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# COMPARISONS OF TARGETED TREATMENT FOR MENTAL DISORDERS BASED ON NETWORK ANALYSIS OVER NON-TARGETED TREATMENT IN ADOLESCENTS

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**Abstract**
Network analysis was widely used to identify core symptoms, with the aim of providing targets for intervention. Whether targeted treatment based on core symptoms identified by network analysis is superior to the non-targeted treatment remains unknown. We utilize simulation to contrast their effects on the symptom network of mental health. In the simulation, intentional and random attacks represent targeted and non-targeted treatments, respectively. The simulation test was conducted by attacking the symptom network using both random attacks and intentional attacks targeting central nodes, as defined by centrality measures. The results showed that the natural connectivity of the network degraded faster in intentional attacks than in random ones. Additionally, abnormal individuals have higher natural connectivity values than normal individuals. The findings indicated that compare to non-targeted treatment methods, centrality based targeted treatment focusing on core symptoms disrupted the connections between symptoms more quickly, generating better treatment effects.

**Keywords:** invulnerability simulation, mental health, network analysis, symptom network, targeted treatment.

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Adolescence, a pivotal phase in human development, encompasses profound and rapid cognitive and emotional growth. Adolescent mental health is in a state of crisis, with a high prevalence of mental disorders such as depression (Noyes et al., 2022), anxiety (Lofthouse et al., 2023), and bipolar disorder (Ortiz-Orendain et al., 2023). The diverse mental disorders frequently co-occur. Among individuals diagnosed with depression, 67% currently also had an anxiety disorder, and 75% had a lifetime history of comorbid anxiety disorder. Among those with a current anxiety disorder, 63% also had a current depressive disorder, and 81% had experienced a depressive disorder at some point in their lives (Lamers et al., 2011). These disorders not only interact with each other (Mustață, 2021) but are also influenced by various factors, forming a complex psychological system. The intricate nature of this system, with its multifaceted dimensions, poses significant challenges to the conventional reductionist approaches traditionally employed in the study of psychological well-being (Blanchard & Heeren, 2020).

Network analysis has emerged as a promising method for investigating complex psychological systems and has been widely utilized in the field of psychiatry. In network analysis, symptoms are conceptualized as nodes, and the connections between these nodes serve as edges. By calculating the topographical characteristics of these intricately connected networks, researchers have gained profound insights into the structural composition and pathological mechanisms of mental disorders (Bringmann et al., 2013; Van Borkulo et al., 2015). Specifically, psychological states can be evaluated through network connectivity. Connectivity indicates the degree of association among different psychological symptoms, higher connectivity implies a stronger correlation between symptoms. One study revealed higher connectivity within the psychological networks of patients suffering from persistent major depression at baseline compared to those in remission (Van Borkulo et al., 2015). Changes in network connectivity have a stable relationship with individual states. Symptom networks with higher connectivity exhibit a sharper transition from a normal state to a depressive one (Cramer et al., 2016; Fried et al., 2017). Additionally, increased connectivity among emotions indicates a transition from a normal state to major depression (Van De Leemput et al., 2014).

In addition to connectivity, network centrality is also extensively utilized, particularly in identifying core symptoms. By calculating network centrality, self-hatred and loneliness have been identified as core symptoms of adolescent depression (Mullarkey et al., 2019). Centrality is a prevalently used parameter in psychiatric studies, valued for its utility in targeted treatment in clinical settings. Centrality helps researchers and clinicians focus on the most important nodes within network, thereby enhancing the effectiveness of intervention strategies (Bringmann et al., 2019; Sobański et al., 2023). Despite its extensive use in psychological networks, the validity of centrality has been challenged. Researchers question the applicability of central nodes, as the effectiveness of utilizing network core symptoms to guide treatment remains inconclusive (Contreras et al., 2019). Conflicting conclusions regarding network centrality have emerged from similar datasets (Bringmann et al., 2016), and there are variations in the identification of core nodes (Borsboom et al., 2017; Forbes et al., 2017). Therefore, there is an urgent need for evidence comparing the effectiveness of network-based targeted treatment with non-targeted treatment.

