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Anxiety symptoms as a hub-mediation nexus in suicidal ideation among depressed patients

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Abstract

Background Suicidal ideation (SI) is defined as death-centered thoughts preceding suicidal behaviors, and demands prompt identification. While depressed patients are disproportionately affected by SI, particularly when comorbid with anxiety, the key triggers driving its emergence remain poorly understood.

Methods This study analyzed clinical data from 9,193 psychiatric outpatients, with in-depth assessments conducted on 281 depressed patients (mean age 41.9 ± 21.5; 73 males) who completed the Self-rating Depression Scale (SDS) and Self-rating Anxiety Scale (SAS). Of these, 85 patients (30.2%) reported SI. To characterize the interplay among symptoms, we applied a dual-network approach: a regularized partial correlation network quantified conditional associations between SDS/SAS symptom dimensions and SI, and a Bayesian network explored potential precursors to SI.

Results In the regularized partial correlation network, SI was associated with two symptom dimensions: 'anxiety and panic' (edge weight = 0.14) and 'depressed mood' (edge weight = 0.16). 'Anxiety and panic' exhibited the highest strength centrality (z = 1.43), indicating its pivotal role in mediating the development of SI. Bayesian network analysis further identified 'anxiety and panic' as a key mediator in all indirect paths linking depressive symptoms to SI.

Conclusions This dual-network approach highlights the utility of computational psychiatry in revealing the relationships among symptoms within a network, yielding clinically actionable information. Here, we uncovered the central role of anxiety within the symptom network underlying SI, offering insights relevant to early identification and suicide prevention of patients with comorbid depression–anxiety.

Keywords Suicidal ideation, Depression, Anxiety, Network analysis, Directed acyclic graph

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Introduction

Suicidal ideation (SI), defined as persistent thoughts or desires to end one's life, is a serious mental health concern that poses a substantial risk for suicidal behaviors [1, 2]. Among clinical populations, patients with major depressive disorder exhibit the highest prevalence of SI, with the lifetime prevalence in China ranging from 42.4% to 63.4% [3]. Nevertheless, not all depressed patients develop SI, underscoring the importance of identifying the key factors that contribute to the emergence of death-centered thoughts. Comorbid anxiety has been shown to increase suicide risk substantially in depressed patients [4–6], suggesting that anxiety symptoms may play a pivotal role in the psychopathological mechanisms underlying SI. However, the overlapping nature of symptom dimensions makes it challenging to disentangle the distinct contributions of individual factors.

Numerous adverse symptoms have shown strong associations with SI, including typical depressive symptoms such as ideational suffering [7] and depressed mood [8], as well as anxiety-related symptoms such as panic [9] and hyperarousal (somatic control) [10]. These symptoms frequently co-occur in depressed patients, and their interactions appear to exacerbate SI [4, 11]. Although widely used assessments like the Self-rating Depression Scale (SDS) [12, 13] and the Self-rating Anxiety Scale (SAS) [14, 15] effectively capture the multidimensional constructs of depression and anxiety, traditional analyses that rely on composite scores tend to obscure the nuanced interactions among individual symptom dimensions. As a result, our understanding of the emergence of SI remains limited, hampering its early identification.

Emerging network analysis offers a powerful framework to address these challenges by systematically investigating the complex interactions among symptom dimensions. In this approach, symptoms are represented as interconnected nodes, allowing researchers to visualize the pattern and strength of relationships among them [16–18]. Unlike traditional correlation analyses, which often produce overly dense connections, network analysis typically uses regularized partial correlations to highlight the most robust connections, providing a clearer view of symptom interactions [19, 20]. It further quantifies the relative importance of each symptom within the network, known as node centrality, thereby identifying the symptoms that are most central to the network [19, 21]. Bayesian networks extend this framework by estimating directed relationships, suggesting which symptoms may be potential precursors to others [16, 17]. By combining both approaches, researchers can not only identify the key symptom but also gain insight into the possible pathways through which symptoms interact. Together, these methods offer a promising way to better understand the development of SI.

Previous network analysis studies have effectively mapped complex symptom interactions in depression and related comorbidities [16, 22], significantly advancing our understanding of disease mechanisms. However, few studies have specifically examined the interrelationships underlying SI within depressed populations, particularly with respect to the potential directional influences among symptoms, leaving a critical gap in understanding [23–25]. To address this gap, we employed a dual-network analytical approach to symptoms reported by outpatients with depression, including those with and without SI. Symptom data were derived from validated rating scales, which allowed us to construct networks at the level of individual symptom dimensions. We first constructed a regularized partial correlation network to identify conditional associations between symptom pairs and quantify node centrality [20], revealing the symptoms most central to driving SI. We then applied a Bayesian network to further explore potential directional relationships among symptoms [16, 17]. Through integrating these two complementary methods, our study aims to bridge critical methodological gaps, offering novel insights into the interactions underlying SI and providing a foundation for its early identification.

