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Emotional symptom networks in ICU nurses: a comparative network analysis of tertiary-A and tertiary-B hospitals in China

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Abstract

Background Intensive Care Unit (ICU) nurses experience significant psychological distress due to the high-stakes and high-intensity nature of their work environments. This study aims to explore the differences in emotional symptom networks between tertiary-A and tertiary-B hospital ICU nurses using network analysis to identify central symptoms and inform targeted interventions.

Method A total of 498 ICU nurses were divided into two groups based on hospital level: the tertiary-A hospital group ($n = 174$) and the tertiary-B hospital group ($n = 324$). Mood states were measured using the Profile of Mood States-Short Form (POMS-SF). Network analysis was employed to estimate and compare the symptom networks between the two groups, identify central symptoms that link distinct symptom clusters, and conduct network comparison tests to assess differences in overall and local network structures.

Results In the tertiary-A hospital group, the most prominent symptoms were POMS4 (Depression-Dejection), POMS1 (Tension-Anxiety), and POMS2 (Anger-Hostility), with the expected influence value indicating that POMS4 (Depression-Dejection) was the most significant. In the tertiary-B hospital group, the most significant central symptoms were POMS1 (Tension-Anxiety), POMS2 (Anger-Hostility), and POMS4 (Depression-Dejection), where POMS1 (Tension-Anxiety) had the highest expected influence value. The network comparison test revealed significant differences in the network invariance test ($M = 0.345$, $P = 0.003$) and the Global expected influence invariance test ($S = 0.173$, $P = 0.020$).

Conclusion This study identifies distinct emotional symptom networks in ICU nurses across tertiary-A and tertiary-B hospitals, with depression-dejection (POMS4) central in tertiary-A hospitals and tension-anxiety (POMS1) more prominent in tertiary-B hospitals. These findings highlight the need for tailored interventions and hospital-tier-specific mental health support to address the unique emotional challenges faced by ICU nurses, ultimately improving nurse well-being and patient care quality.

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Clinical trial registration Not applicable.

Keywords Mood states, ICU nurses, Network analysis, Hospital levels

Introduction

Intensive Care Unit (ICU) nurses face significant psychological challenges due to the high-stakes nature of their work, prolonged exposure to critical patient conditions [1], and frequent ethical dilemmas [2]. These challenges are associated with numerous negative consequences, such as increased morbidity [3], poor performance [4], low productivity [5], and reduced quality of life, which have aroused widespread concerns in society [6]. Studies indicate alarmingly high rates of emotional distress among ICU nurses, with 24.99% exhibiting depressive symptoms [7], and over 31% suffering from emotional exhaustion-rates substantially higher than those observed in general ward nurses [8]. In China, the prevalence is equally concerning, with 50.4% for depression [9]. These figures are exacerbated by understaffing, prolonged shifts, and limited psychological support [10, 11]. These emotional states not only impair nurses' well-being but also compromise patient safety [12]. For instance, emotional exhaustion correlates with increased medication errors and reduced patient satisfaction [1, 13]. Despite growing awareness, most interventions remain generic, failing to address the heterogeneity of emotional distress mechanisms. Existing studies predominantly focus on severe mental disorders such as depression or burnout [14–16]. Despite growing awareness, existing interventions often fail to address the heterogeneity of emotional distress mechanisms, frequently overlooking subclinical emotional symptoms such as persistent tension, irritability, or low vigor, as most research has focused on severe mental health conditions like depression or burnout. However, these subclinical symptoms, if chronic, can escalate into more severe mental health conditions, such as burnout or major depressive episodes [17]. This underscores the critical need to investigate the dynamic interactions among multidimensional mood states to identify targets for early intervention.

Traditional approaches to studying mood states often rely on linear models or aggregated scores, overlooking the dynamic interplay between symptoms. Symptom network analysis, grounded in complexity theory, conceptualizes psychological distress as a system of mutually reinforcing symptoms [18]. Network analysis, an innovative method in psychology, enhances our comprehension of mental disorders by analyzing the intricate non-linear relationships among symptoms [19, 20]. Network analysis posits that mental disorders emerge from causal interactions among symptoms within interconnected networks [20]. This approach not only identifies core symptoms and their sustaining mechanisms but also informs diagnostic and therapeutic strategies. It has been extensively used to model complex relationships, such as examining how depressive symptoms interact with psychosocial factors and suicidal ideation in adolescents [21, 22]. For instance, Zhang et al. [23] revealed that "fatigue" (PHQ4) served as a critical bridge between depression and burnout in ICU nurses during the late COVID-19 pandemic. However, current studies predominantly focus on single constructs (e.g., depression or burnout) or use limited scales, neglecting the multidimensional nature of mood states. The Profile of Mood States (POMS), a validated multidimensional tool, assesses seven dimensions: tension, anger, fatigue, depression, vigor, confusion, and esteem-related affect. Its brief Chinese version (POMS-SF) demonstrates high reliability and sensitivity in capturing transient emotional fluctuations [24]. Integrating POMS with network analysis could provide a holistic view of ICU nurses' emotional landscapes, uncovering how subclinical symptoms (e.g., persistent tension or low self-esteem) interact to perpetuate distress.

