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Psychosocial heterogeneity among hospitalized patients with chronic diseases without a primary caregiver: a multicenter cross-sectional latent profile analysis of anxiety, depression, sleep quality, and perceived social support

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Abstract

Background

Hospitalized patients with chronic diseases who lack a primary caregiver may show heterogeneous psychosocial configurations across emotional symptoms, sleep, and perceived support. This study identified latent profiles of anxiety, depression, sleep quality, and perceived social support and examined demographic and clinical correlates of profile membership.

Methods

A multicenter cross-sectional study was conducted at four healthcare institutions in Hubei Province, China, from February to June 2024. The analytic sample included 1,830 hospitalized adults with chronic diseases and no primary caregiver. Latent profile analysis used standardized Patient Health Questionnaire-9, Generalized Anxiety Disorder-7, Pittsburgh Sleep Quality Index, and reverse-standardized Multidimensional Scale of Perceived Social Support scores. Model selection considered information criteria, classification quality, profile size, stability, parsimony, and interpretability. Associations with profile membership were examined in 1,807 participants using multinomial logistic regression pooled across 200 posterior-probability-based pseudo-class draws, with Benjamini-Hochberg correction for multiple omnibus tests.

Results

A three-profile solution was retained (entropy = 0.891; mean maximum posterior probability = 0.953): relatively low anxiety and depressive symptoms (n = 1,351; 73.83%), depressive symptoms-sleep disturbance (n = 96; 5.25%), and high anxiety and depressive symptoms (n = 383; 20.93%). Profile differences were driven mainly by anxiety, depressive, and sleep symptoms; perceived social support was similar across profiles and was not a major differentiating dimension. Educational attainment showed a nominal association before multiple-testing correction, but no demographic or clinical factor remained stably associated with profile membership after correction. Sensitivity analyses supported the stability of the two larger profiles, whereas the depressive symptoms-sleep disturbance profile was more sensitive to model specification and sample perturbation.

Conclusions

Hospitalized patients with chronic diseases and no primary caregiver exhibited distinct psychosocial configurations characterized primarily by different combinations of emotional and sleep symptoms. Multidimensional assessment may be more informative than relying on routine demographic or clinical

characteristics alone. The smaller depressive symptoms-sleep disturbance profile requires external validation before use for clinical stratification.

Background

Patients with chronic diseases face persistent disease symptoms, treatment demands, and uncertainty about outcomes, all of which may impair daily functioning and psychological adjustment [1, 2]. Hospitalization and sleep problems may further affect emotional status and functional recovery [3]. Anxiety and depression are common across multiple chronic diseases and are interrelated with sleep disturbance [4, 5]. In a systematic review and meta-analysis of 67 studies involving 61,201 patients, Scott et al. found that most patients followed low and stable trajectories of anxiety or depression, whereas only a subset remained at persistently high symptom levels [6]. These findings indicate psychosocial heterogeneity among patients with chronic diseases that may not be adequately captured by overall mean values.

Care arrangements during hospitalization may further shape this heterogeneity. Family members or primary caregivers commonly contribute to personal care, disease management, emotional support, patient-clinician communication, and treatment decision-making [7–10]. A systematic review suggested that family caregiver involvement in inpatient care may be associated with psychological distress, functional status, quality of life, and readmission, although findings were inconsistent [7]. The absence of a primary caregiver during hospitalization represents an objective care arrangement and is not equivalent to perceived social support. The World Health Organization notes that social connection encompasses the structure, function, and quality of relationships; the mere presence of social ties does not ensure that support needs are met [11]. Thus, patients without a primary caregiver may still obtain support from other social networks and may exhibit different combinations of symptoms and psychosocial resources.

The Theory of Unpleasant Symptoms (TOUS) proposes that multiple symptoms can co-occur and interact and that symptom experiences are jointly influenced by physiological, psychological, and situational factors [12–14]. In this study, anxiety, depression, and sleep problems were conceptualized as interrelated symptoms; chronic disease and hospitalization as contextual conditions; and perceived social support as a psychosocial resource. Previous research has examined social support in relation to anxiety, depression, and other symptoms within the TOUS framework [15]. The stress-buffering hypothesis of social support proposes that social support is associated with health outcomes and may attenuate the relationship between stress and adverse psychological outcomes [16]; related reviews likewise support associations between characteristics of social relationships and mental health outcomes [17]. Together, these perspectives suggest that patients facing similar disease and hospitalization contexts may nonetheless show distinct configurations of symptom burden and support resources.

Previous studies have associated greater social support with better sleep and a lower risk of depression [18–20], and complex relationships have been reported among anxiety, depression, sleep quality, and social support [21]. However, correlation, regression, and structural equation models primarily characterize average associations among variables and may not identify multidimensional patterns at the individual level. Patients may exhibit concurrent elevations in anxiety and depression, depression accompanied by sleep problems, or different levels of social support despite similar symptom levels. A person-centered approach is therefore warranted to identify latent subgroups.

Latent profile analysis (LPA) identifies latent subgroups of individuals with similar characteristics on the basis of the joint distribution of multiple continuous indicators [22]. Previous studies have identified distinct symptom profiles among patients with breast cancer, advanced cancer, type 2 diabetes, and older adults with chronic diseases and have shown that these profiles may differ in psychosocial resources [23–28]. Existing research has largely focused on specific diseases or single psychological symptoms, or has treated social support as an external correlate after profile formation, with relatively little attention to the joint configuration of symptoms and psychosocial resources in hospitalized populations. For hospitalized patients with chronic diseases who have no primary caregiver, person-centered evidence remains limited regarding whether anxiety, depression, sleep quality, and perceived social support form distinct joint configurations.

Accordingly, guided primarily by TOUS and supplemented by the stress-buffering perspective on social support, we used a multicenter cross-sectional design and LPA to include anxiety, depression, sleep quality, and perceived social support simultaneously as profile indicators. Our aim was to characterize joint configurations of symptom burden and psychosocial resources without assuming a priori that social support would necessarily define profile boundaries. We further examined associations of demographic and clinical characteristics with profile membership to characterize psychosocial heterogeneity within this population and to inform multidimensional psychosocial assessment in hospitalized patients.

Methods

Study design and participants

This multicenter cross-sectional survey was conducted at four healthcare institutions in Hubei Province, China, from February to June 2024. During the same survey period, data were obtained from 5,778 hospitalized patients with chronic diseases. In accordance with the study objective, patients who reported having no primary caregiver during hospitalization constituted the analytic sample for LPA. Participants were recruited by convenience sampling from endocrinology, cardiology, respiratory medicine, nephrology, psychiatry/psychology, and other clinical departments that routinely admit patients with chronic diseases. The absence of a primary caregiver during hospitalization was operationally defined by self-report on the study-specific general information form (Additional file 1) item, “Is there a primary caregiver during your hospitalization?” Patients who answered “No” entered the

study screening process. This variable was intended to describe the patient's care arrangement during the current hospitalization; the study did not further distinguish potential caregiver type, duration of accompaniment, caregiving frequency, or caregiving intensity, and the variable was not equivalent to the patient's subjective level of perceived social support. Study design, conduct, and reporting followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement [29].

The inclusion criteria were as follows: (1) age ≥ 18 years; (2) a clinically diagnosed chronic disease requiring hospitalization; (3) no primary caregiver during hospitalization; (4) clear consciousness and basic reading, comprehension, and communication abilities; (5) ability to complete the questionnaire independently or, when necessary, with assistance from an investigator who did not influence the responses; and (6) voluntary participation with written informed consent.

Clinical exclusion criteria were as follows: (1) inability to complete the survey validly because of impaired consciousness, severe cognitive impairment, an acute psychiatric disorder, or clinical instability; and (2) unclear information regarding the chronic disease diagnosis. During data cleaning, records were excluded according to standardized quality-control rules if key data were missing for core LPA indicators (PHQ-9, GAD-7, PSQI, or MSPSS) such that scores could not be calculated, if records were clearly duplicated, if serious logical inconsistencies were present, or if data remained unverifiable after review. Patients in severe or critical condition were eligible if they retained the capacity to provide valid responses. All available participants who met the screening criteria during the survey period and had complete scorable data for the core LPA indicators were included; no additional sampling cap was imposed, and the final sample size was determined by the number of eligible participants available during the study period.

