

Reproducible psychosocial–emotional profiles reveal population-level heterogeneity in young adults

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Abstract

Psychosocial and emotional experiences vary substantially across individuals, yet whether this heterogeneity reflects reproducible population-level structure remains unclear. Here, we examined psychosocial–emotional heterogeneity in 628 university students from two independent cohorts using a multidimensional profiling framework integrating environmental and emotional characteristics. Four psychosocial–emotional profiles emerged, each representing a distinct configuration of psychosocial context and emotional burden rather than variation along a single symptom dimension. These profiles exhibited systematically different patterns of psychosocial–emotional network organization, including differences in environmental–emotional connectivity and environmental factor centrality. Importantly, the profile structure was independently recovered in the validation cohort despite substantial between-cohort variation, demonstrating strong cross-sample reproducibility. Supervised profile transfer further showed robust generalizability across cohorts, with profile assignments exceeding 80% agreement with independently identified profiles. Together, these findings suggest that psychosocial–emotional heterogeneity is organized into reproducible population-level configurations that can be reliably identified across independent populations. By integrating multidimensional profiling, network characterization, and cross-cohort validation, this work provides a scalable framework for investigating heterogeneity in population mental health and for developing profile-informed approaches to prevention and intervention.

1. Introduction

Human emotional experiences and psychosocial environments exhibit substantial heterogeneity, yet whether such heterogeneity reflects meaningful population structure or merely continuous variation remains unclear. This challenge is particularly relevant during adolescence and young adulthood, developmental periods characterized by rapid psychological maturation and adaptation, during which emotional experiences related to depression, anxiety, and stress become increasingly salient^{1–3}. College students, who are situated within this developmental stage, often encounter concurrent academic, social, financial, and interpersonal demands^{4,5}. Understanding how psychosocial contexts and emotional experiences jointly organize across individuals may therefore provide important insights into population-level mental health variation.

A major challenge in understanding population mental health lies in explaining individual heterogeneity^{6,7}. Even when exposed to comparable psychosocial environments, individuals may exhibit markedly different emotional responses⁸. For example, under similar social and family conditions, some students display relatively high emotional resilience, whereas others experience substantial emotional burden. Such variability raises a fundamental question: does population heterogeneity reflect reproducible underlying structure, or does it primarily represent continuous individual variation? Addressing this question is essential for developing coherent and generalizable accounts of how psychosocial contexts and emotional experiences jointly shape mental health.

Previous research has addressed heterogeneity by stratifying individuals based on a single predefined characteristic, such as an individual's only-child status⁹, gender¹⁰, or the presence versus absence of co-occurring emotional symptoms¹¹, to reduce variability within groups and facilitate between-group comparisons. Although informative, such approaches treat heterogeneity as variation along a single dimension at a time, and therefore have limited ability to capture the multidimensional patterns through which emotional experiences and psychosocial contexts co-occur. Increasingly, studies have begun to characterize individual differences using multidimensional profiles rather than relying on single-factor stratification¹². Such multidimensional representations allow for the capture of heterogeneous patterns more comprehensively than single-variable splits. In this context, distinct groups may be characterized by joint configurations across multiple emotional dimensions and psychosocial contexts, including depression-, anxiety-, and stress-related experiences alongside family and social environments¹³.

Accordingly, a multivariate approach can be used to capture how emotional experiences co-occur with psychosocial contexts. By jointly considering multiple emotional dimensions alongside family and social resources, multivariate profiling can summarize heterogeneous individuals into interpretable configurations that reflect their shared pattern structure. For example, family environment and social support have consistently been linked to youth psychological well-being^{14,15}, only-child status may influence stress-coping styles and emotional dependence⁹, peer networks reflect available social buffering¹⁶, and parental education level has been associated with resilience-related resources and perceived stress¹⁷. Importantly, these psychosocial statuses are hardly separable from emotional experiences; instead, they tend to co-evolve and form coherent joint configurations¹⁷. We refer to these configurations as **psychosocial-emotional profiles**. Examining and characterizing such profiles provides a structured representation of multidimensional population heterogeneity.

Building on this perspective, the present study aims to develop a data-driven approach to characterize psychosocial-emotional profiles in college students. While many existing approaches have shown promise for modeling complex latent classes and profiles, their practical applicability at the population level is constrained by limited reproducibility and transferability across samples. Considering this background, we address three questions: (1) Can distinct psychosocial-emotional profiles be empirically identified among college students? (2) Do these profiles exhibit distinct profile-specific patterns in the joint organization of emotional experiences and psychosocial contexts? (3) Are the identified psychosocial-emotional profiles stable and reproducible across independent samples?

To address these questions, we analyzed survey data from Chinese college students that included measures of emotional experiences, such as depression, anxiety and stress, alongside key family and social contextual factors. As illustrated in Fig. 1, we implemented a data-driven profiling framework that characterizes psychosocial-emotional profiles based on the joint distribution of emotional and environmental factors. First, psychosocial-emotional profiles were identified using clustering analyses. Next, we characterized each profile in terms of its internal patterns to delineate profile-specific configurations. Finally, the stability and reproducibility of the identified profiles were evaluated through

validation in an independent sample. By organizing heterogeneity into distinct psychosocial-emotional profiles, this study provides a principled framework for understanding population-level variability and supports future efforts toward more personalized and profile-informed intervention strategies.

2. Results

2.1 Cohort characteristics and between-center heterogeneity

Two cohorts ($N = 628$) from *Xiangya School of Medicine* (48.2%) and *Shaoyang Medical College* (51.8%) facilitated a cross-center study to test whether psychosocial–emotional profiles capture stable, reproducible multivariate configurations rather than site-specific patterns. The combined sample consisted of 64.5% males and 35.5% females. The mean age of participants was 20.87 ± 1.424 (Mean $\pm$ Standard Deviation [SD]) years, and the mean grade was 2.74 ± 1.46 out of a total of 4.0. In the Shaoyang cohort ($N = 326$), the sample consisted of 62% males and 38% females, with a mean age of 20.79 ± 1.459 and a mean grade of 2.78 ± 1.5 . A total of 64.7% of students were from rural areas and 35.3% from urban areas. In the Xiangya cohort ($N = 302$), the sample consisted of 67.3% males and 32.7% females, with a mean age of 20.99 ± 1.364 and a mean grade of 2.69 ± 1.41 . A total of 69% of these students were from urban areas and 31% from rural areas⁹.