In China, there are significant differences between tertiary-A and tertiary-B hospitals in terms of resource allocation, work environment, and patient condition complexity [25]. In China, tertiary-A hospitals are large, comprehensive medical centers that handle more complex and critical patient cases, equipped with advanced medical technology and specialized departments. They often serve as teaching and research bases for medical schools [25, 26]. In contrast, tertiary-B hospitals provide a high standard of medical care but may have fewer resources and a less complex patient mix. They focus more on general medical services and relatively stable patient conditions. Research has shown that there are significant differences in the psychological responses of medical staff between hospitals of different levels [27]. Tertiary-A hospitals, with their higher complexity of cases and advanced technological demands, may contribute to higher levels of stress and burnout. Conversely, tertiary-B hospitals, with potentially higher patient turnover and resource constraints, may lead to different stressors, such as increased workload and limited support systems. For example, during the COVID-19 pandemic, the incidence of anxiety and depression among medical staff in tertiary-A hospitals was significantly higher than that in primary-level hospitals [28]. This suggests that the emotional states of ICU nurses can vary greatly depending on the hospital setting, and understanding these differences is crucial for developing targeted psychological interventions to support nurses' mental health.

Tertiary-A hospitals, being large comprehensive centers with advanced technology and research demands, may lead to higher burnout due to increased responsibilities. In contrast, tertiary-B hospitals, with fewer resources and higher patient turnover, may result in greater workload stress. These differences likely contribute to varied emotional responses among ICU nurses. This study aims to explore the differences in the emotional states of ICU nurses between tertiary-A hospitals and tertiary-B hospitals, as well as the underlying mechanisms, through symptom network analysis. The findings will contribute to a deeper understanding of the characteristics of emotional states among ICU nurses in hospitals of different levels and provide a scientific basis for developing targeted psychological interventions. Additionally, this study will offer references for nursing managers to optimize the allocation of nursing human resources and improve the working environment, thereby enhancing the job satisfaction and mental health of ICU nurses and ultimately improving the quality of nursing care.

Method

Participants

This cross-sectional study was conducted among ICU nurses in 18 tertiary hospitals in Jiangsu, Zhejiang, and Shanghai. The data collection took place from February 10 to March 15, 2025, with a total of 498 nurses participating. Based on the 2023 National Health Development Statistical Bulletin, China has 3,855 tertiary hospitals, with 1,795 designated as tertiary-A. Our research encompassed 10 tertiary-A and 8 tertiary-B hospitals, aiming to reflect the variety and breadth of hospital types. These areas were selected due to their substantial population and sophisticated healthcare systems, offering a balanced representation of both tertiary-A and tertiary-B hospitals. The online survey was administered using the WeChat-based "Wenjuanxing" program. WeChat, a social media platform widely used since 2017, currently has over 1.2 billion users in China. Participants met the following inclusion criteria: (1) aged 18 years or older, (2) registered nurses, (3) working in clinical front-line nursing positions. Exclusion criteria included: (1) nursing students in the ICU, (2) individuals with mental or physical illnesses, (3) those on leave.

To ensure the validity of the online survey, we contacted the head nurses of the ICUs in each hospital in advance, informing them of the study's purpose, significance, and inclusion and exclusion criteria. Head nurses sent the online survey link to eligible nurses, informing them of the study's purpose and significance. Each mobile phone number was allowed to scan and fill out the survey only once, and all questions had to be answered before submission. Finally, we checked all participants' responses and removed invalid questionnaires with uniform answers. Based on established guidelines in network analysis, each node (symptom) in the network should have at least 20 samples [29]. Given that our analysis involves 7 key symptoms (nodes), the minimum required sample size is calculated as follows: Minimum Sample Size = 7 nodes×20 samples per node = 140 samples. A total of 508 nurses completed the survey. Six questionnaires were excluded because all responses were identical. Four questionnaires were excluded due to internally inconsistent responses. In total, 10 questionnaires were excluded based on these criteria, resulting in a final sample of 498 valid questionnaires. The effective response rate was 98%.

Measures

Sociodemographic variables

Demographic variables included age, BMI, years of working experience in ICU, weekly working hours, number of night shifts per month, gender, education level, marital status, position, professional title, nursing competency level, patient-to-nurse ratio, monthly income. All of these were measured through self-designed questions.