Conceptual framework

The Theory of Unpleasant Symptoms (TOUS) served as the primary conceptual framework, with the stress-buffering perspective on social support used as a complementary interpretive framework [12, 16]. TOUS emphasizes that multiple symptoms may co-occur and interrelate and that symptom experiences are influenced jointly by physiological, psychological, and situational factors [12]. Consistent with the measures used in this study, anxiety symptoms, depressive symptoms, and sleep problems were conceptualized as interrelated symptom experiences; chronic disease and hospitalization as relevant physiological and situational contexts; and perceived social support as a contextual psychosocial resource. The stress-buffering perspective on social support was used to complement interpretation of the relationship between support resources and psychological responses to disease- and hospitalization-related stress [16]. On this basis, we examined the joint configuration and heterogeneity of symptoms and psychosocial resources from a person-centered perspective. The framework was used to organize variables and interpret findings, not to test mediation, moderation, or directional pathways.

Measures and variables

Questionnaire composition. The survey did not use a newly developed psychometric questionnaire. It comprised a study-specific general information form and four previously published standardized instruments. The general information form was developed for this multicenter survey to collect demographic and clinical characteristics, including the presence of a primary caregiver during hospitalization; an English-language version is provided in Additional file 1. The four standardized instruments were the Patient Health Questionnaire-9 (PHQ-9), Generalized Anxiety Disorder-7 (GAD-7), Pittsburgh Sleep Quality Index (PSQI), and Multidimensional Scale of Perceived Social Support (MSPSS). Published Chinese versions of these instruments were used and are cited below [30–33].

Demographic and clinical variables. Data were collected on age, sex, height, weight, educational attainment, living arrangement, presence of other chronic conditions, condition severity, and disease stage. Body mass index (BMI) was recalculated as weight (kg)/height (m)². Based on medical records, condition severity was categorized as severe/critical or non-severe/non-critical; disease stage was categorized as acute or non-acute, with the non-acute category including stable and recovery stages. Based on prior research, clinical relevance, and data availability, eight variables were included in the analysis of factors associated with profile membership: age, BMI, sex, educational attainment, living arrangement, presence of other chronic conditions, condition severity, and disease stage.

Patient Health Questionnaire-9 (PHQ-9). The PHQ-9 consists of nine items assessing the frequency of depressive symptoms over the previous 2 weeks. Each item is scored from 0 to 3, yielding a total score of 0–27; higher scores indicate more severe depressive symptoms. The Chinese version of the PHQ-9 has demonstrated good reliability and validity in Chinese populations [30].

Generalized Anxiety Disorder-7 (GAD-7). The GAD-7 consists of seven items assessing the frequency of anxiety symptoms over the previous 2 weeks. Each item is scored from 0 to 3, yielding a total score of 0–21; higher scores indicate more severe anxiety symptoms. The Chinese version of the GAD-7 has been psychometrically validated in Chinese clinical populations [31].

Pittsburgh Sleep Quality Index (PSQI). The PSQI assesses sleep quality over the previous month across seven components: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medications, and daytime dysfunction. Each component is scored from 0 to 3, yielding a total score of 0–21; higher scores indicate poorer sleep quality. The Chinese version of the PSQI has undergone reliability and validity evaluation in Chinese populations [32].

Multidimensional Scale of Perceived Social Support (MSPSS). The MSPSS comprises 12 items, each scored from 1 to 7, with no reverse-scored items; total scores range from 12 to 84, with higher scores indicating greater perceived social support. The MSPSS has demonstrated reliability and validity in clinical populations in mainland China [33]. To align the direction of the four LPA indicators, the MSPSS total score was reverse-standardized for modeling as -z(MSPSS), such that higher values indicated lower perceived social support.

Data collection and quality control

The research team established a standardized survey protocol, administration instructions, variable definitions, and quality-control procedures. The nursing department at each center coordinated survey implementation and staff training and worked with relevant clinical departments to collect data. Before formal data collection, investigators at each center received standardized training on the inclusion and exclusion criteria, administration instructions, boundaries for explaining scale items, verification of clinical data, informed consent, and privacy protection. After providing informed consent, participants completed paper questionnaires, preferably independently. For participants who had difficulty reading or writing but had intact comprehension and communication abilities, investigators read each item aloud and recorded responses verbatim without providing leading explanations. Demographic and psychosocial data were primarily self-reported, whereas chronic disease diagnoses, nursing care level, condition severity, and other clinical data were verified against medical and nursing records.

After questionnaire collection, investigators and center coordinators sequentially checked completeness and logical consistency. Questionnaires with missing key items, obvious logical inconsistencies, or discrepancies across data sources were rechecked against the paper questionnaire, medical record, and nursing record. Each center organized data using standardized variable names, coding rules, and scale-scoring procedures, after which data were centrally compiled by the lead research team. Data were independently double-entered and cross-checked. Before analysis, value ranges, scale scoring, logical relationships, outliers, duplicate questionnaires, and missing data were examined. For LPA, PHQ-9, GAD-7, and PSQI total scores were converted to standardized z scores, whereas MSPSS was entered as the reverse-standardized score, -z(MSPSS), to reduce the influence of differences in scale and direction on model estimation.

Statistical analysis

Descriptive analysis and data preprocessing

Continuous variables were summarized, as appropriate to their distributions, using means, standard deviations, medians, and interquartile ranges; categorical variables were summarized as frequencies and percentages, with the corresponding analytic denominator and number of missing observations reported. Before latent profile modeling, PHQ-9, GAD-7, and PSQI total scores were z-standardized, and the MSPSS total score was reverse-standardized. LPA included 1,830 patients with complete scorable data for all four core indicators. Complete-case analysis was used to examine factors associated with profile membership; because BMI was missing for 23 patients, 1,807 patients were included, and the remaining covariates had no missing data. All statistical tests were two-sided, with $P < 0.05$ considered the nominal threshold for statistical significance. For multiple omnibus tests, Benjamini-Hochberg (BH)-adjusted q values were also reported.

Model selection and assessment of classification quality

Candidate models were evaluated jointly with respect to convergence, the Akaike information criterion (AIC), Bayesian information criterion (BIC), sample-size-adjusted BIC (saBIC), profile size, entropy, average posterior probability (AvePP) for each profile, model stability, parsimony, and clinical interpretability [36]. Because fit and classification indices may provide conflicting evidence regarding the number of profiles, we did not select the number of profiles on the basis of a single information criterion or a fixed minimum profile-size threshold. Lower AIC, BIC, and saBIC values indicate better relative fit; entropy values closer to 1 indicate better overall class separation; and AvePP was used to evaluate profile-specific classification quality. Models with empty or small profiles, unstable convergence, or poor classification quality were judged in conjunction with profile characteristics, solution reproducibility, and substantive interpretability. The primary interpretive model was selected from the candidate set, while a competitive alternative solution was retained to transparently represent uncertainty in profile enumeration. Profile labels summarized relative indicator levels within this sample and were not intended to represent clinical diagnoses.

Analysis of factors associated with latent profile membership

After the number of profiles, profile labels, reference profile, and covariate set for the primary interpretive model had been specified, multinomial logistic regression was performed using the “relatively low anxiety and depressive symptoms” profile as the reference category. Age was modeled per 10-year increase and BMI per 5 kg/m² increase. Reference levels for categorical variables were male sex, lower educational attainment (primary school or below, or junior middle school), living with others, no other chronic conditions, non-severe/non-critical status, and non-acute stage (stable or recovery stage). To account for uncertainty in individual profile assignment, multiple pseudo-class draws based on individual posterior class probabilities were used [37, 38]. Specifically, 200 class assignments were sampled from each participant's posterior probabilities, a multinomial logistic regression model was fitted to each sampled data set, and parameter estimates and variances were pooled using Rubin's rules [39]. Relative risk ratios (RRRs), 95% confidence intervals (CIs), and P values were reported. For each of the eight covariates, a 2-df omnibus Wald test was also performed, and the eight omnibus tests were adjusted using the BH procedure. This approach was used to reflect profile-assignment uncertainty conditional on the fixed LPA model.

