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A Study on the Heterogeneity of Sleep Quality and Potential Priority Symptoms for Intervention in the Elderly Population in Shanghai's Communities Based on Latent Profile Analysis and Symptom Networks

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[Abstract]

Background: Sleep disorders in community-dwelling older adults are heterogeneous, yet interventions typically target the population as a whole. Identifying data-driven sleep subtypes and their distinct symptom-level mechanisms may support precision

management. This study aimed to identify sleep quality subtypes among older adults in Shanghai communities using latent profile analysis (LPA) and to characterize subtype-specific symptom networks and potential intervention targets.

Methods: A total of 11,719 community-dwelling adults aged ⩾60 years were recruited from April to August 2019. Sleep quality was assessed with the Pittsburgh Sleep Quality Index (PSQI). LPA was used to identify sleep subtypes. For each subtype, an EBICglasso symptom network was estimated, and networks were compared using the Network Comparison Test (NCT). Two-step Expected Influence (EI-2) was used to rank potential intervention targets, and case-dropping bootstrap assessed stability.

Results: Four sleep subtypes were identified: healthy sleep (*n*=7,443, 63.51%), insufficient nighttime sleep (*n*=2,355, 20.10%), difficulty falling asleep (*n*=751, 6.41%), and severe sleep disorder (*n*=1,170, 9.98%). NCT showed that networks differed significantly in structure across subtypes *(P*=0.002 to *P*<0.001), whereas global strength differed only between the healthy and severe groups *(P*=0.044). EI-2 simulations identified daytime dysfunction as the priority target in the healthy, difficulty-falling-asleep, and severe groups, and subjective sleep quality in the insufficient-sleep group. Symptoms of anxiety and depression, female gender, and histories of coronary heart disease and stroke were risk factors for insufficient nighttime sleep and severe sleep disorder, while adequate daily vegetable intake (⩾300 g) was protective.

Conclusions: Sleep quality in Shanghai community older adults comprises four distinct subtypes with fundamentally different symptom-interaction patterns. Subtype-specific

network structures and EI-2-ranked targets support tailored rather than one-size-fits-all sleep management in this population.

Keywords: Sleep Quality; Latent Profile Analysis; Symptom Network; Elderly People; Intervention Targets

Sleep problems are a common health issue among the elderly[1]. Not only do they directly reduce the quality of life for older adults[2] and impair cognitive function[3] , but they are also closely associated with chronic diseases common in older adults, such as cardiovascular and cerebrovascular diseases[4] and mental and psychological disorders[5] . As such, they are a major risk factor that exacerbates the health burden on the elderly population.Currently, in clinical and population-based studies, the Pittsburgh Sleep Quality Index (PSQI) total score is commonly used to assess sleep quality[6] . Although this method is simple and easy to administer, it can only evaluate sleep quality at a general level[7] . Sleep structure in the elderly is complex, and the manifestations of sleep abnormalities vary significantly from person to person[8] ; for some individuals, difficulty falling asleep is the primary symptom, while for others, insufficient sleep duration or difficulty maintaining sleep predominates, and still others exhibit multidimensional, severe sleep disturbances[9] ; stratification based solely on a single total score makes it difficult to accurately distinguish between different sleep subtypes and fails to identify the independent risk factors for each type of sleep problem, resulting in a lack of targeted prevention and control for sleep issues in the elderly[10] .Traditional analyses typically treat each dimension of the PSQI as an

independent variable and analyze them separately[11] . This approach overlooks the dynamic interactions among symptoms and fails to reveal how they influence and reinforce one another[12] , making it difficult to determine which specific symptom should be prioritized for intervention and leaving precision interventions without a clear point of focus.

As a model-based method for analyzing population heterogeneity, LPA can more accurately identify different sleep quality phenotypes in the elderly population based on the intrinsic patterns of observed indicators[13] . Currently, sleep health management for community-dwelling older adults largely relies on uniform screening criteria and lacks classification and intervention strategies based on population heterogeneity. Furthermore, there is still a shortage of LPA-based studies on sleep quality phenotyping in community-dwelling older adults, and the precision of primary healthcare services needs to be improved[13] . In recent years, symptom network analysis has provided a new perspective for understanding the underlying mechanisms of mental, psychological, and behavioral health issues. Based on Gaussian graphical models, this method estimates partial correlations among symptoms to identify central symptoms within the network as well as priority symptoms for intervention that exhibit statistically significant cascading patterns[14] .In the field of sleep, network analysis has gradually been applied to reveal dynamic interaction patterns among insomnia symptoms; however, existing studies have primarily focused on clinical patients or single populations, and research based on large community samples comparing differences in network structures among different sleep subtypes remains a gap in the

literature[15] .Combining LPA with symptom network analysis not only identifies heterogeneous subtypes at the population level but also elucidates the underlying mechanisms linking these subtypes and identifies potential priority symptoms for intervention at the symptom level, thereby providing a dual basis of "subtype classification and target identification" for the precise prevention and control of sleep disorders among older adults in the community [16].

Based on this, the present study utilized the community population cohort from Renji Hospital, affiliated with Shanghai Jiao Tong University School of Medicine. Drawing on baseline survey data collected from 37 community residents' committees in Shanghai between April and August 2019, the study employed the seven-factor scores of the PSQI as the basis for subtyping and applied the LPA method to classify latent subtypes of sleep quality;EBICglasso was used to construct symptom networks for each subtype, and network comparison tests (NCT) were employed to verify structural differences between groups. Centrality metrics and EI-2 simulation were combined to identify priority symptoms for potential intervention; multivariate logistic regression was used to analyze the influencing factors of each subtype. The study aimed to clarify the heterogeneous characteristics of sleep quality among older adults in Shanghai communities; reveal differences in the structural characteristics of symptom networks across different sleep subtypes and identify core symptoms prioritized for potential intervention;and to screen for modifiable risk and protective factors. This study provides empirical evidence for developing precise prevention and control strategies for sleep disorders among older adults in the community and for improving

the level of health management for this population. The baseline data were collected prior to the outbreak of the novel coronavirus pandemic, representing a representative snapshot of this population's sleep and health status at that time, and can also serve as a reference baseline for subsequent cohort follow-up and intervention studies.

Materials and Methods

1. Study Population

The study included 11,814 residents who participated in community-based health examinations for the elderly at 37 neighborhood committees in Shanghai from April to August 2019. Inclusion criteria: (1) Age $\geqslant$ 60 years, having resided in Shanghai for at least 5 years, and holding local social security status; (2) No severe physical disabilities and the ability to communicate normally; (3) Voluntary participation in the study and signing of an informed consent form agreeing to participate in the questionnaire survey;(4) Information on diseases and deaths was managed by local health authorities. Exclusion criteria: 95 participants with incomplete sleep data. A total of 11,719 older adults were included, with a completion rate of 99.2%. All study participants signed informed consent forms. This study adhered to the Declaration of Helsinki and was approved by the Ethics Committee of Renji Hospital, Affiliated to Shanghai Jiao Tong University School of Medicine (Approval No.: KY2019-101).

2. Survey Content

Interviewers who had undergone standardized and rigorous training conducted face-to-face interviews using a structured questionnaire to collect data from the study

participants. The questionnaire included the following sections:

2.1. Demographic characteristics: gender, chronological age, educational level, and occupation prior to retirement.

2.2. Physical Examination: Measurement of height and weight; Body Mass Index (BMI) calculated using the formula: weight (kg) / height (m^2)[17] .

2.3. Medical History: Inquire whether the study participants have a history of hypertension, diabetes, coronary heart disease, stroke, atrial fibrillation, heart failure, malignant tumors, or other diseases, and the age at diagnosis.

2.4. Assessment of Anxiety and Depression: Anxiety was assessed using the Generalized Anxiety Disorder Scale (GAD-7)[18] , and depression was assessed using the Patient Health Questionnaire-9 (PHQ-9)[19] .The GAD-7 scale has a total score range of 0-21, and the PHQ-9 scale has a total score range of 0-27.In this study, a GAD-7 score of 0-4 was defined as no anxiety symptoms, and 5-21 as anxiety symptoms; a PHQ-9 score of 0-4 was defined as no depressive symptoms, and 5-27 as depressive symptoms. Participants with either anxiety or depressive symptoms, or both, were uniformly classified as having anxiety and depressive symptoms[20] .

