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# Dynamic Coupling Between Resilience and Depression Across Recovery: Evidence from a Cross-Lagged Network Model

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## Abstract

# Background

Understanding the temporal organization of psychological resilience may provide insight into processes associated with recovery from Major Depressive Disorder (MDD).

# Method

Using baseline (T1) and follow-up (T2) data from the Marburg–Münster Affective Disorders Cohort Study (MACS), we examined item-level temporal dependencies within the 25-item Resilience Scale (RS-25) across individuals with acute MDD (depressed at T1, remaining depressed at T2), remitted MDD (depressed at T1, full remission at T2), and healthy controls (HC). Separate cross-lagged panel networks were estimated for each group using nodewise penalized regressions to characterize directed temporal associations from T1 to T2.

# Results

Network organization differed across groups. The HC showed the greatest number of cross-lagged connections and the most favorable overall stability profile, whereas the remitted MDD group showed the fewest temporal associations. The acute MDD group exhibited an intermediate number of cross-lagged connections and the highest mean non-zero edge weight, although centrality stability remained limited. Centrality analyses identified engagement, self-efficacy, and self-friendship as prominent components in acute MDD; self-efficacy, discipline, determination, and self-efficacy-related items in remitted MDD; and purpose-related items and reliability in healthy controls.

# Conclusions

These findings suggest that resilience is characterized by distinct patterns of temporal organization across acute depression, remission, and sustained mental health. CLPN provides a useful framework for identifying prospective item-level associations, although the observed centrality patterns should be interpreted cautiously given the limited stability of several estimates. The identified group-specific components may represent candidate processes for future longitudinal and intervention research.

## 1. Introduction

Major Depressive Disorder (MDD) is a highly prevalent and recurrent psychiatric condition marked by pervasive disruptions in mood, cognition, and motivational processes(1–4). Despite substantial advances in therapeutic strategies, a considerable proportion of individuals continue to experience chronic illness courses or do not achieve full remission(2, 5, 6). This persistent burden underscores the

importance of understanding not only the factors that precipitate depressive episodes, but also those that promote recovery and sustain long-term psychological resilience. Resilience, defined as the capacity to maintain or rapidly regain psychological stability in the face of adversity, has thus become a critical construct to explain heterogeneity in depressive trajectories (7–10). However, the dynamic mechanisms through which resilience and depressive processes mutually influence each other over time remain insufficiently understood (11–13).

Historically, research on resilience in depression has relied heavily on cross-sectional designs that quantify static associations between resilience measures and the severity of depressive symptoms(14–16). While such studies have consistently demonstrated that higher levels of resilience are associated with lower depression severity, their cross-sectional nature fundamentally limits insight into how resilience-related processes interact and exert influence over time (14, 16, 17). Emerging evidence increasingly conceptualizes resilience not as a fixed dispositional attribute but as a dynamic self-regulating system comprising interdependent psychological functions such as adaptability, purpose, cognitive flexibility, and emotional regulation that evolve in tandem to shape mental health outcomes (14, 15, 18). Capturing these reciprocal temporal processes, therefore, requires longitudinal analytic frameworks capable of modelling within-person change, directionality, and dynamics (19–21).

Network-based approaches conceptualize mental disorders as complex, interacting systems rather than as manifestations of latent disease entities (22, 23). Cross-lagged panel network (CLPN) modelling extends traditional network analysis by estimating directed, time-ordered dependencies among psychological variables (24, 25)[23, 24]. Unlike static correlation networks or group-level comparisons, CLPNs provide a framework from which researchers can determine how specific trait resilience components at baseline predict other components at later time points. In doing so, CLPN modeling can reveal directional pathways that illuminate the mechanisms underlying adaptive recovery and vulnerability, thus providing a more mechanistic understanding of how resilience functions within the temporal dynamics of depression(26, 27).

