

# Mapping the Association Between Burnout and Intent to Leave: A Network Analysis of Public Health Workers in China

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## Research Article

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## Abstract

## Background

The COVID-19 pandemic has exacerbated burnout and intent to leave among public health workers worldwide; however, the central and bridge relationships between burnout symptoms and intent to leave remain unclear. This study applies network analysis to visualize the symptom-level interconnections between burnout and intent to leave among public health workers in China, with the aim of identifying key intervention targets.

## Methods

A nationwide cross-sectional online survey was conducted among 1,887 public health workers across China (October-November 2024). The Maslach Burnout Inventory (MBI) and 4-item O'Reilly's Intent to Leave Scale (ITL) were used to assess burnout and intent to leave, respectively. A regularized partial correlation network was estimated to examine the interconnections between all symptoms. Centrality and bridge centrality indices were calculated to identify core and bridging symptoms within the burnout-intent to leave network. The stability and accuracy of the network were evaluated using bootstrap methods.

## Results

A total of 1,887 public health workers, 59.1% were male, 59.4% were aged 31 or above, and 51.8% were public health physicians. The network model revealed dense interconnections between burnout symptoms and intent to leave. The most central node was the *personal accomplishment* item "I feel that I have completed a lot of valuable work" (MBI 14), followed by the *emotional exhaustion* item of "Working all day is indeed very stressful for me" (MBI 4). The key bridge symptoms linking burnout symptoms to intent to leave were two *depersonalization* items: "Since starting this job, I've become increasingly disinterested in it" (MBI6) and "I doubt the significance of the work I do" (MBI8). The network demonstrated good stability and accuracy across all indices.

## Conclusions

The findings identified three central symptoms of burnout, with *depersonalization* emerging as a key bridge symptom linking burnout to intent to leave. These results highlight potentially effective targets for intervention to mitigate burnout-related workforce attrition in public health settings.

## Introduction

The global coronavirus disease 2019 (COVID-19) pandemic has profoundly threatened public health and social stability worldwide. In China, public health workers have faced particularly intense and sustained occupational demands, including prolonged working hours, heightened workloads, and fears of infection. These persistent pressures have contributed to increased levels of burnout and a growing intent to leave the profession [1, 2], raising urgent concerns about workforce sustainability in public health sectors.

Burnout is an occupational syndrome resulting from chronic workplace stress, characterized by three core dimensions: emotional exhaustion, depersonalization, and a reduced sense of personal accomplishment [3]. Beyond its impact on individual well-being, burnout is associated with adverse mental health outcomes[4] and organizational consequences such as absenteeism, job dissatisfaction, interpersonal conflict, impaired job performance, and increased intent to leave, it may further compromise quality of care and patient safety [5, 6].

Burnout among public health workers has drawn heightened attention in the context of the COVID-19 pandemic. A 2023 study of public health workers in Canada showed that burnout was extremely common, affecting 78.7% of respondents, with high rates of exhaustion (85.2%) and disengagement (87.7%)[7]. A 2021 study in South Korea similarly reported high levels of burnout among public health workers during the pandemic [8]. In China, where public health workers have carried sustained responsibilities in outbreak control and population health protection, burnout remains a pressing concern, yet remains understudied relative to other healthcare populations[9, 10].

Intent to leave refers to an employee's perceived likelihood of staying with or leaving their organization in the near future, and it is widely recognized as the single strongest predictor of actual turnover [11]. Adverse psychosocial work conditions and mental distress during the pandemic have contributed to elevated intent to leave among those health workers globally [12]. Previous studies have shown that burnout was one of the strongest predictors of intent to leave [13]. Burnout negatively influences employees' daily behavioral adjustments, as they experiencing burnout tend to avoid it instinctively and are inclined towards resignation.

Although burnout and intent to leave have each been studied independently in public health contexts, the symptom-level relationship between them remain poorly studied [2, 9, 10]. Existing studies have largely relied on aggregate scores or simple regression approaches, which obscure how individual burnout symptoms interact with and propagate toward intent to leave. A more granular understanding of these interconnections is needed to identify specific intervention targets.

Network analysis is a statistical method that can reveal and visualize complex relationships between multiple variables and identify potential intervention targets [14]. In a symptom network, each item is represented as a node, and the associations between items are represented as edges; thicker edges indicate stronger associations between nodes[15]. The aim of network analysis is to identify central symptoms — those most strongly connected to others in the network — and bridge symptoms, which link different symptom clusters and may facilitate the spread of distress from one domain to another [16]. Network analysis has been applied to explore burnout and related constructs across a range of populations, including nurses[17, 18] and intensive care unit

workers[18]; however, to our knowledge, no study has yet applied network analysis to examine the interconnections between burnout and intent to leave among public health workers in China.

Therefore, this study aims to construct a multidimensional symptom network for public health workers in China, offering a visual representation of the interconnections between burnout and intent to leave symptoms, identifying potential core and bridging symptoms, and providing a theoretical foundation for the identification of intervention targets and the development of targeted symptom management strategies.

## Methods

### Study design and participants

This study employed a nationwide cross-sectional online survey design and was conducted between October and November 2024 in China. The study followed the Checklist for Reporting Results of Internet E-Surveys (CHERRIES)[19] and the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines [20] to ensure methodological rigor and transparency. Participants were recruited via a professional WeChat official account focused on public health in mainland China. This account has a well-defined, highly targeted audience consisting primarily of professionals working in public health, including staff at all levels of the Chinese Center for Disease Control and Prevention (CDC), hospital-based public health practitioners, and frontline workers from primary public health institutions. As an influential professional platform in China's public health sector, it enables efficient and representative recruitment of the target study population.

Inclusion criteria were as follows: (1) employment in a public health institution as a public health practitioners whose work aligned with one or more of the following core functions for Public Health in China: population health assessment, health protection, health surveillance, disease and injury prevention, health promotion and/ or emergency preparedness and response. (2) at least one year of work experience at the institution, and (3) provision of informed consent. Exclusion criteria were: (1) interns, (2) individuals who were ill or otherwise unable to complete the survey questionnaires, and (3) those on leave during the survey period.