The profile of mood States -Short form, POMS-SF

The Profile of Mood States -Short Form (POMS-SF), is used to assess the emotional states of the general population [24]. The POMS-SF scale comprises 40 adjectives divided into 7 dimensions: Tension, Depression, Anger, Fatigue, Confusion, Vigor, and Esteem-Related Affect [30]. Respondents can evaluate their mood states over the past week using these adjectives. In terms of data collection, respondents are required to select the adjectives that best describe their mood states based on their actual conditions. Each item is rated on a 5-point scale: 0 (not at all), 1 (a little), 2 (moderately), 3 (quite a bit), and 4 (extremely). Higher scores indicate more negative mood states. The Cronbach's α of the POMS-SF subscales in our study was 0.961, confirming the reliability of the tool in our specific context.

Ethics

Ethical approval For this study was obtained from the Ethics Committee of the Sixth People's Hospital of Nantong (Approval No: NTLYLL2025002). The approval was obtained prior to the start of the study. All participants provided written informed consent prior to participation. Participants were informed about the study's purpose prior to commencing the questionnaire. Their involvement was voluntary, and they were assured of confidentiality, privacy, and anonymity. They were also informed that they could withdraw from the study at any time without any negative consequences. The researchers committed to using the collected data solely for research purposes and maintaining its confidentiality. This study is not a clinical trial and therefore does not require clinical trial registration.

Statistical analysis

Descriptive statistics were used to summarize the demographic characteristics of the study participants. For categorical data, the chi-square test was used for comparisons between groups. For numerical data, the t-test was used for comparisons between groups. All preliminary statistical analyses were conducted using SPSS version 27.0. Network analysis was performed using R version 4.3.3. In the network framework, nodes represent the seven symptoms of mood states, while edges represent the partial correlations between pairs of symptoms, controlling for the influence of all other nodes in the network. Blue solid lines indicate positive correlations, while red dashed lines indicate negative correlations. The thickness of each edge reflects the strength of the association. To ensure accurate interpretation of the networks, centrality measures were calculated to quantify the relative importance of each symptom within the network [31]. The prominence of each symptom was evaluated by computing three principal centrality measures, namely strength, betweenness, and closeness. However, as Owczarek et al. [32]proposed, expected influence (EI) outperforms traditional centrality metrics, especially in networks containing negative correlations. Hence, EI was chosen as the primary criterion for assessing the significance of nodes. To evaluate the robustness of the networks, case-dropping bootstrap procedures were employed. Network stability was assessed using the correlation stability coefficient (CS-coefficient), with values above 0.5 considered acceptable [33]. Centrality stability plots were generated to visualize the consistency of centrality rankings across bootstrap iterations. Network predictability was assessed to determine the extent to which each symptom can be predicted by other symptoms within the network. This metric provides insight into the stability and interconnectedness of the symptoms. Predictability values were calculated using the network analysis framework in R, with higher values indicating greater predictability of a symptom based on its connections within the network. Finally, the Network Comparison Test (NCT) was used to examine potential differences in global network structure and connectivity strength between the pain and no-pain groups. The NCT is a permutation-based hypothesis test that evaluates whether two networks differ significantly in terms of overall structure or specific edge weights. For this analysis, 1000 permutations were performed to ensure robust comparisons. Edge-wise differences between the networks were also examined to identify specific connections that varied significantly between groups. To address the potential issue of multiple comparisons, we adjusted the p-values using the Benjamini-Hochberg procedure, which controls the false discovery rate.

Results

Study sample

Table 1 details sociodemographic characteristics of 498 ICU nurses from tertiary-A ($n = 174$) and tertiary-B ($n = 324$) hospitals. The table reveals significant differences in the number of night shifts per month ($P = 0.035$), gender ($P = 0.001$), patient-to-Nurse Ratio ($P < 0.001$), and monthly income ($P < 0.001$) between groups, indicating distinct work conditions and economic aspects between these hospital levels.

Network structure

The network structures of tertiary-A and tertiary-B hospitals are shown in Fig. 1, with Fig. 1A representing the tertiary-A hospital group and Fig. 1B representing the tertiary-B hospital group. In the network diagrams, nodes represent emotional symptoms, while edges represent the partial correlations between symptoms, controlling for all other variables in the network. Blue solid edges indicate positive correlations, red dashed edges indicate negative correlations, and the thickness of the edges reflects the strength of the association, with thicker lines indicating stronger connections. In the tertiary-A hospital group, the three strongest associations were between POMS5 (Vigor-Activity) and POMS7 (Self-Esteem) (edge = 0.751), POMS2 (Anger-Hostility) and POMS4 (Depression-Dejection) (edge = 0.481), and POMS1 (Tension-Anxiety) and POMS4 (Depression-Dejection) (edge = 0.352). In the tertiary-B hospital group, the three strongest associations were between POMS5 (Vigor-Activity) and POMS7 (Self-Esteem) (edge = 0.805), POMS1 (Tension-Anxiety) and POMS6 (Confusion-Bewilderment) (edge = 0.464), and POMS2 (Anger-Hostility) and POMS4 (Depression-Dejection) (edge = 0.371). The abbreviations and total scores for the seven emotional symptoms are presented in Table 2.