Sensitivity and stability analyses

Sensitivity and stability analyses were conducted to assess the robustness of the primary findings. These included repeating the factor-association analysis without BMI; fitting conventional multinomial logistic regression using maximum-posterior-probability profile assignment as the outcome; adding centered quadratic terms for age and BMI to assess linearity in the logit; comparing classification agreement between the three-profile solution and adjacent numbers of profiles and across covariance

parameterizations; evaluating alternative-model stability across different random starting values, with 20 sets for EE-K4 and 10 sets for E0-K3; and repeatedly fitting the fixed three-profile model to 80% subsamples drawn without replacement. Internal stability in the resampling analysis was assessed using the adjusted Rand index (ARI), class-specific Jaccard indices, and profile proportions. These analyses evaluated the sensitivity of the main conclusions to model specification and sample perturbation.

All analyses were performed in R version 4.5.3 [40]. LPA was implemented using tidySEM version 0.2.11 and OpenMx version 2.22.11 [34, 35], and multinomial logistic regression was performed using nnet version 7.3–20 [41].

Ethical considerations

The study was reviewed and approved by the Ethics Review Committee of Renmin Hospital of Wuhan University (approval no. WDRY2022-K122). Before data collection, researchers explained the study purpose, survey procedures, potential risks, privacy protections, and the right to withdraw, and written informed consent was obtained from all participants. All data were de-identified before analysis and were used solely for this study. The study was conducted in accordance with the principles of the Declaration of Helsinki.

Use of AI-assisted technologies in manuscript preparation

An AI-assisted large language model (ChatGPT, OpenAI) was used during manuscript preparation to support English-language editing, structural refinement, and journal-formatting checks. All outputs were critically reviewed and revised by the authors, who retain full responsibility for the scientific content, analyses, interpretations, references, and final manuscript.

Results

Participant screening and general characteristics

During the multicenter survey period, data were obtained from 5,778 hospitalized patients with chronic diseases. Based on the primary-caregiver item, 1,896 patients reported having no primary caregiver during hospitalization. After excluding 4 patients aged < 18 years, 61 duplicate questionnaires, and 1 questionnaire for which the PSQI could not be fully scored, 1,830 patients were included in the LPA. Because BMI was missing for 23 patients, 1,807 patients were included in the analysis of factors associated with profile membership. The LPA sample had a mean age of 54.09 ± 14.68 years, and 61.64% were men. Mean ± SD scores for the PHQ-9, GAD-7, PSQI, and MSPSS were 3.57 ± 4.34, 2.41 ± 3.58, 5.04 ± 3.09, and 59.14 ± 15.17, respectively (Table 1).

Table 1
General characteristics of the LPA sample (N = 1830)

Variable	Statistic[a]	Missing, n
Age, years	54.09 ± 14.68; 56 [43–65]	0
BMI, kg/m²	23.08 ± 3.64; 22.83 [20.57–25.06]	23
Sex		0
Male	1128 (61.64)	
Female	702 (38.36)	
Educational attainment		0
Lower educational attainment	1065 (58.20)	
High school or above	765 (41.80)	
Living arrangement		0
Living with others	1610 (87.98)	
Living alone	220 (12.02)	
Other chronic condition(s)		0
No	895 (48.91)	
Yes	935 (51.09)	
Condition severity		0
Non-severe/non-critical	1589 (86.83)	
Severe or critical	241 (13.17)	
Disease stage		0
Non-acute	1252 (68.42)	
Acute	578 (31.58)	
PHQ-9 total score	3.57 ± 4.34; 2 [0–6]	0
GAD-7 total score	2.41 ± 3.58; 0 [0–4]	0
PSQI total score	5.04 ± 3.09; 5 [3–7]	0
MSPSS total score	59.14 ± 15.17; 59 [48–70]	0

Note: [a] Continuous variables are presented as mean ± standard deviation; median [Q1-Q3], and categorical variables as n (%). Lower educational attainment included primary school or below and junior middle school. The non-acute stage included stable and recovery stages. Percentages were calculated using nonmissing observations as the denominator.

Comparison and selection of latent profile models

We fitted one- to six-profile solutions under each of four variance/covariance parameterizations, yielding 24 candidate models. Some complex models showed unstable convergence, information-matrix abnormalities, or small profile sizes. Fit and classification indices for the key competing models are shown in Table 2. The three-profile model with equal variances and freely estimated covariances shared across profiles (EE-K3) converged well, with log-likelihood (LL) = -8942.771, AIC = 17933.542, BIC = 18065.832, saBIC = 17989.585, entropy = 0.891, and a smallest-profile proportion of 5.25%.

Compared with EE-K3, some four-profile solutions yielded lower information criteria. In the stability analysis, the better-fitting EE-K4 solution had BIC = 17307.586, saBIC = 17215.454, and entropy = 0.905; however, two of its four profiles each contained < 5% of the sample, and this higher-likelihood solution was reproduced in only 3 of 20 sets of random starting values, indicating limited reproducibility of the solution and its profile boundaries. The alternative covariance specification E0-K3 converged consistently but had a substantially higher BIC than EE-K3.

Considering information criteria, profile size, classification quality, model stability, parsimony, and clinical interpretability jointly, we retained EE-K3 as the primary interpretive model. Because the competing EE-K4 solution performed better on some information criteria, we did not regard the three-profile solution as the only plausible class structure. Instead, EE-K4 was retained as the principal competing solution, and membership agreement across different numbers of profiles was examined in sensitivity analyses to transparently represent uncertainty in profile enumeration.

Table 2
Comparison of fit and classification quality for key LPA candidate models

Model	LL / AIC	BIC / saBIC	Smallest profile, n (%)	Entropy / min AvePP	Overall assessment
EE-K2 (p = 19)	-9024.176 18086.352	18191.081 18130.719	408 (22.30%)	0.907 0.940	Insufficient convergence stability
E0-K3 (p = 18)	-9273.260 18582.521	18681.738 18624.553	113 (6.17%)	0.854 0.759	Acceptable fit
EE-K3* (p = 24)	-8942.771 17933.542	18065.832 17989.585	96 (5.25%)	0.891 0.815	Converged well with high classification quality; retained as the primary interpretive model
EE-K4a (p = 29)	-8904.565 17867.130	18026.980 17934.848	33 (1.80%)	0.902 0.804	Improved information criteria but included a very small profile; local solution under the same parameterization
EE-K4b† (p = 29)	-8544.868 17147.736	17307.586 17215.454	64 (3.50%)	0.905 0.764	Markedly improved information criteria but included small profiles; higher-likelihood solution had limited reproducibility and was retained as a competing solution
EE-K5 (p = 34)	-8902.404 17872.809	18060.219 17952.203	44 (2.40%)	0.758 0.736	Lower classification quality, with suboptimal profile size and convergence stability
EE-K6 (p = 39)	-8505.215 17088.429	17303.400 17179.498	0 (0.00%)	0.664 0.492	Contained an empty profile

Note: E0 denotes equal within-profile variances with covariances fixed at 0; EE denotes equal within-profile variances with freely estimated covariances shared across profiles; K denotes the number of profiles; p denotes the number of free parameters; * indicates the primary interpretive model retained in this study. EE-K4a and EE-K4b represent distinct likelihood solutions obtained for the same parameterization from different random starting values; a denotes the initial local solution, and b† denotes the higher-likelihood competing solution obtained in the stability analysis. LL, log-likelihood; AIC, Akaike information criterion; BIC, Bayesian information criterion; saBIC, sample-size-adjusted Bayesian information criterion; AvePP, average posterior probability.