Clear inter-center differences were observed across multiple environmental and emotional dimensions. Compared with the Shaoyang cohort, students in the Xiangya cohort were slightly older ($t = 2.88, p = 0.04$) and more likely to be from urban areas (69.0% vs. 35.3%; $\chi^2 = 70.07, p < 0.001$). Xiangya students also reported significantly higher parental educational levels for both fathers ($\chi^2 = 49.58, p < 0.001$) and mothers ($\chi^2 = 46.52, p < 0.001$), whereas the proportion of only children was markedly higher in the Shaoyang cohort (81.0% vs. 53.5%; $\chi^2 = 53.15, p < 0.001$). Emotional experience scores also differed across centers. The Xiangya cohort exhibited significantly higher mean levels of anxiety (Generalized Anxiety Disorder-7, GAD-7: 5.7 ± 4.9 vs. 4.1 ± 4.6 ; $t = 4.20, p < 0.001$) and depression (Patient Health Questionnaire-9, PHQ-9: 7.0 ± 5.5 vs. 5.3 ± 5.3 ; $t = 3.93, p < 0.001$). In contrast, perceived stress levels did not differ significantly between centers (Perceived Stress Scale, PSS, $p = 0.802$), indicating comparable global stress exposure despite substantial differences in psychosocial context and emotional expression. No significant inter-center differences were observed for gender distribution, academic grade, or the presence of close friends (all $p > 0.05$). Together, these findings indicate that the two groups differ meaningfully in their social environments and emotional burdens while sharing similar educational and developmental backgrounds. This pattern of structured variance provided a natural data-level testbed for evaluating whether multidimensional profiles reflect stable and reproducible configurations rather than site-specific artifacts. Detailed demographic, social, and emotional characteristics of the overall dataset and the two groups, along with formal inter-center comparisons, are presented in Table 1.

Table 1

Cohort characteristics and between-center heterogeneity in psychosocial and emotional factors

Variable		Overall (N = 628)	Xiangya (N = 302)	Shaoyang (N = 326)	χ^2/t	P value
Age (Mean $\pm$ SD)		20.874 $\pm$ 1.424	20.993 $\pm$ 1.364	20.792 $\pm$ 1.459	t = 2.88	p = 0.04
Grade	Overall (Mean $\pm$ SD)	2.74 $\pm$ 1.46	2.69 $\pm$ 1.41	2.78 $\pm$ 1.5	t = - 0.77	p = 0.444
	1st year	221 (35.1%)	95 (31%)	126 (39%)	/	/
	2nd year	68 (10.8%)	52 (17%)	16 (4.9%)		
	3rd year	36 (5.7%)	32 (11%)	4 (1.2%)		
	4th year	262 (41.7%)	99 (33%)	163 (50%)		
	5th year	42 (6.7%)	25 (8.3%)	17 (5.2%)		
Gender	Male	406 (64.5%)	204 (67.3%)	202 (62%)	$\chi^2=1.75$	p = 0.186
	Female	223 (35.5%)	99 (32.7%)	124 (38%)		
Hometown	Rural	305 (48.5%)	94 (31%)	211 (64.7%)	$\chi^2=70.07$	p < 0.001
	Urban	324 (51.5%)	209 (69%)	115 (35.3%)		
Father's Education	High school or below	440 (70.0%)	171 (56.4%)	269 (82.5%)	$\chi^2=49.58$	p < 0.001
	Above high school	189 (30.0%)	132 (43.6%)	57 (17.5%)		
Mother's Education	High school or below	474 (75.4%)	191 (63%)	283 (86.8%)	$\chi^2=46.52$	p < 0.001
	Above high school	155 (24.6%)	112 (37%)	43 (13.2%)		
Relationship Status	Single	496 (78.9%)	252 (83%)	244 (75%)	$\chi^2=6.0328$	p = 0.0140
	Non-single	133 (21.1%)	51 (17%)	82 (25%)		
Close Friends	No	405 (64.4%)	193 (64%)	212 (65%)	$\chi^2=0.43$	p = 0.806

Variable		Overall (N = 628)	Xiangya (N = 302)	Shaoyang (N = 326)	χ^2/t	P value
	At least 1 friend	224 (35.6%)	110 (35.9%)	114 (34.9%)		
Only Child	Only Child	426 (67.7%)	162 (53.5%)	264 (81%)	$\chi^2=53.15$	p < 0.001
	Has Siblings	203 (32.3%)	141 (46.5%)	62 (19%)		
Scale Scores (Mean $\pm$ SD)	PSS Score	16.9 $\pm$ 4.4	16.9 $\pm$ 4.9	16.8 $\pm$ 4	t = 0.25	p = 0.802
	GAD-7 Score	4.9 $\pm$ 4.8	5.7 $\pm$ 4.9	4.1 $\pm$ 4.6	t = 4.2	p < 0.001
	PHQ-9 Score	6.1 $\pm$ 5.5	7 $\pm$ 5.5	5.3 $\pm$ 5.3	t = 3.93	p < 0.001

2.2 Identification and characterization of psychosocial-emotional profiles

For structured characterization, all variables were organized into seven predefined dimensions, each capturing a distinct aspect of individual context or emotional experience. Specifically, three dimensions reflected environmental context, including Personal Characteristics (PER), Family Background (FAM), and external Emotional Support (EMS). Four dimensions captured emotional experiences, including Anxiety (ANX), Depression (DEP), Perceived Helplessness (PHS), and Perceived Self-Efficacy (PSE; All dimensions are defined in Methods).

To derive population-level psychosocial–emotional profiles, hierarchical clustering was applied to environmental and emotional data in the Shaoyang cohort (see Methods). This data-driven procedure yielded four stable, distinct profiles over environmental and emotional factors. Instead of reflecting variation along a single dimension, these profiles represent compound psychosocial–emotional patterns that differ systematically in both environmental factors and emotional burden.

The four identified psychosocial-emotional profiles showed clear, interpretable distinctions. Profile 1 (n = 67, 20.6%), termed High External Environment–Low Emotional Burden (HEE–LEB), was characterized by higher levels of personal characteristics (PER) and emotional support (EMS), accompanied by uniformly low anxiety (ANX), depression (DEP), and perceived helplessness (PHS). Profile 2 (n = 72, 22.1%), Average External Environment–Low Anxiety and Depression (AEE–LAD), exhibited near-average environmental factors (PER, FAM, EMS) and relatively low levels of anxiety and depression. Profile 3 (n = 67, 20.6%), Low External Environment–High Stress and Depression (LEE–HSD), showed reduced environmental factors together with elevated stress-related dimensions (PSE, PHS) and DEP. Profile 4 (n = 120, 36.8%), Average External Environment–High Emotional Burden (AEE–HEB), was characterized by near-average environmental factors but consistently high levels of ANX, DEP, PSE, and PHS. Detailed

comparisons of these profiles and the overall sample mean are presented in Fig. 2.A-2.D and Supplemental Table S1.

To quantitatively characterize profile separation, we compared the four profiles across all seven dimensions using one-way Analysis of Variance (ANOVA) followed by Tukey tests (see Methods). Significant differences between profiles were observed for all emotional dimensions (ANX, DEP, PHS, and PSE; all ANOVA $p < 0.001$). Among environmental dimensions, the PER showed significant variation across profiles (ANOVA $p < 0.001$), whereas the FAM and EMS did not differ significantly in their mean levels. Overall, viewing the integrated configuration of emotional and environmental factors as the multivariate profile of each participant enabled the identification of four profiles that were sharply differentiated (Fig. 2.E-2.K and Supplemental Table S2).

Tukey test further clarified the separation among the four profiles (Fig. 2.E-2.K and Supplemental Table S2). For the emotional factors, ANX and DEP showed widespread profile separation, nearly all pairwise contrasts were highly significant ($p < 1 \times 10^{-12}$). PHS also demonstrated extensive separation across profiles, with all pairwise comparisons reaching extreme significance ($p < 1 \times 10^{-12}$) except for LEE-HSD versus AEE-HEB ($p = 0.524$), indicating comparable perceived helplessness levels between these two profiles. For PSE, significant contrasts were observed between HEE-LEB and AEE-LAD ($p = 3.69 \times 10^{-4}$) and between AEE-LAD and LEE-HSD ($p = 5.46 \times 10^{-3}$), whereas all remaining comparisons were non-significant.