The most direct evidence may be obtained by comparing the effects of different interventions. Considering the time and other resources invested in interventions, simulation offers an alternative approach. Simulation, which involves using models—whether physical or mathematical—to replicate experiments and research instead of using actual systems, is a well-established practice in fields such as energy (Chen et al., 2023) and medicine (Rudolph et al., 2021). In the domain of psychological network research, this method has been employed to explore transitions between depressive states (Cramer et al., 2016). Simulation-based research offers effective methodologies for exploring psychological networks and facilitates a thorough analysis of the interactions between network structure and psychological well-being.

To determine the relative efficacy of network-based targeted treatment versus non-targeted treatment, this study constructed symptom-based networks and compared their connectivity under different treatment conditions using simulations. Treatment of psychological networks can be likened to attacks on a simulated system. In the network analysis, attack refers to a perturbation to the system, achieved by removing nodes or edges from the network. The impact of an attack on a network can be either positive or negative. For instance, in urban networks, the removal of transportation hubs may cause the urban system to fail, whereas in a large criminal organization network, the entire network can collapse by arresting key individuals (Holme et al., 2002). In this study, consistent with the aforementioned explanation, an attack on psychological networks involved removing a node, which represents the elimination of all connections among a symptom and other symptoms through treatment. Consequently, the connectivity of the psychological network would decrease, which is beneficial for treating mental disorders. Given that psychological networks are susceptible to external influences or attacks (Hallquist et al., 2021; Hayes et al., 2015), we utilized two types of attacks to represent the different treatments. Intentional attacks, which involved the removal of the most important nodes we chose, represented targeted treatment. Correspondingly, random attacks represented non-targeted treatment. The treatment effect was evaluated by calculating network connectivity following node attacks. The network invulnerability test, originally developed in computer science and network analysis, has proven useful in examining the vulnerability and resilience of structures such as the internet and social networks (Albert et al., 2000). This study utilized the network invulnerability test to measure the network's connectivity under various attacks.

## Method

### *Participants and Measurement*

The data were obtained from the National Population Health Sciences Data Center with permission. A total of 9,072 participants were included in this study, all of whom underwent the Symptom Checklist 90 (SCL-90) assessment. All data was collected voluntarily, anonymously and confidentially. The data collection has been approved by the Ethics Committee of Shandong University (20180517) as stated (Dong et al., 2020). The SCL-90 is a widely utilized psychological assessment tool designed to measure a broad range of psychological symptoms. The SCL-90 consists of 90 items that assess ten primary symptom dimensions, including somatization, obsessive-compulsive behavior, interpersonal sensitivity, depression, anxiety, hostility, phobic anxiety, paranoid ideation, psychoticism, among others.

Based on the SCL-90 scores, participants were divided into three groups in our study. The first group consisted of normal participants ($N$ = 5,438, $M_{age}$ = 16.08, $SD$ = 1.29), with total scores of SCL-90 below 160. The second group consisted of suspected patients ($N$ = 2,513, $M_{age}$ = 16.23, $SD$ = 1.16), with total scores between 160 and 200. The third group consisted of psychological abnormalities ($N$ = 1,121, $M_{age}$ = 16.21, $SD$ = 1.16) characterized by total scores exceeding 200 or scores higher than 3 in any dimension.

### *Data Analysis*

The network for each group was constructed following methodologies outlined in previous studies (Mullarkey et al., 2019), with items in the SCL-90 serving as nodes and partial correlations as edges (Epskamp et al., 2012). To eliminate artificial connections, the least absolute shrinkage and selection operator (LASSO) was employed. The construction and subsequent calculation of centrality were conducted using the R packages qgraph (Epskamp et al., 2012) and bootnet (Epskamp et al., 2018). Network Comparison Test (NCT) was used to assess group centrality (EI) (Van Borkulo et al., 2023).

