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Unpacking the bidirectional nexus between suicide risk and NSSI addiction: evidence from in silico intervention and Bayesian network analysis

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Abstract

Background

Individuals with non-suicidal self-injury (NSSI), particularly those with addiction-like features, frequently exhibit comorbid depressive symptoms. However, the symptom-level associations between these conditions remain unclear.

Methods

A total of 387 clinical participants with NSSI were included. Symptom networks were constructed using the binary Ising model and Gaussian Graphical Model (GGM) based on the Ottawa Self-Injury Inventory (OSI) and the 24-item Hamilton Depression Rating Scale (HAMD-24). Bridge centrality, NodeIdentifyR (NIRA), and Bayesian network analyses were performed to identify bridge symptoms, simulate interventions, and explore potential directional relationships.

Results

Suicide (HAMD3) emerged as the strongest bridge symptom linking depressive symptoms and NSSI addiction across network models. NIRA identified HAMD3 as the most effective intervention target, while Bayesian analysis suggested a potential bidirectional relationship between suicide risk and NSSI addiction.

Conclusions

Suicide-related symptoms may represent the key intervention target in NSSI addiction, highlighting the importance of integrating suicide risk assessment and intervention into clinical care.

1. Introduction

Non-suicidal self-injury (NSSI), defined as the direct and intentional destruction of one's own body tissue without suicidal intent or lethal outcome[1], is a common yet clinically significant behavior observed across both community and clinical populations. Previous studies have estimated the lifetime prevalence of NSSI to be approximately 17.2% among adolescents and 5.5% among adults[2]. In China, a cross-sectional epidemiological study further reported prevalence rates of 6.8% and 6.5% among psychiatric outpatients and inpatients, respectively[3]. Owing to its high prevalence and recurrent nature, and strong associations with psychiatric comorbidities, functional impairment, and suicide-related outcomes, NSSI has increasingly been recognized as a major public health concern[4, 5].

Conceptually, NSSI can be characterized across multiple dimensions, including self-injury ideation, frequency, motivational functions, and patterns of repetition[6]. Among these dimensions, the addictive features of repetitive NSSI have attracted increasing attention, as recurrent self-injurious behaviors may be conceptualized as a form of behavioral addiction. Clinical observations, findings from existing assessment instruments, and proposed diagnostic criteria for NSSI disorder suggest that repetitive NSSI exhibits several addictive characteristics, including compelling urges, impaired behavioral control, and the progressive intensification of self-injurious behaviors[7]. Importantly, individuals with addictive NSSI have been reported to exhibit greater suicidality than those with NSSI without addictive features[8], suggesting that addiction-like patterns may represent a marker of greater clinical severity.

From the perspective of emotion regulation and reinforcement models, the addiction-like process underlying repetitive self-injury may be partly driven by individuals' attempts to alleviate negative affect, including depressive emotions[9]. Empirical evidence indicates that self-injury can be reinforced through immediate emotional relief (negative reinforcement) as well as subjectively perceived benefits (positive reinforcement), gradually becoming a strategy for coping with certain depressive symptoms such as anhedonia and emotional numbness[10]. Through these processes, addiction-like features of NSSI may become tightly coupled with depressive symptoms at both the clinical and mechanistic levels, giving rise to a mutually reinforcing and self-sustaining symptom system.

Clinical and epidemiological evidence further supports a high degree of association between depressive symptoms and NSSI. In a nationwide, multicenter cohort study of adolescents with depression, Zhang et al. reported that the detection rate of NSSI among depressed adolescents was as high as 76.06%[11]. Meanwhile, extensive research indicates that many adolescents exhibiting NSSI also present with significant depressive symptoms[12]. Clinically, the presence of depressive symptoms is often associated with greater severity of NSSI behaviors, increased psychological burden, and more complex treatment needs[13]. Prospective evidence further demonstrates that recurrent NSSI in early adolescence significantly increases the risk of subsequent emotional problems[14]. These findings suggest that depressive symptoms and NSSI are closely and interactively linked, potentially forming a dynamic, interactional pattern through symptom-level processes.

In recent years, symptom network analysis has provided a novel framework for elucidating the complex relationship between depression and non-suicidal self-injury[15, 16]. Unlike traditional approaches based on diagnostic categories or total severity scores, network analysis conceptualizes mental disorders as systems of interacting symptoms, emphasizing direct symptom-to-symptom connections and their functional roles within the overall structure[15]. Existing studies have shown that within joint depression–NSSI symptom networks, depressive symptoms tend to occupy structurally central positions, whereas self-injury–related symptoms more often serve as bridge nodes linking the depression and NSSI symptom domains. These findings support the view that the association between depression and NSSI is driven not simply by co-occurrence, but by symptom-level interactions that give rise to an integrated and coupled system[12, 17].

However, several important limitations remain in the current network literature. Most studies have operationalized NSSI primarily in terms of self-injurious behaviors or ideation[12, 17], with relatively little attention to functional differentiation at the mechanistic level. In particular, although addiction-like features of NSSI—such as craving, diminished control, and negative reinforcement—have been proposed and measured in prior research, they have not yet been systematically incorporated into depression–NSSI symptom network models[18]. Moreover, most existing studies rely on cross-sectional network designs[12, 17] and rarely integrate directional modeling or intervention simulations, thereby limiting insights into potential maintenance mechanisms and clinically actionable intervention targets[15, 16]. Against this background, the present study integrates multiple complementary analytic approaches to characterize the symptom network structure between depressive symptoms and addiction-like features of NSSI, aiming to inform future, more targeted intervention strategies.