Centrality measures

Figure 2 displays the centrality measures for both groups, illustrating the relative importance of each symptom within the network. The red line represents the tertiary-A hospital group, while the blue line represents the tertiary-B hospital group. In the tertiary-A hospital group, the top three symptoms with the highest expected influence values are: POMS4 (Depression-Dejection), POMS1 (Tension-Anxiety), and POMS2 (Anger-Hostility). In the tertiary-B hospital group, the top three symptoms are: POMS1 (Tension-Anxiety), POMS2 (Anger-Hostility), and POMS4 (Depression-Dejection).

Table 1 Sociodemographic characteristics of the participants ($N=498$)

Variables	Total (*N*=498) M(SD)/N (%)	Tertiary-A (*n*=174) M(SD)/N (%)	Tertiary-B (*n*=324) M(SD)/N (%)	t/χ^2	*P*
Age (years)	31.8 (6.3)	31.4 (6.5)	32.1 (6.3)	-1.151	0.250
BMI	22.5(3.3)	22.1 (3.1)	22.6 (3.3)	-1.567	0.118
Years of Working Experience in ICU	6.4(5.6)	6.9(5.8)	6.2(5.5)	1.027	0.305
Weekly working hours	38.9(11.4)	38.0(11.4)	39.4(11.4)	-1.304	0.193
Number of night shifts per month	7.2(4.2)	7.8(4.2)	7.0(4.2)	2.115	0.035
Gender				11.692	0.001
Male	36(7.2)	22(12.6)	14(4.3)		
Female	462(92.8)	152(87.4)	310(95.7)		
Education				8.532	0.929
Below bachelor's degree	82(16.5)	29(16.7)	53(16.4)		
Bachelor's degree and above	416 (83.5)	145(83.3)	271(83.6)		
Marital status				1.407	0.495
Single	174 (34.9)	65(37.4)	109(33.6)		
Married	318 (63.9)	106(60.9)	212(65.4)		
Divorced	6 (1.2)	3(1.7)	3(1.0)		
Position				0.107	0.743
Head Nurse	34 (6.8)	11(6.3)	23(7.1)		
Nurse	464 (93.2)	163(93.7)	301(92.9)		
Professional Title				3.334	0.189
Junior	271 (54.4)	103(59.2)	168(51.8)		
Intermediate	196 (39.4)	59(33.9)	137(42.3)		
Senior	31 (6.2)	12(6.9)	19(5.9)		
Nursing Competency Level				3.163	0.367
N0-N1	143 (28.7)	54(31.0)	89(27.5)		
N2	204 (41.0)	62(35.6)	142(43.8)		
N3	128 (25.7)	49(28.2)	79(24.4)		
N4 and above	23 (4.6)	9(5.2)	14(4.3)		
Patient-to-Nurse Ratio				16.526	<0.001
<2:1	135(27.1)	64(36.8)	71(21.7)		
2:1–4:1	313 (62.9)	101(58.0)	212(64.8)		
>4:1	50(10.0)	9(5.2)	41(12.5)		
Monthly income				97.298	<0.001
<5000	78 (15.7)	35(20.1)	43(13.3)		
50,000 – 10,000	343(68.9)	77(44.3)	266(82.1)		
>10,000	77(15.4)	62(35.6)	15(4.6)		

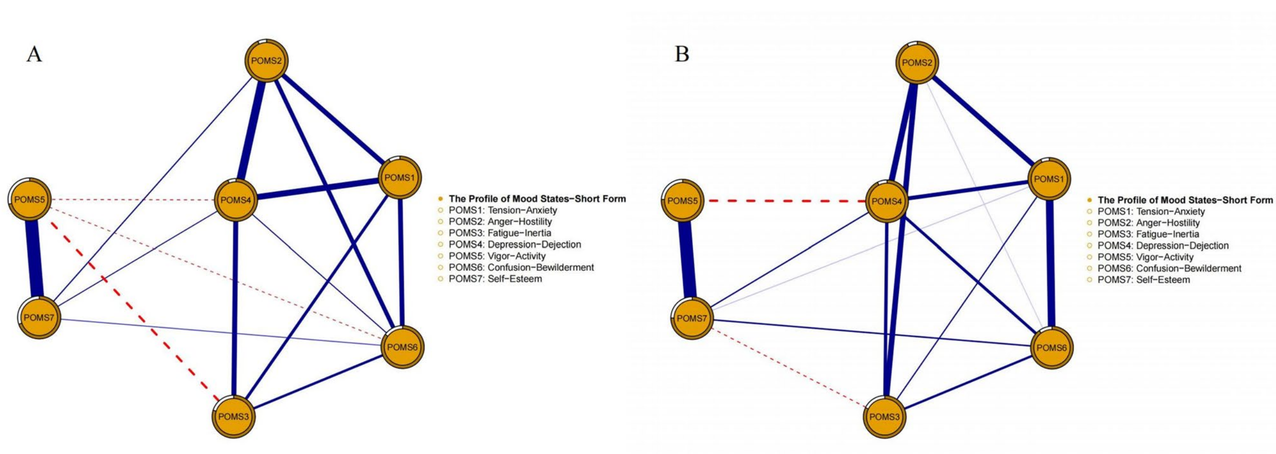

Fig. 1 **A**: Network structure of emotional states in the tertiary-A hospital group. **B**: Network structure of emotional states in the tertiary-B hospital group

