support (Mi et al. 2023; Zhang and Ma 2025), disaster-related media exposure (He et al. 2018; Ma et al. 2019; Ma and Lin 2020), seasonal and community events (Epkins and Harper 2016), and culturally shaped norms for emotion expression and help seeking (Hankin et al. 2010; Liu and Ma 2022)—can amplify or attenuate these trajectories. Together, these perspectives offer a coherent account in which depressive processes exert a sustained influence that promotes anxiety.

4.4 | Implications for Post-Disaster Interventions

Leveraging the finding that depressive symptoms temporally precede subsequent anxiety, post-disaster services can be scheduled in stages to improve yield. In the first 3 months, programs should front-load depression-focused care—behavioral activation and routine restoration to stabilize the sleep–appetite rhythm, brief attention and concentration support to curb spillover from cognitive inefficiency, and assertive suicide safety planning given the short-term persistence of suicidal ideation. As victims move into months 3 to 6, services should pivot to active surveillance for emergent anxiety and deploy brief, transdiagnostic add-ons (emotion-regulation skills, activity pacing, problem solving) targeted at bridge manifestations such as irritability and psychomotor change, while using nervousness as an efficient indicator for stepped-up care. Operationally, this implies triage pathways that allocate more clinician time early to depressive targets, incorporate scheduled monthly check-ins to detect rising anxiety among those with earlier depressive burden, and embed brief modules into primary care and community outreach to match resource constraints. These recommendations translate temporal precedence into actionable timing and focus, while acknowledging that temporal ordering strengthens clinical plausibility but does not by itself establish causation; pragmatic stepped-care trials should evaluate these scheduling choices in real post-disaster service systems.

4.5 | Clinical and Public Health Implications

Our panel-network findings allow us to articulate concrete, testable implications for intervention prioritization in post-disaster care. First, the unusually large outward influence of "Concentration" (highest out-strength) suggests that early, low-intensity attention-focused strategies (e.g., brief attention training or cognitive remediation elements) may prevent downstream escalation of other depressive and even anxiety symptoms. Second, the highest in-strength for "Anhedonia" indicates a highly downstream target that is amenable to behavioral activation and reward-scheduling in stepped-care models. Third, the positive autocorrelation of "Suicide" across 6 months supports assertive safety planning, scheduled follow-ups, and rapid linkage to higher levels of care where indicated. Fourth, "Irritable" and "Motor" as the strongest bridge symptoms provide transdiagnostic leverage: brief emotion-regulation, pacing, and activity-scheduling modules can be positioned to reduce depression-anxiety comorbidity at the network bridges. Fifth, the strongest contemporaneous edge between "Sleep" and "Appetite" argues for integrating sleep-hygiene and CBT-I style routines with regularized eating to disrupt a frequently co-occurring behavioral pair. Importantly, depressive symptoms' temporal precedence over anxiety in our data suggests that targeting depressive processes first may yield secondary anxiety benefits in resource-limited, post-flood services. These implications are hypothesis-generating: panel networks establish temporal precedence but not experimental causality; thus, they should inform the design of pragmatic trials and service planning, rather than function as prescriptive treatment rules.

4.6 | Limitation

Although this study has revealed the dynamic co-occurrence structure of depression and anxiety among flood victims and provided valuable insights for future therapeutic interventions, some limitations still remain. Firstly, we conducted assessments of depression and anxiety among flood victims every 3 months using the PHQ-9 and GAD-7 scales. However, this design may result in inaccuracies in self-reports due to potential recall bias (Coughlin 1990). Secondly, we collected samples through an online platform, which inevitably introduces selection bias. Great caution should be maintained while warranting a generalization of the current results to other flood victims. Further, although our diagnostics did not reject MCAR, listwise inclusion of three-wave completers may still introduce selection due to age/sex-related attrition. We therefore caution that generalization to the full baseline cohort should consider this potential MAR-consistent selection. Because younger and male participants were more likely to drop out, the three-wave completer sample may over-represent older and female victims. Consequently, generalizability is primarily to adherent participants with complete three-wave data, and caution is warranted when extrapolating to the full baseline cohort. Moreover, time frame matters for interpreting symptom relations. Our temporal model targets month-scale propagation (3-month lag), whereas the contemporaneous network reflects same-occasion clustering within the PHQ-9 and GAD-7 2-week recall. Many symptom interactions likely unfold over days to weeks (Ebrahimi et al. 2021; Zhang and Ma 2024, 2025). Accordingly, the present design may underdetect short-lived directional links. Future work should use shorter assessment intervals (e.g., weekly or daily) or measurement-burst designs that embed intensive short-term assessments within panel waves to test time-scale dependence of symptom relations more directly and to separate within-subject dynamics from between-sample differences. Finally, although the temporal network can analyze the relation between symptoms at the previous time point and the next time point, satisfying the requirement of Granger causality (Granger 1969), this temporal relation might be influenced by unmeasured time-varying confounding variables and is not a strict causal relation (Fisher et al. 2017; Fried and Cramer 2017). Future studies can use experimental or other prospective designs to further verify the causal relation between anxiety and depressive symptoms (Luo et al. 2024).

Author Contributions

Conceptualization: Zhihao Ma; Data curation: Zhihao Ma; Formal analysis: Zhihao Ma; Funding acquisition: Zhihao Ma; Investigation:

Zhihao Ma; Methodology: Zhihao Ma; Project administration: Zhihao Ma; Writing – original draft: Zhenfeng Zhou; and Writing – review and editing: Zhihao Ma.

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Ethics Statement

This study protocol was approved by the Academic Committee of the School of Journalism and Communication, Nanjing University. Electronic informed consent was obtained from all participants before the interviews and survey administration. Participants were assured of their anonymity and confidentiality of their information, and their rights of withdrawal were respected.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Table S1: Reference name of items used of depressive and anxiety symptoms. **Table S2:** Descriptive statistics of depressive and anxiety symptoms. **Table S3:** The one-way within-subjects analysis of variance (ANOVA) for differences of three waves in the total score of depression, anxiety, and scores of each item. **Table S4:** The post hoc analysis on one-way within-subjects ANOVA for differences of three waves in the total score of depression, anxiety, and scores of each item. **Table S5:** Edge weights of contemporaneous network. **Table S6:** Edge weights of temporal network. **Table S7:** Node centrality of dynamic networks