In the present study, we used CLPN modeling on baseline (T1) and follow-up (T2) data from the Marburg–Mu¨nster Affective Disorders Cohort Study (MACS) (28) to investigate the dynamic interplay between trait resilience and depressive states across different clinical outcomes of MDD. Three groups were defined based on diagnostic status at baseline and follow-up : (i) *Acute MDD*, defined by MDD at T1 and T2; (ii) *Remitted MDD*, defined by MDD at T1 but not T2; and (iii) *Healthy Controls*. By constructing separate CLPN models for each group, our objective was to describe and contrast the temporal architecture of resilience processes across acute depression, remission, and sustained mental health. We hypothesized that resilience networks in acute MDD would display fragmented, weakly connected temporal dependencies, whereas remitted and healthy participants would demonstrate progressively more connected and coherent network structures. This analytic framework moves beyond static assessments of resilience and instead conceptualizes resilience as a dynamic system whose organization differs across clinically defined outcomes.

# 2. Methods

## 2.1 Participants and Data Collection

Data for this study were sourced from the MACS, a large-scale, multi-center prospective cohort study conducted in Marburg and Mu¨nster, Germany (20). The study included individuals who completed both the T1 (baseline) and T2 (2-year follow-up) assessments. Participants were assigned to three groups named (i) **Acute MDD**, comprising individuals who met criteria for MDD (based on the past 2 weeks) at T1 and also met criteria for MDD at T2,if they belonged to the MDD group and had a HAMD score ≥ 6 at both T1 and T2 (ii) **Remitted MDD**, comprising individuals who met criteria for MDD at T1 but not at T2 if they belonged to the MDD group and had a HAMD score < 6 at both T1 and T2, and (iii) **Healthy Controls**, comprising participants without depressive symptoms at either time point.

Participants were matched across assessment waves using a unique participant identifier, and only individuals meeting the corresponding group definition at both T1 and T2 were retained. The final sample comprised 113 participants in the Acute MDD group, 135 in the Remitted MDD group, and 648 Healthy Controls. At baseline, mean age was 37.91 years (SD = 13.72) in the Acute MDD group, 39.84 years (SD = 13.24) in the Remitted MDD group, and 35.35 years (SD = 13.42) in the Healthy Control group. Women comprised 63.72%, 61.48%, and 64.66% of the Acute MDD, Remitted MDD, and Healthy Control groups, respectively. Baseline HAMD scores were substantially higher in the Acute MDD group (M = 13.93, SD = 5.96) than in the Remitted MDD (M = 1.61, SD = 1.64) and Healthy Control groups (M = 1.38, SD = 2.00), consistent with the HAMD-based group definitions. A full overview of all baseline and follow-up characteristics is provided in *Supplementary Table S1*.

## 2.2 Assessment of Resilience

Trait resilience was assessed using the 25-item Resilience Scale (RS-25) (29, 30), a self-report instrument designed to measure individuals' subjective evaluation of their own resilience. Each item is rated on a Likert scale, with higher scores indicating greater perceived resilience. In the present study, analyses were conducted at the item level. The instrument was administered at both T1 and T2. For analysis, all item scores were converted to a numeric format and checked for validity. A brief description of each RS-25 item is provided in *Supplementary Table S2*. Three baseline covariates were considered: age, sex, and years of education. Covariates with missingness were set to zero after numeric coercion. It should be noted that although the RS-25 is a measure of trait resilience, traits can show high rank-order stability alongside modest, systematic change over time. That is, they are not static. Hence, the RS-25 is an appropriate measure to test whether acutely depressed individuals with MDD exhibit relative differences in resilience across time compared to those with remitted MDD and healthy controls.

## 2.2 Network estimation: Cross-Lagged Panel Network

Longitudinal associations between RS-25 items were examined using CLPN models (31). Separate directed networks were estimated for the acute MDD, remitted MDD, and healthy control groups. For each RS-25 item at T2, a nodewise Gaussian LASSO regression was fitted using all RS-25 items at T1

together with the predefined covariates as predictors. CLPN models estimate directed temporal associations between variables across successive measurement waves, allowing each item at baseline to predict its own future level and the future levels of other items. In the present study, cross-lagged effects were estimated using nodewise LASSO-regularized regression models, with penalty parameters selected by 10-fold cross-validation. This approach allows the identification of item-level temporal dependencies while reducing overfitting and shrinking weak associations toward zero.