Latent profile characteristics and classification quality

The EE-K3 model retained as the primary interpretive model had an entropy of 0.891 and a mean maximum posterior probability of 0.953, indicating good overall classification quality. Based on maximum posterior probability assignment, C1, the “relatively low anxiety and depressive symptoms” profile, included 1,351 patients (73.83%); C2, the “depressive symptoms-sleep disturbance” profile, included 96 patients (5.25%); and C3, the “high anxiety and depressive symptoms” profile, included 383

patients (20.93%). The AvePPs for the three profiles were 0.969, 0.815, and 0.931, respectively. Overall, 114 of 1,830 patients (6.23%) had a maximum posterior probability < 0.70, including 27 of 96 patients (28.13%) in C2. Thus, membership was relatively clear for C1 and C3, whereas individual membership in C2, the smaller latent profile, was more uncertain.

Based on the standardized indicator patterns, C1 had PHQ-9 and GAD-7 scores below the overall sample means (-0.477 and − 0.450, respectively), whereas the PSQI and reverse-standardized MSPSS indicators were close to the overall means; this profile was therefore labeled “relatively low anxiety and depressive symptoms.” C2 had elevated PHQ-9 and PSQI scores (1.163 and 0.699, respectively) but a relatively low GAD-7 score (-0.143), indicating a pattern dominated by depressive symptoms and sleep disturbance; it was therefore labeled “depressive symptoms-sleep disturbance.” C3 had the highest relative PHQ-9 and GAD-7 scores among the three profiles (1.357 and 1.628, respectively), whereas the PSQI and reverse-standardized MSPSS indicators were close to the overall means; it was therefore labeled “high anxiety and depressive symptoms” (Fig. 1 and Table 3). These labels describe relative patterns within this sample and do not represent clinical diagnoses or fixed severity categories. Posterior-probability-weighted raw MSPSS means were 58.89, 58.65, and 60.16 across the three profiles, respectively. The small differences indicate that, although perceived social support contributed to profile estimation, it did not serve as a major differentiating indicator in the retained three-profile solution.

Table 3
Profile characteristics, classification quality, and weighted scale means in the primary EE-K3 model

Profile	Modal n (%)	Posterior n (%)	AvePP	PHQ-9	GAD-7	PSQI	MSPSS
C1: Relatively low anxiety and depressive symptoms	1351 (73.83%)	1343.0 (73.39%)	0.969	1.50	0.80	4.81	58.89
C2: Depressive symptoms-sleep disturbance	96 (5.25%)	106.0 (5.79%)	0.815	8.61	1.90	7.20	58.65
C3: High anxiety and depressive symptoms	383 (20.93%)	380.9 (20.82%)	0.931	9.46	8.25	5.26	60.16

Note: Profile n (%) was determined by maximum posterior probability assignment; posterior expected n (%) is the sum of individual posterior probabilities; AvePP is the mean posterior probability among patients assigned to the corresponding profile. Scale means are posterior-probability-weighted descriptive means. Higher PHQ-9, GAD-7, and PSQI scores indicate more severe depressive symptoms, more severe anxiety symptoms, and greater sleep problems, respectively; higher MSPSS scores indicate greater perceived social support.

Factors associated with latent profile membership

The analysis of factors associated with latent profile membership included 1,807 patients, and model estimation was completed for all 200 posterior-probability-based repeated class draws. Among the

omnibus Wald tests for the eight covariates, only educational attainment reached nominal statistical significance before correction ($\chi^2 = 6.816$, df = 2, P = 0.033); however, the BH-adjusted q value was 0.265. Omnibus P values for all other covariates were ≥ 0.118 (Table 4). After correction for multiple testing, no demographic or clinical factor was stably associated with profile membership.

In specific profile contrasts, compared with lower educational attainment, high school education or above was associated with a lower relative risk of membership in C3, the “high anxiety and depressive symptoms” profile, versus C1, the “relatively low anxiety and depressive symptoms” profile (RRR = 0.686, 95% CI, 0.516–0.911, P = 0.009). No statistically significant difference was observed for membership in C2 versus C1 (RRR = 0.878, 95% CI, 0.517–1.491, P = 0.631). Because the omnibus association for educational attainment was no longer significant after correction for multiple testing, this profile-specific contrast is reported as exploratory rather than as a primary finding. The multivariable-adjusted RRRs and 95% CIs for the C2 versus C1 and C3 versus C1 comparisons are presented in Fig. 2.

Table 4
Multivariable analysis of factors associated with latent profile membership based on posterior-probability pseudo-class draws

Covariate	C2 vs C1, RRR (95% CI); P	C3 vs C1, RRR (95% CI); P	Omnibus P	BH q
Age (per 10-year increase)	1.107 (0.920–1.332) P = 0.281	1.037 (0.941–1.142) P = 0.468	0.469	0.625
BMI (per 5 kg/m² increase)	0.990 (0.709–1.382) P = 0.954	0.889 (0.745–1.062) P = 0.195	0.431	0.625
Female (reference: male)	1.024 (0.628–1.671) P = 0.923	1.092 (0.845–1.411) P = 0.501	0.798	0.912
High school or above (reference: lower educational attainment)	0.878 (0.517–1.491) P = 0.631	0.686 (0.516–0.911) P = 0.009	0.033	0.265
Living alone (reference: living with others)	1.710 (0.910–3.214) P = 0.095	1.327 (0.918–1.918) P = 0.132	0.118	0.274
Other chronic condition(s) (reference: none)	1.306 (0.799–2.135) P = 0.287	1.288 (0.990–1.677) P = 0.060	0.122	0.274
Severe/critical condition (reference: non-severe/non-critical)	1.602 (0.890–2.885) P = 0.116	1.306 (0.917–1.861) P = 0.138	0.137	0.274
Acute stage (reference: non-acute)	1.046 (0.632–1.731) P = 0.861	0.981 (0.750–1.283) P = 0.887	0.971	0.971

Note: C1, relatively low anxiety and depressive symptoms profile; C2, depressive symptoms-sleep disturbance profile; C3, high anxiety and depressive symptoms profile. RRR, relative risk ratio. Omnibus P values were obtained from 2-df joint Wald tests using Rubin's total variance; BH correction was applied only to the eight omnibus tests, and P values for individual coefficients were not adjusted for multiple testing. All variables shown in the table were mutually adjusted.

Sensitivity and stability analyses

The sensitivity model excluding BMI included all 1,830 patients in the LPA sample. In this model, the direction of the association between educational attainment and profile membership was consistent

with that in the primary analysis, but the omnibus test remained nonsignificant after BH correction (q = 0.135). Conventional multinomial logistic regression based on maximum-posterior-probability profile assignment yielded a similar result (q = 0.091). Thus, neither the handling of missing BMI data nor the method of profile assignment altered the principal conclusions after correction for multiple testing (Table 5).

Sensitivity analyses of model specification showed an ARI = 0.620 between the better-fitting EE-K4 solution and the primary EE-K3 model, indicating moderate agreement between the two classifications. Figure 3 illustrates the flow of profile membership between the primary EE-K3 and competing EE-K4 solutions. The ARI between EE-K3 and E0-K3 was 0.765, with more pronounced movement of members in the smaller profile. Uncertainty related to profile enumeration and covariance specification was concentrated primarily in C2 and its boundaries. Omnibus P values for the quadratic terms for age and BMI were 0.515 and 0.064, respectively, providing no clear evidence of nonlinearity. Comparisons across random starting values showed that the higher-likelihood EE-K4 solution was reproduced infrequently, indicating limited stability of the competing four-profile solution.

Across 32 resampling iterations in which 80% of cases were sampled without replacement under a fixed three-profile specification, 25 yielded stable, acceptable model solutions. Compared with the full-sample EE-K3 model, the median ARI was 0.794. After class labels were aligned, median Jaccard indices were 0.919 for C1 and 0.931 for C3, but only 0.188 for C2; the proportion and profile means for C2 also varied over a wider range (Fig. 4). Among iterations yielding stable, acceptable solutions, C1 and C3 showed high consistency in class membership, whereas the boundaries and membership of C2 were more sensitive to sample perturbation. In addition, 7 of 32 resampling iterations did not yield a stable, acceptable solution.