2. Method

2.1 Study population

This study received approval from the Medical Research Ethics Committee of the Brain Hospital Affiliated to Nanjing Medical University and was conducted in accordance with the Declaration of Helsinki. From September 2019 to December 2024, 426 participants aged 10–40 years with NSSI were recruited offline from multiple centers across China, led by the Affiliated Brain Hospital of Nanjing Medical University, in collaboration with the Third Hospital of Mianyang (Sichuan Mental Health Center), Tianjin Anding Hospital, Xuzhou Oriental People's Hospital, Shaanxi Provincial People's Hospital, Xi'an Mental Health Center, the Second People's Hospital of Hunan Province (Brain Hospital of Hunan Province), the Fifth Affiliated Hospital of Sun Yat-Sen University, Suzhou Wujiang District Mental Rehabilitation Hospital, the 904 Hospital of the PLA Joint Logistic Support Force, the First People's Hospital of Changzhou, and Lanzhou Petrochemical General Hospital (the Fourth Affiliated Hospital of Gansu University of Chinese Medicine).Diagnoses of NSSI and other mental disorders were assessed and confirmed by outpatient or inpatient physicians based on the ICD-10 criteria (International Statistical Classification of Diseases and Related Health Problems, 10th Revision). All clinician-rated scales used in the study were administered by systematically trained postgraduate students in psychiatry or psychology. All participants were prescribed medication under the guidance of a psychiatrist. Exclusion criteria included neurological disorders, severe physical illnesses, and pregnancy or lactation. Written informed consent was obtained from all participants, with parental consent provided for those under 18 years of age. After data collection, participants received financial compensation. After excluding participants with missing data, a total of 387 participants were included in the subsequent analysis.

2.2 Measures

2.2.1 Socio-demographic questionnaire and diagnostic information

Following the provision of electronic informed consent, participants completed a section on demographic characteristics (e.g., gender, age, place of residence, only-child status, educational level, student status, and employment status). We collected diagnostic information for all participants, which was confirmed by their outpatient physicians.

2.2.2 Ottawa Self-Injury Inventory (OSI)

The Ottawa Self-Injury Inventory (OSI), a measure with established reliability and validity, was used to assess NSSI, and specifically, its NSSI Addiction subscale was administered to evaluate NSSI addiction characteristics[18]. The instrument comprises seven subscales and is scored on a 0–4 Likert scale, where higher total scores indicate more severe NSSI addiction features. The Cronbach's α for the seven items was 0.82 in this study.

2.2.3 Hamilton Depression Rating Scale-24 (HAMD-24)

The Hamilton Depression Rating Scale-24 (HAMD-24), a clinician-administered tool with documented reliability and validity[19], was adopted to quantify the severity of depressive symptoms. The scale contains 24 items, each rated 0–4, so that higher summed scores reflect greater depressive burden. The Chinese version of the scale has been validated[20]. In the present sample, Cronbach's α for the 24 items was 0.87.

2.3 Statistical analysis

Data analysis was performed using R (v4.5.1) within RStudio. We employed multiple packages for specific tasks: data manipulation (readxl, dplyr), network analysis (bootnet, networktools, nodeIdentifyR, qgraph, bnlearn), and data visualization (ggplot2).

2.4 Network analysis

To address the large number of items in the HAMD-24, we identified redundant items by employing the topological overlap test (networktools R package) with a significance threshold of $p = 0.01$ and a correlation threshold of 0.25[21]. For *in silico* interventions, the Ising model was used to characterize the psychopathological system, which functions by analyzing networks of symptoms represented as binary nodes[22]. Consistent with established methods[23], each symptom in OSI and HAMD-24 was dichotomized (a score of 0 was coded as 0, and a score of ≥ 1 was coded as 1). The resulting binary data were then used to estimate the OSI-HAMD network using the Ising model as implemented in the bootnet package for R. Key parameters include edge weights (logistic regression coefficients showing symptom relationships) and thresholds (regression intercepts indicating baseline activation tendency). A positive threshold denotes a symptom's tendency to activate when others are absent, while a negative threshold suggests a tendency to remain inactive. In the network visualization, blue and red edges respectively encoded positive and negative relationships, with edge thickness proportional to the association strength.

To identify the critical bridge symptoms of NSSI addiction in the HAMD subnetwork, we calculated four bridge centrality metrics: bridge strength (the absolute value of a node's total connectivity to other communities), bridge expected influence (the sum of a node's connections to other communities, which can be positive or negative), bridge closeness (the average distance from a node to all nodes outside its own community), and bridge betweenness (how often a node lies on the shortest path between nodes of different communities)[24].

The stability of the bridge centrality metrics was assessed using a case-dropping subset bootstrap approach, which evaluates the consistency of the metrics as the subset of observed data increases. Stability was quantified by the correlation stability coefficient (CS-coefficient), defined as the maximum proportion of cases that can be excluded while maintaining a 95% probability that the rank correlation between the original and subset-derived metrics remains above 0.7. According to established criteria, a CS-coefficient > 0.5 indicates strong stability, a value between 0.25 and 0.50 suggests acceptable stability, and a value < 0.25 indicates poor stability[25].

2.5 *In silico* interventions

We performed computer simulations of the interventions using the nodeIdentifyR algorithm (NIRA)[26], which offers two types of interventions: alleviating and aggravating. Specifically, for each symptom node within the HAMD sub-network, we conducted two types of simulated interventions (aggravating and alleviating). Alleviating interventions decreased the symptom threshold by subtracting 2 standard deviations from the original threshold parameter, while aggravating interventions increased the symptom threshold by adding 2 standard deviations. Each intervention generated 5,000 observations (i.e., simulated participants). We calculated the average total NSSI addiction score among simulated participants after each simulated intervention, as well as the average total NSSI addiction score under the original threshold parameters. Through the comparison of simulated interventions, the most efficient target was identified as the HAMD symptom node associated with the largest absolute change (quantified as the NIRA value) in the total NSSI addiction score. Aggravating interventions pinpointed the symptom that most strongly exacerbated NSSI addiction, while alleviating interventions highlighted the symptom that most effectively reduced it.

2.6 Bayesian network (BN)

A Bayesian network was constructed using the PC-stable (Peter-Clark stable) algorithm from the bnlearn package[27]. To evaluate the stability of the network structure, a bootstrap procedure with 1000 resamples was employed. The final averaged directed acyclic graph (DAG) was derived by retaining edges that appeared in over 50% of the bootstrapped networks (strength threshold = 0.5). The network was visualized using the Rgraphviz package.