Table 2 Abbreviation, **Key adjective**, and scores of each dimension in POMS

Abbreviation	Key adjective	Mean ± SD	Predictability
POMS-1	Tension-Anxiety		
Tertiary-A hospitals		8.16 ± 5.16	0.914
Tertiary-B hospitals		5.95 ± 5.39	0.935
POMS-2	Anger-Hostility		
Tertiary-A hospitals		8.87 ± 6.58	0.934
Tertiary-B hospitals		6.47 ± 6.41	0.922
POMS-3	Fatigue-Inertia		
Tertiary-A hospitals		7.69 ± 4.98	0.799
Tertiary-B hospitals		6.02 ± 5.02	0.822
POMS-4	Depression-Dejection		
Tertiary-A hospitals		7.28 ± 5.82	0.939
Tertiary-B hospitals		5.30 ± 5.60	0.926
POMS-5	Vigor-Activity		
Tertiary-A hospitals		11.16 ± 4.57	0.714
Tertiary-B hospitals		11.72 ± 5.43	0.760
POMS-6	Confusion-Bewilderment		
Tertiary-A hospitals		6.78 ± 4.30	0.851
Tertiary-B hospitals		5.02 ± 4.34	0.898
POMS-7	Self-Esteem		
Tertiary-A hospitals		8.47 ± 3.28	0.699
Tertiary-B hospitals		8.64 ± 3.80	0.751

Stability analysis

The case-dropping bootstrap procedure confirmed the reliability of the networks. Stability is shown in Fig. 3, with Fig. 3A representing the stability of the tertiary-A hospital group, which has a correlation stability coefficient (cs coefficient) of 0.747 for strength centrality. Figure 3B represents the stability of the tertiary-B hospital group, with a cs coefficient of 0.750 for strength centrality. Both exceed the recommended threshold of 0.5 [33], indicating minimal fluctuation in centrality rankings across bootstrap iterations and supporting the robustness of the results.

Network predictability

In the tertiary-A hospital group, the top three symptoms by network predictability are POMS4 (Depression-Dejection), POMS2 (Anger-Hostility), and POMS1 (Tension-Anxiety). In the tertiary-B hospital group, the top three symptoms by network predictability are POMS1 (Tension-Anxiety), POMS4 (Depression-Dejection), and POMS2 (Anger-Hostility). Predictability values are shown in Table 2.

Network comparison

The network invariance test yielded a statistic $M = 0.345$ ($P = 0.003$), indicating significant differences in the overall network structure between tertiary-A and tertiary-B hospitals. The global expected influence invariance test resulted in a statistic $S = 0.173$ ($P = 0.020$), suggesting that the expected influence of the nodes is not invariant between the two hospital groups. These results highlight distinct emotional symptom networks in ICU nurses across different hospital levels. The differences are mainly reflected in four edges: POMS2 (Anger-Hostility)-POMS 3(Fatigue-Inertia) ($P < 0.001$), POMS3 (Fatigue-Inertia)-POMS5 (Vigor-Activity) ($P = 0.029$), POMS1 (Tension-Anxiety)-POMS6 (Confusion-Bewilderment) ($P = 0.036$), and POMS2 (Anger-Hostility)-POMS6 (Confusion-Bewilderment) ($P = 0.017$), and three nodes: POMS3 (Fatigue-Inertia) ($P = 0.022$), POMS4 (Depression-Dejection) ($P = 0.034$), and POMS5 (Vigor-Activity) ($P = 0.038$).

Discussion

The current study aimed to explore the differences in emotional symptom networks between ICU nurses in tertiary-A and tertiary-B hospitals. The findings provide valuable insights into the distinct emotional challenges faced by ICU nurses in different hospital settings and highlight the importance of tailored interventions to address these challenges.