To identify targets in the simulation of targeted treatment, we quantified the significance of each node in the network using the expected influence (EI). This measure is more suitable for networks that contain both positive and negative edges compared to the traditional centrality index (McNally, 2016; Robinaugh et al., 2016). Nodes with higher EI were deemed more important in the network. The network invulnerability test evaluates a network's ability to maintain connectivity when nodes are compromised. The process involves exposing network nodes to predetermined attack strategies and conducting simulation experiments to observe changes in connectivity following each attack. To quantify the stability and connectivity of the inferred networks, we employed a reliable and sensitive measure—natural connectivity (Jun et al., 2010).

This study performs network attacks focusing on the abnormal group to simulate treatment. In random attacks, each node or edge in the network was targeted with equal probability. The outcome was the network's average natural connectivity after surviving 6,000 random attacks. For intentional attacks, two distinct strategies were employed, a similar to previous study (Holme et al., 2002). The first strategy involved selecting nodes in the initial network based on their EI values in descending order. It gradually removed nodes, starting with the one with the highest EI. This attack strategy utilized the initial EI distribution and is therefore referred to as the IEI (initial expected influence) attack in this study. The second strategy, employed a recalculated EI distribution at each step of node removal, is referred to as the REI (recalculated expected influence) attack.

## Results

### *Network Structure*

In the symptom network of the abnormal group, 936 out of the 4005 possible edges (23.4%) were non-zero, indicating intense interconnectedness between symptoms. The network exhibited an average degree of 20.8 and a clustering coefficient of 0.36, indicating the likelihood that a node’s neighbors are also interconnected. The structure of the network for the abnormal group was illustrated in Figure 1.

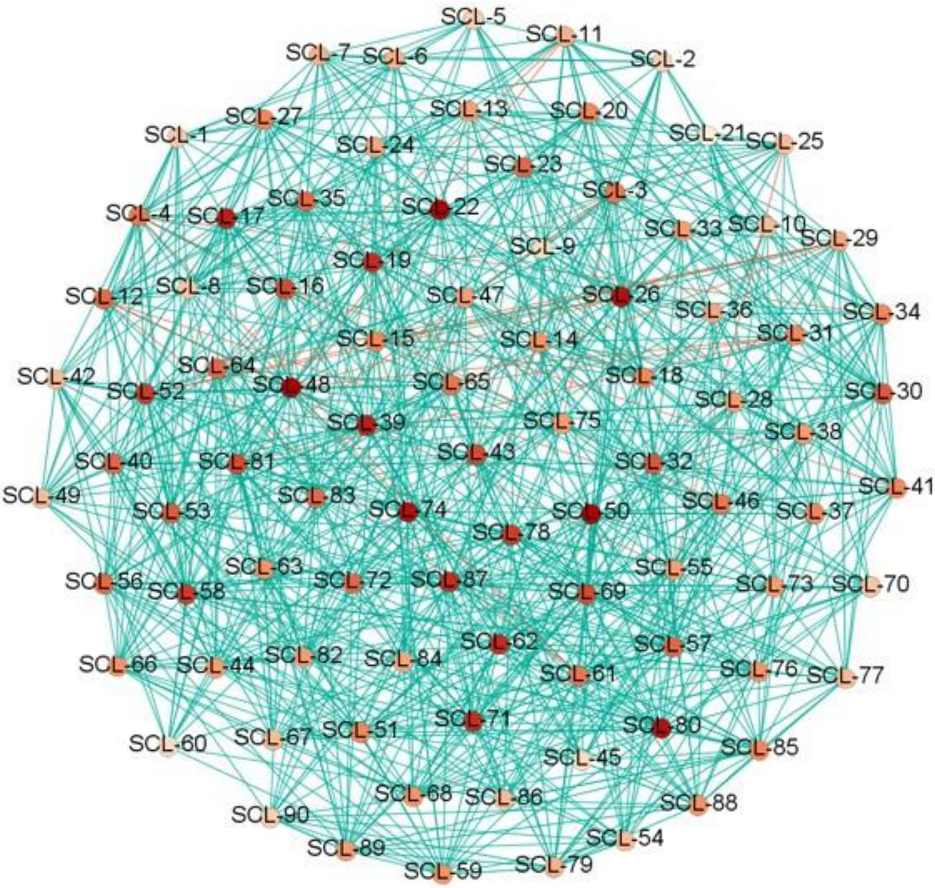

**Figure 1**. Network structure for the abnormal group. Darker colour indicates higher degree of nodes, green edges represent positive associations and red edges represent negative relations.