2.7 Sensitivity analysis

Furthermore, to compensate for the potential information loss in the Ising network model, we also constructed a Gaussian Graphical Model (GGM). Bridge centrality metrics were computed within the

GGM framework, and their stability was assessed. This supplementary analysis aimed to validate the bridge centrality findings derived from the Ising model.

3. Results

3.1 Baseline characteristics of the study participants

The baseline characteristics of the 387 study participants are summarized in Table 1. The cohort had a mean age of 19.1 years (SE = 5.19), was predominantly female (84.0%), and urban-dwelling (69.0%). The most common clinical diagnosis was Major Depressive Disorder (53.7%).

Table 1
Baseline characteristics of the study participants

Characteristic	**Overall** **N = 387**
Gender	
Male	62 (16.0%)
Female	325 (84.0%)
Age (years)	19.1± (5.19)
Diagnosis	
BD	98 (25.3%)
BPD	38 (9.8%)
MDD	208 (53.7%)
Other	29 (7.5%)
Missing	14 (3.6%)
Residence	
Urban	267 (69.0%)
Rural	107 (27.6%)
Missing	13 (3.3%)
Only child	
Yes	211 (54.5%)
No	176 (45.5%)
Education level	
Junior high school or below	96 (24.8%)
Senior high school or equivalent	122 (31.5%)
College or above	157 (40.6%)
Missing	12 (3.1%)
Mean± (SE) for continuous variables.	
n (%) for categorical variables.	
Abbreviations: BPD, Borderline Personality Disorder; BD, Bipolar Disorder; MDD, Major Depressive Disorder; SE, Standard Error	

Characteristic	Overall N = 387
Student status	
Yes	292 (75.5%)
No	94 (24.3%)
Missing	1 (0.3%)
Employment status	
Yes	52 (13.4%)
No	332 (85.8%)
Missing	3 (0.8%)
Mean± (SE) for continuous variables.	
n (%) for categorical variables.	
Abbreviations: BPD, Borderline Personality Disorder; BD, Bipolar Disorder; MDD, Major Depressive Disorder; SE, Standard Error	

3.2 OSI-HAMD network

The network analysis revealed several redundant and low-variance symptoms. A topological overlap test indicated that HAMD5 (Insomnia-middle), HAMD22 (Helplessness), and HAMD24 (Worthlessness) had highly similar correlation patterns with other symptom nodes. In each case, the proportion of significantly different correlations was under 25%, suggesting that these items were largely redundant in what they measured. In addition, the estimateNetwork algorithm identified HAMD14 (Genital Symptoms), HAMD15 (Hypochondriasis), HAMD16 (Loss of weight), and HAMD17 (Insight) as nodes with too little variance, leading to their exclusion from the network due to insufficient variability. In line with the algorithm's recommendations for improving network parsimony, interpretability, and stability, we removed all of the above symptom node. Details on the redundant symptoms are provided in Supplementary Table 1.

Figure 1 illustrates the estimated network structure for the OSI-HAMD. In this network, each node represents a depressive symptom or an NSSI addiction symptom from the respective scales. The network comprises two distinct sub-networks, the HAMD sub-network and the OSI sub-network. Several nodes in the HAMD sub-network were linked to nodes in the OSI sub-network via bridge edges. The three bridge edges with the highest weights were observed between HAMD1 (Depressed mood) and OSI3 (Development of tolerance) (0.66), HAMD3 (Suicide) and OSI3 (Development of tolerance) (0.48), and HAMD3 (Suicide) and OSI2 (Increasing severity of consequences) (0.42). The exact weights of all bridge edges are reported in Supplementary Table 2. Aside from the connections between symptoms, each

node's threshold value which reflects its baseline level of activation is another key parameter. The threshold values for the HAMD sub-network symptoms are provided in Supplementary Table 3.

To explore which symptoms in the HAMD sub-network serve as key bridge symptoms influencing NSSI addiction, we calculated each node's bridge strength, bridge expected influence, bridge closeness, and bridge betweenness, as shown in Fig. 2. We found that within the HAMD sub-network, HAMD3 (Suicide) had the highest value on all four bridge centrality metrics. We also examined the stability of the four bridge centrality metrics. As detailed in Supplementary Fig. 1, all measures demonstrated low stability (all CS coefficients < 0.25).

3.3 Results of *in silico* interventions

We conducted computer-simulated interventions (*in silico* interventions) to determine which symptoms in the HAMD sub-network would be the most impactful targets for changing NSSI addiction severity. For each node in the HAMD sub-network, we simulated both an aggravating intervention and an alleviating intervention, and we observed the resulting changes in the overall OSI score. As shown in Fig. 3, interventions on different HAMD sub-network symptoms had differential effects on NSSI addiction. In the aggravation scenario (Fig. 3A), increasing HAMD3 (Suicide) produced the largest rise in the expected OSI total score, from 4.91 to 5.05 (NIRA = 0.14, t = 4.68, $p < 0.001$). In the alleviation scenario (Fig. 3B), reducing HAMD3 yielded the greatest drop in the expected OSI total score, from 4.98 to 4.83 (NIRA = 0.15, t = − 4.68, $p < 0.001$). Thus, HAMD3 (Suicide) emerged as the most potent target for both exacerbating and mitigating NSSI addiction symptoms. In other words, this symptom appears to be the most effective intervention target for clinical practice in terms of both preventing deterioration and promoting improvement.

Figure 4 further examines the relationship between NIRA and the threshold and bridge expected influence of each HAMD sub-network symptom. In Fig. 4A, the NIRA outcomes of both aggravating and alleviating interventions were not related to thresholds ($p > 0.05$), indicating that the thresholds of symptoms did not predict the impact of interventions. In Fig. 4B, the NIRA outcomes in alleviating interventions were significantly associated with bridge expected influence values (r = 0.75, $p < 0.001$). Symptoms with higher bridge expected influence values (i.e. those with greater overall influence in the network) were more likely to be effective targets for alleviating interventions. In contrast, the NIRA outcomes of aggravating interventions showed no significant relationship with bridge expected influence values ($p > 0.05$). As previously stated, HAMD3 (Suicide) was the most influential node in the network, supporting the idea that bridge expected influence can serve as a useful indicator for selecting intervention targets.