2.5. Daily Behavioral Habits: In this study, daily behavioral habits are defined as follows: (1) Smoking: At least one cigarette per day for at least 6 months; (2) Tea consumption: At least 3 times per week for at least 6 consecutive months; (3) Coffee consumption: At least one cup per week for at least 6 months;(4) Alcohol consumption: At least once a week over the past year. Daily adequate vegetable intake was recorded. Additionally, the International Physical Activity Questionnaire (IPAQ) was used to

record the time spent weekly on physical exercise, commuting, and housework. The IPAQ uses metabolic equivalents (MET) as the unit of measurement and calculates total weekly physical activity using the following formula:Weekly physical activity level (MET-min/week) = MET value × daily physical activity duration (min/day) × number of active days per week (days/week). Individual physical activity levels were classified into three categories-low, moderate, and high-based on the classification criteria recommended by the International Physical Activity Committee. A high level of physical activity is defined as meeting one of the following criteria: (1)A total of ⩾ 3 days of various high-intensity physical activities per week, and a total physical activity level of ⩾1,500 MET-min/week. (2) A total of ⩾7 days of physical activities across three intensity levels per week, and a total physical activity level of ⩾ 3,000 MET-min/week. A moderate physical activity level is defined as meeting one of the following criteria: (1) At least 20 minutes of various high-intensity physical activities per day, totaling ⩾3 days per week.(2) At least 30 minutes of any type of moderate-intensity physical activity daily, totaling ⩾5 days per week. (3) A total of ⩾5 days per week of physical activity across three intensity levels, with a total physical activity level of ⩾ 600 MET-min/week.A low level of physical activity is defined as reporting no activity or reporting some activity that does not meet the criteria for moderate or high levels of physical activity[21] .

2.6. Sleep Quality Survey: The PSQI scale was used to collect information on the participants' sleep over the past month. The PSQI evaluates participants' sleep quality based on the total score across seven sleep dimensions: self-reported sleep quality, time

to fall asleep, sleep duration, sleep efficiency, sleep disturbances, frequency of hypnotic medication use per week, and daytime functioning[22] .Factor 1 (Subjective Sleep Quality): Scored directly based on the response to Question C16, with “Very Good” scored as 0, “Fairly Good” as 1, “Fairly Poor” as 2, and “Very Poor” as 3.Factor 2 (sleep latency): A composite score based on Question C2 (time required to fall asleep; 0 points for ⩽15 minutes, 1 point for 16-30 minutes, 2 points for 31-60 minutes, and 3 points for >60 minutes) and Question C6(frequency of difficulty falling asleep: “None” = 0 points; “< 1 time/week” = 1 point; “1-2 times/week” = 2 points; “⩾ 3 times/week” = 3 points). The scores from both questions are added together, and based on the total score (0 points = 0 points; 1-2 points = 1 point; 3-4 points = 2 points; 5-6 points = 3 points), a score of 0-3 points is assigned accordingly.Factor 3 (Sleep Duration): Based on the actual number of hours slept reported in Question C4, >7 hours is scored as 0 points, 6-7 hours as 1 point, 5-6 hours as 2 points, and <5 hours as 3 points.Factor 4 (Sleep Efficiency): First, calculate the time spent in bed using Question C1 (time of going to bed) and Question C3 (time of waking up). Then, calculate the sleep efficiency percentage by dividing the actual sleep duration from Question C4 by the time spent in bed. A score of ⩾85% is scored as 0 points; 75%-84% as 1 point; 65%-74% as 2 points; and <65% as 3 points.Factor 5 (Sleep Disturbances): Score each of questions C7 through C15 (a total of 9 items regarding factors affecting sleep, including waking frequently during the night or waking too early, nighttime trips to the bathroom, difficulty breathing, coughing or loud snoring, feeling cold, feeling hot, having nightmares, pain or discomfort, and other issues affecting sleep) based on frequency

(“None” scores 0 points, “<1 time per week” scores 1 point,“1-2 times/week” scores 2 points, “≥3 times/week” scores 3 points). Add the scores from all 9 questions, then assign a score of 0-3 points based on the total score (0 points for 0 points, 1-9 points scores 1 point, 10-18 points scores 2 points, 19-27 points scores 3 points).Factor 6 (Use of Hypnotics): Based on the frequency of use reported in Question C17, “None” counts as 0 points, “< 1 time per week” counts as 1 point, “1-2 times per week” counts as 2 points, and “≥ 3 times per week” counts as 3 points.Factor 7 (Daytime Impairment): Combining Question C18 (frequency of feeling drowsy; “None” = 0 points, “< 1 time/week” = 1 point, “1-2 times/week” = 2 points, “≥ 3 times/week” = 3 points) and Question C19 (degree of lack of energy for activities; “None” = 0 points, “occasionally” scores 1 point, “sometimes” scores 2 points, and “often” scores 3 points). Add the scores from both questions, and assign a score of 0-3 points based on the total (0 points for 0 points, 1-2 points for 1 point, 3-4 points for 2 points, and 5-6 points for 3 points)[23] .

3. Quality Control

This study implemented strict quality control throughout the entire process—from questionnaire design, field surveys, and data entry to statistical analysis—to ensure that the data are authentic, accurate, and reliable. During the questionnaire design phase, items were optimized through expert consultation and pilot surveys, and the survey process was standardized. All interviewers underwent uniform, rigorous, and standardized training and assessment to ensure consistency in interview tone and methodology.A three-tier quality control system was implemented during the field survey: Tier 1 quality control involved field quality control officers reviewing each

questionnaire individually to check for missing values, outliers, and logical inconsistencies; Tier 2 quality control involved data administrators conducting batch checks on the database through program audits and logical validation; Tier 3 quality control involved third-party personnel randomly selecting 5% of the study participants to verify the information and confirm the authenticity of the data.During the data management phase, data was entered independently by two people in two separate passes, and data was locked prior to analysis to ensure the scientific reliability of the study results.

4. Statistical Methods

Data entry and verification were performed using Access 2021 database management software, while computer-based logical checks were conducted using SPSS 25.0 and SAS 9.4. Data analysis was performed using R 4.5.0. Normally distributed continuous variables were described using the $\bar{x} \pm s$; non-normally distributed continuous variables were described using the median (interquartile range) [$M(Q_1, Q_3)$];categorical data were expressed as counts (%). Intergroup differences were compared using the χ^2 test. Based on cross-sectional survey data, LPA identified statistically heterogeneous subtypes based on the seven-factor PSQI scores, rather than clinical diagnostic categories. LPA was used to determine the latent classifications of sleep in older adults and their proportions, specifically using the seven PSQI factors as observed variables and setting the number of categories from 1 to 5 for LPA model fitting and estimation.In accordance with methodological recommendations, the following criteria were used: the Akaike Information Criterion (AIC), the Bayesian

Information Criterion (BIC), the adjusted Bayesian Information Criterion (aBIC), the entropy index,the Lo-Mendell-Rubin (LMR) test and the Bootstrapped Likelihood Ratio Test (BLRT) to evaluate model fit. Smaller values of AIC, BIC, and aBIC indicate better model fit; the entropy index ranges from 0 to 1, with values closer to 1 indicating higher precision;The LMR and BLRT were statistically significant ($P < 0.05$), indicating that the k-model outperforms the k-1 model. Factors showing statistical differences in the univariate analysis were used as independent variables, and the results of the latent profile analysis were used as dependent variables. Multivariate logistic regression was performed, adjusting for confounding factors such as age, sex, educational level, pre-retirement occupation, smoking, alcohol consumption, BMI, physical activity level, and vegetable intake;There were a small number of missing values for BMI, physical activity level, daily vegetable intake, and history of stroke (71, 104, 225, and 2 cases, respectively, all <2%); continuous variables were imputed using the mean, and categorical variables using the mode. Symptom network analysis was based on partial correlation networks estimated using the EBICglasso algorithm, revealing statistical association patterns among the seven PSQI factors rather than causal directions or dynamic evolutionary sequences.The EBICglasso algorithm was used to estimate the regularized partial correlation networks for each subtype. The EBIC tuning parameter γ was set to 0.5 to balance model fit and sparsity. To ensure cross-group comparability of the four sets of network diagrams, averageLayout was used to unify node coordinates, and the maximum absolute edge weight across the four groups served as the global scale for standardizing edge colors and thickness.Strength

centrality (i.e., out-degree) was calculated to identify core symptoms for each subtype. The 2-step Expected Influence (EI-2) simulates latent cascade patterns based on statistical associations—that is, "if a symptom node is statistically highly associated with other nodes, then intervening on that symptom may produce changes in associations within the statistical network"—rather than causal validation based on longitudinal or experimental data.Furthermore, EI-2 is used to simulate priority symptoms for potential intervention, where EI-2 = 1-step EI + the sum of the 1-step EI values of neighboring nodes; the symptom with the highest EI-2 value is identified as the priority symptom for potential intervention in that subtype. The stability of the centrality ranking is assessed using case-dropping bootstrap analysis to calculate the CS-coefficient (correlation stability);A CS-coefficient > 0.5 indicates an acceptable centrality ranking, while > 0.7 indicates good stability. The Network Comparison Test (NCT) was used to compare structural differences between the two networks, with 1,000 permutations. Test metrics included global strength differences and network structural invariance. Two-sided tests were conducted at a significance level of $\alpha = 0.05$.

Results

1. Results of the Latent Profile Analysis of Sleep Quality Among the Elderly in Shanghai Communities

Using the seven PSQI factors as indicators, latent profile models with 1 to 5 categories were fitted stepwise (Table 1).The results show that as the number of categories increased, the values of information criteria (AIC, BIC, and aBIC) gradually decreased, indicating a continuous improvement in model fit. When the model was

expanded from 4 categories to 5 categories, the BLRT *P*-value was 0.237 ($P > 0.05$), suggesting that the 5-category model did not represent a significant improvement over the 4-category model.For models with 2, 3, and 4 categories, the *P*-values for both the LMR and BLRT were all <0.001. Based on these metrics, the 4-category model provided the best fit, classifying the 11,719 study participants into four latent categories with the following category probabilities: the healthy sleep group at 63.51% (n = 7,443),the group with insufficient nighttime sleep at 20.10% (n = 2,355), the group with difficulty falling asleep at 6.41% (n = 751), and the group with severe sleep disorders at 9.98% (n = 1,170). See Table 1 for details.