Methods

Participants

We conducted a retrospective analysis of clinical records from 9,193 psychiatric outpatients who visited Shanghai Xuhui Mental Health Center between September 1st, 2017, and August 1st, 2023. During this period, 1,832 outpatients sought treatment for depression, including 544 males (29.7%). To ensure standardized symptom data for network analysis, we selected outpatients who had completed the SDS assessment and met the following inclusion criteria: (1) diagnosis of depression, (2) age between 12 and 80 years, and (3) completion of both SDS and SAS scales on the day of their visit. The dataset development process is illustrated in Fig. 1. Based on these criteria, 15% of the total depressed outpatients met the inclusion criteria, resulting in a final sample of 281 patients for further analysis. Next, two independent researchers reviewed the electronic medical records of eligible outpatients to identify SI cases. A total of 85 outpatients were identified as having SI, based on explicit documentation of suicidal thoughts or suicide attempts in their chief complaints during the visit. This study was approved by the Ethics Committee of Shanghai Xuhui Mental Health Center [KY2023-20]. Informed consent was waived as all data were anonymized, so no identifiable private information was available to the research team.

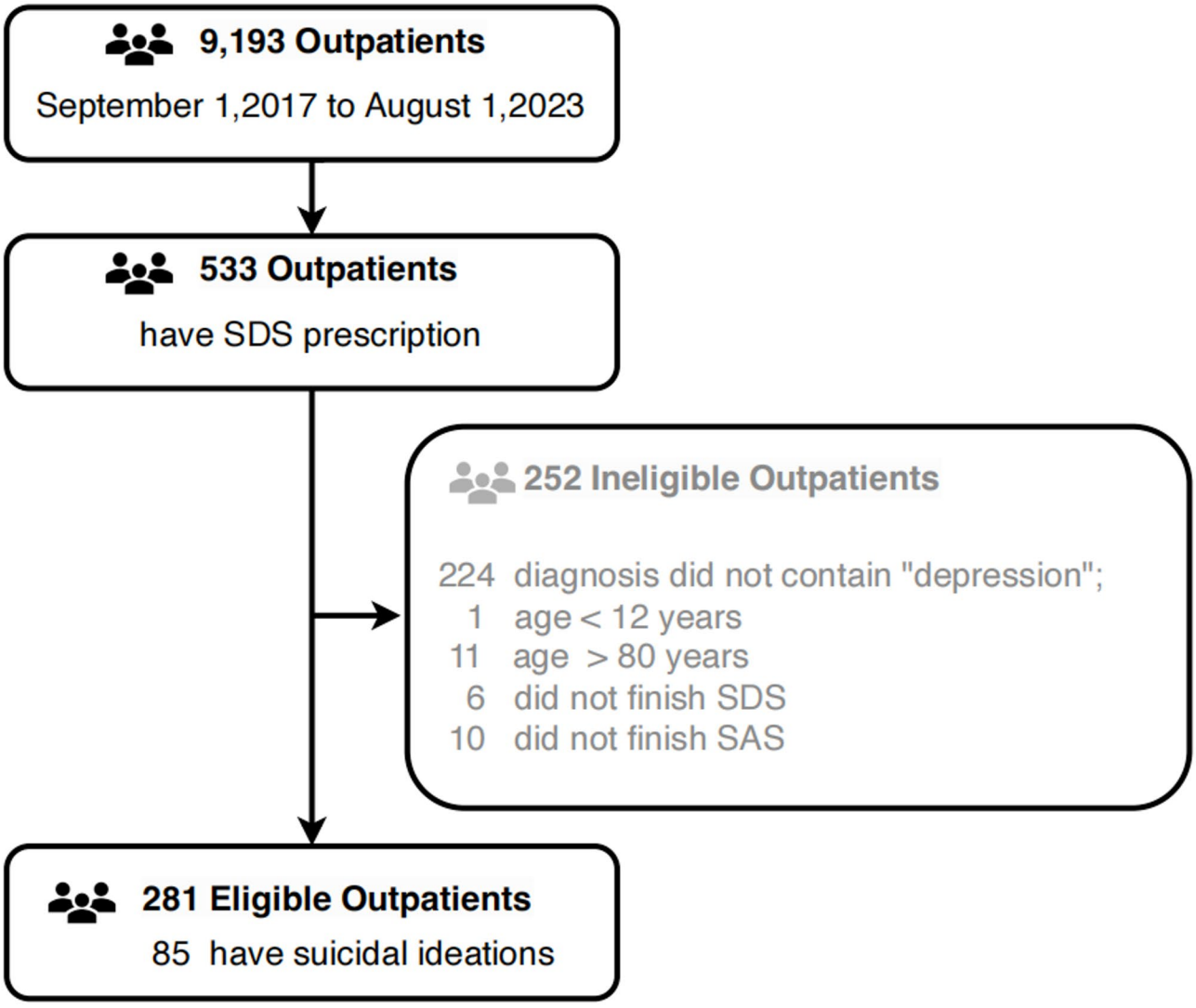

Fig. 1 Flowchart and details for the dataset development. SDS refers to the Self-rating Depression Scale, and SAS refers to the Self-rating Anxiety Scale