Eligible participants were invited to complete an online, survey questionnaires administrated via Wenjuanxing ([www.wjx.cn](http://www.wjx.cn)), a widely used survey platform in China that has been employed in previous studies[21]. After providing electronic informed consent, participants completed to a self-administrated survey in mandarin Chinese, which included questions of socio-demographic information, burnout and intent to leave. Completion of the survey was voluntary and required approximately 10 minutes.

### Sample size determination

According to the sample size recommendations for network analysis[14], when using network analysis methods, the sample size should be at least greater than the total number of parameters (number of nodes + (number of nodes × (number of nodes – 1)/2)). In this study, burnout symptoms comprise 15 nodes, intent to leave symptoms comprise 4 nodes, resulting in a total of 19 nodes. Assuming an approximate 20% loss to follow-up (dropout rate), the minimum required sample size was 206. Initially, 2,458 completed questionnaires were received. To ensure data quality, 571 questionnaires were excluded if the completion time was less than 5 minutes (300 s) or more than 20 minutes (1200 s). Thus, 1,887 questionnaires were included for the final analysis. Participants whose questionnaires were included did not differ significantly from those excluded in terms of age and sex, indicating minimal selection bias.

## Measures

### Socio-demographic information

Socio-demographic information was collected through the self-administered questionnaire, included sex (male or female), age (years), marital status (unmarried, married, widowed, or devided), educational level (diploma, BSc degree, or MSc degree and above), years of working, health facility type, majors, profession type and professional title.

### Burnout

Burnout was measured by the Maslach Burnout Inventory (MBI)[22], which is translated by former study[23] and demonstrated to have good reliability and validity in the Chinese context[24–26]. The Chinese version scale included 15 items under three dimensions: *emotional exhaustion* (EE, 5 items), *depersonalization* (DP, 4 items), and *induced personal accomplishment* (PA, 6 items). The items were scored on a 7-point Likert scale ranging from ('never') to 6 ('every day'), where higher scores represented a higher degree of burnout. The internal consistency coefficients of the three dimensions were 0.900, 0.935 and 0.831, respectively. In this study, the overall Cronbach's alpha coefficient was 0.812.

### Intent to leave

Intent to leave was measured by the 4-item intent to leave scale designed by O'Reilly[27].

capturing participants' intentions to leave their current job. An example item is: "I would prefer another more ideal job than the one I now work in" with response options ranging from 1 (completely disagree) to 5 (completely agree). The total score ranges from 4 to 20, with higher scores indicating stronger intent to leave among public health workers. In this study, the Cronbach's  $\alpha$  of this scale was 0.724.

## Statistical analysis

Descriptive statistical analyses were conducted using R studio. Categorical variables are presented as frequencies and percentages, and continuous variables are presented as means and standard deviations.

A Gaussian graphical model was constructed using the "qgraph 1.9.8" package in R[14, 15]. The graphical least absolute shrinkage and selection operator (LASSO) with extended Bayesian information criterion was applied to obtain a conservative network model[15]. In this network model, each item from the burnout and intent to leave scales was treated as a node. Relationships between two nodes were termed edges, while each "edge" represented the partial correlation coefficient between node pairs. Considering the ordinal distribution of scores, partial correlation coefficients were calculated using Spearman's correlation while controlling for all other nodes. Solid lines indicating positive correlations, Dashed lines indicating negative correlations and Edge thickness proportional to the strength of the association (thicker edges = stronger relationships).

The centrality and predictability of nodes were assessed using five metrics: strength, closeness, betweenness, expected influence (EI), and bridge expected influence (BEI)[28]. When both positive and negative correlations coexist in the network analysis, traditional centrality measures (strength, closeness, and betweenness) become less sensitive. In such cases, Expected Influence (EI) should be used to evaluate a node's role in the network. A higher Expected Influence (EI) value indicates that the node has stronger and more extensive connections with other nodes in the network, reflecting its greater importance. Predictability refers to the degree to which a given node can be predicted by all other nodes in the network, which is calculated using the mgm package in R.

To assess the accuracy and stability of the results, bootstrapping with nonparametric bootstrap samples was used to assess model stability. We repeatedly estimated the network model and calculated 95% confidence intervals for edge weights to assess edge stability. Node stability coefficients were evaluated by iteratively removing samples during bootstrapping to assess the node stability. Node stability coefficients indicate the maximum acceptable level of sample reduction, exceeds 0.7, with a minimum threshold of 0.25 and  $\geq 0.5$  indicating relatively stable node indices [14].

## Results

### Socio-demographic characteristics of the study participants

Among the 1,887 public health workers included in this study, 59.1% were male, and 59.4% were aged 31 or above. The majority of participants were married (62.1%), had a bachelor's degree (75.0%), had 6–10 years of work experience (50.0%), worked as public health physicians (51.8%), and had middle professional titles (51.1%). The sample characteristics are presented in Table S1.

Table S1  
Demographic characteristics of the participants.

| Characteristics                   | N    | %    |
|-----------------------------------|------|------|
| Sex                               |      |      |
| Male                              | 1115 | 59.1 |
| Female                            | 772  | 40.9 |
| Age(years)                        |      |      |
| ≤ 30                              | 766  | 40.6 |
| 31 or above                       | 1121 | 59.4 |
| Marital status                    |      | 0.0  |
| Married                           | 1171 | 62.1 |
| Single/Divorced/Separated/Widowed | 716  | 37.9 |
| Educational level                 |      |      |
| Diploma                           | 32   | 1.7  |
| BSc degree                        | 1415 | 75.0 |
| MSc degree and above              | 440  | 23.3 |
| Work Experience(years)            |      |      |
| ≤ 5 years                         | 886  | 47.0 |
| 6–10 years                        | 943  | 50.0 |
| ≥ 11 years                        | 58   | 3.1  |
| Health facility type              |      |      |
| CDC                               | 559  | 29.6 |
| Hospital                          | 1012 | 53.6 |
| Others                            | 92   | 4.9  |
| Majors                            |      |      |
| Clinical Medicine                 | 13   | 0.7  |
| Preventive medicine               | 1071 | 56.8 |
| Nursing Science                   | 740  | 39.2 |
| Other Subjects Allied to Medicine | 55   | 2.9  |
| Non-medical majors                | 8    | 0.4  |
| Profession type                   |      |      |
| Administrator                     | 69   | 3.7  |
| Nurse                             | 738  | 39.1 |
| Public health physician           | 978  | 51.8 |
| Others                            | 102  | 5.4  |
| Professional title                |      |      |
| No title                          | 150  | 7.9  |
| Junior                            | 754  | 40.0 |
| Middle                            | 965  | 51.1 |
| Senior                            | 18   | 1.0  |