We estimated directed, item-level temporal dependencies (T1→T2) via a nodewise LASSO procedure. For each RS-25 target item *j* at T2, we fit a 10-fold cross-validated Gaussian LASSO:

$$Y_{\{j,T2\}} \sim \beta_{\{0j\}} + \sum_{\{i=1\}}^{\{25\}\beta}{}_{\{ij\}} X_{\{i,T1\}} + \sum_{\{c \in \setminus mathcal\{C\}\}} \gamma_{\{cj\}} Z_{\{c,T1\}}$$

where C indexes the available covariates. Penalty strength $\lambda$ was chosen by cv. glmnet

using lambda.min. Coefficients were extracted at $\lambda_{min}$, forming a 25 × 25 adjacency (rows: sources at T1; columns: targets at T2). To focus on cross-lagged effects, autoregressive (diagonal) entries were set to zero description and plotting. Signs and magnitudes of the standardized coefficients ($\beta$) encode, respectively, the direction (positive vs. negative) and strength of temporal association while controlling for all other items and covariates.

We quantified item importance using cross-lagged *Out-Expected Influence* (Out- EI; prospective influence on other items) and *In-Expected Influence* (In-EI; degree to which an item is driven by others). Centrality indices were computed and z-scored within groups for display.

Edge-weight uncertainty and centrality stability were assessed with the bootnet R package. Non-parametric bootstrapping yielded 95% confidence intervals for edge coefficients. Case-drop subset bootstrapping (1,000 resamples) was used to evaluate stability under sample perturbation by correlating the estimated network (or centrmanuscriptality ranks) from each subsample with the original full-sample solution across progressive case-retention levels (90% to 25%). We calculated correlation stability (CS) coefficients for Out-EI and In-EI; larger CS implies greater robustness of centrality ordering to case removal. Group-specific case-drop stability curves were subsequently inspected to visualize the robustness of Out-EI and In-EI estimates across increasing proportions of case removal (32).

# 2.3 Network Comparison Across Clinical Groups

To examine whether temporal item dynamics differed across clinical states, separate CLPN models were estimated for acute MDD, remitted MDD, and healthy control groups using identical estimation procedures to ensure comparability. Network similarity between groups was quantified using the Jaccard index applied to cross-lagged edges only. After excluding autoregressive paths, edges exceeding a standardized effect-size threshold (|β| ≥ 0.05) were retained. The Jaccard index was calculated as the proportion of overlapping non-zero cross-lagged edges relative to the total number of unique cross-lagged edges across two networks, providing a summary measure of structural similarity in

directed temporal symptom interactions between clinical groups (25). In addition, Pearson correlations between the corresponding cross-lagged edge-weight vectors were calculated for each pair of networks to quantify similarity in the overall pattern of temporal associations. For each pair of networks, we additionally calculated the proportion of corresponding cross-lagged edges showing the same direction of association.

To evaluate group differences in symptom-level predictive importance, cross-lagged Out-Expected Influence and In-Expected Influence centrality indices were computed from adjacency matrices after removal of autoregressive effects. To examine the similarity of centrality profiles across groups, Pearson correlations were calculated pairwise for Out-EI and In-EI values across the 25 RS items. Core resilience components were operationally defined as nodes with standardized Out-EI values greater than 1 ($Z > 1$).

All analyses were conducted in R version 4.5.2. Key R packages included glmnet, qgraph, bootnet, igraph, dplyr, tidyr, and ggplot2.