Descriptive results for the means and SDs for the three groups on the nodes with the highest EI, and the statistically significant differences between each of the group were presented in Table 1-3. In Tables 1, 2, and 3, the fourth and fifth columns represented the significance of the differences in node EI values between the current group and the other two groups. A *p*-value less than 0.05 indicated a significant difference in node EI values. Significant differences between groups were marked in the table as follows: "$^{+}$" denoted a significant difference between the normal and suspected groups, "$^{*}$" indicated a significant difference between the normal and abnormal groups, and "$^{\Delta}$" signified a significant difference between the suspected and abnormal groups.

**Table 1.** Top 10 nodes based on EI for abnormal group and group differences

| Node | Mean | *SD* | *P*-value compared with Normal | *P*-value compared with Suspected | Description | Dimension |
|---|---|---|---|---|---|---|
| SCL-79$^{*}$ | 1.20 | 0.05 | <0.01 | 0.16 | Feelings of worthlessness | Depression |
| SCL-23$^{*}$ | 1.19 | 0.05 | <0.01 | 0.09 | Suddenly scared for no reason | Anxiety |
| SCL-72$^{*}$ | 1.19 | 0.05 | <0.01 | 0.37 | Spells of terror or panic | Anxiety |
| SCL-78$^{*}$ | 1.18 | 0.05 | <0.01 | 0.16 | Feeling so restless you couldn't sit still | Anxiety |
| SCL-81$^{*}$ | 1.16 | 0.06 | <0.01 | 0.63 | Shouting or throwing things | Anger-hostility |
| SCL-52$^{*}$ | 1.16 | 0.06 | <0.01 | 0.49 | Numbness or tingling in parts of your body | Somatization |
| SCL-71$^{*}$ | 1.15 | 0.06 | <0.01 | 0.37 | Feeling everything is an effort | Depression |
| SCL-58$^{*}$ | 1.14 | 0.06 | <0.01 | 0.37 | Heavy feelings in your arms or legs | Somatization |
| SCL-33 | 1.14 | 0.06 | 0.07 | 0.37 | Feeling fearful | Anxiety |
| SCL-30 | 1.12 | 0.06 | 0.78 | 0.97 | Feeling blue | Depression |

**Table 2.** Top 10 nodes based on EI for suspected group and group differences

| Node | Mean | *SD* | *P*-value compared with Normal | *P*-value compared with Abnormal | Description | Dimension |
|---|---|---|---|---|---|---|
| SCL-78$^{+}$ | 1.29 | 0.04 | <0.01 | 0.16 | Feeling so restless you couldn't sit still | Anxiety |
| SCL-72$^{+}$ | 1.27 | 0.05 | <0.01 | 0.37 | Spells of terror or panic | Anxiety |
| SCL-33$^{+}$ | 1.22 | 0.05 | <0.01 | 0.37 | Feeling fearful | Anxiety |
| SCL-58$^{+}$ | 1.20 | 0.05 | <0.01 | 0.37 | Heavy feelings in your arms or legs | Somatization |
| SCL-89$^{+\Delta}$ | 1.18 | 0.04 | <0.01 | 0.01 | Feelings of guilt | Additional Items |
| SCL-30 | 1.14 | 0.05 | 0.53 | 0.97 | Feeling blue | Depression |
| SCL-22$^{+}$ | 1.12 | 0.05 | <0.01 | 0.58 | Feeling of being trapped or caught | Depression |
| SCL-81$^{+}$ | 1.12 | 0.05 | <0.01 | 0.63 | Shouting or throwing things | Anger-hostility |
| SCL-79$^{+}$ | 1.10 | 0.05 | <0.01 | 0.16 | Feelings of worthlessness | Depression |

| Node | Mean | *SD* | *P*-value compared with Normal | *P*-value compared with Abnormal | Description | Dimension |
|---|---|---|---|---|---|---|
| SCL-56$^{+}$ | 1.09 | 0.05 | 0.04 | 0.16 | Feeling weak in parts of your body | Somatization |