The centrality profiles of emotional symptoms diverged markedly between tertiary-A and tertiary-B hospitals. In tertiary-A hospitals, Depression-Dejection (POMS4) occupied the highest expected influence, whereas Tension-Anxiety (POMS1) dominated in tertiary-B hospitals. This tier-specific hierarchy suggests that emotional distress manifests through distinct pathways depending on institutional context. Tertiary-A Hospitals: The prominence of Depression-Dejection aligns with studies linking prolonged exposure to critical patient outcomes to emotional exhaustion and hopelessness among nurses [34]. Tertiary-A hospitals, typically managing higher-acuity cases and research-oriented workloads, may engender chronic stress that depletes coping resources, predisposing nurses to depressive symptoms [34, 35]. This aligns with the Job Demands-Resources model, where excessive demands without adequate support precipitate depressive responses [36]. Tertiary-B Hospitals: The centrality of Tension-Anxiety may reflect acute stressors such as understaffing, rapid patient turnover, or administrative pressures common in tertiary-B hospitals focused on high-volume care [37]. Anxiety often arises

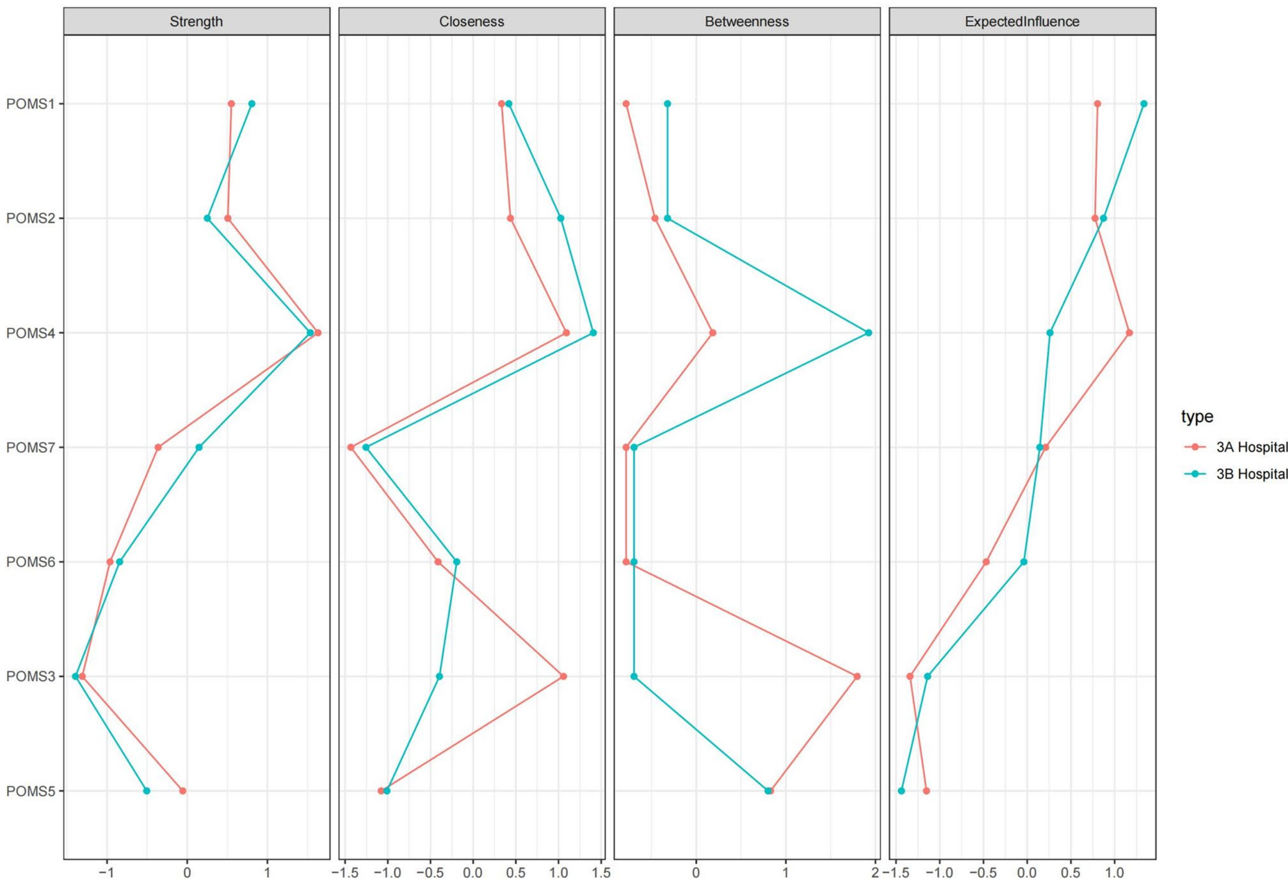

Fig. 2 Comparison of centrality measures between the tertiary-A and tertiary-B hospital groups