Although all participants were recruited from similar social and educational backgrounds, some between-profile differences were still observed. For example, PER showed a significant contrast between HEE-LEB and AEE-HEB ($p = 2.04 \times 10^{-2}$). While mean levels of environmental factors showed limited between-profile differences, this pattern suggests that profile differentiation may not be fully captured by score distributions alone. Collectively, these findings delineate a coherent taxonomy of psychosocial-emotional profiles shaped by the joint configuration of environmental factors and emotional patterns.

2.3 Profile-specific association patterns in psychosocial-emotional networks

To characterize association patterns between environmental and emotional factors across the four psychosocial-emotional profiles, profile-specific psychosocial-emotional networks were constructed (see Methods). Network properties were examined at three levels: global network topology (Fig. 3.A-3.D), network stability (Fig. 3.E-3.H), and node-strength distributions (Fig. 3.I-3.N).

At the level of the global network, the four psychosocial-emotional profiles exhibited distinct association patterns between environmental and emotional factors (Fig. 3.A-3.D). HEE-LEB showed the sparsest network structure (average degree = 5.346), characterized by the fewest edges and several prominent negative associations, including a negative association between FAM and ANX (Fig. 3.A). In contrast, AEE-LAD (average degree = 5.945), LEE-HSD (average degree = 5.951) and AEE-HEB (average degree =

5.863) exhibited more densely connected structures. Specifically, AEE-LAD displayed generally weak associations between environmental factors and ANX and DEP (Fig. 3.B). LEE-HSD exhibited strong positive associations linking EMS to PHS and PSE (Fig. 3.C). AEE-HEB demonstrated widespread positive associations among emotional factors and relatively uniform coupling between environmental factors and emotional factors (Fig. 3.D).

Differences across psychosocial-emotional profiles were further reflected in global network metrics, including average degree, network diameter, global efficiency, and average strength (Fig. 3.I-3.L). Consistent with its sparse network structure, HEE-LEB exhibited the lowest average degree, global efficiency, and clustering coefficient, as well as the largest network diameter. In contrast, AEE-LAD, LEE-HSD, and AEE-HEB showed broadly comparable values across these metrics, indicating higher overall connectivity. Incorporating edge weights revealed additional differentiation across profiles. HEE-LEB showed the lowest average strength (-0.254 ± 0.053), driven primarily by strong negative associations, particularly between FAM-ANX and DEP-PHS. LEE-HSD exhibited a mixture of strong positive and negative associations, yielding an average strength close to zero (-0.013 ± 0.053). AEE-LAD and AEE-HEB displayed predominantly positive edge-weight patterns.

Focusing on environmental factors, node-strength analysis revealed distinct distribution patterns across psychosocial-emotional profiles (Fig. 3.N). In the HEE-LEB profile, FAM, EMS, and PER all exhibited relatively low node strengths, with FAM showing the lowest overall strength. In AEE-LAD, FAM demonstrated the highest node strength, indicating a stronger overall association between family-related environmental and emotional factors within this profile. In LEE-HSD, EMS showed markedly elevated node strength relative to the other profiles, whereas FAM and PER exhibited comparatively lower values. In contrast, AEE-HEB had the highest node strength for PER, while FAM and EMS showed more moderate values. Together, these results indicate that the relative contribution of environmental factors to the psychosocial-emotional network differs systematically across profiles, with distinct patterns of node strength distribution observed for FAM, EMS, and PER.

To ensure the robustness of these findings, we performed nonparametric bootstrapping on all profile-specific networks (see Methods). Across all profiles, edge weights remained highly consistent and fell within narrow confidence intervals (Fig. 3.E-3.H), indicating that the estimated network structures reflected stable statistical properties rather than sampling fluctuations.

Taking together, these analyses demonstrate that association patterns between environmental and emotional factors differ systematically across psychosocial-emotional profiles. Profiles showed distinct node-strength distributions and connectivity patterns involving FAM, EMS, and PER, particularly in their associations with stress-related and affective dimensions. These results highlight profile-specific configurations of associations between environmental and emotional factors within psychosocial-emotional networks.

2.4 Reproducibility and cross-dataset consistency of psychosocial-emotional profiles

To evaluate the reproducibility and cross-dataset consistency of the identified psychosocial-emotional profiles, we conducted validation analyses in an independent cohort from Xiangya (see Methods). Two complementary validation strategies were implemented. The first strategy assessed whether the profile structure could be independently recovered through direct re-identification using the same unsupervised profiling procedure. The second strategy examined whether profile membership could be reliably assigned across datasets through supervised classification, using profile labels derived from the discovery cohort. Consistency between these two strategies was subsequently evaluated to determine the stability and portability of the profile solution across analytical approaches and samples (Fig. 4).

Under the first re-identification strategy, the same profile identification procedure established in the Shaoyang cohort was independently applied to the Xiangya dataset (Appendix II and Figure S1). This unsupervised re-identification yielded four profiles with configuration patterns highly similar to those observed in the discovery cohort (Fig. 4.A–4.D). Meanwhile, psychosocial-emotional networks reconstructed within the Xiangya cohort exhibited stable structural properties (Appendix II, Tables S5–S6 and Figure S1). Together, these findings demonstrate that the psychosocial-emotional profiles identified in the Shaoyang cohort are reproducible at the structural level in an independent dataset.

Under the second classification strategy, profile membership was examined using supervised classification models trained on the Shaoyang cohort and applied to the Xiangya dataset. Six algorithms were trained using profile labels derived from hierarchical clustering and evaluated via five-fold cross-validation (see Methods). Across models, cross-validation results demonstrated consistently high discriminative performance in distinguishing psychosocial-emotional profiles (Fig. 4.E–4.H). RF and SVM achieved the highest area under the receiver operating characteristic curve (AUC = 0.992, CI: 0.988–0.996), followed by DNN (AUC = 0.989), ElasticNet (AUC = 0.988), XGBoost (AUC = 0.986), and LDA (AUC = 0.977; Fig. 4.I). Importantly, this performance reflects the internal separability of the empirically derived profiles rather than clinical or diagnostic classification. These results were used to identify a stable and well-performing classifier for subsequent cross-dataset application, rather than to claim predictive performance per se.

We next evaluated profile-level classification performance by treating the Xiangya cohort as an independent test set. Profile assignments obtained through independent re-identification in Xiangya were used as reference labels. All six classification models trained on the Shaoyang cohort were applied to the Xiangya data. Among them, the RF model demonstrated the most stable and consistent generalization performance across internal cross-validation and external testing (AUC = 0.950, 95% CI: 0.948–0.951; Fig. 4.J), outperforming the other algorithms. Based on this consistency, RF was therefore used as the primary classifier for subsequent cross-dataset analyses. Feature contribution patterns were further examined using SHapley Additive exPlanations (SHAP) analysis (see Methods), revealing distinct contribution profiles across psychosocial-emotional profiles (Appendix II and Figure S2).