Table 5
Results of sensitivity and stability analyses

Analysis and sample/comparison	Main result	Interpretation
Model excluding BMI N = 1830; 200/200 completed	Educational attainment omnibus P = 0.019, q = 0.135; C3 vs C1 RRR = 0.667 (0.503–0.886)	Direction consistent with the primary model; nonsignificant after correction for multiple testing
Maximum-posterior-probability class regression N = 1807	Educational attainment omnibus P = 0.011, q = 0.091	Does not account for uncertainty in profile assignment
Alternative four-profile vs three-profile comparison EE-K4 vs EE-K3	ARI = 0.620; K4 further separated sleep disturbance and an extremely high anxiety/depression profile	Improved information criteria but included small profiles; profile enumeration remained uncertain
Covariance specification E0-K3 vs EE-K3	ARI = 0.765	Membership in the smaller profile was sensitive to covariance specification
Functional form of continuous variables N = 1807; 200/200 completed	Age quadratic term P = 0.515; BMI quadratic term P = 0.064	No clear evidence of nonlinearity; BMI was close to the nominal threshold
Case-deletion resampling 80% subsamples; fixed K = 3	25/32 repetitions yielded stable, acceptable solutions; median ARI = 0.794 (0.714–0.986)	High membership consistency for C1/C3; C2 boundaries and membership were sensitive
Stability across random starting values EE-K4: 20 sets; E0-K3: 10 sets	EE-K4: 14/20 sets yielded acceptable solutions; the higher-LL solution was reproduced in 3/20 sets and the lower-LL solution in 11/20 sets. E0-K3: 10/10 sets yielded the same best LL.	Used to evaluate convergence stability of alternative models

Note: ARI, adjusted Rand index. The case-deletion analysis was conducted under a fixed three-profile model and included only repetitions that yielded stable, acceptable solutions to assess internal stability of the classification. Analyses with different random starting values were used to evaluate convergence stability of alternative models.

Discussion

In the retained three-profile solution, hospitalized patients with chronic diseases and no primary caregiver exhibited three main psychosocial configurations: a relatively low anxiety and depressive symptoms profile, a depressive symptoms-sleep disturbance profile, and a high anxiety and depressive

symptoms profile. Differences among profiles were driven primarily by distinct combinations of anxiety, depressive, and sleep symptoms, whereas perceived social support did not emerge as a major differentiating dimension. After BH correction, age, sex, BMI, educational attainment, living arrangement, multimorbidity, condition severity, and disease stage were not stably associated with profile membership. The competing four-profile solution and internal stability analyses indicated that uncertainty in profile enumeration was concentrated primarily in the smaller depressive symptoms-sleep disturbance profile.

Psychosocial heterogeneity and clinical characteristics of the latent profiles

In this study, 73.83% of patients were classified into the relatively low anxiety and depressive symptoms profile. In a systematic review and meta-analysis of 67 studies involving 61,201 patients with chronic diseases, Scott et al. found that most patients followed low and relatively stable anxiety or depression trajectories, whereas only a subset had persistently high symptom levels [6]. Previous latent class or latent profile studies in breast cancer, advanced cancer, and chronic disease populations have likewise shown that low symptom burden often constitutes the largest subgroup, with smaller subgroups characterized by distinct symptom combinations and higher burden [23, 24, 27]. Our findings further show that even within the shared care context of hospitalization without a primary caregiver, psychosocial status remains heterogeneous. The absence of a primary caregiver during hospitalization primarily describes the care arrangement at that time; patients may still receive support from sources outside the family, support from healthcare professionals, or draw on prior experience adapting to chronic illness to cope with hospitalization. Because we did not include a concurrent comparison group of patients with a primary caregiver, the present findings are limited to describing heterogeneity within patients without a primary caregiver.

The high anxiety and depressive symptoms profile accounted for 20.93% of the sample. Anxiety and depressive symptom indicators were relatively highest in this profile, whereas sleep problems were not, suggesting that anxiety, depression, and sleep do not necessarily increase in parallel along a single severity dimension. The relationship between chronic physical illness and depression is complex and involves multiple levels of influence, including disease burden, functional limitations, and the social environment [42]. High-burden latent profiles characterized by anxiety, depression, and other psychosomatic symptoms have also been reported among patients with chronic diseases such as type 2 diabetes [26]. This configuration suggests that inpatient psychological assessment should include both anxiety and depressive symptoms rather than using a single emotional indicator as a proxy for overall psychological status. Importantly, the profile label summarizes the relative indicator pattern within this sample and does not imply a clinical diagnosis of an anxiety or depressive disorder.

The depressive symptoms-sleep disturbance profile accounted for 5.25% of the sample and was characterized by concurrent elevations in depressive symptoms and sleep problems with relatively low anxiety. This symptom combination differed from that of the high anxiety and depressive symptoms

profile. Previous latent profile studies among patients with advanced cancer, breast cancer, and those undergoing peritoneal dialysis have similarly shown that sleep disturbance, anxiety, depression, pain, and fatigue can form distinct symptom combinations [24, 25, 43]. Sleep and depression are closely related [5], and sleep during hospitalization may also be affected by ward noise, nighttime lighting, interruptions for nursing care, pain, and treatment schedules; a relevant systematic review supports associations of environmental, patient-related, and healthcare factors with impaired inpatient sleep [44]. Thus, this profile suggests that clinical assessment should jointly address depressive symptoms and sleep status. However, because this profile was small, its interpretation should be considered alongside the subsequent stability results.

The AvePP for C2, the proportion of individuals with low posterior probabilities, and the case-deletion resampling results all indicated that C2 membership was less stable than C1 and C3 membership. Movement of members was also more apparent across solutions with different numbers of profiles and different covariance specifications. A methodological review of latent class research emphasized that decisions about the number of classes should integrate class size, classification quality, reproducibility, model parsimony, and substantive interpretability rather than rely on a single information criterion [45]. In our study, the competing four-profile solution performed better on some information criteria but contained small profiles, and the higher-likelihood solution showed limited reproducibility across random starting values. On the basis of the available results, the three-profile solution provides a parsimonious and clinically interpretable primary representation of this sample. At the same time, C2 should be regarded as a smaller latent profile with substantive interpretability but sensitive boundaries; its reproducibility should be tested in independent samples.

Role of perceived social support in the absence of a primary caregiver

Compared with anxiety, depression, and sleep indicators, perceived social support did not form a clear boundary between profiles, and posterior-probability-weighted MSPSS means were similar across the three profiles. The World Health Organization conceptualizes social connection in terms of interrelated but noninterchangeable dimensions of relationship structure, function, and quality [11]. In this study, the presence or absence of a primary caregiver during hospitalization described a care arrangement, whereas the MSPSS captured patients' subjective perceptions of support from family, friends, and significant others; these are distinct constructs. Because all participants reported having no primary caregiver during hospitalization, the present findings cannot be used to compare social support across different caregiver-status groups. Rather, they indicate that, within the same operationally defined care arrangement, perceived social support did not emerge as a primary classification axis in the retained three-profile solution.

Previous studies have linked perceived social support with mental health and sleep outcomes. An umbrella review of social relationships and mental health found that social support, loneliness, social isolation, and social networks were each associated with mental health outcomes, while capturing

different aspects of social experience [17]. A meta-analysis of social support and sleep likewise found that greater social support was generally associated with better sleep outcomes [18]. From the stress-buffering perspective, support resources may relate to psychological responses through stress appraisal and coping processes [16]. In the present study, perceived social support did not show a clear gradient across the three symptom configurations, underscoring the need to assess objective care arrangements and subjective support experiences separately. In addition to recording whether a primary caregiver is present during hospitalization, clinical assessment may consider sources of support, support availability, and patients' subjective perceptions of support.