# 3. Results

## 3.1 Cross-lagged Panel Network Models

Figure 1 presents the CLPN structures across the three groups, showing differences in the number and configuration of cross-lagged associations. As shown in Table 1, the HC group had the most non-zero cross-lagged edges (n = 220), followed by acute MDD (n = 160) and remitted MDD (n = 111). Positive associations predominated across all networks, comprising 82.5% of edges in acute MDD, 73.0% in remitted MDD, and 79.5% in HC. Mean non-zero edge weights were highest in acute MDD (M = 0.032, SD = 0.065), followed by remitted MDD (M = 0.029, SD = 0.081) and healthy controls (M = 0.025, SD = 0.044). Pairwise edge-weight correlations were generally small: acute-remitted (r = 0.05) and remitted-HC (r = 0.07) were not significant, whereas acute-HC showed a small but significant correlation (r = 0.16, p = 0.001). Structural overlap was also limited, with Jaccard coefficients of 0.092 for acute-remitted, 0.078 for acute-HC, and 0.116 for remitted-HC. Overall, these findings indicate distinct patterns of cross-lagged connectivity across the three groups.

Table 1
Comparison of cross-lagged network structure across the acute MDD, remitted MDD, and HC groups.

| Group | Cross-lagged edges(n) | % Positive | Edge weight M ± SD | Pearson *r* | P-value | Jaccard |
|---|---|---|---|---|---|---|
| Acute MDD | 160 | 82.5% | 0.032 ± 0.065 | — | | — |
| Remitted MDD | 111 | 73.0% | 0.029 ± 0.081 | — | | — |
| HC | 220 | 79.5% | 0.025 ± 0.044 | — | | — |
| Acute vs. Remitted | — | | — | 0.05 | 0.221 | 0.092 |
| Acute vs. HC | — | | — | 0.16* | 0.001 | 0.078 |
| Remitted vs. HC | — | | — | 0.07 | 0.087 | 0.116 |

# 3.2 Centrality

Regarding centrality patterns, the correlations of out-EI across the three networks were not significant. Specifically, the out-EI correlations were r = − 0.01, p = 0.956 between the acute and remitted MDD networks, r = − 0.00, p = 0.984 between the acute MDD and HC networks, and r = − 0.13, p = 0.522 between the remitted MDD and HC networks. In contrast, the pattern of in-EI showed significant positive correlations between the acute MDD and HC networks (r = 0.58, p = 0.003) and between the remitted MDD and HC networks (r = 0.59, p = 0.002), whereas the correlation between the acute and remitted MDD networks was not significant (r = 0.36, p = 0.074).

Using an out-EI threshold of Z > 1 to identify core components, RS15 (Engagement) showed the highest out-EI in the acute MDD network (Z = 2.13), followed by RS13 (Self-efficacy) (Z = 1.92) and RS8 (Self-friendship) (Z = 1.63) as additional core components. In the remitted MDD network, RS17 (Self-efficacy) had the highest out-EI (Z = 2.29), followed by RS14 (Discipline) (Z = 2.19), RS10 (Determination) (Z = 1.82), and RS13 (Self-efficacy) (Z = 1.04), which also exceeded the core-component threshold. In the HC network, RS6 (Pride/Purpose) showed the highest out-EI (Z = 2.35), followed by RS21 (Purpose) (Z = 1.76) and RS18 (Reliability) (Z = 1.64).

More specifically, in the acute MDD network, RS15 (engagement) at T1 positively predicted RS16 (humor) (β = 0.12), RS1 (perseverance) (β = 0.11), and RS8 (self-friendship) (β = 0.11) at T2. In the remitted MDD network, RS17 (self-efficacy) at T1 showed its strongest positive cross-lagged associations with RS13 (self-efficacy) (β = 0.16), RS12 (mindfulness) (β = 0.15), and RS22 (acceptance) (β = 0.14) at T2. In the HC network, RS6 (purpose) at T1 most strongly predicted RS17 (self-efficacy) (β = 0.13), RS2 (adaptability) (β = 0.11), and RS1 (perseverance) (β = 0.08) at T2.