**Table 3.** Top 10 nodes based on EI for normal group and group differences

| Node | *EI* | *SD* | *P*-value compared with Suspected | *P*-value compared with Abnormal | Description | Dimension |
|---|---|---|---|---|---|---|
| SCL-61$^{+*}$ | 1.31 | 0.04 | <0.01 | <0.01 | Feeling uneasy when people are watching or talking about you | Interpersonal Sensibility |
| SCL-46$^{+*}$ | 1.25 | 0.04 | <0.01 | <0.01 | Difficulty making decisions | Obsessive-compulsive |
| SCL-29$^{+*}$ | 1.23 | 0.04 | <0.01 | <0.01 | Feeling lonely | Depression |
| SCL-11$^{+*}$ | 1.22 | 0.03 | <0.01 | <0.01 | Feeling easily annoyed or irritated | Anger-hostility |
| SCL-9$^{+*}$ | 1.22 | 0.03 | <0.01 | <0.01 | Trouble remembering things | Obsessive-compulsive |
| SCL-57$^{+*}$ | 1.19 | 0.04 | <0.01 | <0.01 | Feeling tense or keyed up | Anxiety |
| SCL-55$^{+*}$ | 1.19 | 0.04 | <0.01 | <0.01 | Trouble concentrating | Obsessive-compulsive |
| SCL-28$^{+*}$ | 1.13 | 0.04 | <0.01 | <0.01 | Feeling blocked in getting things done | Obsessive-compulsive |
| SCL-41$^{+*}$ | 1.13 | 0.04 | <0.01 | <0.01 | Feeling inferior to others | Interpersonal Sensibility |
| SCL-3$^{+*}$ | 1.13 | 0.04 | <0.01 | <0.01 | Unwanted thoughts, words, or ideas that won't leave your mind | Obsessive-compulsive |

As can be seen from Table 1, in the group of psychological anomalies, SCL-79 exhibited the highest expected influence value, followed by SCL-23, SCL-72, and SCL-78, indicating that these symptoms were the most influential within the network. In contrast, symptoms such as SCL-60 and SCL-21 demonstrated a marginal impact within the network. Most of the top ten nodes were associated with the anxiety, depression, and somatization dimensions, indicating that these three dimensions were the most influential within the overall symptom network model. Interestingly, six of the top ten nodes in the abnormal group were the same as those in the suspected group, whereas none overlapped with the normal group was found.

Results from NCT revealed that the difference in EI values between network nodes in the abnormal group and the normal group is the most pronounced, with significant differences observed in nearly all of the top 10 nodes. In contrast, the difference between the suspected group and the abnormal group was smaller, with almost no significant differences among the top 10 nodes.

*Invulnerability*

To evaluate the effects of various attack strategies, the invulnerability test was performed. The results revealed distinct pattern from the three types of attacks within the abnormal group (Figure 2). The initial values of the three curves denote the network connectivity of the abnormal group. Figure 2 clearly indicated that abnormal group had higher values than the suspected group, which in turn had higher values than the normal group. As the number of removed nodes increased from 0 to 64, natural connectivity decreased across all simulated treatments, indicating that the network's connectivity was sensitive to disturbance. During the IEI attack, the network's natural connectivity deteriorated more rapidly than during the random attack. Meanwhile, the values of natural connectivity in the REI attack deteriorated more rapidly than in the IEI attack.