Factors associated with latent profile membership and their interpretation

After correction for multiple testing, no demographic or clinical factor was stably associated with latent profile membership. Educational attainment showed a nominal association before correction: patients with a high school education or above had a lower RRR for the high anxiety and depressive symptoms profile versus the relatively low anxiety and depressive symptoms profile. However, the omnibus association was no longer significant after BH correction and should therefore be considered exploratory. Educational attainment may reflect multiple dimensions, including access to health information, understanding of illness, socioeconomic resources, and health literacy. A previous systematic review and meta-analysis found that higher health literacy was associated with a lower risk of depression [46]. Future studies could directly include health literacy and related measures that more closely capture the ability to process disease information and manage healthcare tasks.

Age, sex, BMI, multimorbidity, condition severity, and disease stage were likewise not stably associated with profile membership. Although a previous meta-analysis found that multimorbidity was generally associated with a higher risk of depression [47], our study represented multimorbidity only as a binary indicator of whether other chronic conditions were present and therefore did not capture the number of diseases, specific disease combinations, degree of functional limitation, or treatment burden. Research on anxiety and depression trajectories across chronic diseases has also shown substantial between-study heterogeneity in associated factors [6]. Thus, the routinely collected demographic and clinical variables examined here did not reliably distinguish profile membership. Future studies could incorporate process-related factors such as illness perceptions, illness uncertainty, treatment burden, pain, loneliness, coping style, self-efficacy, health literacy, and the inpatient sleep environment.

Theoretical interpretation and implications for clinical nursing

The findings are consistent with the TOUS perspective on co-occurring symptoms and contextual dependence. TOUS posits that different symptoms may co-occur and influence one another and that symptom experiences are shaped by physiological, psychological, and situational factors [12]. A subsequent integrative review further emphasized the co-experience of multiple symptoms as an

important application of TOUS in symptom science [14]. The depressive symptoms-sleep disturbance profile and the high anxiety and depressive symptoms profile show that, within the retained three-profile solution, different patients may exhibit different symptom combinations, providing a person-centered complement to understanding the co-experience of multiple symptoms at the patient level. The fact that perceived social support did not form a primary classification axis further suggests that symptom experiences and contextual psychosocial resources do not necessarily vary along the same dimension. In this study, TOUS and the stress-buffering perspective on social support were used primarily to organize variables and interpret the observed joint configurations.

From a clinical nursing perspective, these findings suggest that psychosocial assessment during hospitalization should jointly cover emotional symptoms, sleep, and social support rather than infer patients' psychosocial status solely from demographic characteristics or the presence or absence of a primary caregiver. For patients with concurrent elevations in depressive symptoms and sleep disturbance, further assessment may address nighttime pain, ward noise and lighting, interruptions for nursing care, medication use, and sleep habits. A systematic review of inpatient sleep identified multiple environmental and care-related contributors to sleep impairment [44], and a systematic review of randomized controlled trials suggested that nurse-delivered or nurse-supported environmental, behavioral, and multicomponent nonpharmacological interventions may improve sleep in hospitalized patients [48]. For patients with concomitantly elevated anxiety and depressive symptoms, both domains should be assessed, together with their effects on disease management and functional status; referral may be considered when indicated by clinical assessment [49]. Patients in the relatively low anxiety and depressive symptoms profile may still warrant ongoing monitoring as hospitalization progresses. At present, these profiles are best viewed as prompts for multidimensional screening and further assessment; their value for clinical stratification requires external validation.

Strengths, limitations, and future directions

This study focused on the clinical care context of hospitalization without a primary caregiver and simultaneously examined anxiety, depression, sleep, and perceived social support in a relatively large sample drawn from four healthcare institutions. LPA identified joint configurations of psychosocial indicators at the patient level, adding information about heterogeneity that cannot be readily captured by overall means or average intervariable associations. Model selection integrated fit indices, profile size, classification quality, stability, parsimony, and clinical interpretability. Uncertainty in the class structure was transparently characterized through comparisons with competing numbers of profiles and alternative covariance structures, evaluations across random starting values, and 80% case-deletion resampling.

Several limitations should be acknowledged. First, the cross-sectional design precludes determination of temporal ordering, and no concurrent comparison group of patients with a primary caregiver was included; thus, the findings primarily characterize psychosocial heterogeneity among hospitalized patients without a primary caregiver. Primary-caregiver status was operationalized using a single self-reported item, without further information on caregiver type, duration of accompaniment, frequency, or

intensity of care. Second, participants were recruited by convenience sampling from four healthcare institutions in Hubei Province and represented multiple clinical departments and chronic disease types. We did not model study center, primary disease, or clinical department hierarchically or by stratification; therefore, differences in care practices, disease mix, and departmental composition across institutions may have influenced the observed profile structure, and generalization to other regions or disease-specific populations should consider their clinical composition. Third, anxiety, depression, sleep, and social support were all assessed using self-report scales and may therefore be affected by recall and common-method factors. The measurement time frames of the PHQ-9, GAD-7, and PSQI were not identical, and the MSPSS reflects general perceived social support rather than context-specific resources such as instrumental care during hospitalization, nighttime accompaniment, informational support, or support for treatment decision-making. PHQ-9 and GAD-7 scores were concentrated at the lower end in this sample, and the distribution of these continuous total scores may have influenced the Gaussian mixture model's identification of profile boundaries and small profiles. Finally, C2 comprised a small proportion of the sample and was sensitive to model specification and sample perturbation; the competing four-profile solution further improved some information criteria, indicating residual uncertainty in profile enumeration and small-profile boundaries. The analysis of associated factors also included a limited range of psychosocial process variables.

Future research should replicate the latent profiles in independent, geographically diverse samples, with particular emphasis on the reproducibility of the depressive symptoms-sleep disturbance profile, and should include concurrent comparisons with patients who have a primary caregiver. Longitudinal studies could repeatedly assess psychosocial status at admission, discharge, and postdischarge follow-up and use latent transition analysis to examine movement between profiles and associated clinical outcomes. Future studies could also incorporate hospital-context-specific social support, illness uncertainty [2], loneliness and social connection [17], health literacy [46], treatment burden, and symptom burden to further explain how psychosocial configurations develop and change.

Conclusions

Among hospitalized patients with chronic diseases and no primary caregiver, we retained a clinically interpretable three-profile solution comprising a relatively low anxiety and depressive symptoms profile, a depressive symptoms-sleep disturbance profile, and a high anxiety and depressive symptoms profile. Differences among profiles were driven primarily by distinct combinations of anxiety, depressive, and sleep symptoms, whereas perceived social support did not emerge as a major differentiating dimension. After correction for multiple testing, no routinely collected demographic or clinical factor was stably associated with profile membership. In inpatient nursing care, emotional symptoms, sleep, and social support may be assessed jointly, with symptom combinations used to prioritize further assessment. The smaller depressive symptoms-sleep disturbance profile showed comparatively weak stability, and its reproducibility should be evaluated in independent samples.

Abbreviations

AIC
Akaike information criterion
ARI
adjusted Rand index
AvePP
average posterior probability
BH
Benjamini-Hochberg
BIC
Bayesian information criterion
BMI
body mass index
CI
confidence interval
E0
equal within-profile variances with covariances fixed at zero
EE
equal within-profile variances with freely estimated covariances shared across profiles
GAD-7
Generalized Anxiety Disorder-7
LL
log-likelihood
LPA
latent profile analysis
MSPSS
Multidimensional Scale of Perceived Social Support
PHQ-9
Patient Health Questionnaire-9
PSQI
Pittsburgh Sleep Quality Index
RRR
relative risk ratio
saBIC
sample-size-adjusted Bayesian information criterion
STROBE
Strengthening the Reporting of Observational Studies in Epidemiology
TOUS
Theory of Unpleasant Symptoms.

Declarations

Ethics approval and consent to participate

The study was reviewed and approved by the Ethics Review Committee of Renmin Hospital of Wuhan University (approval no. WDRY2022-K122). Written informed consent was obtained from all participants before data collection. All data were de-identified before analysis, and the study was conducted in accordance with the Declaration of Helsinki.