3.4 Results of Bayesian network

Figure 5 demonstrates the DAG generated by Bayesian network analysis, clarifying the directional relationships between depressive symptoms and NSSI addiction. The nodes represent the HAMD

symptoms and the OSI score (which is the sum of 7 NSSI addiction items), the directed arrows indicate putative causal influences, and the thickness of each arrow corresponds to the strength of the inferred causal connection (with thicker arrows denoting stronger relationships). The Bayesian network had a Bayesian Information Criterion (BIC) score of − 10363.77, indicating a good fit to the data.

Analysis of the DAG revealed a prominent direct pathway from NSSI addiction to HAMD3 (Suicide) with a maximal strength value of 1.00. This finding implies that NSSI addiction may be a definitive exacerbating factor for suicide. As an upstream variable in the network, OSI also exerted influence on other depressive symptoms, including HAMD11 (Anxiety-somatic) and on the downstream symptom HAMD2 (Feelings of guilt). Additionally, HAMD9 (Agitation), HAMD12 (Somatic symptoms-gastrointestinal), and HAMD7 (Work and interests) were positioned upstream in the network. Together with OSI, these upstream nodes impacted important downstream symptoms through multiple pathways, notably affecting HAMD1 (Depressed mood), HAMD2 (Feelings of guilt), and HAMD23 (Hopelessness).

3.5 Sensitivity analysis

Given that the Ising network model dichotomizes symptom variables which could result in some loss of information, we performed a sensitivity analysis using a GGM constructed on the original continuous symptom scores as presented in Supplementary Fig. 2. Under the GGM, we recalculated the bridge centrality metrics of each node, as shown in Supplementary Fig. 3. We found that HAMD3 (Suicide) remained the node with the highest bridge strength, bridge expected influence, bridge betweenness, and bridge closeness. Moreover, the stability of the bridge strength (CS-coefficient = 0.517) and bridge expected influence (CS-coefficient = 0.517) metrics was good under the GGM, while bridge closeness (CS-coefficient = 0.439) was acceptable, as shown in Supplementary Fig. 4.

4. Discussion

Our study used network analysis and NIRA to systematically investigate the relationship between depressive symptoms and NSSI addiction and to identify effective targets for intervention. Our findings revealed a novel insight that HAMD3 (Suicide) was the depressive symptom with the strongest influence on NSSI addiction. Network analysis indicated that in both the Ising model and GGM, HAMD3 (Suicide) was identified as the node with the highest bridge centrality, highlighting its critical role in linking depressive symptoms with NSSI addiction. Furthermore, the NIRA results demonstrated that alleviating interventions targeting HAMD3 (Suicide) significantly reduced NSSI addiction, whereas aggravating interventions targeting HAMD3 (Suicide) significantly increased NSSI addiction. These findings contribute conceptually and clinically by providing valuable insights for future interventions of NSSI addiction.

The network analysis indicated that HAMD3 (Suicide) was the depressive symptom most strongly influencing NSSI addiction. This finding aligns with previous network analyses of Chinese adolescents, which also identified suicidal ideation as the depressive symptom most strongly linked to NSSI[17, 28, 29]. The HAMD3 assesses suicide risk, including suicidal ideation and planning, as well as suicidal

behaviors or attempts with lethal intent[30, 31], and is clinically considered as an important index of increasing depression severity[32]. Compared with other depressive symptoms, the presence of suicidal thoughts or behaviors generally reflect more intense and sustained negative affect (e.g., depressed mood, hopelessness, anxiety)[33–35], and is associated with higher impulsivity, specifically the emotion-driven facet of impulsivity, which involves a tendency to act immediately and seek rapid relief in response to strong emotional states[36, 37]. In this context, NSSI may be repeatedly used due to its capacity to produce immediate emotional relief[38, 39]. Through psychological reinforcement mechanisms[39, 40], and neurobiological pathways involving the endogenous opioid and dopamine[41, 42], NSSI can develop into an addiction-like behavior characterized by tolerance, strong craving and escalation of consequences. Therefore, depressed patients exhibiting high suicide risk may be more prone to developing addictive features of NSSI. Notably, most prior studies supported that NSSI, especially high-frequency or severe self-injury (i.e., self-injury with addictive features) is a significant predictor of suicide[30, 43–46]. Getting addictive to NSSI can lead to diminished affective relief, which may reinforce the belief that “suicide is the only escape”, thereby intensifying suicidal ideation[47]. However, the potential reverse pathway by which suicide might promote NSSI and its addictive features has not been systematically explored, few research found that suicide risk can conversely predicts later increases in NSSI[48]. Our network analysis creatively suggests a potential bidirectional association between suicide risk and NSSI addiction, extends existing unidirectional theories. In other words, suicide risk may not only be influenced by NSSI, but also a key driving force behind the addiction of NSSI.

Furthermore, by constructing a Bayesian network and plotting DAG, our study provided potential directional insights based on the network analysis results. The findings showed that OSI was positioned upstream in DAG, indicating a high causal priority. And there was a significant direct path of influence from OSI to HAMD3 (Suicide), consistent with the prevailing view that NSSI is a high-risk factor for suicide. It should be emphasized that a Bayesian network applied to cross-sectional data is mainly used to generate hypotheses about directionality rather than to confirm causality. Accordingly, these results are not inconsistent with the associations identified by the Ising model and GGM. Instead, from different perspectives, both approaches point to the possibility of a bidirectional influence pathway between NSSI and suicide risk.