Classification performance was further characterized using the RF confusion matrix (Fig. 4.K). The AEE-HEB profile showed the highest sensitivity, correctly classifying 115 of 120 cases (95.8%). HEE-LEB also showed strong separability (20/24, 83.3%), followed by AEE-LAD (51/65, 78.5%). Lower classification accuracy was observed for LEE-HSD (56/93, 60.2%), with most misclassifications occurring as AEE-HEB (33/93, 35.5%). These results indicate profile-specific differences in classification separability while demonstrating the overall robustness of cross-dataset profile assignment.

Taken together, the substantial overlap between profile assignments obtained from direct re-identification and cross-dataset classification provides convergent evidence for the stability and consistency of the psychosocial-emotional profile structure. As illustrated by the Sankey diagram (Fig. 4.L), the majority of individuals showed concordant profile assignments across the two strategies, with overall agreement exceeding 80.1%. This convergence across unsupervised re-identification and supervised classification demonstrates that the identified psychosocial-emotional profiles are neither sample-specific nor method-dependent, but rather reflect stable and generalizable organizational patterns of emotional and environmental factors. Such cross-dataset consistency strengthens the methodological validity and translational potential of the proposed profiling framework, providing a robust foundation for future applications in population-level screening and profile-informed intervention strategies.

3. Discussion

This study demonstrated that psychosocial-emotional heterogeneity among young adults was organized into a small number of stable and reproducible configurations, defined by the joint embedding of environmental factors with emotional factors. Using a data-driven profiling framework, we identified four psychosocial-emotional profiles among Chinese college students that capture distinct multivariate patterns integrating psychosocial context with emotional burden, rather than variation along a single symptom dimension^{6,18}. Importantly, this organizational structure was consistently confirmed in an independent cohort and showed strong cross-dataset consistency through supervised classification, supporting the stability and generalizability of the identified profiles. Together, these findings established a transferable and reproducible approach for organizing and characterizing population-level heterogeneity in environmental resources and emotional experiences, providing a structured basis for subsequent characterization and feature application.

By jointly modeling environmental factors and emotional factors within a unified, data-driven structure, the present profiling approach moved beyond traditional single-variable stratification approaches. Crucially, the robustness of this profile structure was supported by two complementary validation strategies, unsupervised re-identification and cross-dataset supervised classification, which converged on highly consistent profile assignments. This convergence indicated that the identified profiles reflected stable population-level profile patterns, rather than cohort-specific artifacts or modeling idiosyncrasies. From a population-oriented perspective, such reproducibility is essential, as psychosocial heterogeneity is often sensitive to sampling, measurement, and analytical choices. A profiling approach that can be

consistently recovered across cohorts and methodological paradigms provides a necessary foundation for scalable population-level characterization and profile-informed applications.

Integrating symptom-level differences and profile-specific network organization observed in the results, the four psychosocial-emotional profiles can be interpreted as reflecting distinct modes through which environmental context is incorporated into emotional systems. The HEE-LEB profile reflects a context-buffered emotional organization, in which favorable environmental conditions appear to decouple emotional processes and protect against the accumulation of emotional burden. The AEE-LAD profile represents a relatively compartmentalized organization, where emotional experiences remain weakly interconnected despite average environmental conditions, suggesting limited internal amplification of emotional dimensions. In contrast, the LEE-HSD profile is characterized by a stress-amplified organization, in which social contextual factors become tightly integrated with stress-related emotional dimensions, potentially reinforcing emotional vulnerability. The AEE-HEB profile reflects a densely integrated emotional organization, in which emotional dimensions are strongly interlinked and environmental influences are broadly embedded, consistent with a generalized susceptibility to emotional burden.

Based on the node-strength pattern of environmental factors, the four psychosocial-emotional profiles can be interpreted as showing different modes of environmental influence. Specifically, the HEE-LEB profile aligns with an external positive support pattern, in which environmental factors are weakly or negatively associated with emotional burden. The AEE-LAD profile reflects a negative family support pattern, characterized by selective coupling between family-related factors and stress-related emotional dimensions. The LEE-HSD profile corresponds to a negative social support pattern, in which emotional support is strongly linked to stress and depressive experiences. Finally, the AEE-HEB profile can be viewed as a negative personal support pattern, in which personal characteristic factors are embedded within a densely interconnected emotional system associated with a high emotional burden. Together, these patterns provide a practical interpretation of how different environmental factors are differentially involved across profiles, complementing the profile-level and network-level findings.

When interpreted from a population-management perspective, the four psychosocial-emotional profiles may imply emphases in different management and intervention approaches. For the HEE-LEB profile, environmental factors already exert a positive influence, and individuals display a low emotional burden. Interventions may therefore focus on maintaining existing support systems, strengthening resilience, and providing light-touch stress-management programs¹⁹. For the AEE-LAD profile, although FAM broadly shapes its external manifestations, individuals remain in a generally low-anxiety and low-depression state. Intervention strategies may therefore emphasize low-intensity communication training to reduce family-related stressors²⁰. In the LEE-HSD profile, elevated stress levels may result from interpersonal demands exceeding coping capacity. Suitable interventions could target social-pressure management, boundary-setting, and restructuring maladaptive expectations regarding emotional support²⁰. For the AEE-HEB profile, individuals exhibit substantial emotional burden. Given its internal

association, intervention strategies such as emotion regulation training and self-efficacy enhancement may be most beneficial²¹.

Integrating the profile-specific patterns into a broader perspective, our findings reveal a systematic mapping between environmental factors and emotional factors at the population level²². At a broader level, FAM and EMS show stronger effects on stress-related dimensions, whereas PER has a greater influence on anxiety and depression. Such insights provide a conceptual basis for population-level mental health strategies in university settings, indicating that group-based interventions may benefit from prioritizing family- and peer-related stress management on the one hand, and support for academic and personal development challenges on the other.

This study can be improved in several directions. First, participants were recruited exclusively from medical universities, which may affect the generalizability of our findings to the broader college student population. We anticipate that differences in social context or demographic composition may limit the reproducibility of the identified profiles in more diverse populations. Second, a cross-sectional design prevented us from drawing conclusions about temporal stability or causal pathways among psychosocial and symptom features, an issue that is particularly important for informing future intervention research. Third, the assessment of psychosocial and symptom dimensions relied on specific questionnaires and self-reported contextual factors, which may introduce measurement biases; thus, determining which external and internal factors should be prioritized in future models remains an important methodological question²³. Finally, incorporating additional ecological data, such as digital behavior, sleep patterns, or physiological signals, may further enhance the precision of profile modeling and deepen mechanistic understanding in future studies²⁴.

4. Conclusion

In conclusion, this study identifies a reproducible and transferable organization psychosocial–emotional heterogeneity among college students. By jointly modeling environmental factors and emotional factors, we identified a stable four-profile structure that captured distinct multifactorial configurations of emotional burden and psychosocial context, rather than variation along single dimensions. The identified profiles were independently confirmed across cohorts and showed strong cross-dataset consistency through both unsupervised re-identification and supervised profile transfer, indicating that they reflect robust population-level profiles rather than cohort-specific patterns. By integrating multivariate profiling with network-based characterization, this study provides a structured representation of how environmental context is embedded within emotional systems in young adults, offering a principled foundation for future longitudinal and population-oriented investigations of psychosocial–emotional profile.