During the REI attack, natural connectivity declined over time, approaching zero, significantly lower than in the other two attacks. This indicates a substantial disruption in the network connectivity and a significant loss of interconnections between nodes. Consequently, the network no longer met the essential criteria for optimal operation and could not sustain its original functionality.

It is important to note that the objective was not to completely dismantle the network. Given that a total breakdown of the network represented a state of psychological abnormality, the aim of the treatment was not to fully dismantle the network structure, i.e., to achieve near-zero natural connectivity. The treatment aimed to reduce network connectivity to levels comparable to those of the normal population, as illustrated in Figure 2.

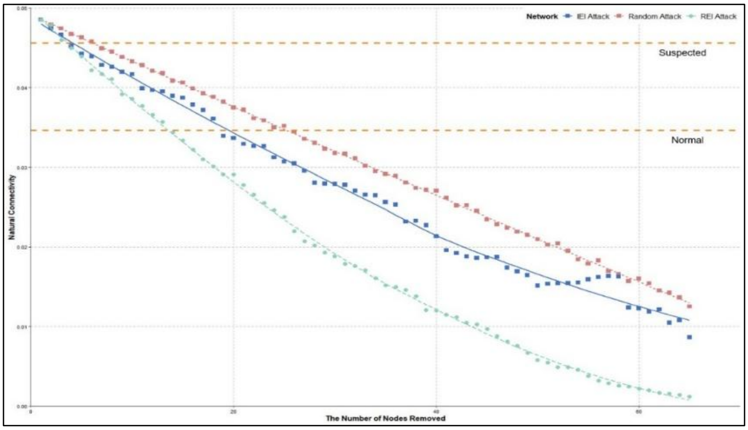


**Figure 2**. The natural connectivity of symptom networks under different attacks. The upper and lower orange lines parallel to the x-axis depict the natural connectivity of the suspected and normal, respectively.

To validate our findings, the same analysis was performed using the network constructed from the ten dimensions of the SCL-90. Consistent with the previous results, the intentional attack exhibited a more pronounced decreasing trend in natural connectivity compared to the random attack, as shown in Figure 3.

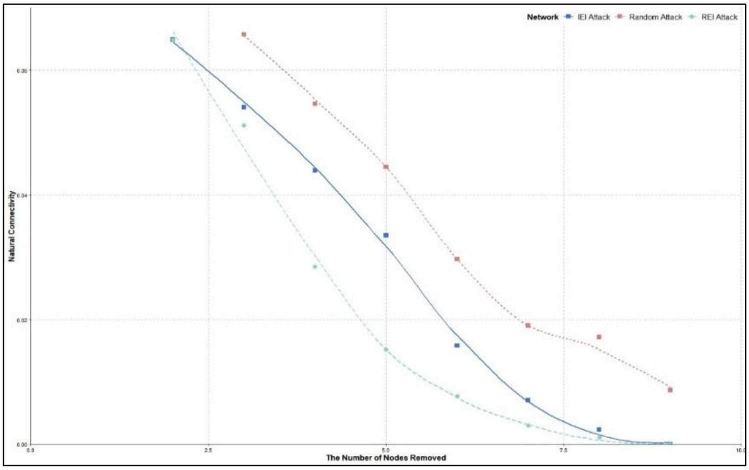


**Figure 3**. The natural connectivity of dimension networks under different attacks

## Discussion

To the best of our knowledge, this is the first study to directly compare the outcomes of targeted and non-targeted treatments using simulations based on network analysis. In the invulnerability test, the random attack represented non-targeted treatment, whereas the IEI and REI attacks represented targeted treatment. The results revealed distinct patterns of invulnerability evolution in the abnormal group under the three attack conditions. The intentional attacks resulted in a faster decline in network connectivity overall, suggesting a more effective method for disrupting connections between symptoms and improving treatment outcomes. The connectivity value of the network after the REI attack was lower than that after the IEI attack. Our findings clearly demonstrate the superiority of treatment approaches that target network centrality over non-targeted treatments. Network centrality is a viable strategy for identifying potential targets in effective treatments.