The mean statistics with the standard deviation and the predictability of each network node were presented. MBI 4(Working all day is indeed very stressful for me) accounted for 0.854 in predictability (mean:3.76, SD:1.58; see Table 1)

Table 1  
Basic information of and descriptive item statistics of the burnout-intent to leave scale

| Items  | Item Description                                                               | Predictability | Mean (SD)   |
|--------|--------------------------------------------------------------------------------|----------------|-------------|
| MBI 1  | Work makes me feel physically and mentally exhausted.                          | 0.771          | 2.76 ± 1.31 |
| MBI 2  | When I finish work, I feel completely drained.                                 | 0.756          | 3.1 ± 1.23  |
| MBI 3  | Getting up in the morning to face another day of work, I feel extremely tired. | 0.777          | 3.14 ± 1.30 |
| MBI 4  | Working all day is indeed very stressful for me.                               | 0.854          | 3.76 ± 1.58 |
| MBI 5  | Work makes me feel like I'm on the verge of a breakdown.                       | 0.808          | 3.03 ± 1.29 |
| MBI 6  | Since starting this job, I've become increasingly disinterested in it.         | 0.808          | 3.05 ± 1.30 |
| MBI 7  | I'm not as enthusiastic about work as I used to be.                            | 0.816          | 3.56 ± 1.35 |
| MBI 8  | I doubt the significance of the work I do.                                     | 0.762          | 3.15 ± 1.37 |
| MBI 9  | I'm becoming less concerned about whether my work makes a contribution.        | 0.717          | 3.11 ± 1.34 |
| MBI 10 | I am able to effectively solve problems that arise in my work.                 | 0.677          | 3.07 ± 1.31 |
| MBI 11 | I feel that I am making a valuable contribution to my organization.            | 0.597          | 3.02 ± 1.20 |
| MBI 12 | I believe I am skilled at my job.                                              | 0.657          | 2.9 ± 1.16  |
| MBI 13 | I feel very pleased when I accomplish tasks at work.                           | 0.637          | 2.57 ± 1.26 |
| MBI 14 | I feel that I have completed a lot of valuable work.                           | 0.794          | 2.47 ± 1.67 |
| MBI 15 | I am confident in my ability to efficiently complete tasks.                    | 0.631          | 2.78 ± 1.18 |
| ITL1   | I would prefer another more ideal job than the one I now work in.              | 0.577          | 3.66 ± 0.90 |
| ITL2   | I have thought seriously about changing agencies since I began working here.   | 0.594          | 3.43 ± 0.95 |
| ITL3   | I hope to be working for this agency until I retire(R)                         | 0.336          | 2.88 ± 0.87 |
| ITL4   | I seriously intend to look for another job within the next year.               | 0.566          | 3.38 ± 1.05 |

## Network structure

Figure 1 shows the network structure of burnout symptoms-intent to leave. The network comprised 19 nodes and 118 non-zero edges, representing a network density was 69.01%. Within the burnout symptoms, the strongest connection was observed between MBI4 ("Working all day is indeed very stressful for me") and MBI5 ("Work makes me feel like I'm on the verge of a breakdown") (edge weight = 0.508), followed by MBI6 ("Since starting this job, I've become increasingly disinterested in it") and MBI7 ("I'm not as enthusiastic about work as I used to be") (edge weight = 0.483), and MBI13 ("I feel very pleased when I accomplish tasks at work") and MBI14 ("I feel that I have completed a lot of valuable work") (edge weight = 0.434). Within the intent to leave cluster, the strongest connections were between ITL1 ("I would prefer another more ideal job than the one I now work in") and ITL4 ("I seriously intend to look for another job within the next year") (edge weight = 0.372), ITL1 and ITL2 ("I have thought seriously about changing agencies since I began working here") (edge weight = 0.310), and ITL2 and ITL4 (edge weight = 0.197). All edge weights are provided in Table 2.

Nodes: orange nodes= emotional exhaustion, blue nodes = depersonalization, green nodes = reduced personal accomplishment, yellow nodes = intent to leave. Blue edges = positive partial correlations; red edges = negative correlations. Thicker edges indicate stronger associations.