Although previous studies have found that suicidal ideation is the depressive symptom most strongly associated with NSSI[17, 28, 29], they did not further verify its status as a core intervention target or quantify the potential benefits of targeting it through simulation. Using NIRA, our study determined that the most effective target for both the treatment and prevention of NSSI addiction is HAMD3, since alleviating or aggravating this symptom produced the greatest change in overall network severity. The effectiveness of alleviating HAMD3 can be explained by its high bridge expected influence rather than its threshold. HAMD3 has the highest bridge expected influence in the network and serves as the key link connecting the depressive symptoms and the NSSI addiction symptoms. Thus, alleviating suicidal thoughts and behaviors can efficiently sever the pathways between two networks, thereby yielding the largest reduction in NSSI addiction severity. On the other hand, the effectiveness of aggravation was not significantly associated with bridge expected influence or threshold, while aggravating HAMD3 still

exacerbated the severity of NSSI addiction. This is because HAMD3 fits the target for prevention, which is often something that hasn't happened yet but would have severe consequences if they did. HAMD3 has a low prevalence among NSSI patients and is not easily activated under normal conditions[49, 50], making it a "latent risk point." However, once this core bridge node is activated, it can trigger a cascade of depressive symptoms, which in turn exacerbates NSSI addiction severity. Therefore, HAMD3 exhibits dual characteristics as both a treatment target and a prevention target. These findings suggest that in clinical practice, interventions targeting suicide-related symptoms should be integrated into the management of NSSI addiction. Psychosocial interventions play a critical role in addressing both NSSI addiction and suicide risk. Cognitive behavioral therapy (CBT), by focusing on unreasonable cognitive and behavioral patterns, helps patients identify and correct distorted beliefs related to suicide, replace them with more rational thinking, and reshape their perception of personal control, ultimately reducing the recurrence of NSSI[51, 52]. Additionally, dialectical behavior therapy (DBT), originally developed for patients with borderline personality disorder, has been shown to effectively reduce suicidal ideation and NSSI behaviors[53]. DBT imparts core skills such as distress tolerance and emotion regulation, which foster the acceptance of negative emotions and the use of effective coping strategies, thereby helping individuals resist intense suicidal or self-injurious urges[54, 55]. For severe cases, adjunctive pharmacotherapy under close monitoring may also be considered. Lithium is thought to have a potential anti-suicidal effect[56], and preliminary evidence suggests it may reduce self-injurious behavior through opioid-mediated analgesic effects[57]. In summary, the NIRA findings underscore the value of targeting suicide-related symptoms in alleviating NSSI addiction, providing clear targets and a theoretical basis for its clinical intervention.

Finally, this study still has several limitations. First, as a cross-sectional network analysis, it could only reveal correlations between symptoms, making it difficult to infer causal relationships or capture the temporal dynamics of the symptom network. The simulated intervention results were also derived from cross-sectional data via computer-based simulations, and the practical effect lacks clinical validation. Future studies should employ longitudinal designs to construct symptom association models across time, such as cross-lagged panel networks (CLPN). Experimental research also should be carried out to verify the effects of simulated interventions and assess the efficacy of such interventions over time. Second, the raw scores of the HAMD-24 and OSI scales were dichotomized in our analysis, which may have led to the loss of important quantitative information on symptom severity. Moreover, because both the HAMD-24 and OSI are self-report instruments, the results might be influenced by participants' subjective reporting biases. Future research should endeavor to integrate objective measures.

5. Conclusion

HAMD3 (Suicide) showed the highest bridge centrality, underscoring its pivotal role in bridging depressive symptoms and NSSI addiction. That means HAMD3 (Suicide) emerged as the depressive symptom showing strongest influence on NSSI addiction. NIRA simulations further indicated that modifying HAMD3 produced the largest shifts in NSSI severity. These findings offer valuable theoretical and clinical guidance for targeting NSSI addiction in future interventions.

Declarations

CRediT authorship contribution statement

Chanhuan Xu, Huihui Wang: Writing – original draft.Lvheng Zhang: Conceptualization, Formal analysis, Visualization. Chunyan Yin, Jing Long, Yuan Liu, Yan Sun, Xianliang Wu, Guangya Liu, Xianglan Wang, Hua Lv, Zhuowei Zhang, Suhong Wang, Xiaomei Jiang: Investigation, Data curation. Ning Zhang, Chun Wang: Supervision, Writing – review & editing.

Ethics approval

This study adhered to the principles of the Declaration of Helsinki and received approval from the Ethical Committee of The Affiliated Brain Hospital of Nanjing Medical University (2019-KY043-01).

Consent for publication

All authors have approved the manuscript and agree with its submission.

Declaration of Competing Interest

The authors declare no conflict of interest.

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Author Contribution

Ch.X., Hh.W.: Writing – original draft.Lh.Z.: Conceptualization, Formal analysis, Visualization. Cy. Y., J.L., Y. L., Y.S., Xl. W., Gy. L., Xl.W., H.L., Zw. Z., Sh. W., Xm. J.: Investigation, Data curation. N.Z., C.W.: Supervision, Writing – review & editing.

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Data availability

The datasets generated and/or analyzed during the current study are not publicly available to protect participant privacy and comply with ethical guidelines, but they can be provided by the corresponding author on reasonable request.