2. Characteristics and Nomenclature of the Latent Profile Analysis of Sleep Quality Among Older Adults in Shanghai Communities

Using the four sleep patterns identified by LPA, we conducted an in-depth comparison of their scoring characteristics across the seven dimensions of the PSQI. Based on the fitting results in Table 1, we plotted latent profiles of sleep patterns among community-dwelling older adults, with the results shown in Figure 1. The “healthy sleep group” refers to the group with the lowest scores across all PSQI dimensions; older adults in this group generally have good overall sleep quality.The “Insufficient Nighttime Sleep Group” refers to the group with the highest score on the sleep duration dimension among groups without severe overall disturbance, indicating significantly insufficient sleep; scores on the sleep efficiency dimension are also relatively high, suggesting that this group faces dual issues of insufficient sleep duration and low sleep efficiency.The “Difficulty Falling Asleep Group” refers to the group with elevated

scores on the“Time to Fall Asleep” dimension, second only to the severe group; difficulty falling asleep is the core characteristic of this group. The “Severe Sleep Disorder Group” refers to the group with high scores across all seven dimensions, particularly in the “Sleep Duration” and “Sleep Efficiency” dimensions, indicating that this group has the most severe overall sleep problems and that sleep disorders have already had a significant impact on daytime functioning.

3. Univariate Analysis of Potential Sleep Quality Categories Among Older Adults in Shanghai Communities

The results of the univariate analysis showed that the four sleep patterns differed statistically significantly in terms of gender, age, educational level, pre-retirement occupation, smoking, alcohol consumption, BMI, IPAQ, daily adequate vegetable intake, symptoms of anxiety and depression, history of coronary heart disease, and history of stroke (all $P < 0.05$). See Table 2 for details.

4. Multivariate Logistic Regression Analysis of Different Latent Categories of Sleep Quality Among Older Adults in Shanghai Communities

After adjusting for confounding factors via multivariate logistic regression analysis, the results showed that the associated factors for different subtypes of sleep disorders exhibited both common characteristics and subtype-specific features. Analysis of common factors revealed that anxiety and depression symptoms, female gender, and a history of coronary heart disease were significantly associated with all types of sleep disorders, and the strength of these associations increased with the severity of the sleep disorder.Among these, anxiety and depression symptoms had the

most significant effect; the *OR* values for insufficient nighttime sleep, difficulty falling asleep, and severe sleep disorders were 2.79 (95% *CI*: 2.44–3.18), 6.90 (95% *CI*: 5.81–8.20), and 12.18 (95% *CI*: 10.52–14.09), respectively;For women, the corresponding *OR*s were 1.22 (95% *CI*: 1.08–1.38), 1.63 (95% *CI*: 1.31–2.03), and 1.79 (95% *CI*: 1.48–2.17);The corresponding *OR*s for a history of coronary heart disease were 1.31 (95% *CI*: 1.13–1.52), 1.32 (95% *CI*: 1.06–1.66), and 2.17 (95% *CI*: 1.82–2.59).A history of stroke was associated with the group with insufficient nighttime sleep duration (*OR* = 1.43, 95% *CI*: 1.08–1.89) and the group with severe sleep disorders (*OR* = 1.78, 95% *CI*: 1.25 – 2.53). Compared with the normal BMI group, the groups with a BMI of 24.0 – <28.0 kg/m² and ⩾28.0 kg/m² were both associated with a reduced risk of of sleep abnormalities, with *OR* values of 0.88 (0.80 – 0.98), 0.80 (0.67 – 0.94),0.81 (0.69 – 0.93), 0.87 (0.75 – 1.01), 0.73 (0.57 – 0.93), and 0.67 (0.54 – 0.83), respectively.Daily vegetable intake of ⩾300 g was associated with a reduced risk of difficulty falling asleep (*OR* = 0.49, 95% *CI*: 0.40–0.59) and severe sleep disturbances (*OR* = 0.61, 95% *CI*: 0.53–0.72); however, an inverse association was observed in the group with insufficient nighttime sleep duration (*OR* = 1.14,95% *CI*: 1.03–1.26), which may be related to residual confounders such as occupational composition in this group and should be interpreted with caution. Subgroup-specific analysis: A high school education or higher was a protective factor only for insufficient nighttime sleep duration (*OR* = 0.78, 95% *CI*: 0.62–0.99);being a farmer was associated with a reduced risk of insufficient nighttime sleep and severe sleep disorders, with *OR* values of 0.66 (95% *CI*: 0.59–0.74) and 0.74 (95% *CI*: 0.63–0.87), respectively. The differences in

characteristics and influencing factors among the four sleep subtypes described above provide a population-based foundation for developing stratified management strategies. See Table 3 for details.

5. Structural Characteristics of the PSQI Seven-Factor Symptom Network Across Four Sleep Subtypes

This study utilized the EBICglasso algorithm to construct the PSQI seven-factor symptom networks for the four sleep subtypes (Figure 2). The network structure of the healthy sleep group was relatively dense, with the strongest edge weight observed between “Subjective Sleep Quality” and “Sleep Disturbance,” and “Daytime Functioning” exhibiting strong associations with multiple nodes; the weighted strength centrality (CS-coefficient) was 0.75, the EI centrality (CS-coefficient) was 0.75, and both demonstrated good stability.In the network of the insufficient nighttime sleep group, “Sleep Duration” was associated with multiple symptom nodes, including “Subjective Sleep Quality,” “Sleep Disturbance,” and “Sleep Efficiency”; the weighted strength centrality (CS-coefficient) was 0.672, the EI centrality (CS-coefficient) was 0.672, and stability was acceptable.The network structure of the “difficulty falling asleep” group was relatively sparse; the “sleep duration” node was not connected to other symptoms, while the edge weight between “subjective sleep quality” and “time to fall asleep” was strong; the weighted strength centrality (CS) coefficient was 0.517 (acceptable), but the EI centrality (CS) coefficient was 0.439 (<0.5), suggesting insufficient stability in the EI centrality ranking for this group, and caution is warranted in interpreting the results.The network in the severe sleep disorder group is densely

connected, with the strongest edge weight between “Daytime Dysfunction” and “Sleep Disorder”; the weighted strength centrality (CS-coefficient) is 0.673, and the EI centrality (CS-coefficient) is 0.673, with both stability levels considered acceptable. A comparison of weighted strength centrality for sleep symptom networks across the four groups is shown in Figure 2e. See Table 4 for details.

6. Simulation of Network Interventions and Priority Symptoms for Potential Interventions

This study used the 2-step Expected Influence (EI-2) metric to assess the intervention priority of each symptom node (Table 5, Figure 3). A higher EI-2 value indicates that intervening on that symptom is more likely to produce a cascade of beneficial effects throughout the network. In the healthy sleep group, “daytime dysfunction” had the highest EI-2 value (1.703), making it the top potential priority for intervention in this group;followed by “sleep disturbance” (1.614) and “subjective sleep quality” (1.492). In the insufficient nighttime sleep group, “subjective sleep quality” had the highest EI-2 value (1.134), making it the top potential priority for intervention in this group.In the difficulty falling asleep group, “daytime dysfunction” had the highest EI-2 value (0.741); however, it should be noted that the EI-2 values for “time to fall asleep” and “sleep efficiency” in this groups network were negative (both -0.137), suggesting the presence of negative spurious correlation edges in this group’s network;Given the relatively small sample size in this group (n = 751) and the sparse network structure, the negative edges may stem from sampling fluctuations or inhibitory effects; their validity must be carefully assessed in conjunction with the

Bootstrap confidence intervals for edge weights (Figure 4).Given that the EI centrality CS-coefficient for this group is only 0.439 (<0.5), the EI-2 ranking results for this group should be used solely as exploratory, hypothesis-generating references.In the severe sleep disorder group, “daytime dysfunction” had the highest EI-2 value (1.317), making it the top potential target for intervention in this group, followed by "subjective sleep quality" (1.093) and "hypnotic medications" (1.005).

7. Network Stability Tests and Network Comparison Tests

Bootstrap analysis of edge weight confidence intervals showed (Figure 4) that, with the exception of the difficulty falling asleep group—where some edge weight confidence intervals were relatively wide—the estimates of primary edge weights were relatively stable across all other groups.This study combined subtype severity and clinical significance to predefine three key intergroup network comparisons. NCT results showed that the difference in global strength between the healthy sleep group and the severe sleep disorder group was statistically significant ($P = 0.044$), and the difference in network structure was significant ($P < 0.001$);there was no statistically significant difference in global strength between the healthy sleep group and the insufficient nighttime sleep group ($P = 0.927$), but the difference in network structure was significant ($P < 0.001$); there was no statistically significant difference in global strength between the difficulty falling asleep group and the severe sleep disorder group ($P = 0.775$), but the difference in network structure was significant ($P = 0.002$). See Table 6 for details.