5. Methods

5.1 Participants

The study enrolled 628 medical students from two institutions, Xiangya School of Medicine (n = 302) and Shaoyang Medical College (n = 326). These two cohorts provided an opportunity to examine psychosocial-emotional profiles across distinct social contexts within a comparable developmental stage. The study protocol was approved by the Ethics Committee of Xiangya Hospital, Central South University (Approval No. 202201002), and informed consent was obtained electronically from all participants prior to data collection. A detailed summary of demographic variables for each cohort is presented in Table 1. Between-cohort differences in categorical variables were evaluated using chi-square tests to characterize baseline heterogeneity across sites.

5.2 Measurements

The research questionnaire was divided into two sections. The first section focused on collecting sociodemographic information and family background to serve as environmental factors. The second section included three widely used psychological scales, the Patient Health Questionnaire-9 (PHQ-9)²⁵, the Generalized Anxiety Disorder-7 (GAD-7)²⁶, and the Perceived Stress Scale-10 (PSS-10)^{27,28}. The questionnaire was designed to be completed in approximately 3 to 5 minutes. Participation was voluntary, and the data collection process was monitored by WeChat group administrators to ensure validity and reliability.

Binarization was adopted to harmonize variables measured on heterogeneous scales and to emphasize the presence–absence patterns of psychosocial and emotional features at the population level. Variables that were not originally binary were processed as follows: Grade level was coded as 0 for students in years below year 3 and 1 for those in years above year 3. The number of close friends was dichotomized as 0 (none) or 1 (at least one). For the PSS-10, four reverse-scored items were recorded to align with the direction of positively scored items. Subsequently, all individual items from the three psychometric scales (PHQ-9, GAD-7, and PSS-10) were dichotomized as 0 (symptom absent) or 1 (symptom present).

To identify psychosocial-emotional profiles, we categorized all items into seven distinct dimensions designed to capture a comprehensive range of constructs: Personal Characteristics (PER, including gender and grade); Family Background (FAM, including hometown and parental education); Emotional Support (EMS, including relationship status, friends and only-child status); Anxiety (ANX, GAD-7 items); Depression (DEP, PHQ-9 items); Perceived Helplessness^{29–31} (PHS, positive-scoring PSS items); and Perceived Self-Efficacy^{29–31} (PSE, negative-scoring PSS items). These dimensions were conceptually grouped into environmental dimensions (PER, FAM, EMS) and emotional dimensions (ANX, DEP, PHS, PSE). Although individual items were binarized, dimension-level scores were derived by summing item-level indicators, yielding ordinal-valued composite scores with a finite range, analogous to conventional scale scores.

5.3 Identification of psychosocial-emotional profiles

To characterize population-level psychosocial-emotional profiles, agglomerative hierarchical clustering was applied using the *hclust* function in R (stats package). Hierarchical clustering provides a deterministic and assumption-light framework for organizing individuals based on multivariate similarity without requiring prior specification of the number of profiles. Pairwise dissimilarity between individuals was quantified using Euclidean distance, and cluster linkage was performed using Ward's minimum variance method³².

Rather than treating the number of clusters as an intrinsic model parameter, we examined clustering resolutions ($K = 2-5$) to identify a solution that best captured an interpretable, stable multivariate pattern. Candidate solutions were evaluated based on the coherence of profile patterns and the degree of separation across psychosocial-emotional profiles, using heatmap visualization and quantitative comparisons of dimension-level distributions (Appendix I and Figure S1). Based on these complementary criteria, a four-profile solution ($K = 4$) was selected as providing the most parsimonious and interpretable representation of population-level psychosocial-emotional profile.

One-way ANOVA (*stats::aov function*) was used to assess differences in each factor across the derived psychosocial-emotional profiles. For factors showing significant omnibus effects, Tukey tests (*stats::TukeyHSD function*) were conducted to characterize pairwise differences between profiles³³.

5.4 Psychosocial-emotional network construction and analysis

We employed the Graphical LASSO (Glasso) method^{34,35} to construct profile-specific psychosocial-emotional networks based on seven psychosocial and emotional dimensions. This approach estimates a Gaussian Graphical Model (GGM) by applying regularization through the Least Absolute Shrinkage and Selection Operator (LASSO), resulting in a sparse inverse covariance matrix. The LASSO penalty (L1 penalty) eliminates potential bias to create a sparse network, a method widely used in psychological research³⁶. The mathematical formulation for the estimator is as follows³⁴:

$$\widehat{K} = \operatorname{argmin}_K (trSK - \log \det K + \alpha ||K||_1)$$

Where K is the sparse inverse covariance matrix to be estimated; S is the covariance matrix of the sample; and $||K||_1$ is the sum of the absolute values of the off-diagonal coefficients of K . α is the sparsity parameter. The Graphical LASSO estimator was implemented using the scikit-learn library in Python³⁷.

To improve analytical accuracy, we are setting the diagonal elements to zero. This approach focuses solely on the association strength between different nodes, disregarding self-association. In the constructed network, an edge was defined between any node pair (i, j) if the corresponding element in the matrix was non-zero, with the edge weight determined by the matrix value. To evaluate network stability, we performed non-parametric bootstrapping^{38,39}. We randomly resampled 90% of the full

dataset and re-estimated the network structure. This process was repeated 1,000 times to obtain distributions, 95% confidence intervals, and mean values for each metric.

5.5 External validation and reproducibility analysis

To evaluate the cross-dataset transferability, reproducibility, and consistency of the psychosocial–emotional profile solution, we implemented a supervised machine-learning framework in Python using scikit-learn³⁷. Six commonly used classification algorithms with distinct inductive biases were benchmarked, including Support Vector Machines (SVM) with a Radial Basis Function (RBF) kernel⁴⁰, Random Forest (RF) ensembles (100 estimators)⁴¹, eXtreme Gradient Boosting (XGBoost)⁴², Logistic Regression with Elastic Net regularization⁴³, Linear Discriminant Analysis (LDA)⁴⁴, and a Deep Neural Network (DNN) featuring a dual hidden-layer architecture (128 and 64 neurons)⁴⁵.

An automated preprocessing pipeline was applied to minimize data leakage, with feature standardization performed within each training fold using StandardScaler. The Shaoyang cohort served as the discovery dataset for model development. Classification performance was assessed using stratified five-fold cross-validation to preserve the proportional distribution of psychosocial–emotional profiles across folds.

For external validation, models trained on the full Shaoyang cohort were subsequently applied to the independent Xiangya cohort without retraining or parameter updates. Reference profile labels for the Xiangya cohort were independently derived using the same hierarchical clustering procedure applied to the discovery cohort, enabling an assessment of cross-dataset label correspondence rather than supervised ground-truth prediction. Model performance in the external cohort was quantified using the macro-averaged area under the receiver operating characteristic curve (AUC) and overall classification accuracy.

Among the evaluated models, the Random Forest classifier demonstrated consistently strong performance across internal cross-validation and external validation and was therefore selected for subsequent interpretability analysis. To provide descriptive insights into model decision patterns, we applied SHapley Additive exPlanations (SHAP) using the TreeExplainer algorithm⁴⁶. SHAP values were computed to estimate feature-level contributions to model predictions and were normalized for visualization. This analysis was intended to facilitate the qualitative interpretation of profile-related feature patterns rather than to infer causal relationships.