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Figures

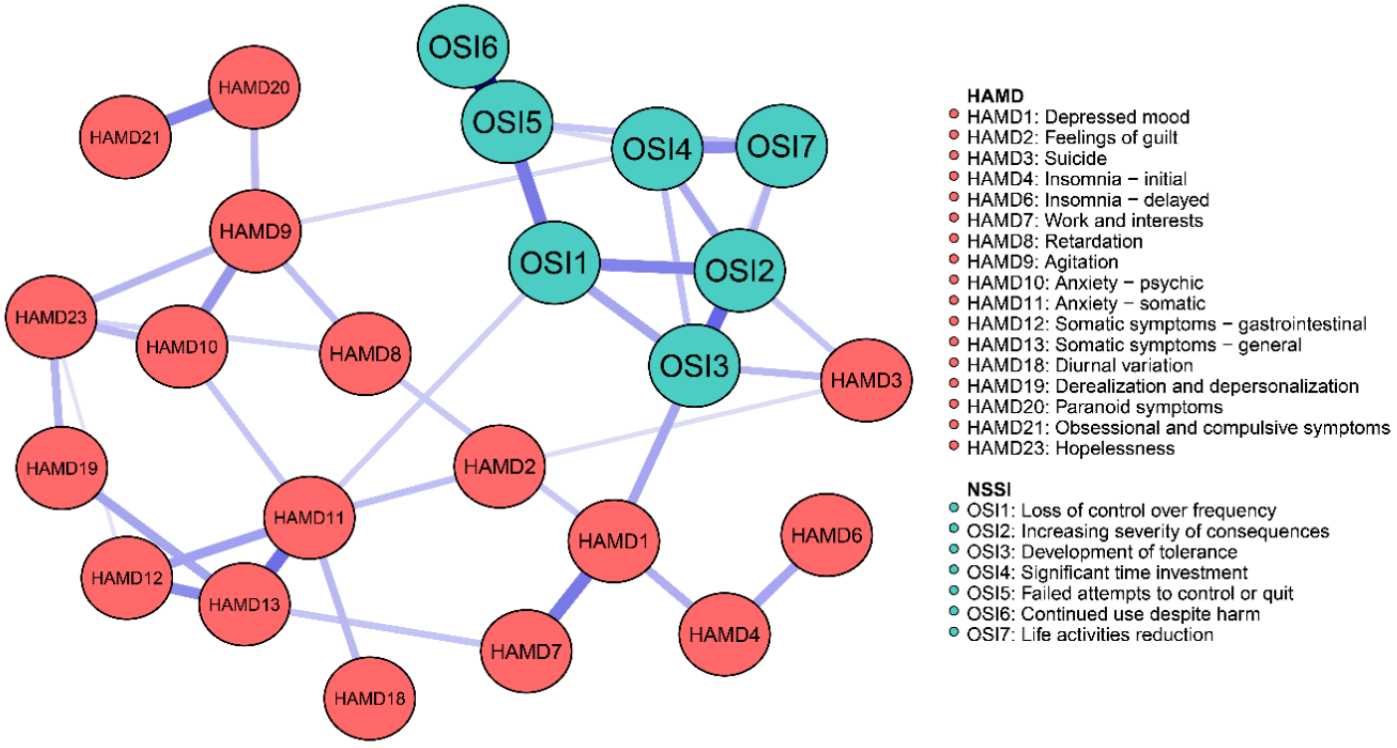


Figure 1

The Ising network estimated from the data with dichotomization. Notes: Blue edges indicate positive associations; edge thickness proportional to the association strength.

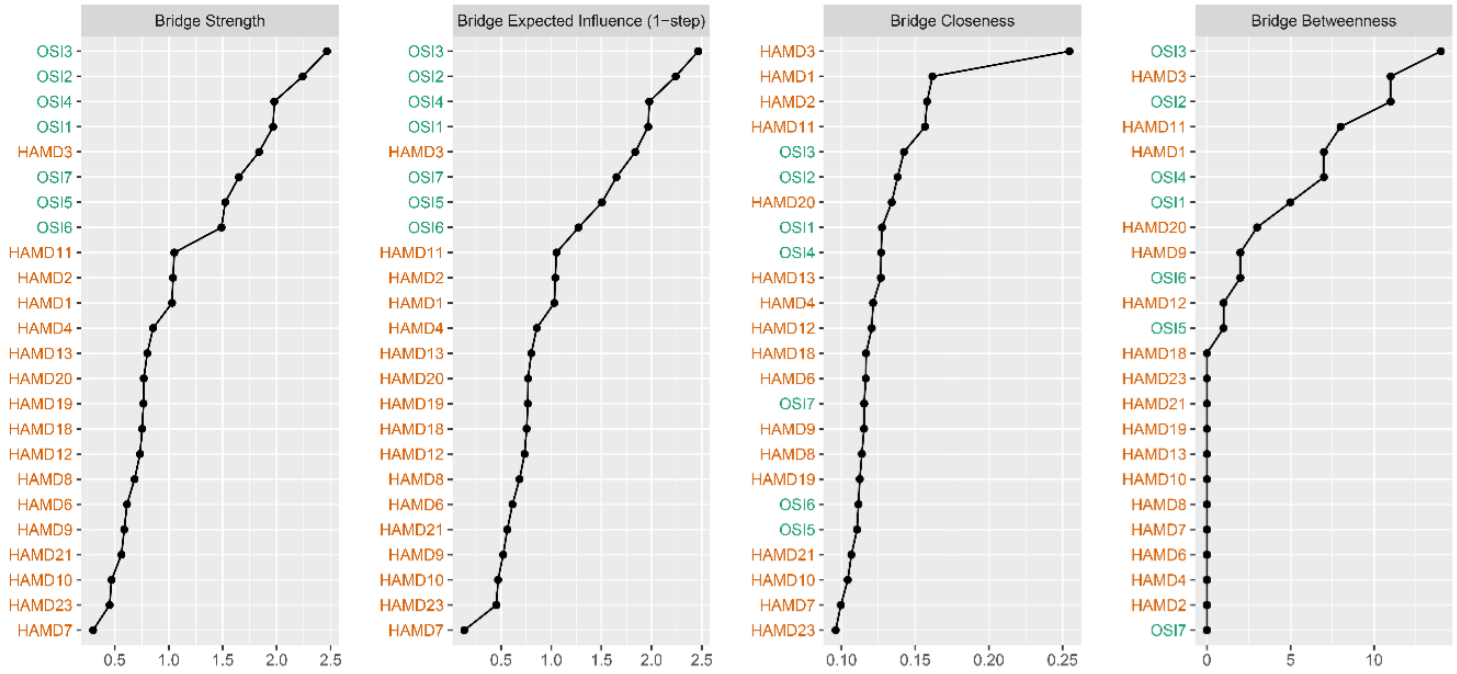


Figure 2

Bridge centrality of nodes in the two subnetworks of the Ising network (standardized z-scores).