Discussion

This study used LPA to perform heterogeneity-based clustering of sleep quality among older adults in Shanghai communities. The results showed that the sleep patterns of this population can be classified into four subtypes: healthy sleep, insufficient nighttime sleep duration, difficulty falling asleep, and severe sleep disorders, suggesting that there is significant population heterogeneity in sleep quality among older adults in urban communities in China.Among the 11,719 older adults included in the study, only 63.51% exhibited healthy sleep, while nearly 36.49% presented with sleep abnormalities of various types and degrees of severity. Insufficient nighttime sleep duration was the most common, and severe sleep disorders accounted for nearly 10%, indicating that sleep problems in older adults have become a prominent public health issue.

This study further revealed, through symptom network analysis, that the mechanisms underlying the associations among the seven PSQI factors within each sleep subtype exhibit significant heterogeneity, and that this heterogeneity has clear clinical implications.The NCT results of this study show that, although there were no significant differences in global connection strength among some subtypes, the differences in network structure were all statistically significant ($P < 0.01$), indicating that there are fundamental differences in the “interaction patterns” between symptoms across different sleep subtypes, rather than merely in the strength of associations[24] .This finding echoes the network analysis of insomnia symptoms among healthcare workers during the COVID-19 pandemic conducted by Bai et al.[25] : that

study also found daytime dysfunction to be the most central symptom in the network, yet nighttime and daytime symptoms remained closely connected within the network;In contrast, the severe sleep disorder group in the present study exhibited a characteristic "radial structure" with "daytime dysfunction" as the sole core, and the "time to fall asleep" node was completely isolated. This suggests that difficulty falling asleep at night among individuals with severe sleep disorders in the community may have become detached from the main symptom network, evolving into a relatively independent clinical phenotype that may respond only limitedly to sleep-inducing medications[26] .In this study, the healthy sleep group formed a dual core comprising "subjective sleep quality" and "sleep disturbance," while the group with insufficient nighttime sleep exhibited extensive connections between "sleep duration" and multiple nodes. This "relay-like shift" in core symptoms indicates[27] that, as the severity of sleep disturbance increases, the hub of the symptom network shifts from nocturnal symptoms to daytime consequences, consistent with the "cognitive arousal–daytime functioning" core pathway theory proposed by Roland A et al.[28] . The network in the difficulty falling asleep group was the sparsest, with the "sleep duration" node isolated and a lack of effective interconnections among symptoms; this may be related to the relatively simple clinical phenotype of this group, characterized by prominent core symptoms and few accompanying symptoms[29] .The EI centrality stability in the difficulty falling asleep group was insufficient (CS coefficient < 0.5), suggesting that the reliability of the centrality ranking for this group's network is low, and related interpretations should be made with caution[26] . Future studies should expand the sample size for this subtype

to further validate these findings.

In this study, regarding the identification of potential priority symptoms for intervention, the EI-2 metric was used to assess the intervention priority of each symptom node; this method was selected based on important methodological considerations.Traditional strength centrality identifies only the symptom nodes with the most connections in a network; however, highly connected nodes are not necessarily the targets that will yield the greatest cascading improvements following an intervention. If a node has many connections but most of them are weak or unidirectional, intervening on that node may not effectively drive improvements across the entire network.By integrating a node's own 1-step Expected Influence with that of its neighboring nodes, EI-2 simulates the "total statistical association cascade pattern generated by the propagation of an intervention through the network," making it more suitable for guiding the precise allocation of intervention resources at the community level[30] .The simulation results of this study show that various centrality metrics (including 1-step and 2-step EI) exhibit inconsistent efficacy in identifying valid intervention targets; a high centrality ranking does not necessarily equate to the greatest cascade improvement following an intervention. Therefore, the EI-2 results from this study should be regarded as exploratory evidence for candidate intervention targets , used to generate intervention hypotheses rather than directly serving as intervention prescriptions.The EI-2 simulation results suggest that the top priority potential intervention symptom for both the severe sleep disorder group and the difficulty falling asleep group is "daytime dysfunction," rather than "sleep onset time" or "sleep

duration," which are the primary focuses of traditional interventions; similarly, the healthy sleep group also identified "daytime dysfunction" as the node with the highest EI-2 score.This finding has significant implications for clinical practice: for older adults with severe sleep disorders and difficulty falling asleep, community-based

interventions should move beyond the traditional model of "focusing solely on nighttime sleep" and prioritize the assessment and improvement of daytime functioning, thereby driving improvements in nighttime sleep symptoms through a network-based statistical association cascade model.The underlying mechanisms may involve the following pathways: Impaired daytime functioning is often accompanied by hyperarousal and a delayed circadian rhythm phase; circadian rhythm homeostasis can be restored through structured daytime activities, light exposure, and behavioral activation;Daytime sleepiness and functional decline reinforce patients' anxious expectations regarding nighttime sleep, creating a "worry-insomnia" cognitive cycle; improving daytime functioning can break this vicious cycle; reduced daytime social activities among community-dwelling older adults are an independent risk factor for sleep problems; restoring daytime functioning implies increased social participation and exposure to natural light, which indirectly promotes the normalization of the nighttime melatonin secretion rhythm.The priority target for the group with insufficient nighttime sleep duration is "subjective sleep quality," suggesting that sleep education and correction of misperceptions regarding sleep quality may yield the greatest intervention benefits for this group. This finding is consistent with the bridging role of "sleep dissatisfaction" in the clinical insomnia network, as identified by Zhao N et

al.[31] .The significant differences in network structures among the four subtypes (NCT, $P < 0.01$) further corroborate the necessity of LPA-based classification at the level of symptom-association mechanisms.If the traditional one-size-fits-all approach of using the PSQI total score were adopted, it would overlook the fundamental differences in the "interaction patterns" of symptoms within different subtypes: the group with insufficient nighttime sleep requires network-level cascading improvements through the cognitive restructuring of "subjective sleep quality," while the group with severe sleep disorders requires multidimensional interventions centered on "daytime functioning"[32] .This precise "subtype-target" correspondence is precisely what gives LPA subtyping its clinical translational value through network analysis.

Compared to the traditional PSQI total score stratification method, LPA subtyping overcomes the limitations of a single total score assessment and can accurately capture the core characteristics of different sleep problems: the difficulty falling asleep subgroup is characterized by prolonged sleep latency and difficulty initiating sleep; the insufficient nighttime sleep subgroup is characterized by shortened sleep duration and low sleep efficiency;the severe sleep disorder group encompasses multidimensional severe abnormalities, including difficulty falling asleep, poor sleep maintenance, and impaired daytime functioning. The clinical phenotypic differences among these three subtypes are significant, suggesting that sleep disorders in the elderly do not represent a single disease phenotype but rather exhibit heterogeneous subtypes. Developing differentiated intervention strategies tailored to specific subtypes is far more targeted and effective than generic sleep interventions.

A U.S. study of non-institutionalized older adults aged 65 and older, which—after sample weighting—is representative of a population of approximately 32 million older adults, used the LPA method to classify subgroups based on 24-hour activity pattern features measured by accelerometers and further investigated the association between different activity patterns and depressive symptoms[33] .A prospective study conducted by the UK Biobank used a 0–7-point sleep health score and latent class analysis (LCA) to identify data-driven sleep health patterns. A total of 7,458 all-cause dementia events were recorded during the follow-up period. Cox proportional hazards models were used to analyze the association between multidimensional sleep health status and the risk of developing dementia subtypes, such as Alzheimer's disease and vascular dementia[34] . Related domestic studies have reached similar conclusions. A study on sleep quality among 1,480 shift-working nurses in Fuyang, Anhui, classified participants into four sleep quality categories using LPA and found that perceived stress, frequency of night shifts, and sleep-wake patterns were key indicators distinguishing different sleep categories, confirming the heterogeneous characteristics of sleep quality in specific occupational groups[35] .A multicenter study in Jiangsu recruited 287 older adults from communities in four cities—Nanjing, Changzhou, Nantong, and Xuzhou. Using LPA, the study identified three sleep subtypes: "relatively good sleep," "insufficient sleep," and "difficulty falling asleep—medication-induced sleep." It found that gender, smartphone use, and depressive tendencies were the primary influencing factors, further confirming the significant individual and population-level heterogeneity in sleep quality among older adults[36] .