Declarations

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Author contributions

Conceptualization: W.Z., J.K., S.Q., and F.W. Methodology: C.P., F.Z., and Y.T. Software: F.Z., Y.T., and C.P. Validation: C.P. Formal Analysis: C.P., F.Z., and Y.T. Investigation: F.W. and J.K. Resources: J.K., W.Z., and F.W. Data Collection & Curation: J.K., R.P., F.Z. and Y.T. Writing – Original Draft: C.P., F.Z., and Y.T. Writing – Review & Editing: All authors. Visualization: F.Z. and C.P. Supervision: W.Z., J.K., and F.W. Project Administration: W.Z. and S.Q. Funding Acquisition: W.Z. and J.K.

Data Availability

The datasets generated and analyzed during the current study consist of questionnaire-based survey data collected from university students. These data are not publicly available due to privacy and ethical restrictions related to participant confidentiality. De-identified data may be made available from the corresponding author upon reasonable request and with permission from the relevant institutional ethics committee.

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Figures

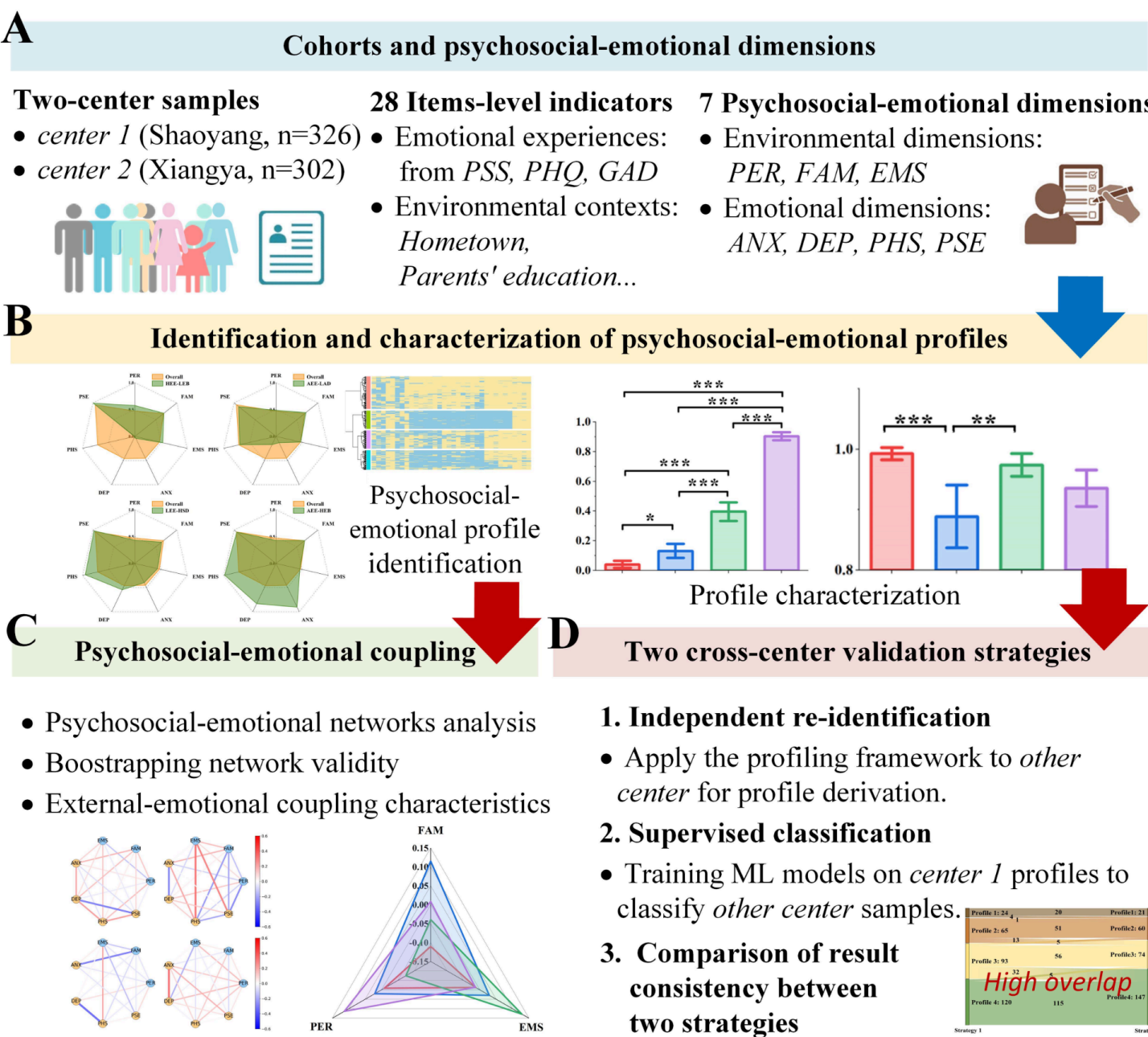


Figure 1

Schematic overview of the study design and analytical workflow. **(A)** Cohorts and psychosocial–emotional dimensions. Data were collected from two independent cohorts of medical university students. Item-level indicators capturing environmental contexts and individual emotional experiences were systematically organized into seven psychosocial–emotional dimensions. **(B)** Identification and characterization of psychosocial–emotional profiles. Distinct psychosocial–emotional profiles were identified in the Shaoyang cohort using a data-driven profiling framework. Each profile was characterized by its multivariate configuration across psychosocial–emotional dimensions, and between-profile differences were evaluated at the group level. **(C)** Profile-specific psychosocial–emotional coupling. To examine how environmental and emotional factors are jointly organized within each profile, profile-specific psychosocial–emotional networks were constructed. This analysis also focused on assessing network stability and delineating profile-specific patterns of feature coupling. **(D)** Cross-center validation. The robustness and generalizability of the identified profiles were evaluated in the independent Xiangya cohort using two complementary strategies: (1) independent re-identification of psychosocial–emotional profiles to assess structural reproducibility; and (2) profile assignment via supervised classification models trained on the discovery cohort to evaluate cross-dataset transferability. The high level of agreement between these two validation strategies provided convergent evidence for the stability and robustness of the identified psychosocial-emotional profiles.