Measures

Suicidal ideation (SI)

SI was operationalized as a binary variable (present/absent) based on electronic medical records. We defined SI as active suicidal thoughts occurring within 30 days preceding clinical evaluation, including expressions of life feeling meaningless, thoughts of not wanting to live, or thoughts of committing suicidal behavior, such as jumping off a building or cutting oneself. Details of the medical history records for these 85 outpatients with SI are provided in Fig. 2 and Supplementary Table S1.

Zung's self-rating depression scale (SDS)

The SDS is a self-report instrument that evaluates the severity of depressive symptoms based on an individual's subjective experiences over the past week [12]. It covers five symptom dimensions, namely: 'depressed mood,' 'rhythmic disturbances,' 'somatic disturbances,' 'psychomotor activities,' and 'ideational suffering' (see Supplementary Table S2 for item-to-dimension assignments) [12]. This scale consists of 20 items scored from 1 (*a little of the time*) to 4 (*most of the time*), yielding raw scores ranging from 20 to 80. Raw scores are converted to standard scores from 25 to 100 by multiplying by 1.25 and rounding to the nearest integer. The SDS cut-off value is a standard score of 50: 50–59 indicates mild depression, 60–69 moderate depression, and ≥ 70 severe depression [13]. The Chinese version of the SDS has demonstrated robust psychometric properties across diverse populations [26–28], with internal consistency (Cronbach's α) ranging from 0.78 to 0.86. In the current study, Cronbach's α was 0.85.

Zung's self-rating anxiety scale (SAS)

The SAS is a self-report instrument that evaluates the severity of anxiety symptoms based on an individual's