The results of the multivariate logistic regression analysis in this study showed that symptoms of anxiety and depression, female gender, and a history of coronary heart disease were common risk factors across all abnormal sleep subtypes, with differences in effect sizes among subtypes. Among these, the association with symptoms of anxiety and depression was the most significant, with an OR as high as 12.18 in the severe sleep disorder group, confirming that psychosomatic comorbidity is a key factor in sleep disorders among the elderly.There is a bidirectional vicious cycle between anxiety and depression and sleep disorders in the elderly: negative emotions can activate the sympathetic nervous system, disrupt circadian rhythms, and induce difficulties in sleep onset and maintenance; conversely, long-term sleep disturbances further exacerbate the decline in emotional regulation, worsening symptoms of depression and anxiety[37] .Older women face a higher risk of sleep disturbances, which may be related to physiological and psychological factors such as a sharp drop in estrogen levels after menopause, neuroendocrine disorders, as well as women's greater sensitivity to sleep discomfort and higher emotional sensitivity[38] .Coronary heart disease is closely associated with sleep subtypes in the elderly. The underlying mechanism may be that cardiovascular and cerebrovascular lesions can lead to insufficient blood and oxygen supply to the brain and an imbalance of central nervous system neurotransmitters, thereby disrupting the function of the sleep regulatory center[39] ; a history of stroke was associated with the groups with insufficient nighttime sleep duration and severe sleep disorders, and was linked to the group with difficulty falling asleep, though this association was not statistically significant. This suggests that different cardiovascular

and cerebrovascular conditions have specific effects on various dimensions of sleep, providing insights for targeted interventions for chronic cardiovascular and cerebrovascular diseases complicated by sleep disorders[40] .In this study, adequate daily vegetable intake (⩾300 grams) was associated with a reduced risk in the groups with difficulty falling asleep and severe sleep disorders. Vegetables are rich in dietary fiber, vitamins, minerals, and polyphenols, which can reduce oxidative stress in the body, improve the balance of the gut microbiota, and regulate neurotransmitter secretion, thereby optimizing sleep structure and enhancing sleep quality. This suggests that dietary intervention is a low-cost, easily implementable measure for improving sleep in older adults[41]. In this study, the groups with difficulty falling asleep, insufficient nighttime sleep, and severe sleep disorders were all negatively correlated with elevated BMI. Sleep abnormalities and BMI do not exhibit a simple positive association; their underlying metabolic and behavioral mechanisms require further clarification through longitudinal studies.The associations between smoking and various subtypes of sleep abnormalities did not reach statistical significance; this may be related to selection bias among smokers in this study and the bidirectional effects of nicotine on the central nervous system. This conclusion requires further validation through longitudinal studies[42] ; a high school education or higher provided a protective effect only for the insufficient sleep group. It is speculated that older adults with higher educational attainment possess greater health literacy, better sleep hygiene habits, and place greater emphasis on regular daily routines and health management.Compared to factory workers, farmers exhibit a protective effect against insufficient sleep and severe

sleep disorders. The mechanisms underlying this may be related to factors such as farmers' adherence to natural circadian rhythms, ample exposure to natural daylight, absence of shift work or night shifts, sufficient physical labor in the fields, a quiet rural sleep environment with minimal disturbances, high autonomy and control over their work, low levels of chronic psychological stress, regular daily routines, and robust social support[43] In contrast, workers often experience irregular schedules, disrupted light exposure, musculoskeletal strain from prolonged sitting, high workplace stress, and numerous disturbances in urban environments, all of which increase the risk of sleep abnormalities[44] .

This study, conducted in collaboration with 37 community residents' committees in Shanghai, recruited over 11,000 older adults aged 60 and above. With its broad coverage and highly representative sample, the study accurately reflects the current state of sleep quality among older adults in Shanghai's communities. The findings have good generalizability and can serve as a reference for the prevention and control of sleep disorders among older adults in major Chinese cities.Furthermore, the data were collected in 2019, representing a representative snapshot of the population's sleep status prior to the outbreak of the COVID-19 pandemic, and can serve as a baseline reference for subsequent cohort follow-ups and intervention evaluations. The use of LPA to precisely identify heterogeneous subtypes of sleep disorders in the elderly better aligns with the complex clinical characteristics of sleep problems in this population, providing methodological insights for population-based subtyping studies in geriatric sleep medicine.The combination of LPA and symptom network analysis achieved cross-level

integration from “population stratification” to “symptom mechanisms,” providing a dual “stratification-target” basis for the precise prevention and control of sleep disorders among older adults in the community. This analytical framework is still in its infancy in the field of sleep research among older adults in China.By controlling for multiple confounding factors—such as age and cardiovascular and cerebrovascular diseases—and systematically analyzing the impact of multidimensional factors (including sociodemographic characteristics, lifestyle, physical health, and psychological status) on different sleep subtypes, this study identifies the specific risk and protective factors for each subtype, providing an evidence-based foundation for targeted interventions.By focusing on the key population of community-dwelling older adults and examining population stratification and influencing factors related to sleep quality, the study’s conclusions can be directly translated into practical strategies for health management, sleep screening, and intervention among this population, demonstrating significant public health value.

This study also has some limitations and shortcomings: First, as a cross-sectional study, it can only reveal the associations between sleep subtypes and influencing factors but cannot determine causal sequences. In particular, the bidirectional associations between anxiety and depression, BMI, cardiovascular and cerebrovascular diseases, and sleep disorders require follow-up cohort studies to validate causal effects.Furthermore, the symptom network analysis was constructed based on cross-sectional data; while it can reveal statistical association patterns among symptoms, it cannot determine the causal direction or dynamic evolutionary sequence among

symptoms. In the future, time-series network or cross-lagged panel network analyses could be conducted using intensive longitudinal data to verify whether the potential priority intervention symptoms identified in this study indeed exhibit statistical association cascade patterns over time.Second, this study used the PSQI scale to assess sleep quality and did not incorporate objective sleep monitoring methods such as polysomnography (PSG) or actigraphy, which may introduce self-report bias. Future studies could combine subjective and objective measures to improve assessment accuracy. Third, the study sample consisted solely of older adults in Shanghai communities and did not include older adults in rural areas or those residing in long-term care facilities; therefore, caution is warranted when extrapolating the results to older adults in other regions or with different living arrangements.Fourth, there were a small number of missing values for some variables. Although the missing value rates were all <2% and imputation was performed, this may still have resulted in some loss of information; future studies could employ methods such as multiple imputation to further improve the robustness of the estimates. Based on this, it is recommended that sleep health management for community-dwelling older adults adopt the PSQI seven-factor LPA classification, implement differentiated management according to risk levels, and conduct annual dynamic reassessments. At the same time, by combining the symptom network characteristics of each subtype with the potential priority intervention symptoms identified by EI-2, a “classification-target” linked precision intervention plan should be formulated: for the “good sleep” subtype, the focus should be on maintenance and promotion, including maintaining a healthy weight;the

“Insufficient Nighttime Sleep” subtype should prioritize early intervention, strengthen nighttime monitoring of high-risk stroke populations, and conduct sleep awareness education targeting “subjective sleep quality”; the “Difficulty Falling Asleep” subtype should intensify CBT-I and referrals to psychiatric services, emphasize adequate vegetable intake, prioritize “daytime dysfunction” as a key target, and promote nighttime improvement through structured daytime activities and light exposure;The severe sleep disorder group is subject to intensive management; patients with anxiety, depression, or coronary heart disease are referred to multidisciplinary teams; the approach moves beyond the use of sleep-inducing medications alone and incorporates the restoration of daytime functioning as a core efficacy indicator. This model is expected to integrate with community-based health management services for older adults and, leveraging regional health information platforms, enable dynamic monitoring and early warning systems, thereby providing a reference for the precision management of sleep health in older adults under the “Healthy China 2030” initiative.

Declarations

Ethics approval and consent to participate

This study adhered to the Declaration of Helsinki and was approved by the Ethics Committee of Renji Hospital, Affiliated to Shanghai Jiao Tong University School of Medicine (Approval No.: KY2019-101). All participants provided written informed consent before enrollment.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used and analyzed during the current study are available from the corresponding authors on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

LBJ: participated in data cleaning, statistical analysis, data interpretation, and manuscript drafting. ZW: directly participated in study design, organization and implementation, data collection, data interpretation, manuscript drafting, and statistical analysis. XW, TH, GS, LY, MH, CX, SL, ZS and WJ: participated in the organization and implementation, data collection, and provided administrative, technical, and material support. PJ: directly participated in study design, organization and implementation, secured research funding, and critically revised the manuscript for important intellectual content. All authors read and approved the final manuscript.