Consent for publication

Not applicable.

Availability of data and materials

The datasets generated and/or analysed during the current study are not publicly available because they contain potentially sensitive information from hospitalized patients and are subject to institutional and ethical restrictions. De-identified data may be available from the corresponding author on reasonable request, subject to approval by the relevant institution and compliance with applicable ethical and data-protection requirements.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

TL, ZW, and YS contributed equally to this work and share first authorship. All three authors contributed to the conception and design of the study, data acquisition and curation, interpretation of the findings, and drafting and critical revision of the manuscript. TL and ZW contributed to the methodological design and statistical analysis. TL supervised the study and coordinated manuscript preparation and submission. All authors read and approved the final manuscript.

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Figures

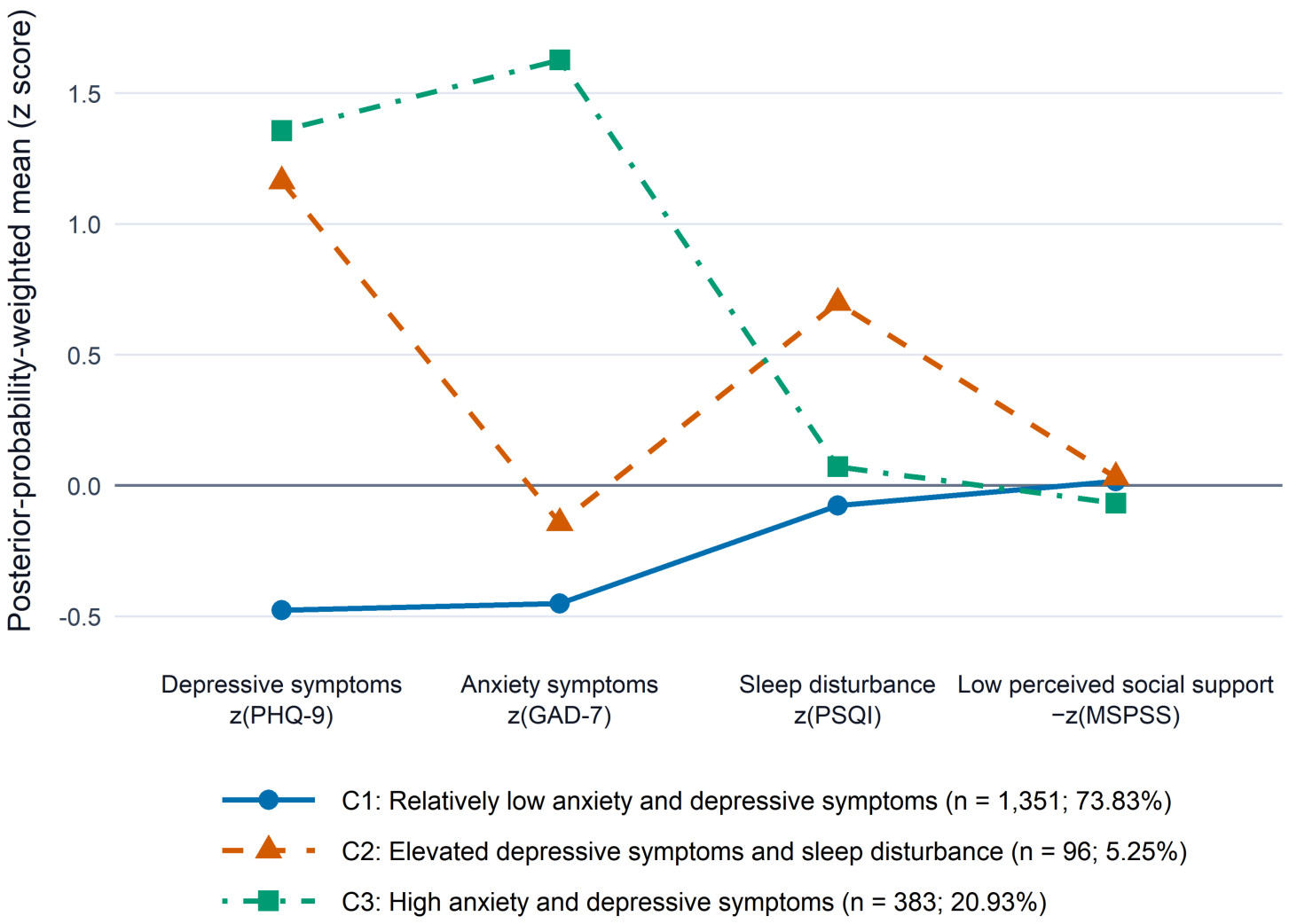


Figure 1

Posterior-probability-weighted standardized means of each indicator in the primary interpretive EE-K3 model (N=1,830). Higher values indicate, respectively, more severe depressive symptoms, more severe anxiety symptoms, greater sleep disturbance, and lower perceived social support. Values of n and percentages are based on maximum posterior probability assignment. Profile labels describe relative patterns within this sample and do not represent clinical diagnoses.

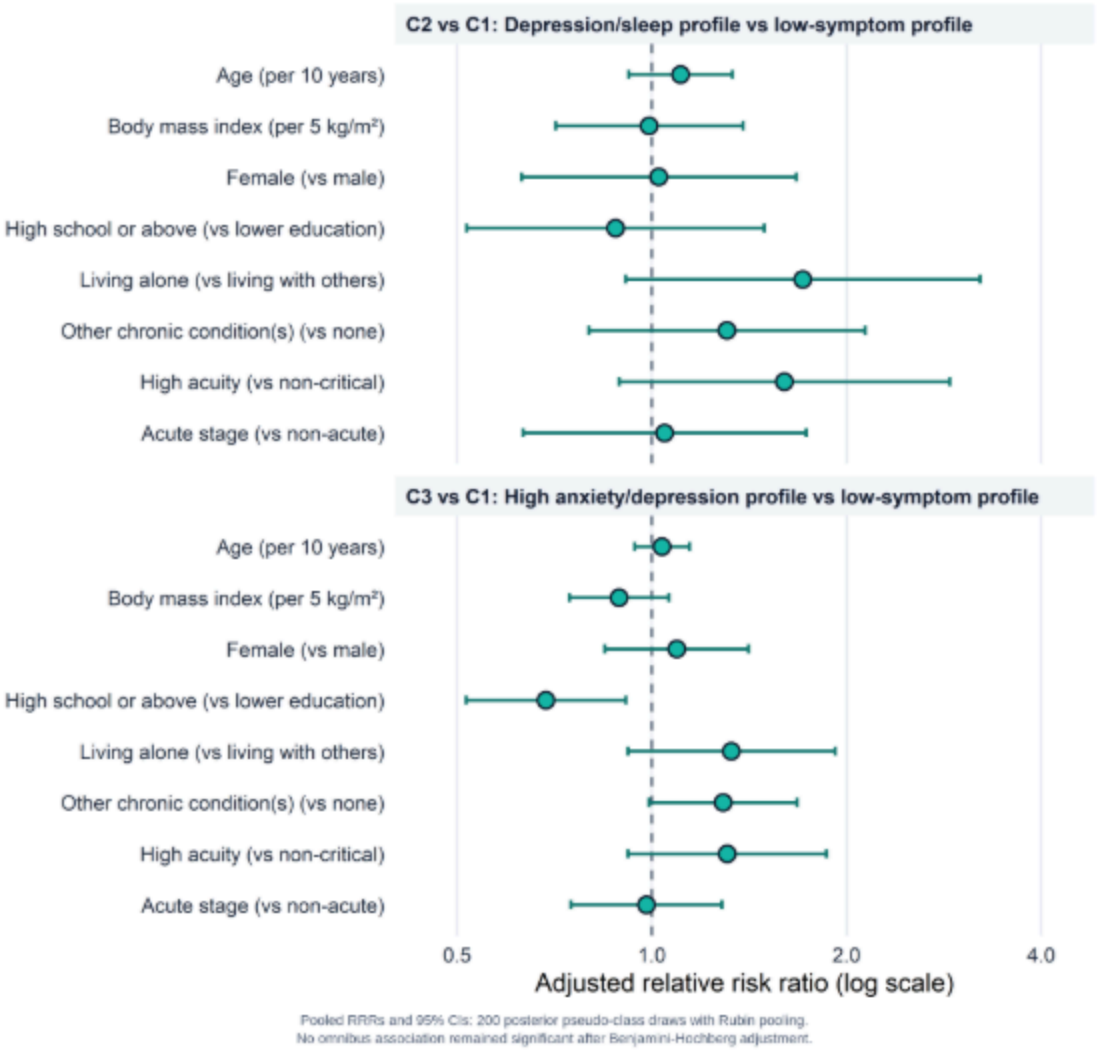


Figure 2

Multivariable-adjusted RRRs and 95% CIs for latent profile membership from multinomial logistic regression. Points and error bars represent RRRs and 95% CIs pooled using Rubin's rules across 200 posterior-probability-based repeated class draws. The model simultaneously adjusted for eight covariates. This analysis was used to reflect uncertainty in profile assignment conditional on the fixed LPA model. After BH correction, none of the omnibus associations for the covariates reached statistical significance.