# 3.3 Network stability and accuracy

The bootstrapped CIs around the edge weights demonstrated variable accuracy across the three networks, with relatively wider confidence intervals in the acute and remitted groups and generally narrower confidence intervals in the healthy control group (Fig. 2). The case-drop bootstrapping results revealed low-to-small stability for in-EI in the acute group (CS-C = 0.124) and moderate stability in the healthy control group (CS-C = 0.438), whereas small-to-moderate stability was observed in the remitted group (CS-C = 0.281). In terms of out-EI, low-to-small stability was observed in both the acute group (CS-C = 0.124) and the remitted group (CS-C = 0.126), while small-to-moderate stability was observed in the healthy control group (CS-C = 0.284).

# 4. Discussion

The present study investigated how resilience-related processes dynamically interact with clinical states in MDD. Using CLPN modeling, we delineated distinct temporal architectures of resilience in individuals experiencing acute depression, those in full remission, and healthy controls. Leveraging longitudinal data, our findings illuminate the mechanisms through which resilience operates as a self-regulating system that adaptively reorganizes—or fails to do so along the depression–recovery continuum.

Consistent with our hypotheses, the acute MDD group showed a comparatively sparse and heterogeneous network configuration, with an intermediate number of cross-lagged connections and limited stability of centrality estimates, suggesting a less robust temporal organization of resilience components (32, 33). This pattern may reflect reduced coordination among adaptive psychological resources, in line with evidence that depressive states are associated with diminished flexibility in emotional regulation, motivation, and self-related cognition (34–38). In contrast, the remitted MDD group exhibited the fewest cross-lagged associations and slightly lower mean edge weights than the acute MDD group, while centrality stability remained limited

(39). These findings suggest that remission was not characterized by a simple increase in network connectivity, but rather by a distinct reorganization of temporal associations among resilience-related processes (40–43). The healthy control group displayed the densest network and the most favorable overall stability profile, consistent with the view that resilience in mentally healthy individuals is organized within a more broadly integrated and comparatively robust system (44–47).

Centrality analyses revealed both overlapping and distinct RS-25 items that played dominant roles across groups (32, 46, 48). In the acute MDD group, engagement showed the highest out-expected influence, followed by items reflecting self-efficacy and self-friendship, suggesting that sustained involvement and self-related adaptive processes may play a particularly important prospective role during acute depression (34, 36, 49). In the remitted MDD group, self-efficacy emerged as the most influential component, with discipline, determination, and an additional self-efficacy-related item also showing prominent prospective influence, which may reflect the reorganization of adaptive self-regulatory resources during remission (18, 50). Among healthy individuals, purpose-related items and reliability were among the most influential components, consistent with a more broadly integrated

resilience structure involving meaning, goal-directedness, and dependable self-regulation (42–45, 51–53). Together, these patterns support the view that resilience operates as a dynamic and context-dependent network whose organization differs between clinical and healthy populations (39, 47, 54).

Finally, our results highlight the methodological value of longitudinal network approaches in psychiatric research (55, 56). Traditional analyses that rely on mean-level comparisons or cross-sectional correlations are unable to capture how psychological mechanisms causally shape one another over time (31, 57). In contrast, CLPN modeling reveals directional temporal dependencies, enabling the identification of pathways through which specific resilience factors either foster or hinder recovery (30). Notably, although the RS-25 is conceptualized as a trait measure, our findings indicate that its network organization does not demonstrate comparable temporal stability in individuals with MDD as observed in healthy controls, suggesting that cross-sectional applications in clinical samples may provide an incomplete or potentially misleading representation of resilience structure. By adopting this dynamic systems perspective, we advance a mechanistic understanding of depression as an evolving process rather than a static diagnostic category (58–60).

# 4.1 Potential Clinical Implications

The temporal network features identified in this study indicate that resilience not only differs during depressive states but reorganizes in qualitatively distinct ways across the depression–recovery continuum. Network density, edge sign structure, centrality patterns, and temporal stability collectively differentiated Acute MDD, Remitted MDD, and Healthy groups, supporting the notion of resilience as a dynamic regulatory system whose organization varies across clinical states. Acute MDD was characterized by an intermediate number of cross-lagged associations and limited centrality stability, Remitted MDD by the fewest cross-lagged associations and limited stability, and health by the densest network and the most favorable overall stability profile.