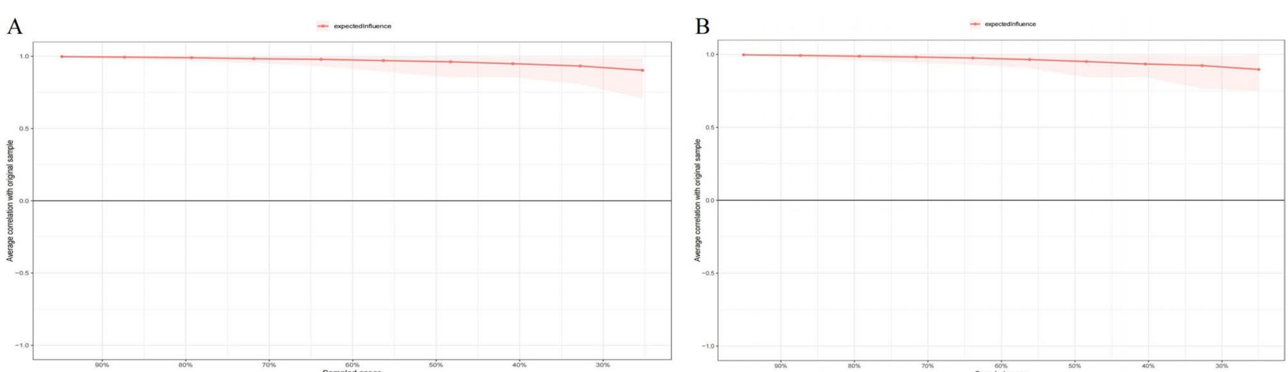

Fig. 3 **A**: Stability of Expected Influence (EI) indices in the tertiary-A hospital group using case-dropping bootstrap. **B**: Stability of Expected Influence (EI) indices in the tertiary-B hospital group using case-dropping bootstrap

from anticipatory stress about workload or perceived inadequacy in meeting institutional benchmarks, consistent with the "stress-appraisal" framework. For tertiary-A hospitals, interventions targeting depressive symptoms, such as cognitive-behavioral therapy, and improving work conditions to reduce stress and anger are recommended [38]. For tertiary-B hospitals, strategies to reduce anxiety through mindfulness programs and address fatigue by optimizing shift schedules and providing rest opportunities are suggested. Efficient resource allocation to support nurse well-being is also crucial in tertiary-B hospitals [39]. The secondary centrality of Anger-Hostility (POMS2) in both groups highlights its significant role in the emotional symptom network [40]. This suggests that Anger-Hostility is a common emotional response that may contribute to the overall distress experienced by nurses in both types of hospitals [41]. Its presence underscores the importance of addressing this symptom in therapeutic interventions to mitigate emotional distress across different settings.

The strongest associations in both networks involved Vigor-Activity (POMS5) and Self-Esteem (POMS7), underscoring the protective role of personal resources in buffering emotional distress [42]. High vigor and self-esteem likely enhance resilience [43], enabling nurses to navigate stressors without succumbing to negative affect. However, the weakened Fatigue-Inertia (POMS3)-Vigor-Activity edge in tertiary-B hospitals suggests that chronic fatigue in high-volume settings depletes vitality, creating a vulnerability loop where exhaustion diminishes coping capacity [44, 45].

The marked edge differences in network comparisons-particularly the stronger Anger-Hostility–Fatigue-Inertia connection in tertiary-B hospitals-reveal a "burnout-anger cycle." In resource-constrained environments, unrelenting physical and cognitive demands may amplify irritability, which exacerbates fatigue through maladaptive coping [46]. This bidirectional relationship aligns with the Conservation of Resources theory, where resource loss spirals perpetuate distress [47].

The network predictability analysis revealed that depression-dejection (POMS4) and tension-anxiety (POMS1) were the most predictable symptoms in both tertiary-A and tertiary-B hospitals. This suggests that these symptoms are not only central but also highly influential in the overall emotional network. The predictability values provide further evidence that these symptoms are key drivers of emotional distress and should be targeted in interventions to improve nurse well-being. For example, a study by Zeng et al. [48] found that anxiety, mental degeneration, and depression were central symptoms in the network of psychological symptoms among ICU nurses, emphasizing the need for targeted interventions to address these symptoms.

The network comparison test revealed significant global and local differences between tertiary-A and B hospitals, with four edges and three nodes differing in strength. These disparities likely reflect institutional disparities in workload, resources, and organizational culture: The stronger Anger-Hostility(POMS2)-Fatigue-Inertia (POMS3) connection in tertiary-B group may indicate a "burnout-anger cycle," where chronic fatigue exacerbates irritability, consistent with the effort-recovery model [49]. The weaker Tension-Anxiety (POMS1)-Confusion-Bewilderment (POMS6) link in tertiary-A hospitals could reflect better cognitive coping strategies or institutional support buffering anxiety's cognitive impacts [50]. These differences likely reflect variations in workload, resources, and organizational culture. The heightened strength of Fatigue-Inertia (POMS3) in tertiary-B hospitals may stem from resource constraints, forcing nurses into sustained physical and emotional exertion without recovery [51]. These structural nuances underscore the need for context-sensitive interventions. For example, tertiary-B hospitals might prioritize fatigue management, while tertiary-A hospitals could focus on depressive symptom mitigation through peer support programs.