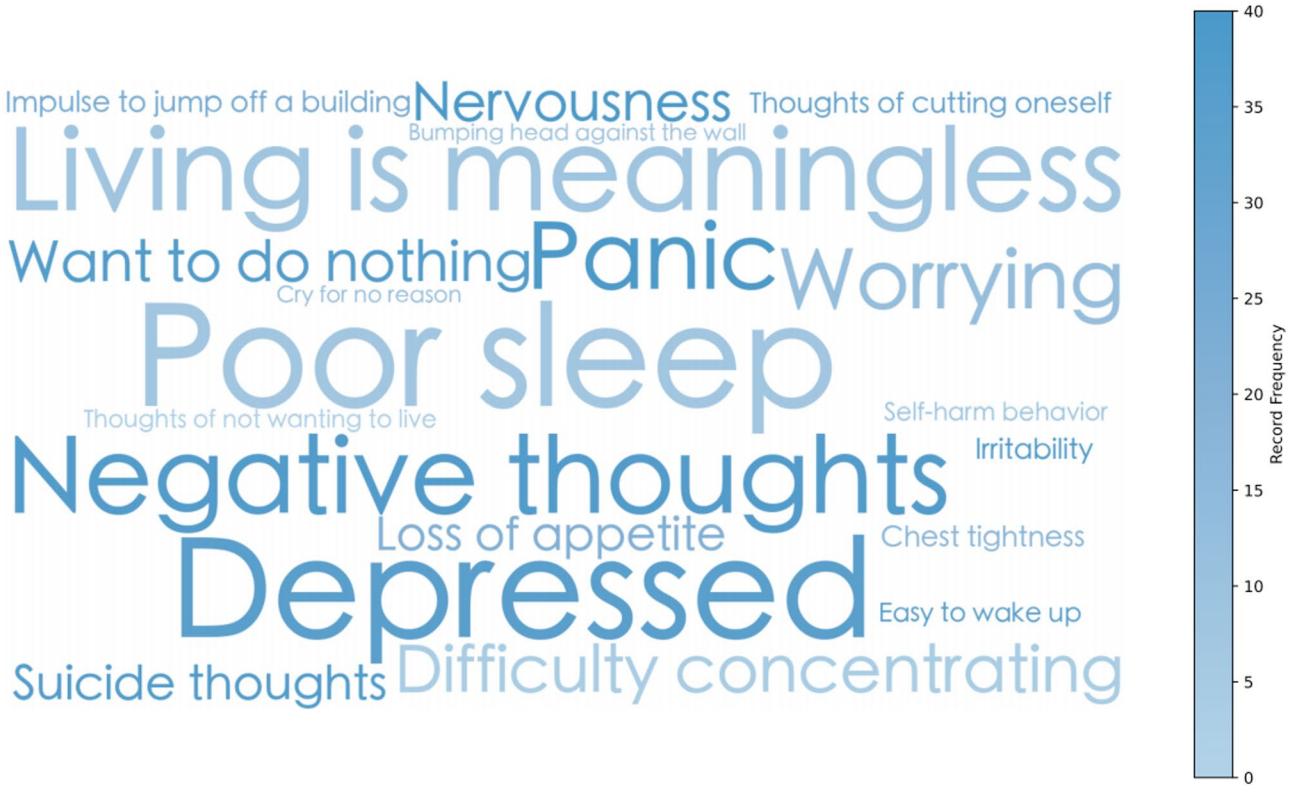

Fig. 2 Word cloud of typical symptoms in the medical history records of outpatients with suicidal ideation. The visualization is based on medical history records of the 85 outpatients with SI, with word size reflecting the frequency of keywords across records. Each keyword is counted only once per record, regardless of how many times it appears. Detailed word frequency data are summarized in Supplementary Table S1

subjective experiences over the past week [14]. It covers four symptom dimensions, namely: 'anxiety and panic,' 'somatic control,' 'vestibular sensations,' and 'gastrointestinal/muscle sensations.' (see Supplementary Table S3 for item-to-dimension assignments) [15]. Similar to the SDS, it consists of 20 items scored from 1 (*a little of the time*) to 4 (*most of the time*), yielding raw scores of 20–80, which are converted to standard scores of 25–100. The SAS cut-off value is a standard score of 50: 50–59 indicates mild anxiety, 60–69 moderate anxiety, and ≥ 70 severe anxiety [29]. The Chinese version of the SAS has demonstrated robust psychometric properties across clinical and non-clinical populations [27, 30], with Cronbach's α ranging from 0.82 to 0.85. In the current study, Cronbach's α was 0.90.

Statistical analysis

Descriptive statistics and network analyses were conducted in R (version 4.2.2). Group comparisons were performed between the SI and non-SI groups: categorical variables were analyzed with chi-square tests, while continuous variables were examined with methods appropriate to their distribution. Here, age showed significant deviation from normality according to the Shapiro-Wilk test and was therefore compared using the Mann-Whitney U test. Statistical significance was set at two-sided $p < 0.05$.

Regularized partial correlation network

Network estimation We included 12 variables in the network analysis: five depression dimensions from the SDS, four anxiety dimensions from the SAS, two demographic variables, and one variable related to SI. Each variable was represented as a node, with edges indicating the associations between pairs of nodes. To estimate the network structure, we applied a Mixed Graphical Model (MGM) using the *estimateNetwork* function in the R package *qgraph* [20]. MGMs are well-suited for clinical data because they can simultaneously handle continuous variables (e.g., symptom scores) and categorical variables (e.g., SI presence) [31]. The resulting model was a regularized partial correlation network, where edges reflected the unique associations between variables after controlling for all others (see Supplementary Fig. 1A for an illustration). To improve stability and interpretability, weak or noisy associations were removed through regularization using the Least Absolute Shrinkage and Selection Operator (LASSO) penalty, which shrank small edge weights to zero and retained only the most robust connections. Specifically, we applied the graphical LASSO with the

Extended Bayesian Information Criterion, referred to as EBICglasso, to define the final network. The final network thus provided a clear visualization of the strongest and most reliable relationships among nodes.

Network centrality To identify the most influential symptoms or variables in the network, we calculated two centrality measures: strength and betweenness (see Supplementary Fig. 1B) [21]. Strength centrality represents the sum of the absolute weights of all edges directly connected to a node, reflecting the overall level of connection a node has with other nodes and indicating how strongly changes in this symptom may affect the rest of the network. Betweenness centrality was calculated by first identifying the shortest path length between all pairs of nodes and then counting how often a given node appeared along these paths. This metric indicates how frequently a node connects two otherwise unlinked nodes and suggests its role in bridging different symptom clusters [32]. Nodes with higher centrality are considered more influential within the network. Although these measures capture different aspects of importance, prior research suggests that strength centrality is the most stable and clinically informative index [20]. Accordingly, our discussion primarily focuses on strength centrality.

Network stability To evaluate the network stability, we used the R-package *bootnet* [20] to assess the accuracy of the current network structure. First, we applied a non-parametric bootstrap procedure with 1,000 resamples to estimate 95% confidence intervals (CIs) for the edge weights. Narrower CIs indicate greater precision in estimating the strength of connections, whereas wider CIs suggest less reliable estimates. Next, we conducted a case-dropping bootstrap to test the robustness of the centrality measures. In this procedure, subsets of participants were systematically removed, and correlations between the centrality indices of the subsets and the full sample were calculated. From this, we derived the *correlation stability coefficient* (CS-coefficient), which represents the maximum proportion of cases that can be dropped while still maintaining a 95% probability that the correlation between original and subset centrality values remains ≥ 0.7. A CS-coefficient above 0.25 indicates acceptable stability, and a CS-coefficient above 0.5 is preferable.