Centrality profiles further indicated that the resilience components with the greatest prospective influence differed across clinical states (61, 62). In the acute MDD group, engagement emerged as the most influential component, accompanied by items reflecting self-efficacy and self-friendship, suggesting a prominent role for motivational persistence and perceived competence during acute illness (47). In the remitted MDD group, self-efficacy showed the highest prospective influence, with discipline and determination also contributing prominently, which may reflect the reactivation of adaptive self-regulatory resources during remission (63, 64). Among healthy individuals, purpose-related items and reliability were the most influential, consistent with a more broadly organized resilience structure centered on meaning, goal-directedness, and dependable self-regulation (65, 66). Together, these structural and functional fingerprints underscore that resilience varies not only in level but in organizational form across clinical states, offering mechanistic markers that may enhance patient stratification (18, 61).

# 4.2 Limitations and Future Directions

Several limitations should be considered when interpreting these findings. First, the analysis was based on only two measurement waves, constraining our ability to capture nonlinear, cyclic, or delayed dynamics that may unfold over the longer term. Studies incorporating multi-wave longitudinal designs would enable a more precise characterization of temporal dependencies and allow for the examination of potential bidirectional feedback loops between resilience processes and depressive symptoms. Second, the network structure was estimated using self-reported RS-25 items, which, although psychometrically robust, may not fully capture the multidimensional nature of resilience—particularly its neurobiological, behavioral, and environmental determinants.

Third, although the use of penalized regression reduces the risk of overfitting, differences in sample size across groups—especially within the clinical cohorts—may have influenced edge stability and the comparability of network structures. Future research employing larger and more balanced samples is needed to validate the group-specific patterns observed here. Finally, the CLPN model cannot distinguish between within- and between-person effects, and thus, the temporal effects cannot be considered as causal effects.

Despite these limitations, the present study offers a valuable foundation for conceptualizing resilience as a temporally evolving system and underscores the relevance of longitudinal, person-centered methods in clinical network research. Future work should aim to integrate these network approaches into predictive modeling frameworks capable of forecasting individualized recovery trajectories and informing mechanism-based, personalized interventions for MDD.

# 5. Conclusion

In summary, this study shows that the temporal organization of resilience differs across acute MDD, remitted MDD, and healthy individuals. Healthy controls displayed the densest network and the most favorable overall stability profile, whereas the remitted MDD group showed the fewest cross-lagged connections. Acute MDD showed an intermediate number of temporal associations and the highest mean non-zero edge weight, although centrality stability remained limited. Together, these findings support the view that resilience is not simply a fixed personal attribute, but a context-dependent system whose internal organization varies across clinical states.

Methodologically, CLPN provided a useful framework for examining directed temporal associations among resilience components across two measurement occasions. However, these associations should not be interpreted as causal or as purely within-person effects. The group-specific centrality patterns identified engagement, self-efficacy, and self-friendship as prominent components in acute MDD; self-efficacy, discipline, and determination in remitted MDD; and purpose-related items and reliability in healthy controls. Given the limited stability of several centrality estimates, particularly in the clinical groups, these components should be considered candidate processes for future replication rather than established intervention targets. Future studies using larger and more balanced samples, additional

measurement waves, and broader resilience domains may help clarify the clinical relevance and robustness of these temporal network patterns.

# Declarations

6.1 Ethics Approval and Consent to Participate

The study complied with the Declaration of Helsinki. This study was approved by the ethics committees of the Medical Faculties at the University of Marburg (AZ: 07/14) and the University of Mu¨nster (AZ: 2014-422-b-S). All participants provided written informed consent. Clinical trial number: not applicable.

6.2 Availability of data and materials

The dataset is part of the Marburg/Münster Affective Disorders Cohort and may be made available upon reasonable request, subject to institutional approval and applicable ethical and data protection regulations, via the Collaborative Research Center (CRC) https://www.sfb-trr393.de/. The authors declare no competing interests.