Table 2  
The edge weights within the burnout-intent to leave network

| MBI1  | MBI1   | MBI2   | MBI3   | MBI4   | MBI5   | MBI6   | MBI7   | MBI8   | MBI9   | MBI10  | MBI11  | MBI12  | MBI13  | MBI14  | MBI15  |
|-------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
|       | 0      | 0.335  | 0.200  | -0.184 | 0.230  | 0.078  | -0.048 | 0.054  | 0.003  | -0.184 | -0.031 | 0      | 0.025  | 0.178  | 0      |
| MBI2  | 0.335  | 0      | 0.318  | 0.148  | 0.160  | 0.016  | 0      | 0      | 0      | -0.002 | 0      | -0.008 | 0      | -0.016 | 0      |
| MBI3  | 0.200  | 0.318  | 0      | 0.172  | 0.196  | 0.083  | 0.002  | 0.040  | 0.019  | -0.054 | 0      | 0      | 0      | 0.027  | 0.030  |
| MBI4  | -0.184 | 0.148  | 0.172  | 0      | 0.508  | 0      | 0.147  | 0.000  | 0      | 0.170  | 0      | 0.023  | -0.017 | -0.260 | 0.029  |
| MBI5  | 0.230  | 0.160  | 0.196  | 0.508  | 0      | 0.033  | 0      | 0      | 0      | 0      | 0      | 0      | 0      | 0.009  | 0.015  |
| MBI6  | 0.078  | 0.016  | 0.083  | 0      | 0.0330 | 0      | 0.483  | 0.231  | 0.118  | -0.011 | 0      | 0      | 0.053  | 0      | 0      |
| MBI7  | -0.048 | 0      | 0.002  | 0.147  | 0      | 0.483  | 0      | 0.161  | 0.251  | 0.034  | 0.022  | 0      | -0.025 | -0.083 | 0      |
| MBI8  | 0.054  | 0      | 0.040  | 0.000  | 0      | 0.231  | 0.161  | 0      | 0.398  | 0      | 0.005  | -0.005 | 0      | 0.085  | -0.027 |
| MBI9  | 0.003  | 0      | 0.019  | 0      | 0      | 0.118  | 0.251  | 0.398  | 0      | 0      | 0.010  | 0      | 0.006  | 0.094  | -0.027 |
| MBI10 | -0.184 | -0.002 | -0.054 | 0.170  | 0      | -0.011 | 0.034  | 0      | 0      | 0      | 0.298  | 0.178  | 0.033  | -0.169 | 0.267  |
| MBI11 | -0.031 | 0      | 0      | 0      | 0      | 0      | 0.022  | 0.005  | 0.010  | 0.298  | 0      | 0.217  | 0.066  | 0.301  | 0.034  |
| MBI12 | 0      | -0.008 | 0      | 0.023  | 0      | 0      | 0      | -0.005 | 0      | 0.178  | 0.217  | 0      | 0.176  | 0.076  | 0.393  |
| MBI13 | 0.025  | 0      | 0      | -0.017 | 0      | 0.053  | -0.025 | 0      | 0.006  | 0.033  | 0.066  | 0.176  | 0      | 0.434  | 0.165  |
| MBI14 | 0.178  | -0.016 | 0.027  | -0.260 | 0.009  | 0      | -0.083 | 0.085  | 0.094  | -0.169 | 0.301  | 0.076  | 0.434  | 0      | 0.081  |
| MBI15 | 0      | 0      | 0.030  | 0.029  | 0.015  | 0      | 0      | -0.027 | -0.027 | 0.267  | 0.034  | 0.393  | 0.165  | 0.081  | 0      |
| ITL1  | -0.026 | 0      | -0.045 | 0.101  | -0.004 | 0.020  | 0.070  | 0.058  | 0.001  | 0.028  | -0.019 | -0.001 | 0      | -0.037 | 0      |
| ITL2  | 0.110  | 0      | 0.060  | -0.131 | 0      | 0.014  | 0      | 0.033  | 0      | -0.192 | 0.019  | 0      | 0.036  | 0.164  | -0.046 |
| ITL3  | -0.024 | -0.011 | -0.009 | 0      | 0      | -0.010 | -0.011 | -0.037 | 0      | 0      | -0.024 | 0      | -0.037 | -0.071 | 0      |
| ITL4  | -0.061 | 0      | -0.008 | 0.090  | 0      | 0      | 0.008  | 0      | 0      | 0.165  | 0.014  | 0      | 0      | -0.166 | 0      |

## Network centrality estimation

Centrality indices for each node in the burnout–intent to leave network are presented in Table 3 and Fig. 2. In terms of node strength, MBI14 ("I feel that I have completed a lot of valuable work") emerged as the most central node (strength = 2.250, closeness = 0.00715, betweenness = 80), indicating its pivotal role within the network. MBI4 ("Working all day is indeed very stressful for me") demonstrated the second highest centrality (strength = 1.980, closeness = 0.00692, betweenness = 90), followed by MBI10 ("I am able to effectively solve problems that arise in my work") (strength = 1.784, closeness = 0.00635, betweenness = 60). In terms of bridge expected influence, the key bridge nodes linking burnout symptoms to intent to leave were MBI6 ("Since starting this job, I've become increasingly disinterested in it") and MBI8 ("I doubt the significance of the work I do"), both of which are depersonalization items. Figure 2 shows the centrality and bridge strength of each node in the burnout–intent to leave network. The most predictable symptoms were MBI4, MBI7, and MBI14, with corresponding  $R^2$  values of 85.4%, 81.6%, and 79.4%, respectively. For bridge centrality, MBI6 (rbs = 5.247), MBI8 (rbs = 5.032), and MBI7 (rbs = 4.821) had the highest bridge centrality values (Table 3).