Table 1 Demographic and clinical characteristics of the eligible outpatients

	Overall (*N* = 281)	Patients without SI (*N* = 196)	Patients with SI (*N* = 85)	*P* value
Gender				0.007
Male	73 (26.0%)	60 (30.6%)	13 (15.3%)	
Female	208 (74.0%)	136 (69.4%)	72 (84.7%)	
Age (year)				0.018
Mean (SD)	41.9 (21.5)	43.9 (21.7)	37.5 (20.5)	
Median [IQR]	39.0 [44.0]	39.0 [42.3]	35.0 [39.0]	
Self-Rating Depression				0.002
None (SDS < 50)	21 (7.5%)	19 (9.7%)	2 (2.4%)	
Mild (50 ≤ SDS < 60)	56 (19.9%)	45 (23.0%)	11 (12.9%)	
Moderate (60 ≤ SDS < 70)	106 (37.7%)	76 (38.8%)	30 (35.3%)	
Severe (SDS ≥ 70)	98 (34.9%)	56 (28.6%)	42 (49.4%)	
Self-Rating Anxiety				< 0.001
None (SAS < 50)	92 (32.7%)	77 (39.3%)	15 (17.6%)	
Mild (50 ≤ SAS < 60)	71 (25.3%)	55 (28.1%)	16 (18.8%)	
Moderate (60 ≤ SAS < 70)	78 (27.8%)	47 (24.0%)	31 (36.5%)	
Severe (SAS ≥ 70)	40 (14.2%)	17 (8.7%)	23 (27.1%)	

Note: SDS refers to Self-rating Depression Scale, SAS refers to Self-rating Anxiety Scale, and SI refers to suicidal ideations. Categorical variables were compared using chi-square tests, and continuous variables (i.e., age) were compared using the Mann–Whitney U test due to non-normal distribution

Bayesian directed network (Directed Acyclic Graph [DAG])

We used the R package *bnlearn* [33] to compute a Bayesian network using the *hill-climbing* algorithm [16]. This algorithm iteratively improves the model by adding, deleting, or reversing edges between nodes until the best fit is achieved, thereby determining both the presence and structure of connections. To enhance reliability, we bootstrapped the data 50,000 times, computed a network for each sample, and then averaged them. In the final DAG, only edges that appeared in at least 70% of the bootstrapped networks were retained. Edge directions were assigned if they pointed from one node to another in more than 50% of the bootstrapped networks (see Supplementary Fig. 1C). The final DAG was visualized with edge thickness indicating the probability of directionality.

Results

The demographic and clinical characteristics of the 281 eligible outpatients, categorized by SI status, are summarized in Table 1. Of these, 196 outpatients did not report SI, while 85 did (30.2%), with females predominating in both groups (84.7% in SI outpatients, and 69.4% in non-SI outpatients, p = 0.007). On average, outpatients with SI were younger (37.5 ± 20.5 years) than outpatients without SI (43.9 ± 21.7 years, p = 0.018). Notably, 49.4% of outpatients with SI exhibited severe depression (SDS ≥ 70), nearly twice the proportion observed in non-SI outpatients (28.6%, p = 0.002). Similarly, severe anxiety (SAS ≥ 70) was more prevalent among outpatients with SI (27.1%) compared to non-SI outpatients (8.7%, p < 0.001). These findings highlight the clinical differences between SI and non-SI outpatients, indicating that outpatients with SI tend to be younger and more often female, and present with more severe depressive and anxious symptoms, consistent with previous studies [2]. Such

differences underscore the need to further clarify how depressive and anxious symptoms interrelate with SI, to identify key drivers of SI in depressed outpatients.

Centrality mapping identifies anxiety symptoms as network hub in suicidal ideation

We first applied a regularized partial correlation network analysis to examine the interactions among depressive symptoms (SDS dimensions), anxiety symptoms (SAS dimensions), demographic variables, and SI. In the visualization, edges with weights less than 0.1 were omitted to enhance clarity [34, 35]. As shown in Fig. 3A, the network model included 12 nodes, with two symptom dimensions exhibiting significant associations with SI: SAS1 ('anxiety and panic', weight = 0.14) and SDS1 ('depressed mood', weight = 0.16). This network structure suggests that core symptoms of anxiety and depression may jointly contribute to SI through distinct neuropsychological paths. The full network weight matrix is provided in Supplementary Fig. 2.

To quantify the relative importance of each node within the network, we calculated strength and betweenness centrality metrics. Normalized values are visualized in Fig. 3B, ranked by strength in descending order. SAS1 ('anxiety and panic') emerged as the most central node, showing the highest centrality values for both strength (z = 1.43) and betweenness (z = 1.44). While SDS5 ('ideational suffering') ranked equally high in betweenness, its strength was comparatively lower (z = 0.97). These findings highlight the pivotal role of anxiety symptoms in mediating the development of SI. Full numerical values for these centrality measures are listed in Supplementary Table S4.