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7.1 Authors' Contributions

SK, HJ, AA, RF, and IN contributed to the coding and implementation of analyses. SK, TM, YE, AA, and IN were involved in the conceptualization and discussions. NA, AJ, TM, EJ, SM, TK, and IN provided support and access to the study data. SK and IN wrote the original draft. All authors contributed to the review and editing of the manuscript.

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# Figures

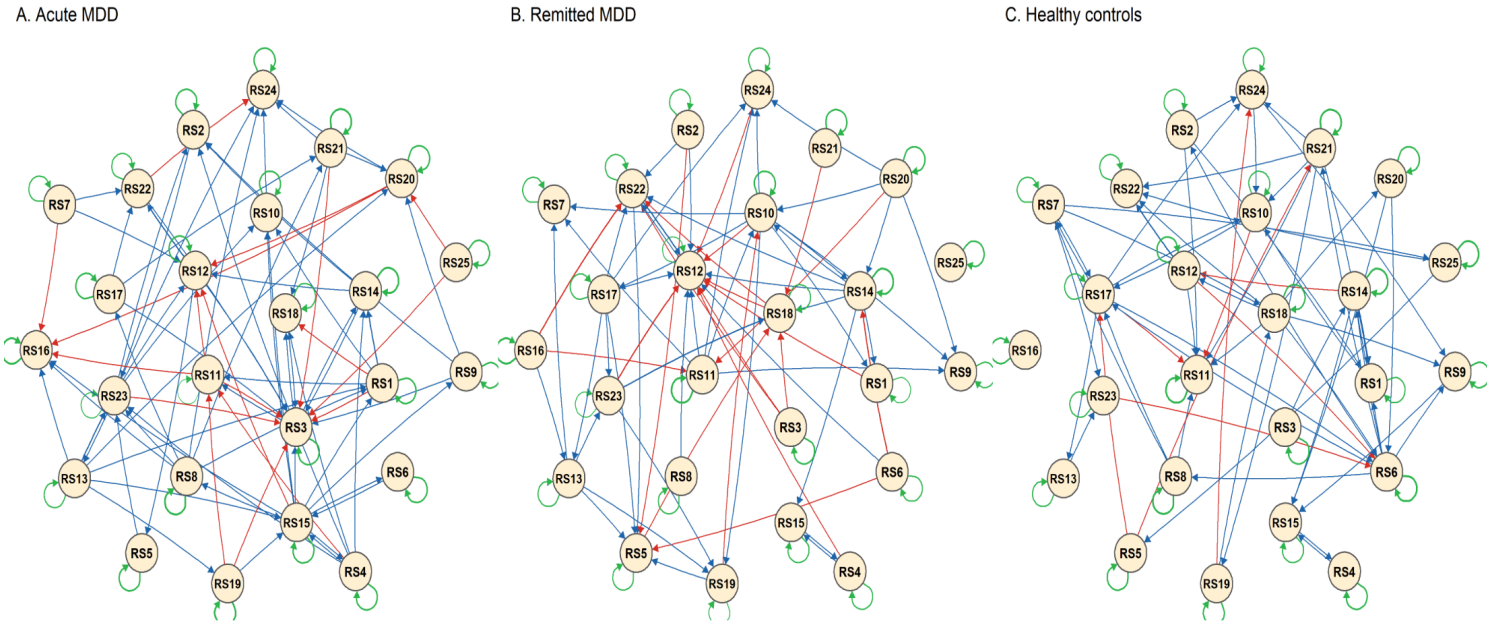



**Figure 1**

Cross-lagged panel networks across three groups.