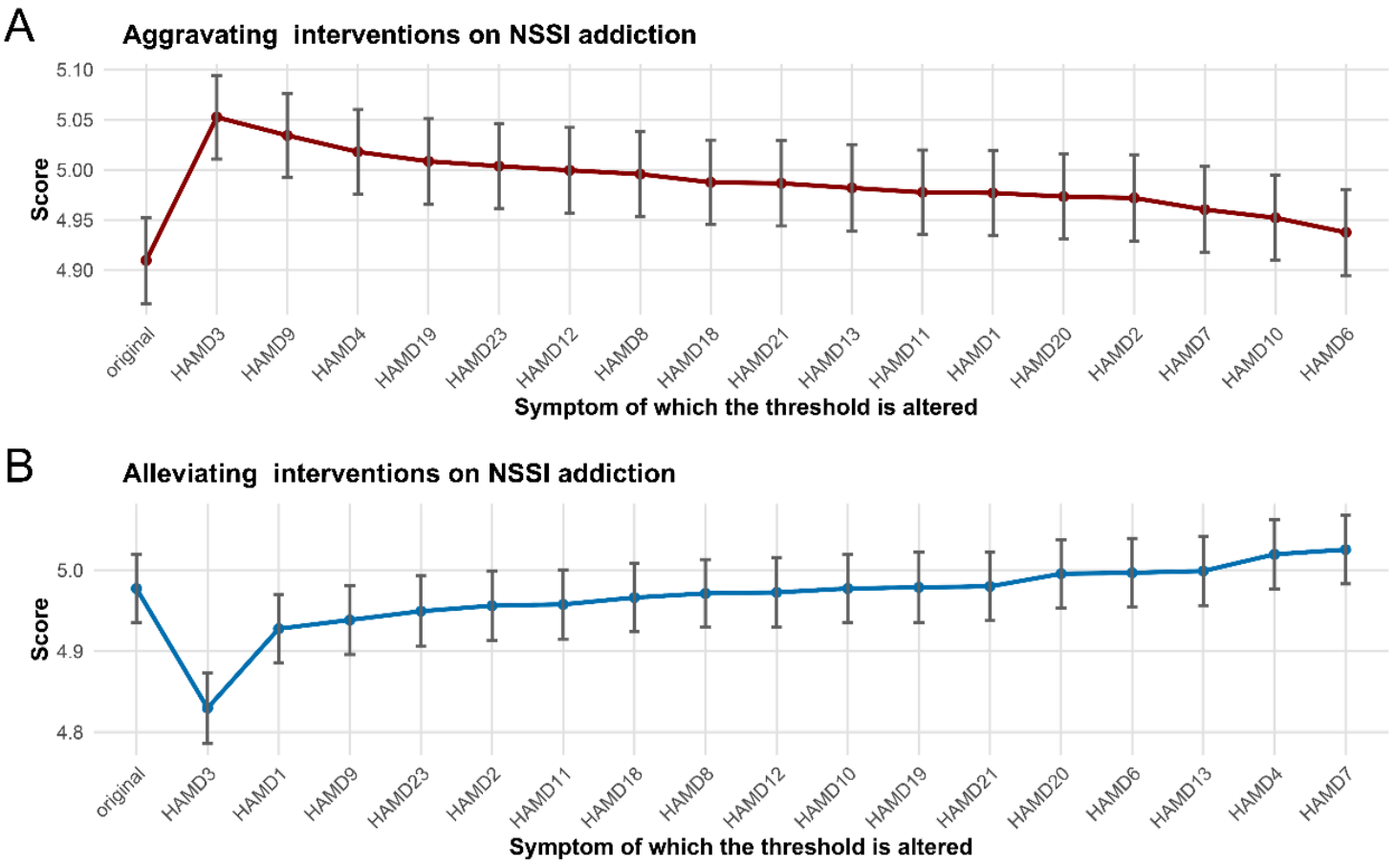


Figure 3

Simulation of Aggravating (A) and Alleviating (B) Interventions. Notes: Dots denote network sum scores, with lines indicating 95% confidence intervals. Symptoms are ordered according to the magnitude of the intervention effects, alongside the baseline total score prior to intervention.