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Table 1 Fitting metrics for the latent profile model of sleep patterns among 11,719 older adults in Shanghai communities

Model	AIC	BIC	aBIC	Entropy	*P*-value		Category probability
					LMR	BLRT	
1	185329.87	185388.82	185363.40	-	-	-	-
2	157359.07	157476.97	157426.13	0.921	<0.001	<0.001	23.21/76.79
3	151250.21	151427.07	151350.80	0.881	<0.001	<0.001	11.50/66.66/21.84
4	147820.47	148056.28	147954.59	0.898	<0.001	<0.001	9.98/63.51/20.10/6.41
5	138853.72	139148.48	139021.36	0.816	<0.001	0.237	12.80/31.23/40.79/8.27/6.91

Table 2: Univariate Analysis of Potential Categories of Sleep Quality Among Older Adults Aged ⩾60 Years in Shanghai Communities

Study Variables	Sleep Pattern Group				X^2/*t-value*	*P*-value
	Healthy Sleep Group (n=7 443)	Insufficient Nighttime Sleep Group (n=2 355)	Difficulty Falling Asleep Group (n=751)	Severe Sleep Disturbance Group (n=1 170)		
Gender[n(%)]					215.18	<0.001
Male	3 803 (51.1)	1 072 (45.5)	258 (34.4)	367 (31.4)		
Female	3 640 (48.9)	1 283 (54.5)	493 (65.6)	803 (68.6)		
Age($\bar{x} \pm s$, years)	67.55 ± 5.68	67.91 ± 5.80	68.11 ± 6.09	68.09 ± 5.97	5.70	<0.001
Educational Attainment [n(%)]					32.22	<0.001
No formal education	588 (7.9)	210 (8.9)	82 (10.9)	135 (11.5)		
Elementary school	2 459 (33.0)	779 (33.1)	253 (33.7)	412 (35.2)		
Middle School	3 500 (47.0)	1 117 (47.4)	332 (44.2)	500 (42.7)		
High school and above	896 (12.0)	249 (10.6)	84 (11.2)	123 (10.5)		

Occupation before retirement[n(%)]					46.51	<0.001
Laborer	1 797 (24.1)	721 (30.6)	167 (22.2)	297 (25.4)		
Farmers	5 478 (73.6)	1 578 (67.0)	565 (75.2)	853 (72.9)		
Other	168 (2.3)	56 (2.4)	19 (2.5)	20 (1.7)		
History of smoking[n(%)]	1 942 (26.1)	509 (21.6)	122 (16.2)	172 (14.7)	105.05	<0.001
History of alcohol use [n(%)]	1 270 (17.1)	386 (16.4)	85 (11.3)	128 (10.9)	41.14	<0.001
BMI[n(%)]					42.95	<0.001
<18.5 kg/m^2	240 (3.2)	84 (3.6)	27 (3.6)	44 (3.8)		
18.5~<24.0 kg/m^2	3 020 (40.6)	1 036 (44.0)	358 (47.7)	565 (48.3)		
24.0~<28.0 kg/m^2	3 111 (41.8)	912 (38.7)	271 (36.1)	423 (36.2)		
≥28.0 kg/m^2	1 072 (14.4)	323 (13.7)	95 (12.6)	138 (11.8)		

IPAQ[n(%)]					43.49	<0.001
Low	365 (4.9)	87 (3.7)	42 (5.6)	69 (5.9)		
Medium	6 784 (91.1)	2 209 (93.8)	697 (92.8)	1 083 (92.6)		
High	294 (4.0)	59 (2.5)	12 (1.6)	18 (1.5)		
Daily Adequate Vegetable Intake [grams ,n(%)]					117.63	<0.001
<300g	4 992 (67.1)	1 499 (63.7)	605 (80.6)	896 (76.6)		
⩾300g	2 451 (32.9)	856 (36.3)	146 (19.4)	274 (23.4)		
Symptoms of anxiety and depression [n(%)]	600 (8.1)	477 (20.3)	296 (39.4)	631 (53.9)	1828.87	<0.001
History of coronary heart disease [n(%)]	729 (9.8)	312 (13.2)	113 (15.0)	269 (23.0)	176.19	<0.001
History of stroke[n(%)]	167 (2.2)	78 (3.3)	25 (3.3)	54 (4.6)	25.94	<0.001

Table 3: Multivariate Logistic Regression Analysis of Potential Categories of Sleep Quality Among Older Adults in Shanghai Communities

Study Variables	Healthy Sleep Group (*n* = 7 443)	Insufficient Nighttime Sleep Group (*n* = 2 355)	*OR* (95% *CI*)	*P*-value	Difficulty Falling Asleep Group (*n* = 751)	*OR* (95% *CI*)	*P*-value	Severe Sleep Disturbance Group(*n*= 1 170)	*OR* (95% *CI*)	*P*-value
Gender[n(%)]										
Male	3 803 (51.1)	1 072 (45.5)	1.00 (ref)		258 (34.4)	1.00 (ref)		367 (31.4)	1.00 (ref)	
Female	3 640 (48.9)	1 283 (54.5)	1.22 (1.08~1.38)	0.002	493 (65.6)	1.63(1.31~2.03)	<0.001	803 (68.6)	1.79 (1.48~2.17)	<0.001
Educational Attainment [n(%)]										
No formal education	588 (7.9)	210 (8.9)	1.00 (ref)		82 (10.9)	1.00 (ref)		135 (11.5)	1.00 (ref)	
Elementary school	2 459 (33.0)	779 (33.1)	0.96 (0.80~1.16)	0.695	253 (33.7)	0.93 (0.70~1.23)	0.596	412 (35.2)	0.93 (0.73~1.19)	0.567
Middle School	3 500 (47.0)	1 117 (47.4)	0.98 (0.81~1.19)	0.872	332 (44.2)	0.98 (0.73~1.33)	0.918	500 (42.7)	0.90 (0.70~1.16)	0.420
High school and above	896 (12.1)	249 (10.6)	0.78 (0.62~0.99)	0.044	84 (11.2)	0.93 (0.64~1.36)	0.717	123 (10.5)	0.84 (0.60~1.16)	0.283

Occupation before retirement[n(%)]										
Laborer	1 797 (24.1)	721 (30.6)	1.00 (ref)		167 (22.2)	1.00 (ref)		297 (25.4)	1.00 (ref)	
Farmers	5 478 (73.6)	1 578 (67.0)	0.66 (0.59~0.74)	<0.001	565 (75.2)	0.93 (0.77~1.13)	0.481	853 (72.9)	0.74 (0.63~0.87)	<0.001
Other	168 (2.3)	56 (2.4)	0.91 (0.65~1.26)	0.560	19 (2.5)	1.10 (0.64~1.88)	0.728	20 (1.7)	0.63 (0.37~1.08)	0.095
History of smoking[n(%)]										
No	5 501(73.9)	1 846(78.4)	1.00 (ref)		629(83.8)	1.00 (ref)		998(85.3)	1.00 (ref)	
Yes	1 942(26.1)	509(21.6)	0.90(0.78~1.04)	0.160	122(16.2)	0.87 (0.66~1.13)	0.286	172(14.7)	0.87(0.69~1.10)	0.252
BMI [n(%)]										
18.5~<24.0 kg/m^2	3 020 (40.6)	1 036 (44.0)	1.00 (ref)		358 (47.7)	1.00 (ref)		565 (48.3)	1.00 (ref)	
<18.5 kg/m^2	240 (3.2)	84 (3.6)	0.94 (0.73~1.23)	0.671	27 (3.6)	0.82 (0.53~1.26)	0.360	44 (3.8)	0.79 (0.55~1.14)	0.201
24.0~<28.0 kg/m^2	3 111 (41.8)	912 (38.7)	0.88 (0.80~0.98)	0.019	271 (36.1)	0.80 (0.67~0.94)	0.009	423 (36.2)	0.81 (0.69~0.93)	0.004
⩾28.0 kg/m^2	1 072 (14.4)	323 (13.7)	0.87 (0.75~1.01)	0.069	95 (12.6)	0.73 (0.57~0.93)	0.012	139 (11.9)	0.67 (0.54~0.83)	<0.001
IPAQ[n(%)]										
Low	365 (4.9)	87 (3.7)	1.00 (ref)		42 (5.6)	1.00 (ref)		69 (5.9)	1.00 (ref)	
Medium	6 784 (91.1)	2 209 (93.8)	1.25 (0.98~1.60)	0.076	697 (92.8)	0.73 (0.52~1.03)	0.077	1 083 (92.6)	0.64 (0.47~0.86)	0.003

High		294 (4.0)	59 (2.5)	0.85 (0.59~1.23)	0.381	12 (1.6)	0.39 (0.20~0.76)	0.006	18 (1.5)	0.39 (0.22~0.69)	0.001
Daily Adequate Vegetable Intake [grams ,n(%)]											
<300g	4 992 (67.1)	1 499 (63.7)	1.00 (ref)		605 (80.6)	1.00 (ref)		896 (76.6)	1.00 (ref)		
⩾300g	2 451 (32.9)	856 (36.3)	1.14 (1.03~1.26)	0.008	146 (19.4)	0.49 (0.40~0.59)	<0.001	274 (23.4)	0.61 (0.53~0.72)	<0.001	
Symptoms of anxiety and depression [n(%)]											
No	6 843 (91.9)	1 878 (79.7)	1.00 (ref)		455 (60.6)	1.00 (ref)		539 (46.1)	1.00 (ref)		
Yes	600 (8.1)	477 (20.3)	2.79 (2.44~3.18)	<0.001	296 (39.4)	6.90 (5.81~8.20)	<0.001	631 (53.9)	12.18 (10.52~14.09)	<0.001	
History of coronary heart disease [n(%)]											
No	6 714 (90.2)	2 043 (86.8)	1.00 (ref)		638 (85.0)	1.00 (ref)		901 (77.0)	1.00 (ref)		
Yes	729 (9.8)	312 (13.2)	1.31 (1.13~1.52)	<0.001	113 (15.0)	1.32 (1.06~1.66)	0.014	269 (23.0)	2.17 (1.82~2.59)	<0.001	
History of stroke[n(%)]											

No	7 276 (97.8)	2 277 (96.7)	1.00 (ref)		726 (96.7)	1.00 (ref)		1 116 (95.4)	1.00 (ref)	
Yes	167 (2.2)	78 (3.3)	1.43 (1.08~1.89)	0.012	25 (3.3)	1.38 (0.88~2.15)	0.158	54 (4.6)	1.78 (1.25~2.53)	0.001

Note: 1. The OR, 95% CI, and P values for the insufficient nighttime sleep group, difficulty falling asleep group, and severe sleep disorder group were all calculated from a multivariate logistic regression model (Model 3). Using the healthy sleep group as a reference, the adjusted variables included age, gender, education level, occupation before retirement, smoking, alcohol consumption, BMI, IPAQ, adequate daily vegetable intake, symptoms of anxiety and depression, history of coronary heart disease, and history of stroke; 2. BMI was missing in 71 cases, IPAQ in 104 cases, adequate daily vegetable intake in 225 cases, and stroke history missing in 2 cases, accounting for <2%, with mean interpolation used to fill the gap.