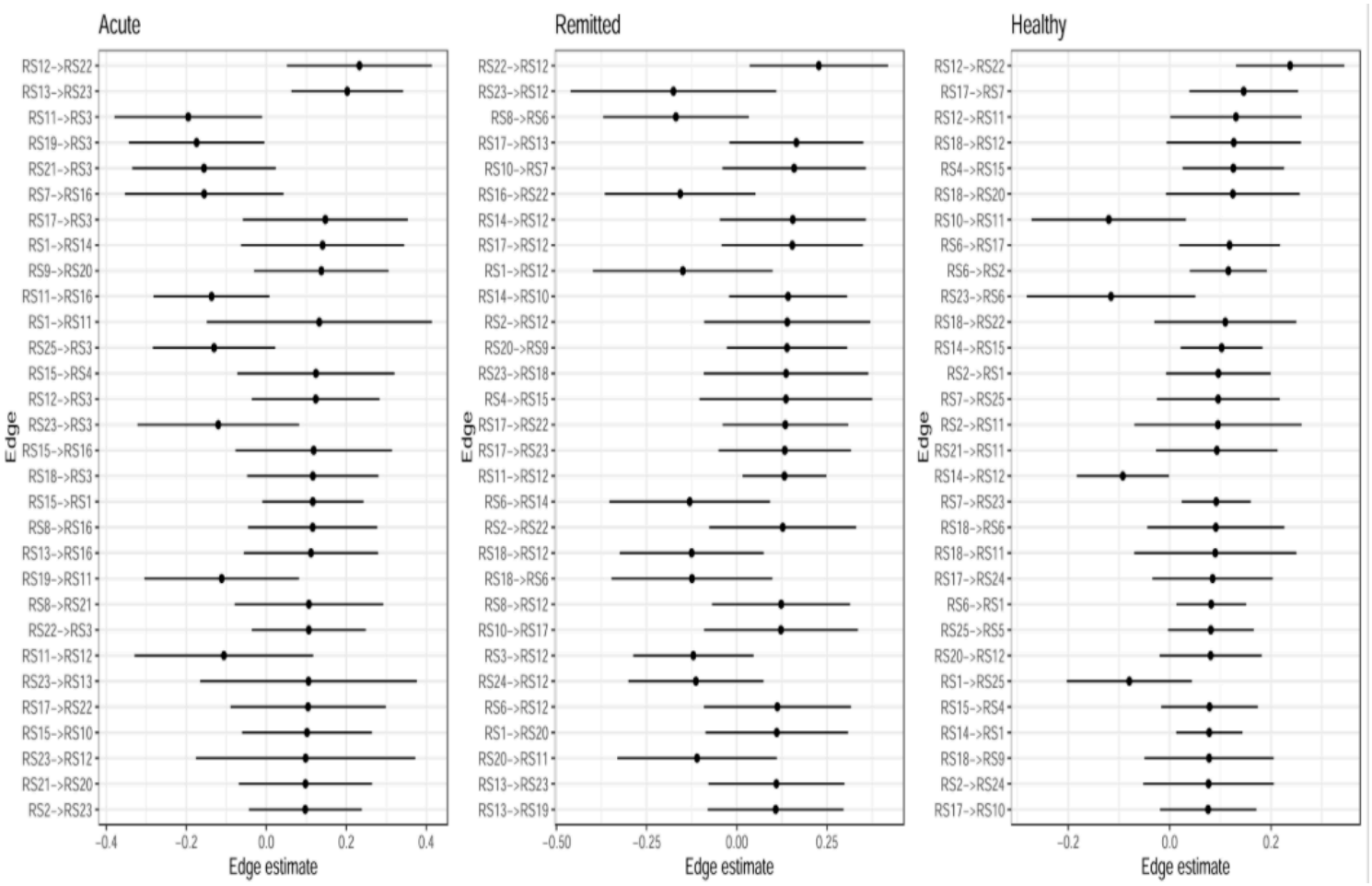



**Figure 2**

Bootstrapped confidence intervals for the strongest cross-lagged edges in each group. Points represent estimated edge coefficients ($\beta$), and horizontal lines represent 95% bootstrap intervals. Narrower intervals indicate more stable edge estimation across samples.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryMaterial.Resilience.docx