Table 3  
Centrality estimates of each item in the network analysis

| Items  | Betweenness | Closeness   | Strength  | Bridge Strength | Bridge Closeness | Bridge Expected Influence (1-step) |
|--------|-------------|-------------|-----------|-----------------|------------------|------------------------------------|
| MBI 1  | 26          | 0.005805071 | 1.7711477 | 4.063314        | 0.10956468       | 2.8471161                          |
| MBI 2  | 0           | 0.00474832  | 1.0144382 | 3.728459        | 0.10726376       | 2.9857186                          |
| MBI 3  | 4           | 0.004627598 | 1.2633892 | 4.144303        | 0.10817543       | 3.3826981                          |
| MBI 4  | 90          | 0.006916078 | 1.9802911 | 3.984887        | 0.11173242       | 2.5816593                          |
| MBI 5  | 0           | 0.00588798  | 1.1549959 | 3.720738        | 0.10833529       | 3.1505697                          |
| MBI 6  | 6           | 0.00410501  | 1.1487311 | 5.247249        | 0.11717262       | 4.50027                            |
| MBI 7  | 42          | 0.004609374 | 1.3439813 | 4.821436        | 0.1141492        | 4.1828209                          |
| MBI 8  | 0           | 0.003713521 | 1.1355518 | 5.031847        | 0.11652589       | 4.2243244                          |
| MBI 9  | 0           | 0.003961624 | 0.9260446 | 4.578683        | 0.11484177       | 3.949036                           |
| MBI 10 | 60          | 0.006354846 | 1.7842527 | 1.689439        | 0.096969         | 0.2981451                          |
| MBI 11 | 6           | 0.005647661 | 1.0599785 | 1.317454        | 0.09001129       | 0.9832626                          |
| MBI 12 | 0           | 0.004487646 | 1.0765662 | 1.304284        | 0.08904922       | 1.0183515                          |
| MBI 13 | 6           | 0.005887286 | 1.0725471 | 2.371368        | 0.09642633       | 1.4742115                          |
| MBI 14 | 80          | 0.007151215 | 2.2495209 | 2.800393        | 0.10118979       | 0.7216009                          |
| MBI 15 | 0           | 0.004893241 | 1.1141268 | 1.173188        | 0.08857718       | 0.8608566                          |
| ITL1   | 0           | 0.004724112 | 1.1888218 | 3.5004          | 0.24015351       | 3.3046654                          |
| ITL2   | 34          | 0.005563163 | 1.4813527 | 3.742286        | 0.26361553       | 3.158018                           |
| ITL3   | 0           | 0.00365966  | 0.6731084 | 3.649121        | 0.0126581        | -3.622524                          |
| ITL4   | 14          | 0.005052284 | 1.2538313 | 3.074           | 0.23374501       | 2.5199024                          |

Figure 3 shows the raw BEI values of each node. The node MBI6 “Since starting this job, I’ve become increasingly disinterested in it” and the node MBI8 “I doubt the significance of the work I do.” had the highest BEI values overall (BEI = 4.50 and 4.22, respectively). This indicates that these two nodes represent critical bridge symptoms.

The results demonstrate that the CS coefficients for bridge strength, closeness, and strength are all 0.75, suggesting that the network’s structure remains substantially unchanged when 75% of the sample is omitted, indicating good stability.

To further test the network accuracy and stability, edge-weight bootstrapping and CS-coefficient were calculated. The results of edge-weight bootstrapping showed in Figure. 4, the bootstrapped 95% CI (the grey area) was narrow, suggesting that the estimation of edge weights was accurate and stable.

The accuracy of the centrality indices, shown in Figure. 5, is high for bridge strength, closeness, and strength, followed by betweenness. These findings indicate that the network model for burnout and intent to leave is both accurate and stable.

## Discussion

Network analysis was used to explore the symptom-level interconnections between burnout and intent to leave among public health workers in China. To our knowledge, this is the first study to apply network analysis to examine these interconnections in this population. In the burnout–intent to leave network, MBI14 (“I feel that I have completed a lot of valuable work”), MBI4 (“Working all day is indeed very stressful for me”), and MBI10 (“I am able to effectively solve problems that arise in my work”) emerged as the most central nodes. The key bridge symptoms linking burnout to intent to leave were the depersonalization items MBI6 (“Since starting this job, I’ve become increasingly disinterested in it”) and MBI8 (“I doubt the significance of the work I do”). These findings may help deepen our understanding of how burnout propagates toward intent to leave among public health workers, reveal the mechanisms through which burnout and turnover cognitions are mutually maintained, and provide more precise targets for organizational intervention and workforce retention strategies.

In this study, public health workers in China reported moderate to high levels of burnout across all three dimensions, consistent with findings from other studies conducted during and after the pandemic[1, 7, 8]. The sustained occupational demands placed on this workforce, including extended working hours, heightened responsibilities in outbreak response, and persistent fears of infection, likely contributed to elevated burnout levels in this sample [29].

A higher strength value of a node indicates stronger connections with other nodes in the network, reflecting greater influence over the activation and maintenance of surrounding symptoms[14]. In this study, MBI14 (“I feel that I have completed a lot of valuable work”) was the most central node in the burnout–intent to leave network. This finding is consistent with prior research demonstrating that perceived work accomplishment is a critical buffer against burnout and intent to leave, as it reinforces employees’ professional identity and sense of purpose[17, 30]. For public health workers in China, who have

carried prolonged and often underrecognized responsibilities during the pandemic, a diminished sense of accomplishment may represent a particularly significant vulnerability. When workers feel that their contributions are not valued or visible, this perception may erode their motivation and hasten disengagement from the profession [31]. This finding suggests that organizational interventions aimed at strengthening workers' sense of accomplishment, such as regular supervisory feedback highlighting the impact of their work, redesigning roles to align more closely with professional values, and cultivating a workplace culture that connects daily tasks to broader public health outcomes, may be especially effective in reducing both burnout and intent to leave.

Furthermore, MBI4 ("Working all day is indeed very stressful for me") was the second most central node in the network, indicating that chronic occupational stress plays a pivotal role in sustaining the burnout–intent to leave network among Chinese public health workers. This finding is particularly salient in the post-COVID-19 context, where public health workers have assumed critical and sustained responsibilities in outbreak control and population health protection under persistently high-pressure conditions[29]. This result aligns with the Job Demands-Resources (JD-R) model, which posits that excessive job demands deplete employees' energy reserves and increase the risk of burnout[32]. The strong connection between MBI4 and MBI5 ("Work makes me feel like I'm on the verge of a breakdown") (edge weight = 0.508) further underscores the role of chronic stress in driving emotional exhaustion. Interventions targeting workload management, including task redistribution, flexible scheduling, and adequate staffing, may help mitigate the impact of occupational stress and its downstream effects on workforce retention.

In addition, MBI10 ("I am able to effectively solve problems that arise in my work") was identified as an important central node, reflecting the significance of professional efficacy within this network. This finding is consistent with network theory in psychopathology, wherein central symptoms act as hubs that sustain the activation of related constructs across the network[14, 16]. When public health workers perceive themselves as capable and effective in their roles, this sense of competence may serve as a protective resource against both burnout and the inclination to leave. Conversely, diminished professional efficacy may amplify feelings of exhaustion and disengagement, further reinforcing the burnout–intent to leave cycle. Organizations may therefore benefit from investing in continuing professional development, clinical supervision, and peer support mechanisms that enhance workers' perceived competence and self-efficacy.