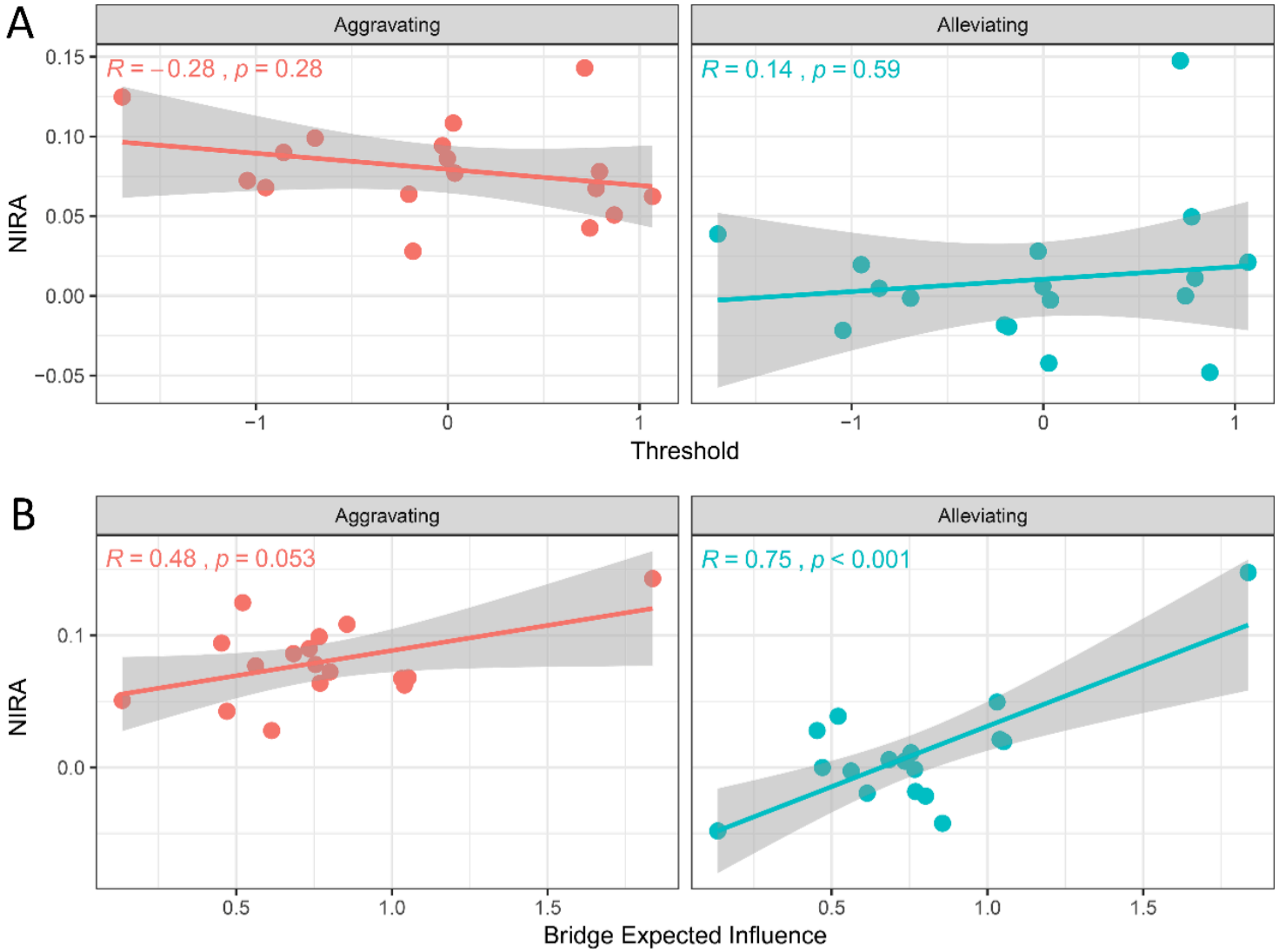


Figure 4

Relationships of thresholds (A) and bridge expected influence (B) to intervention effect sizes. Notes: Thresholds (A) and bridge expected influence (B) are shown on the x-axis. The y-axis shows the magnitude of the intervention effect, calculated as the absolute difference in total network scores before versus after intervention. The shaded band indicates the 95% confidence interval.

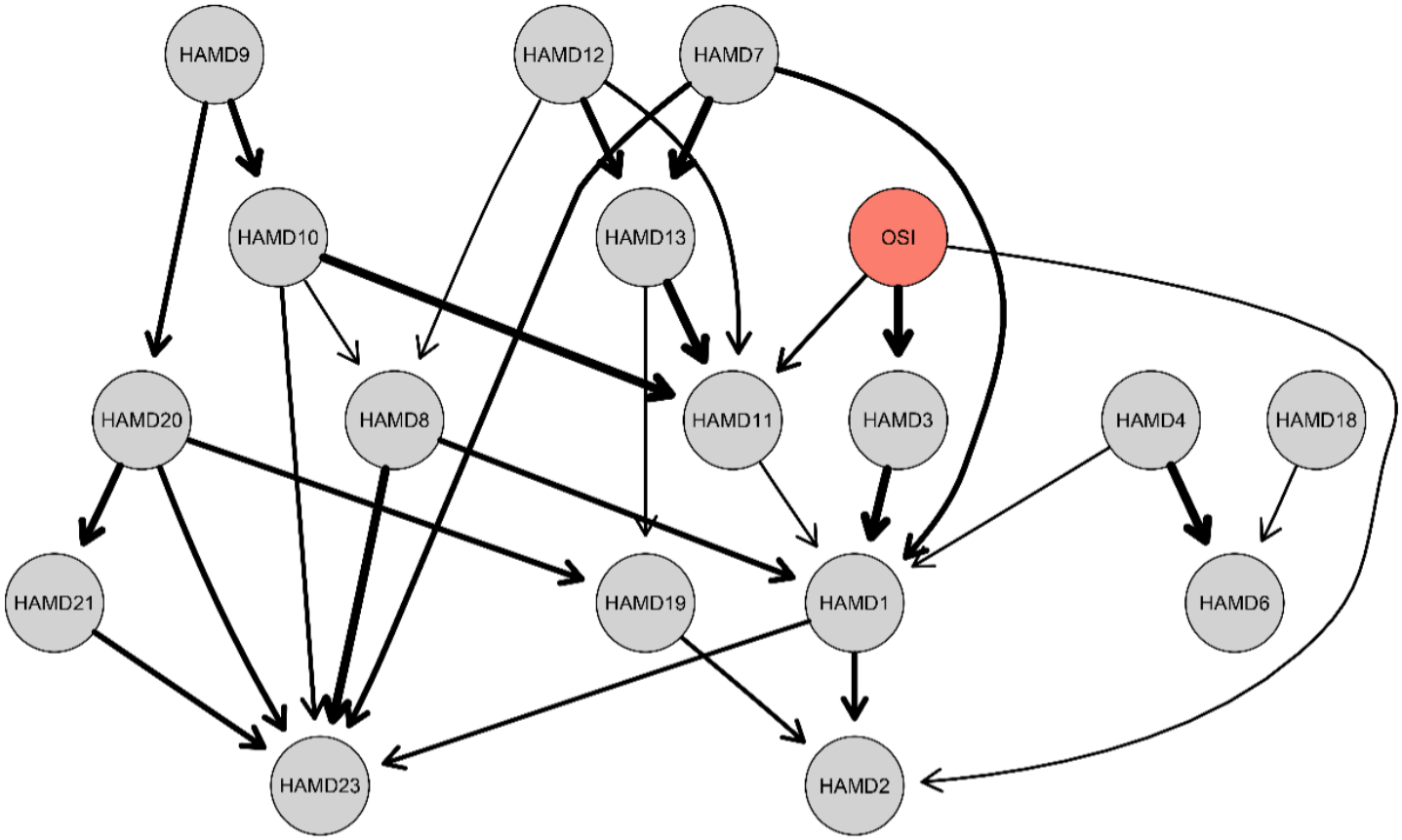


Figure 5

Directed Acyclic Graph generated by Bayesian network analysis. Notes: Nodes represent HAMD symptoms and the OSI score (the sum of 7 NSSI addiction items). Directed arrows indicate hypothesized causal influences, with arrow thickness corresponding to the strength of the inferred causal relationship (thicker arrows denote stronger relationships).