We also assessed the accuracy and stability of the regularized partial correlation network. The results of edge-weight accuracy and centrality stability are shown in Supplementary Figs. 3 and 4. Centrality stability was evaluated using the correlation stability coefficient (CS-coefficient), which represents the maximum proportion of cases that can be dropped while maintaining a 95% probability that the correlation between the original and subset centrality indices remains ≥ 0.7 [20]. In our case-dropping stability analysis, the strength centrality showed sufficient stability (CS-coefficients = 0.67), whereas the

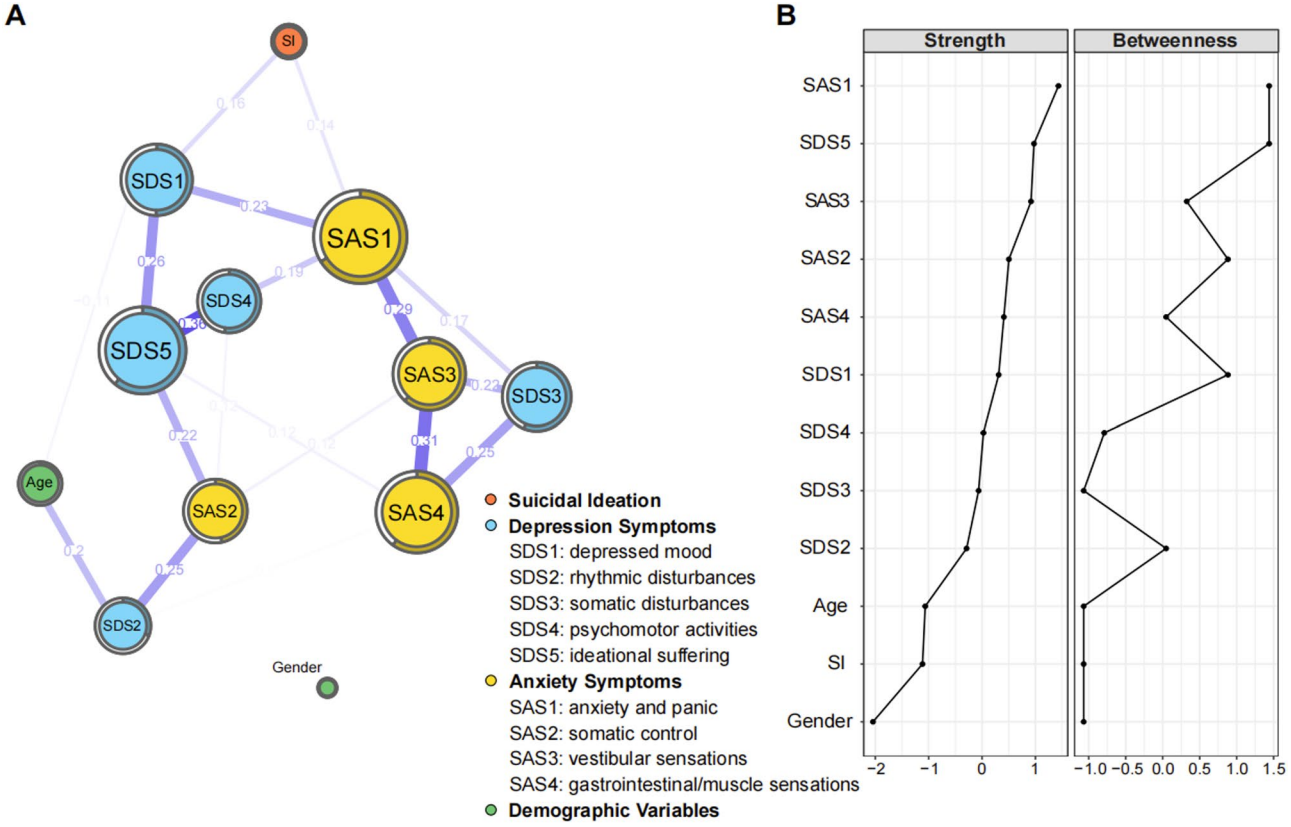

Fig. 3 Estimated network structure and the corresponding z-scored centrality indices (strength, betweenness). (**A**) Regularized partial correlation network. Node size reflects strength centrality, with larger nodes indicating greater influence. Edges represent regularized partial correlations, with thickness indicating effect size. The full network weight matrix is reported in Supplementary Fig. 2. (**B**) Standardized centrality metrics ranked by strength. High strength indicates that the symptom is highly connected to other symptoms. High betweenness indicates that a symptom often appears on the shortest path between two other symptoms. Numerical values are reported in Supplementary Table S4