The high predictability of Depression-Dejection (tertiary-A) and Tension-Anxiety (tertiary-B) indicates that these symptoms are deeply embedded within their respective networks, with their states heavily influenced by neighboring nodes. For instance, in tertiary-A hospitals, the Depression-Dejection node's predictability may stem from its strong linkages to Anger-Hostility and Tension-Anxiety, forming a self-reinforcing triad of despair [52]. Conversely, in tertiary-B hospitals, Tension-Anxiety's predictability likely arises from its connections to Confusion-Bewilderment and Anger-Hostility, illustrating how anxiety propagates cognitive and interpersonal strain [53]. The findings suggest that interventions targeting upstream symptoms could effectively disrupt network-wide distress. Specifically, in tertiary-A hospitals, cognitive-behavioral interventions aimed at addressing depressive rumination may weaken the connections between Depression-Dejection and Anger-Hostility. Additionally, team-building exercises could enhance the connections between Self-Esteem and Vigor-Activity [54]. In tertiary-B hospitals, mindfulness-based stress reduction programs may help decouple Tension-Anxiety from Confusion-Bewilderment [55], while redistributing workloads could alleviate the connections between Fatigue-Inertia and Anger-Hostility [56–58].

The network invariance test confirmed significant global and nodal differences between hospital tiers, with Fatigue-Inertia, Depression-Dejection, and Vigor-Activity exhibiting divergent influences. These disparities likely reflect systemic inequities. The heightened centrality of Fatigue-Inertia in tertiary-B hospitals may stem from understaffing and prolonged shifts, which force nurses into unsustainable work-rest ratios [59]. The weakened Vigor-Activity in tertiary-B hospitals signals a resource-driven erosion of personal resilience, necessitating institutional reforms such as mandatory rest periods and acuity-adjusted staffing [60]. Such structural insights argue for tier-specific policy reforms. Tertiary-A hospitals might invest in mental health days and peer support networks to counteract depressive cores, while tertiary-B hospitals could prioritize fatigue audits and real-time stress monitoring systems.

While this study provides novel insights, several limitations warrant attention: First, the cross-sectional design of this study limits our understanding of the temporal relationships between symptoms. Longitudinal network analyses could reveal causal pathways and intervention timelines, providing more comprehensive insights into the dynamics of emotional symptom networks. Second, the focus on tertiary hospitals within a single healthcare system restricts the generalizability of our findings to primary care settings or other countries. Replication in diverse settings is critical to validate the applicability of our results across different healthcare contexts. Third, unmeasured confounders such as shift patterns, leadership quality, and social support were not analyzed in this study. Future research should explore the effectiveness of targeted interventions for depression-dejection in tertiary-A ICU nurses and tension-anxiety in tertiary-B ICU nurses through randomized controlled trials of cognitive-behavioral therapy (CBT), mindfulness-based stress reduction (MBSR), and peer support groups. Longitudinal studies could investigate the causal pathways behind the "burnout-anger cycle" in tertiary-B hospitals by tracking emotional symptoms over time to identify triggers and mediating factors such as workload and organizational support. Additionally, research should examine the causal relationships between work environment factors (e.g., patient-to-nurse ratio, shift patterns) and emotional symptoms in ICU nurses using both qualitative and quantitative methods. While our study identified significant differences in the emotional symptom networks between tertiary-A and tertiary-B hospitals, it is important to consider the potential limitations related to statistical power. Given the sample sizes, our study was adequately powered to detect medium to large effect sizes in network structure and centrality measures. However, the power to detect smaller effect sizes may be limited, particularly for some of the less central nodes or edges with weaker connections. This limitation should be taken into account when interpreting non-significant findings for certain comparisons.

Conclusion

Our study identified distinct emotional symptom networks in ICU nurses from tertiary-A and tertiary-B hospitals, with depression-dejection being more central in tertiary-A hospitals and tension-anxiety in tertiary-B hospitals. These results indicate that emotional distress manifests differently across hospital levels, necessitating customized mental health support. Tertiary-A hospitals should focus on addressing depressive symptoms through specialized counseling and peer support programs, while tertiary-B hospitals need to prioritize anxiety reduction via mindfulness training and improved fatigue management. By implementing these hospital-specific strategies, healthcare institutions can enhance ICU nurses' emotional well-being, leading to better patient outcomes and nursing workforce stability.

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Author contributions
Y.W completed the writing of this article. S.S was instrumental in collecting the survey data. X.L and J.G put forward important revision suggestions and made corresponding modifications for this article. All authors contributed to the article and approved the submitted version.

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Data availability
The raw data of the current study would be available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
The study was reviewed and approved by the Ethics Committee of the Sixth People's Hospital of Nantong (Approval No: NTLYLL2025002). All procedures complied with the ethical standards of the Declaration of Helsinki. Written informed consent was obtained from all participants, including explicit agreement for the publication of anonymized data. Participation was voluntary with guaranteed confidentiality and the right to withdraw without penalty.

Consent for publication
All participants consented to publication of anonymized data through signed informed consent forms.

Competing interests
The authors declare no competing interests.

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