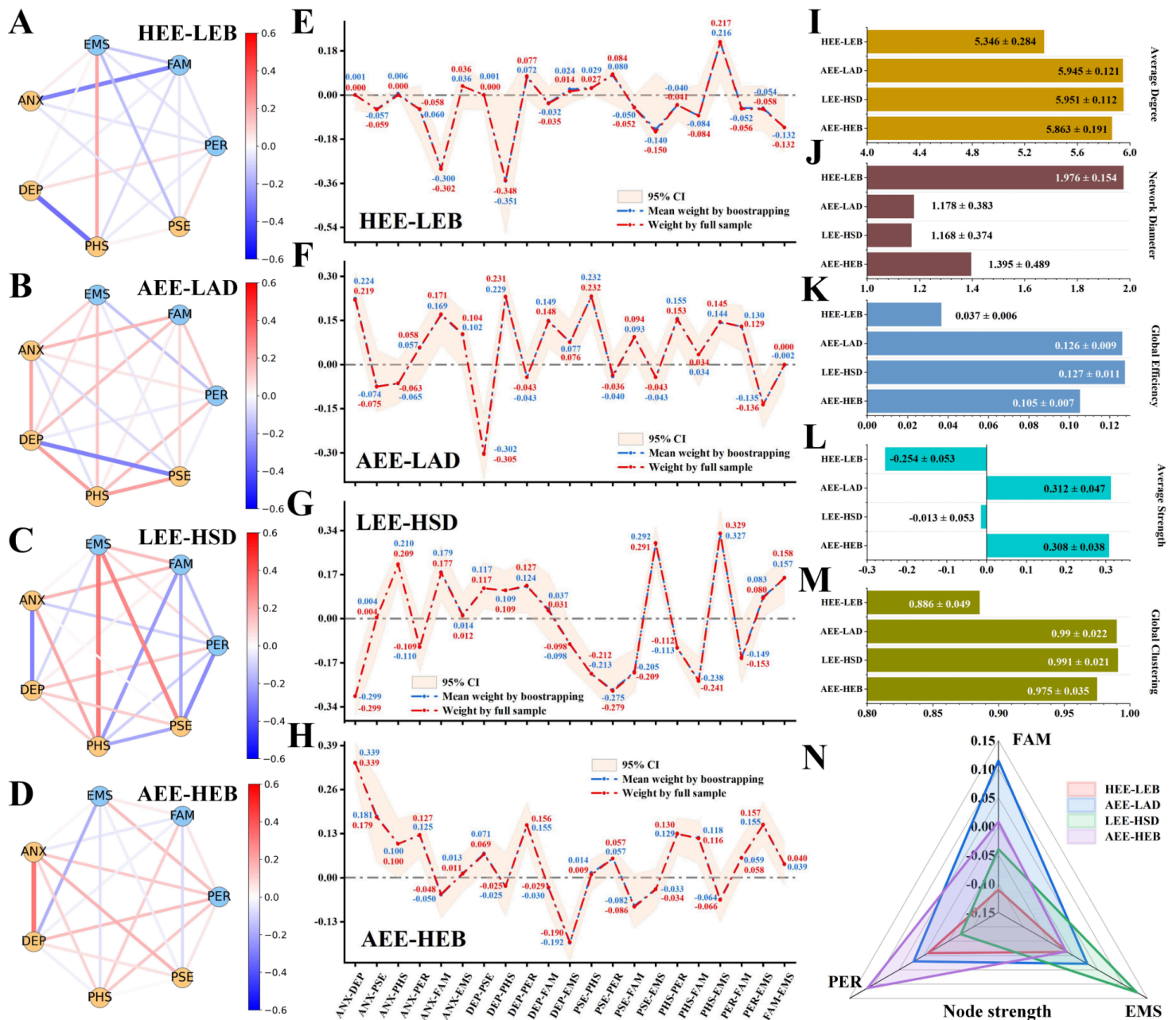


Figure 2

Profile-specific psychosocial-emotional networks across psychosocial-emotional profiles. (A–D)

Profile-specific psychosocial-emotional networks. Depicting pairwise associations between emotional factors (orange nodes) and environmental factors (blue nodes) within each psychosocial-emotional profile. Edge colors indicate the direction of associations (blue, negative; red, positive), and edge thickness reflects the magnitude of the association strength. **(E–H)** Edge-weight stability assessment. Edge-weight estimates for each profile were evaluated using non-parametric bootstrapping. Solid red lines denote edge weights estimated from the full dataset, dashed blue lines represent mean edge weights across bootstrap samples, and shaded regions indicate the 95% confidence intervals. Greater overlap between the solid red and dashed blue lines indicates higher edge stability and reliability across bootstrap samples. **(I–M)** Descriptive comparison of global network properties across profiles, including

(I) average degree, (J) network diameter, (K) global efficiency, (L) average strength, and (M) global clustering coefficient. (N) Environmental node strength profiles. Radar plots summarize the relative node strength of environmental factors across the four profiles, illustrating profile-specific differences in the prominence of environmental dimensions within the psychosocial-emotional networks.