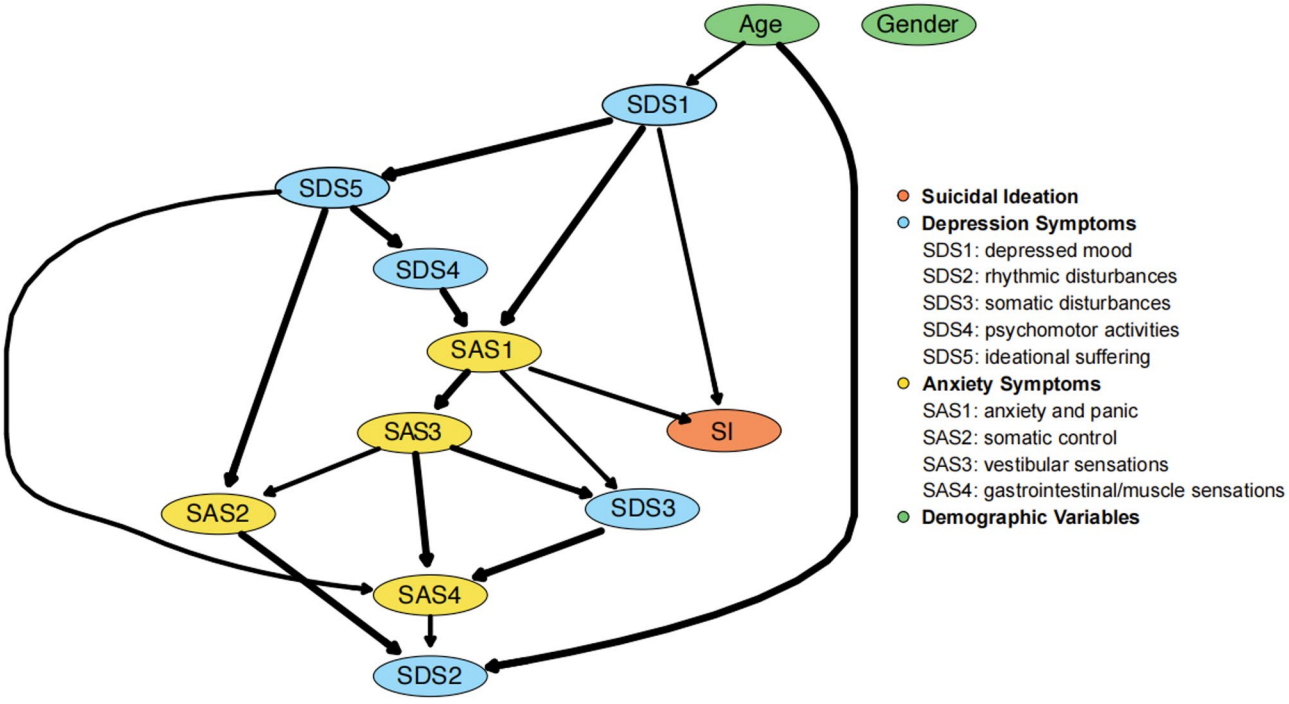

Fig. 4 Directed acyclic graph illustrating the relationships among depression, anxiety, demographic variables, and suicidal ideation. Arrows represent probable directional relationships under the DAG assumption of unidirectional, acyclic structure

betweenness centrality showed poor stability (CS-coefficients = 0.13), falling below the recommended threshold of > 0.25. Consistent with previous studies indicating that strength centrality is more reliable, our interpretation primarily focuses on this metric.

Bayesian network uncovers anxiety's gateway role in depression-to-SI pathways

To explore potential causal relationships among nodes, we constructed a directed acyclic graph (DAG) by averaging 50,000 bootstrapped Bayesian networks (see Fig. 4). Crucially, while the directional edges in the DAG do not represent definitive causal effects, they provide probabilistic insights that can inform future longitudinal or experimental investigations. The averaged model revealed three distinct paths directed from SDS1 ('depressed mood') to SI: (1) a direct path (SDS1 → SI), (2) an indirect path mediated by SAS1 ('anxiety and panic') (SDS1 → SAS1→ SI), and (3) a multi-step path involving SDS5 ('ideational suffering') and SDS4 ('psychomotor activities') (SDS1 → SDS5 → SDS4 → SAS1 → SI). SDS1 ('depressed mood') and SAS1 ('anxiety and panic') remained the only nodes with direct connections to SI. Notably, SAS1 ('anxiety and panic') emerged as a critical mediator across all indirect paths leading to SI, highlighting its dual role as both a central hub and key mediator in the network underlying SI.

Discussion

This study employed a dual network analytic approach to systematically characterize the symptom interactions underlying SI in depressed patients. The regularized partial correlation network showed that SI had moderate associations with both 'depressed mood' and 'anxiety and panic', with the latter emerging as the most central node. The Bayesian network further identified 'anxiety and panic' as a potential precursor to SI, serving as the key mediator in all indirect paths from 'depressed mood' to SI. Taken together, these findings indicate that 'anxiety and panic' occupy a pivotal position in the psychopathological network of SI.