Notably, the bridge symptoms identified in this study as, MBI6 ("Since starting this job, I've become increasingly disinterested in it") and MBI8 ("I doubt the significance of the work I do"), were both depersonalization items. Bridge symptoms connect different symptom clusters within a network and facilitate the transmission of distress from one domain to another [16]. The identification of these two depersonalization items as bridges suggests that the erosion of work interest and perceived work significance represents a critical pathway through which burnout propagates toward intent to leave. This finding aligns with prior network studies of burnout and turnover intention among nurses[17, 18], which similarly identified depersonalization as a key conduit between burnout symptoms and withdrawal cognitions. Deactivating these bridge symptoms, through interventions that restore a sense of meaning, engagement, and professional identity, may effectively disrupt the pathway from burnout to intent to leave and reduce the risk of workforce attrition[16, 33].

The study also identified strong within-cluster connections among the intent to leave items, particularly between ITL1 ("I would prefer another more ideal job") and ITL4 ("I seriously intend to look for another job within the next year") (edge weight = 0.372), and between ITL1 and ITL2 ("I have thought seriously about changing agencies") (edge weight = 0.310). The dense interconnections among these items suggest that once turnover cognitions are activated, they tend to reinforce one another rapidly, moving workers from vague job dissatisfaction to concrete plans to leave. During sustained crises such as the COVID-19 pandemic, chronic stressors may accelerate this process, transforming passive disengagement into active turnover behavior[34]. These findings point to the importance of early organizational detection and intervention, before withdrawal cognitions become entrenched.

The central and bridge symptoms identified through network analysis in this study carry important implications for workforce retention policy and practice. According to network theory of psychopathology, interventions targeting central symptoms are likely to have the greatest disruptive effect on the overall network, reducing its overall severity and preventing the cascading activation of related symptoms[14, 35]. This suggests that effective interventions addressing MBI14 (perceived work accomplishment), MBI4 (occupational stress), and MBI10 (professional efficacy) may yield the most substantial reductions in both burnout and intent to leave among public health workers. In addition, targeting bridge symptoms such as MBI6 and MBI8 — for instance, through job redesign, meaning-centred supervision, or cognitive-behavioral approaches — can disrupt the connections between burnout and intent to leave, and thus reduce the likelihood of burnout-driven workforce attrition[16]. Taken together, the network-identified central and bridge symptoms offer a data-driven and parsimonious foundation for the development of targeted retention strategies in public health settings.

## Strengths and limitations

Several strengths of this study should be noted. This is the first study to apply network analysis to examine the interconnections between burnout and intent to leave among public health workers in China, offering a novel symptom-level perspective that goes beyond traditional aggregate approaches. The large, nationwide sample enhances the generalizability of the findings within the Chinese public health context, and the use of bootstrap procedures ensures the stability and reliability of the network model.

However, several limitations should be acknowledged when interpreting these findings. First, the cross-sectional design of this study precludes causal inference regarding the directionality of symptom relationships. Future longitudinal studies are needed to verify the temporal dynamics and causal pathways identified in the network. Second, data were collected via self-report, which may be subject to recall bias and social desirability effects, and self-reported symptoms cannot be treated as clinically confirmed diagnoses. Third, although the overall sample was large, subgroup analyses by profession type, facility type, or geographic region were not performed; different subgroups may exhibit distinct network structures, and this warrants investigation in future research. Finally, potentially relevant covariates such as age, sex, and institutional characteristics were not incorporated into the network model, which may have influenced the observed associations.

## Conclusions

This study is one of the first studies to apply network analysis to examine the symptom-level interconnections between burnout and intent to leave among public health workers in China. Using a large, nationwide sample and robust network estimation procedures, we identified three central symptoms as the most influential nodes sustaining the burnout–intent to leave network. Critically, two items of *depersonalization* emerged as the primary bridge symptoms linking burnout to intent to leave, suggesting that erosion of work interest and perceived meaning represents the central pathway through which burnout escalates into turnover cognitions. Further interventions should strengthen public health workers' sense of accomplishment, manage chronic workload, enhance professional self-efficacy, and restore a sense of professional meaning and engagement are likely to exert the greatest impact on disrupting the burnout–intent to leave cycle. Early organizational detection of disengagement, particularly diminished interest in work and doubts about its value, may be especially important given the dense within-cluster connections observed among intent to leave items, which suggest that once withdrawal cognitions are activated they rapidly reinforce one another. Overall, the symptom-level, network-based approach adopted here offers a more granular and actionable framework for understanding and addressing burnout-driven workforce attrition in public health, with particular relevance for systems navigating the sustained occupational consequences of the COVID-19 pandemic in China.

## Abbreviations

MBI, Maslach Burnout Inventory; ITL, Intent to Leave; EE, Emotional Exhaustion; DP, Depersonalization; PA, Personal Accomplishment.

## Declarations

### Ethics approval and consent to participate

This study was approved by the Ethics Committee of Zhongnan Hospital of Wuhan University (Approval No. 2025085K). All procedures involving human participants were performed in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Electronic informed consent was obtained from all participants prior to their participation in the study.

### Consent for publication

Not applicable.

### Availability of data and materials

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

### Competing interests

The authors declare that they have no competing interests.

### Funding

This research received no external funding.

### Authors' contributions

KJ and KL conceived and designed the study. CGM, ZXX, and XH contributed to study design. CGM, ZSH, WL, ZS, and LJ collected the data. CGM and WSJ analyzed the data. CGM, WSJ, KJ, and KL interpreted the data. CGM, WSJ, ZXX, and KL drafted the manuscript. All authors read and approved the final manuscript.