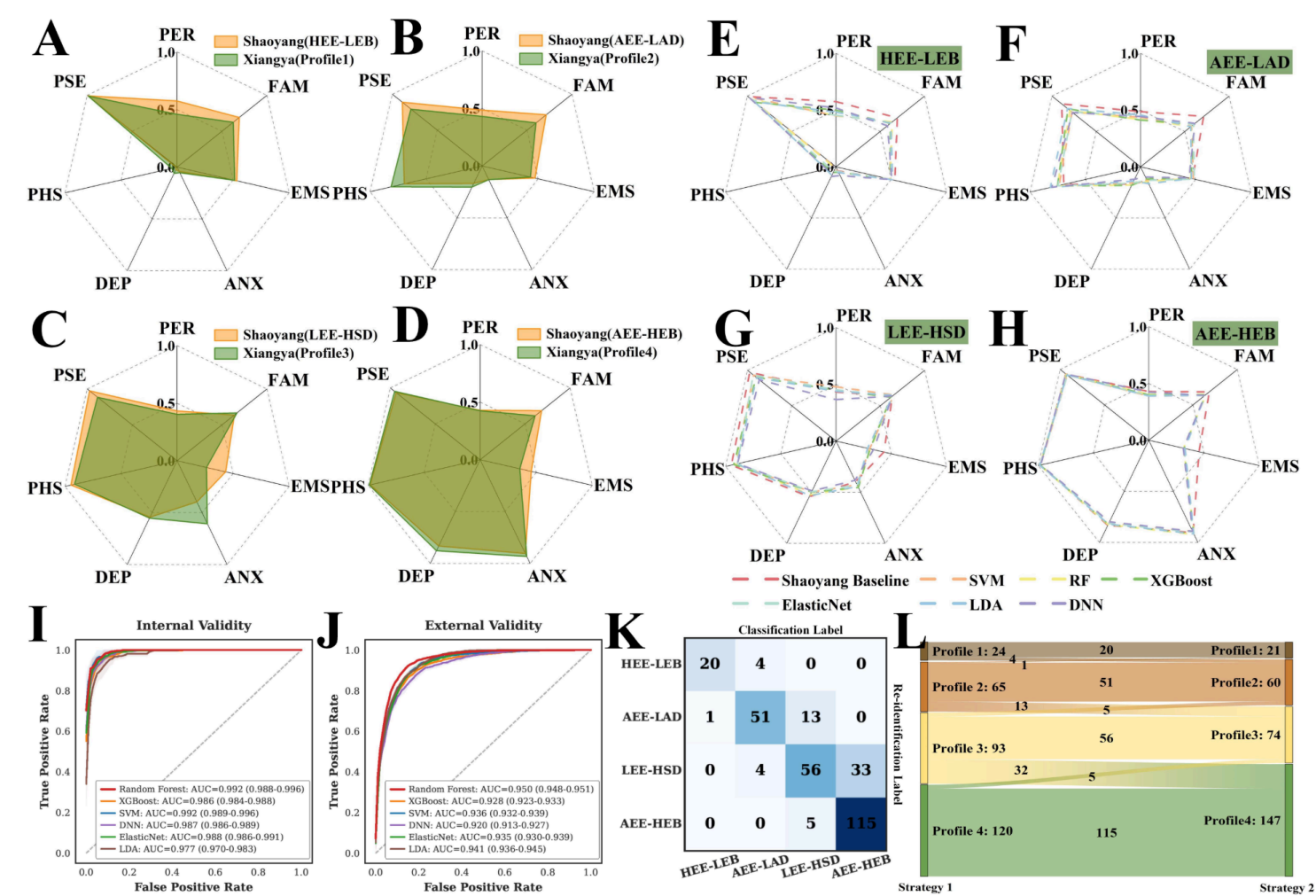


Figure 3

Cross-dataset reproducibility and profile transfer of psychosocial-emotional profiles. (A-D) Cross-cohort profile pattern comparison. Radar plots compare psychosocial-emotional profile configurations between the discovery cohort (Shaoyang, orange) and the independent validation cohort (Xiangya, green). High concordance of profile-specific multivariate patterns is observed across all four profiles. (E-H) Supervised profile transfer and pattern consistency. Radar plots show profile patterns obtained via supervised profile transfer using six classification algorithms, overlaid against the reference profile patterns derived from the Shaoyang cohort. Consistent recovery of profile signatures across models indicates robustness of the underlying profile structure rather than model-specific effects. (I) Internal validation. ROC curves from stratified five-fold cross-validation within the Shaoyang cohort summarize within-dataset separability of psychosocial-emotional profiles across classifiers. (J) External validation. ROC curves obtained by applying classifiers trained on the Shaoyang cohort to the independent Xiangya

cohort demonstrate strong cross-dataset profile transferability, with the Random Forest model achieving an area under the curve (AUC = 0.950). **(K-L)** Consistency between unsupervised re-identification and supervised classification profile transfer. **(K)** Confusion matrix summarizing correspondence between supervised profile assignments and independently derived profile labels obtained via unsupervised re-identification in the Xiangya cohort. **(L)** Sankey diagram visualizing alignment between profile labels obtained from unsupervised re-identification (left) and supervised cross-dataset profile classification (right), demonstrating high overall concordance between the two validation strategies.

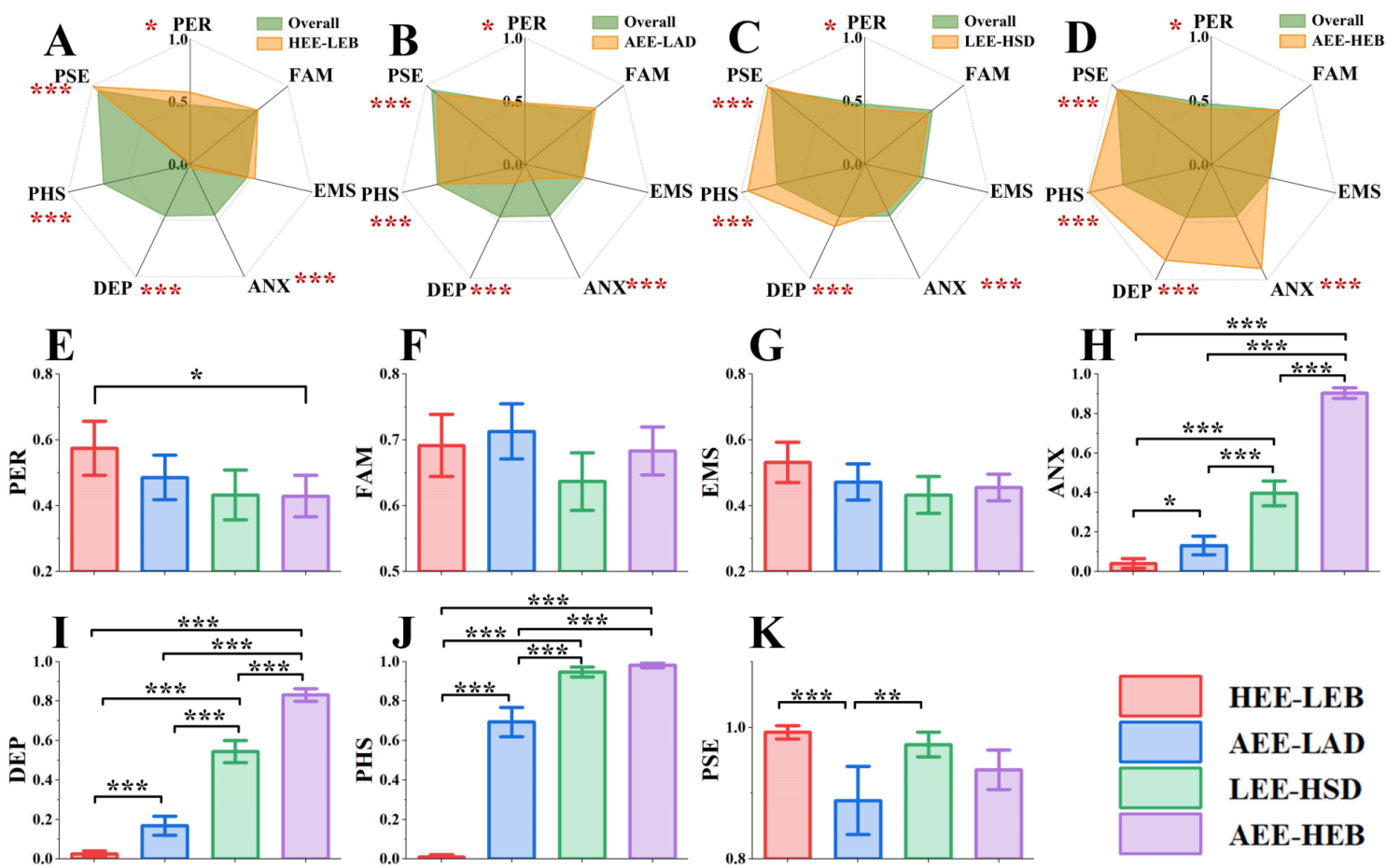


Figure 4

Identification and characterization of four distinct psychosocial-emotional profiles. **(A)** High External Environment-Low Emotional Burden profile(HEE-LEB); **(B)** Average External Environment-Low Anxiety and Depression profile (AEE-LAD); **(C)** Low External Environment-High Stress and Depression profile (LEE-HSD); and **(D)** Average External Environment-High Emotional Burden profile (AEE-HEB). Radar charts in (A)-(D) illustrate the multidimensional profiles of the four empirically derived profiles (green polygons) relative to the overall sample mean (orange polygons). Red asterisks adjacent to axis labels indicate significant differences across groups for that dimension (ANOVA). **(E-K)** Bar charts display normalized scores of environmental factors and emotional factors across the four profiles, including Personal Characteristics (PER), Family Background (FAM), Emotional Support (EMS), Anxiety (ANX), Depression (DEP), Perceived Helplessness (PHS), and Perceived Self-Efficacy (PSE). Error bars represent standard

errors. Statistical Significance: *, $p < 0.05$; **, $p < 0.01$; ***, $p < 0.001$. Significance markers in (E–K) indicate pairwise differences derived from Tukey post hoc tests.

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