The symptom dimension of 'anxiety and panic' primarily reflects a subjective sense of losing control, accompanied by panic-related thoughts [15]. In contrast to somatic manifestations of anxiety, these subjective experiences are more difficult for patients to articulate and for others to detect, which may contribute to their frequent under-recognition in practice [36]. Moreover, addressing such symptoms typically requires psychological interventions, such as cognitive behavioral therapy, rather than pharmacological treatment alone [37, 38]. However, psychological interventions demand a considerable time commitment and (in many health care systems) financial investment, limiting their accessibility and leaving patients vulnerable to insufficient treatment.

The distinctive nature of 'anxiety and panic' relative to other anxiety dimensions may explain its central role

in the SI symptom network, reflecting the cumulative effects of unrecognized emotional distress. Due to their internalized nature, 'anxiety and panic' are often overlooked in depressed patients, as clinical attention typically focuses on depressive and overt somatic symptoms. This unaddressed distress may accumulate over time, ultimately becoming intolerable and giving rise to death-centered thoughts [39]. Panic-related thoughts, such as catastrophic interpretations of bodily sensations and fears of losing control, may further amplify this process by causing individuals to overestimate potential suffering while underestimating their coping capacity, thereby deepening psychological distress and intensifying SI [40, 41]. The emergence of 'anxiety and panic' as a central component in the network suggests that emotional dysregulation may play a critical role in driving aberrant motivational dynamics [42, 43]. When accumulated distress reaches a critical threshold, it may precipitate the transition to SI [44]. These observations emphasize the importance of early detection and intervention for subthreshold emotional disturbances, rather than focusing solely on overt suicidal behaviors.

Together, these findings underscore the clinical importance of monitoring anxiety symptoms in depressed patients and emphasize the value of addressing early emotional disturbances proactively. Beyond focusing solely on depressive symptoms, clinicians should assess subjective experiences of loss of control and panic-related thoughts, as these may serve as early indicators of heightened SI risk. Furthermore, targeted psychological interventions, such as cognitive behavioral therapy tailored to anxiety subtypes [37, 45], may help mitigate these risk pathways and reduce SI. By prioritizing interventions for the most central symptom dimensions, clinicians can implement more precise treatment strategies to prevent SI in depressed patients, ultimately reducing the overall prevalence and severity of SI.

Several limitations should be considered. First, as the study was conducted at a single center, the generalizability of our findings to other clinical settings may be limited. Second, the moderate sample size (N = 281) limited our capacity to conduct item-level network analyses, which could provide more precise insight into intervention targets. Third, only one-quarter of the sample were males, which may influence the observed relationship between gender and SI, as emerging research evidence indicates significant gender differences in depression [46]. Finally, the cross-sectional network analysis was exploratory, primarily identifying core symptoms that warrant prioritization in SI prevention. While the Bayesian network analysis offers preliminary insights into potential causal pathways, robust causal inference requires longitudinal or experimental validation.

Conclusions

In summary, by combining partial correlation and Bayesian network methods, this study provides novel evidence that 'anxiety and panic' symptoms constitute a central nexus mediating the development of SI among depressed patients. Our findings underscore the importance of integrating symptom-specific monitoring and targeted cognitive interventions into clinical practice and offer a pathway toward more effective suicide prevention strategies for outpatients suffering from depression.

Abbreviations

SI	Suicidal Ideation
SDS	Self-rating Depression Scale
SAS	Self-rating Anxiety Scale
MGM	Mixed Graphical Model
LASSO	Least Absolute Shrinkage and Selection Operator
CI	Confidence Interval
CS-coefficient	Correlation Stability coefficient
DAG	Directed Acyclic Graph

Supplementary Information

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Supplementary Material 1

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Author contributions

Conceptualization, HTC, TCH, and XYG; Methodology and Formal analysis, HTC and RJR; Investigation, HTC and RJR; Resources, GLZ and HN; Data curation, HN, JMQ, LB, CML, ZL, LYS, and HTC; Writing—original draft preparation, GLZ, HTC, and RJR; Writing—review and editing, HN, JMQ, LB, CML, ZL, LYS, TCH, and XYG; Visualization, HTC and RJR; Supervision and project administration, TCH and XYG; Funding acquisition, GLZ, HTC, TCH and XYG. All authors have read and given final approval of the submitted and published versions.

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Data availability

The dataset supporting the conclusions of this article is available upon request from the corresponding author.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of Shanghai Xuhui Mental Health Center [Approval No. KY2023-20]. Informed consent was waived as all data

were anonymized, so no identifiable private information was available to the research team. Clinical trial number: not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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