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## Figures

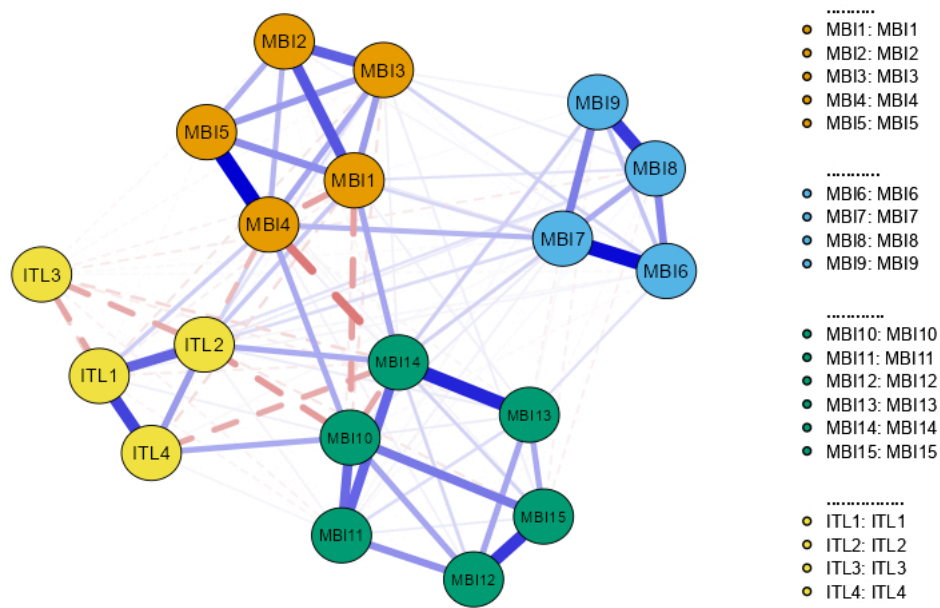


**Figure 1**

**Network structure of burnout and intent to leave among public health workers.**

Nodes: orange nodes= emotional exhaustion, blue nodes = depersonalization, green nodes = reduced personal accomplishment, yellow nodes = intent to leave. Blue edges = positive partial correlations; red edges = negative correlations. Thicker edges indicate stronger associations.

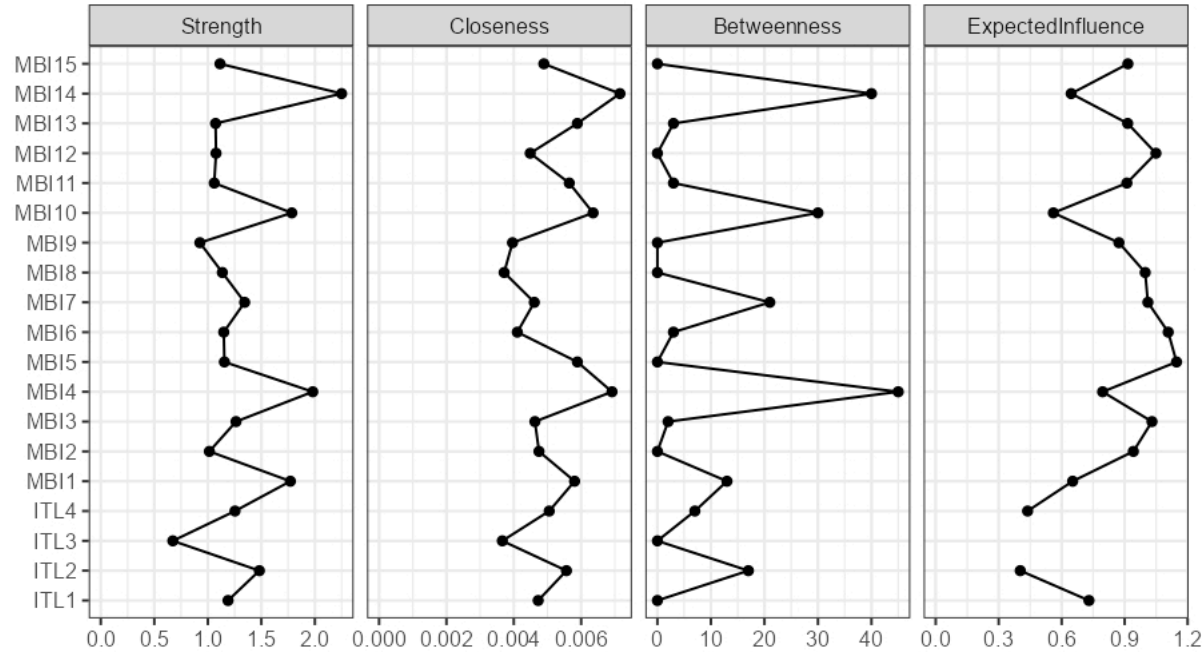


**Figure 2**

presents line graphs of the centrality indices for symptoms within the burnout and intent to leave symptom cluster network.