Table 4 Network stability assessment across the four sleep subtypes

Group	Sample	Strength centrality CS-coefficien	EI centrality, CS-coefficient
Healthy Sleep Group	7 443	0.75	0.75
Insufficient Nighttime Sleep Group	2 355	0.672	0.672
Difficulty Falling Asleep Group	751	0.517	0.439
Severe Sleep Disturbance Group	1 170	0.673	0.673

Note: The CS-coefficient (correlation stability) was obtained via case-dropping bootstrap. A value >0.5 indicates acceptable stability of the centrality ranking, and >0.7 indicates good stability. The stability of EI centrality in the difficulty falling asleep group was below the acceptable threshold (0.439) and should be considered exploratory.

Table 5 Simulation of network-based interventions for the seven PSQI factors across four sleep subtypes (2-step Expected Influence)

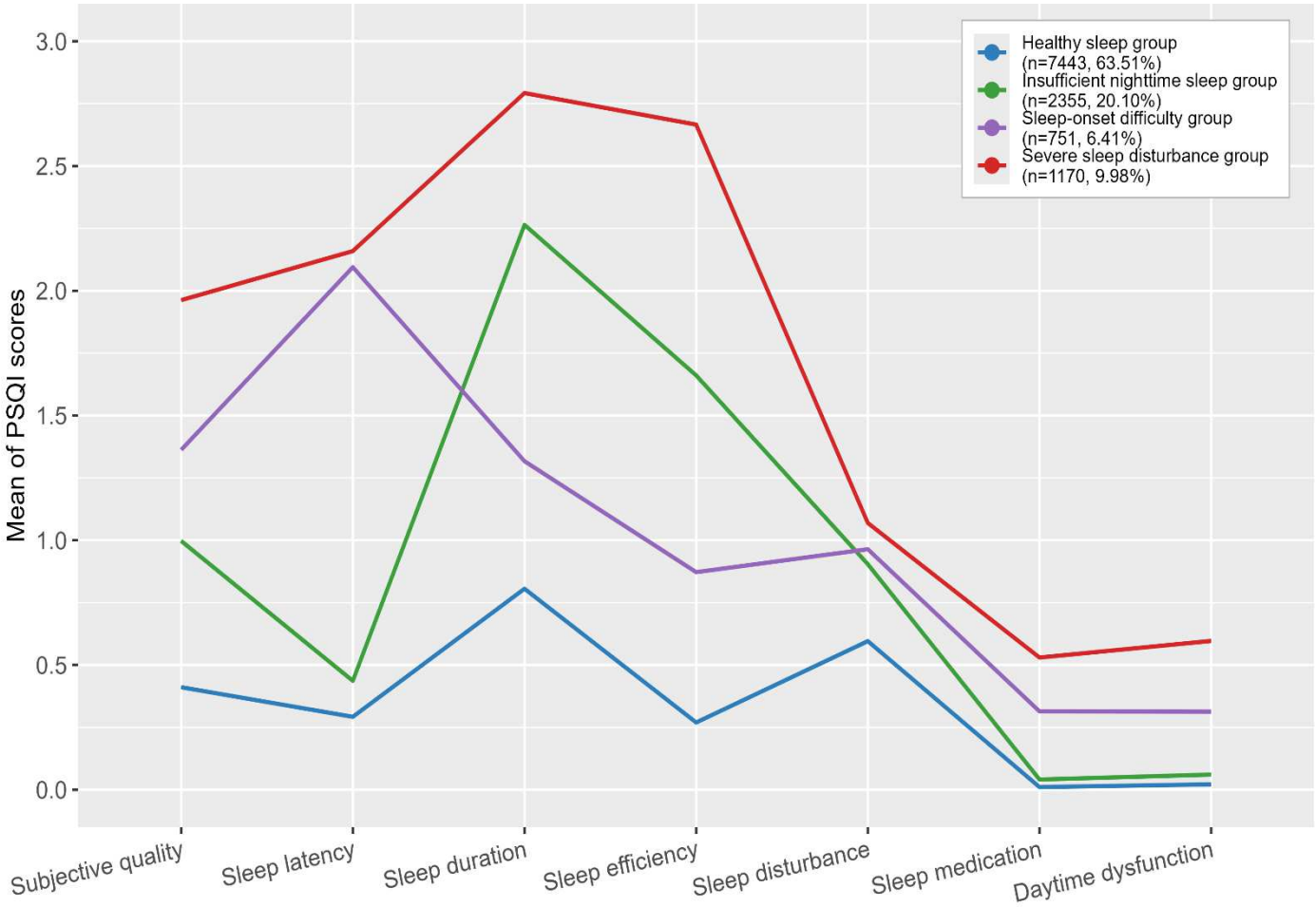
PSQI Factors	Healthy Sleep Group (n=7 443)	Insufficient Nighttime Sleep Group (n=2 355)	Difficulty Falling Asleep Group (n=751)	Severe Sleep Disturbance Group (n=1 170)
Subjective Sleep Quality	1.492	1.134★	0.524	1.093
Time to Fall Asleep	0.946	0.989	−0.137	0
Sleep Duration	1.408	1.052	0	0.395
Sleep Efficiency	1.408	0.625	−0.137	0.884
Sleep Disorders	1.614	0.907	0.575	0.795
Hypnotics	0.947	0.671	0.621	1.005
Daytime Dysfunction	1.703★	0.907	0.741★	1.317★

Note: ★ indicates the symptom with the highest 2-step Expected Influence (EI) in this group (priority symptom for potential intervention). EI-2 = 1-step EI (direct effect) + the sum of 1-step EIs of neighboring nodes (indirect effect); a higher value indicates that intervening on this symptom is more likely to produce a cascading improvement effect through the network.

Table6 Network comparison test (NCT) across the four sleep subtypes

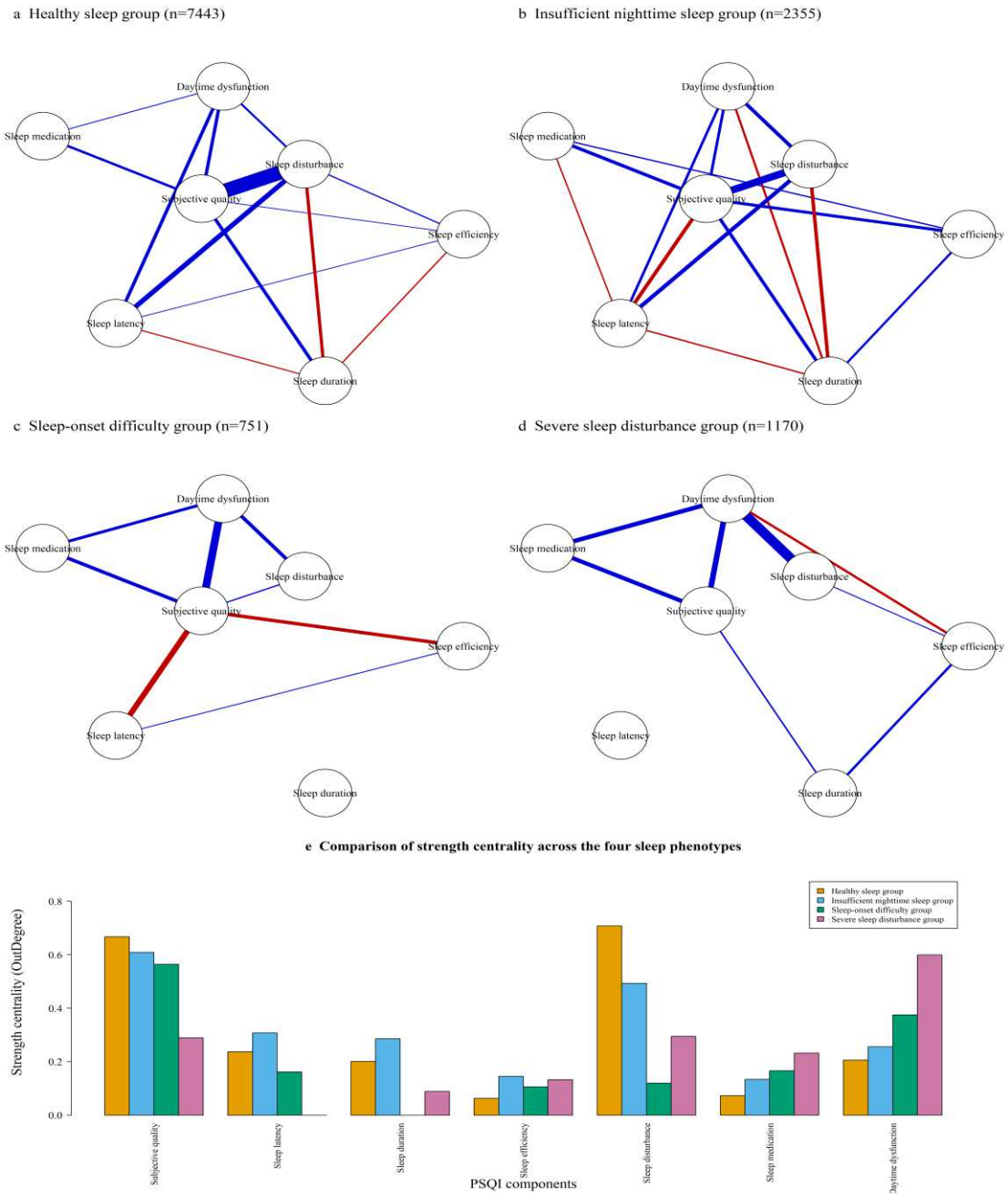
Comparison	Global strength difference, *P*	Significant	Network structure difference, *P*	Significant	No. of symptoms with significant strength centrality difference /7	No. of symptoms with significant EI centrality difference /7
Healthy sleep vs. severe sleep disorder	0.044	Yes	<0.001	Yes	0/7	0/7
Healthy sleep vs. insufficient nighttime sleep	0.927	No	<0.001	Yes	0/7	0/7
Difficulty falling asleep vs. severe sleep disorder	0.775	No	0.002	Yes	0/7	0/7