The primary finding of this study was that intentional attacks targeting central nodes induced a more rapid decrease in network connectivity compared to random attacks. Larger connectivity indicated worse psychological states (Cramer et al., 2016; Fried et al., 2017; Van Borkulo et al., 2016), the intentional and random attacks represented targeted and non-targeted treatments, respectively. These results suggested that targeted treatment based on central nodes was more effective than non-targeted treatment in addressing mental disorders. Despite ongoing controversy regarding the potential of centrality in determining intervention targets (Bringmann et al., 2016, 2019; Borsboom et al., 2017; Forbes et al., 2017), our results indirectly support the notion that high-centrality symptoms are suitable targets for clinical intervention.

In accordance with the findings of this study, the top eight symptoms listed in Table 1 warrant substantial attention in clinical treatment, as they exhibit higher values of EI for the abnormal group and differ significantly from the normal group. Among these, “Feelings of worthlessness” should be prioritized due to its highest EI value. Research has shown that addressing “feelings of worthlessness” in clinical settings can significantly enhance mental health outcomes. For example, in reminiscence therapy, strengthening self-worth and self-acceptance in young adults with moderate depressive symptoms could generate positive experiences and alleviate depression (Hallford et al., 2018).

Another significant finding arises from the comparison between the REI and IEI attack. IEI was considered a targeted treatment based on the initial assessment of each symptom's importance, treating according to initial evaluations. In contrast, REI was considered a targeted treatment that reassessed the importance of the patient's symptoms before each treatment session, thereby treating according to ongoing assessments. As connectivity decreased more rapidly in the REI attack than in the IEI attack, consistent with the findings of Holme’s study (2002), it can be concluded that reassessment-based treatment is more effective than treatment based solely on initial results. Furthermore, our results indicate that psychological assessment plays a crucial role in clinical decision-making. Regular assessment of the patient at consistent intervals during the treatment episode can provide invaluable feedback (Lambert, 2010). Assessments of the patient's mental health prior to each session and tailoring the treatment plan accordingly are strongly recommended.

Overall, the results demonstrated a hierarchical trend in connectivity evolution: individuals with psychological abnormalities > individuals with suspected psychological abnormalities > normal individuals. This pattern suggests a nuanced link between mental health and network connectivity, consistent with findings from previous network research (Cramer et al., 2016; Fried et al., 2017; Van Borkulo et al., 2016). Unlike previous studies that compared only two groups (Van Borkolu et al., 2016; Van De Leemput et al., 2014), our study further validated the relationship between network connectivity values and mental health by including a suspected group and utilizing a larger sample. Moreover, results from NCT of differences in EI suggested that the network structure of the suspected group has undergone significant changes compared to the normal group and closely resembles that of the abnormal group, reflecting shifts in the mental health status of the suspected group. Therefore, consistent with a previous study (Yang et al., 2024), we also suggested that the suspected group should be treated differently from the normal and abnormal groups.

This study has several limitations. First, the simulation process assumed a maximum destruction probability of 100% for symptom nodes. Given that certain symptoms are persistent and pose significant challenges for complete eradication, achieving a 100% destruction probability for these nodes may be unrealistic. Second, the simulation process overlooks the dynamic nature of the network. Although this study assumed a static network, it is crucial to recognize that clinical treatment is an ongoing process. The network may evolve as treatment progresses. Future research should delve deeper into exploring these two aspects.

In conclusion, lower values of network connectivity were consistently observed under intentional attacks compared to random attacks. This study validated the viability of network centrality in identifying treatment targets. Regularly updating assessments is recommended to accurately calculate the most representative centrality. This study not only provides theoretical support for targeted treatment of psychological abnormalities but also offers valuable insights for future research and clinical practice.

## Authors' Notes

**Study conception and design:** Weixia Zhang, Kechuang Zhang, Shubin Si, Min Xi.

**Data analysis and interpretation of results:** Kechuang Zhang, Shubin Si, Mengbi Yang; draft manuscript preparation: Kechuang Zhang, Weixia Zhang, Min Xi.

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