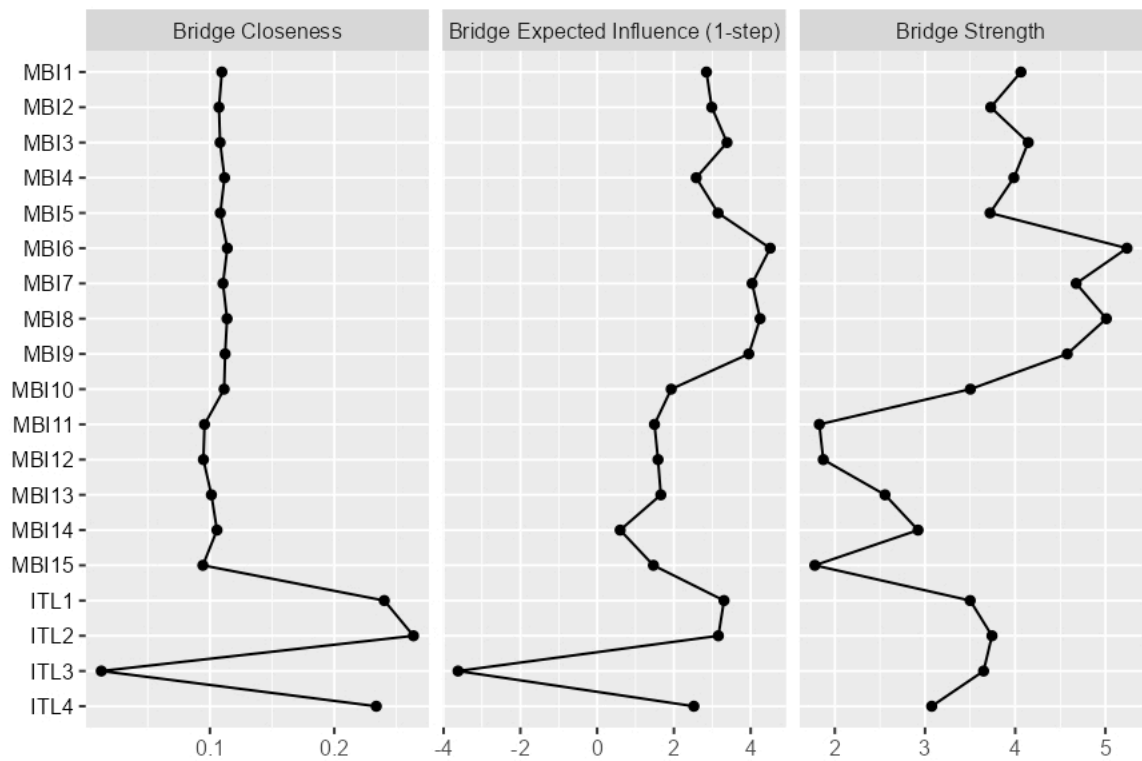


**Figure 3**  
the raw BEI values of each node.

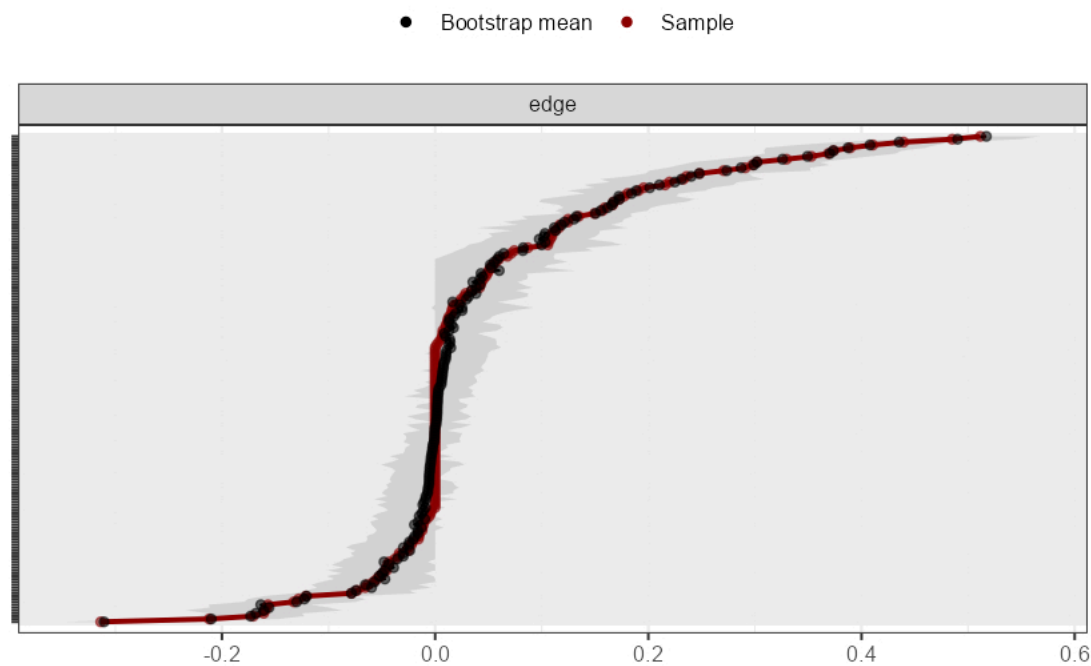


**Figure 4**  
Accuracy of edge weights in the network. The red line depicts the sample edge weights, the black line represents bootstrap means, and the grey bar depicts the bootstrapped confidence interval.

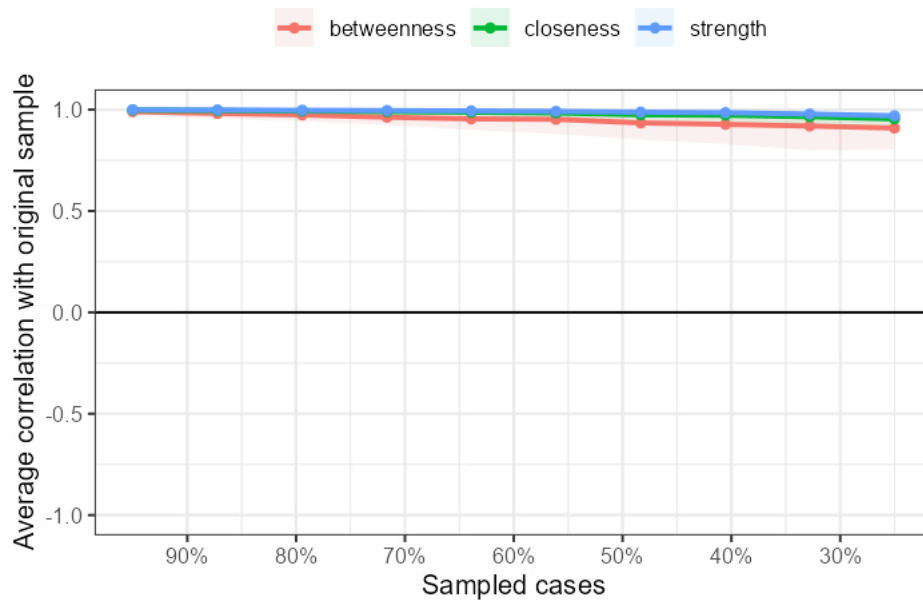


**Figure 5**

Average correlation with original sample for different centrality measures across

### Supplementary Files

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

- [LicensefortheMaslachBurnoutInventory.pdf](#)