Note: NCT = Network Comparison Test, based on 1,000 permutation tests. The global strength test examines whether the overall connectivity of the two networks differs; the network structure test examines whether the edge weight matrices differ. The number of significantly different symptoms indicates, among the seven PSQI factors, how many differed at $p < 0.05$ for the given centrality index.



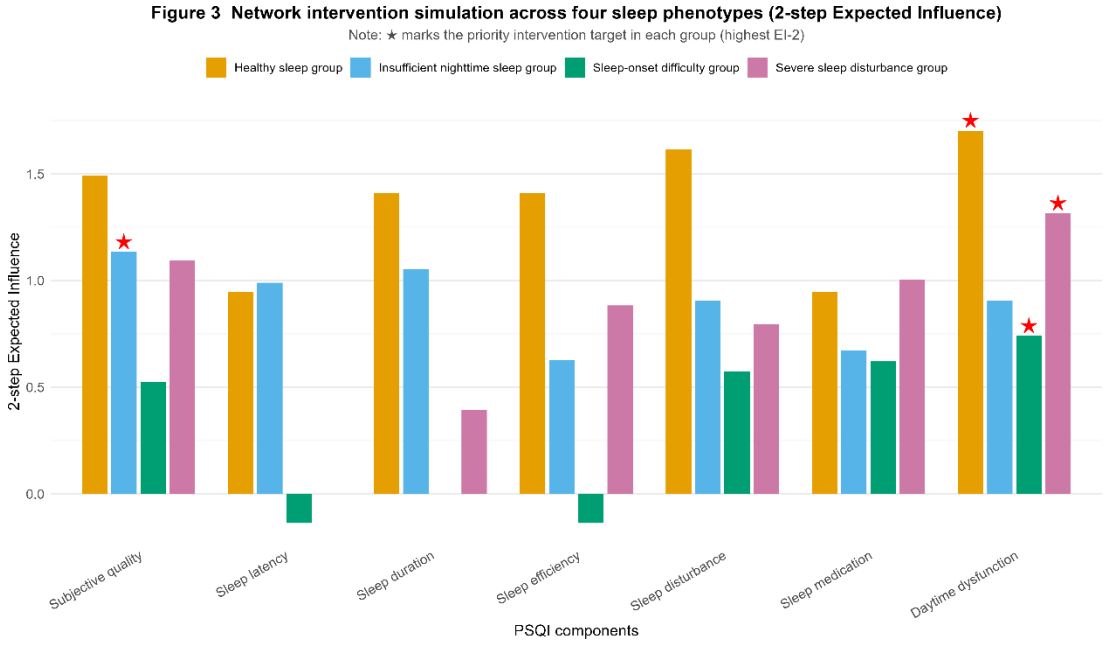
Note: PSQI = Pittsburgh Sleep Quality Index. Scores on each component range from 0 to 3, with higher scores indicating more severe sleep problems in that domain.

Figure 1 Distribution of characteristics across the four latent classes of 11,719 community-dwelling older adults



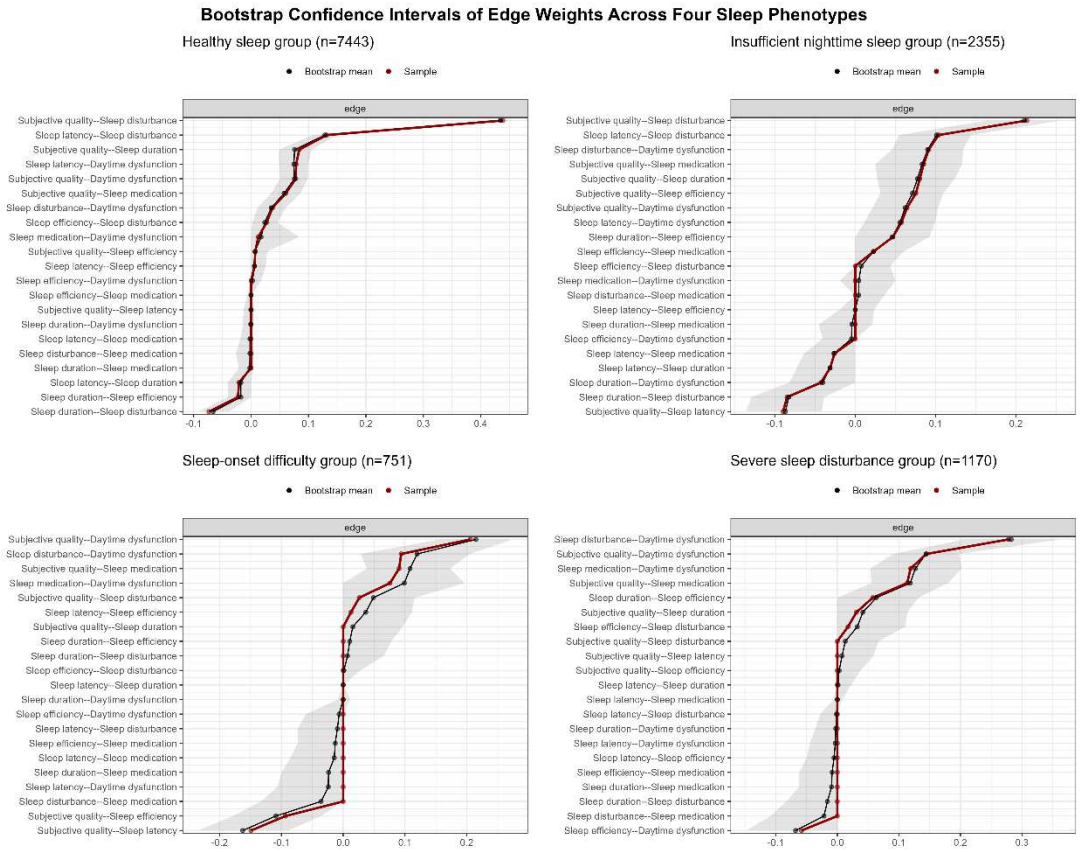
Note: a-d are the network structure diagrams of the regularized partial correlation for the healthy sleep group, insufficient nighttime sleep time, difficulty falling asleep, and severe sleep disorder group (blue solid line = positive correlation, red solid line = negative correlation, edge thickness represents absolute weight value); e is the out-degree comparison bar chart of the network strength centrality (OutDegree) of the seven PSQI factors in four groups.

Figure 2 Comparison of the four-class sleep subtype PSQI seven-factor network model and OutDegree intensity centrality



Note: ★ Indicates the symptom with the highest 2-step Expected Influence in this group (priority latent priority intervention symptom). EI - 2 = 1-step EI (direct effect) + sum of neighboring node's 1-step EI (indirect effect); the larger the value, the more likely the intervention to produce cascading improvement effects through the network.

Figure 3 Four-Sleep Subtypes PSQI Seven-Factor Network Intervention Simulation (2-step Expected Influence)



Note: Black dots represent the Bootstrap mean, red dots represent the sample estimates, and gray shades represent the 95% confidence interval. Each subgraph corresponds to (a) healthy sleep group, (b) insufficient nighttime sleep group, (c) difficulty falling asleep group, and (d) severe sleep disorder group. Sorted by absolute weight from highest to lowest.

Figure 4 Bootstrap confidence intervals of the PSQI seven-factor network edge weights in four sleep subtypes.