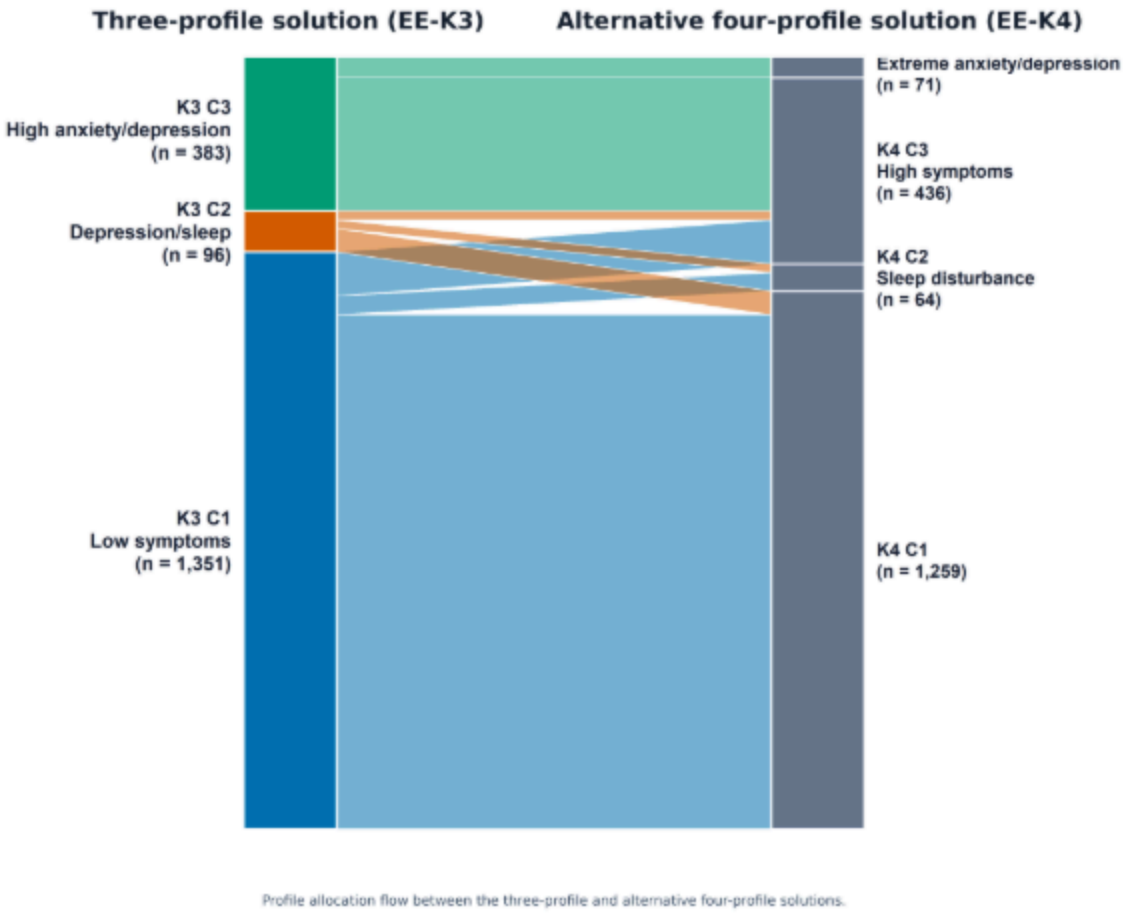


Figure 3

Profile membership flow between the primary EE-K3 and competing EE-K4 solutions. The figure illustrates movement in individual profile assignments across solutions with different numbers of profiles.

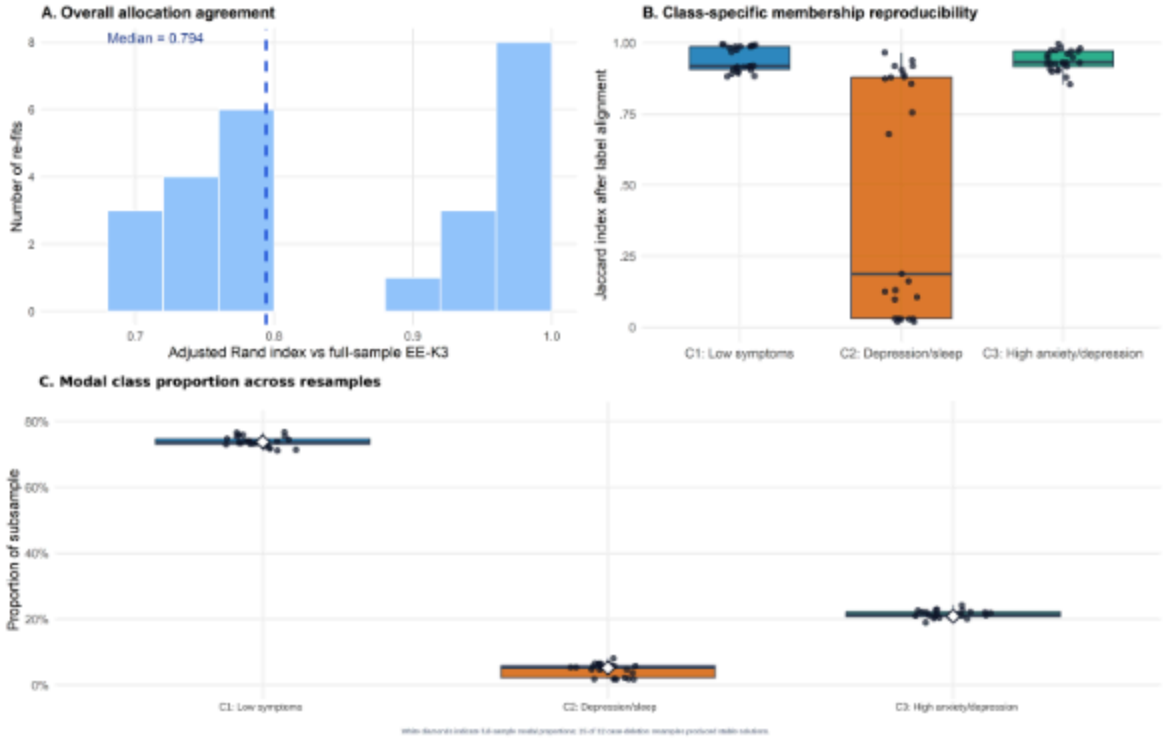


Figure 4

Internal stability of the primary interpretive EE-K3 model under 80% case-deletion resampling. Results are shown for the 25 of 32 repetitions that yielded stable, acceptable solutions; class labels were aligned with the full-sample EE-K3 solution. Panel A shows overall classification agreement, panel B shows class-specific Jaccard indices, and panel C shows profile proportions.

Supplementary Files

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

- AdditionalFile1EnglishGeneralInformationForm.docx