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Uncovering Latent Mental Health Profiles Among Engineering Students Using Clustering

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Uncovering Latent Mental Health Profiles Among Undergraduate Engineering Students Using Clustering And Machine Learning

Abstract
Engineering students experience higher rates of anxiety and depression than their non-engineering peers. In this study, we used clustering methods to identify latent profiles among undergraduate engineering students' underlying anxiety, depression, and flourishing. We analyzed flourishing, anxiety (GAD-7), and depression (PHQ-9) scores from 37,673 engineering students in the Healthy Minds Study (2020–2024). We first gathered validity evidence for the measures using factor analysis with a subset of the engineering student population. Then we compared multiple clustering models and covariance structures across 1,000 runs. The optimal solution revealed four clusters with varying levels of distress: (1) High Distress, (2) Mild Distress, (3) Moderate Distress, and (4) Low Distress. Further exploration demonstrated that there was an unequal representation of women and non-binary students in the Moderate and High Distress clusters. Findings and their implications are discussed further.

Introduction

Engineering programs are often associated with a culture of stress, which explains why students in engineering programs report higher rates of anxiety and depression than their peers [1], [2], [3]. Heavy workloads, GPA pressure, a lack of support in comparison to other programs, and a generally competitive environment reinforce norms that frame these challenges as a "natural" part of engineering [4], [5]. As a result, students internalize the belief that they must manage distress on their own [6]. Untreated mental health issues undermine students' well-being and contribute to poor academic outcomes [7], [8]. This stress culture also discourages help-seeking by reinforcing stigma around mental health [9]. Engineering environments not only intensify stress but also shape how students interpret and respond to their struggles, leading to greater potential for serious mental health concerns among students in engineering.

While many studies have documented risk factors for poor mental health [10], [11], fewer studies have examined positive mental health indicators and protective factors [12]. Recently, studies have also applied person-centered approaches to uncover hidden subgroups within engineering populations [13]. However, few studies have investigated which demographic groups are at greater risk of poor mental health outcomes in engineering [14]. Identifying meaningful student subgroups and examining how they vary across demographic and cultural factors is important for understanding who is most at risk for mental health concerns in engineering and how different groups cope and seek support [4], [15], [16], [17].

The purpose of this study is thus to identify distinct profiles of flourishing, anxiety, and depression among engineering students and to understand how different demographic groupings are situated amongst such profiles. Flourishing was included because it may moderate the association between anxiety and depression and overall distress [18]. This study seeks to answer the following research questions (RQs):

1. **RQ1.** How do engineering students cluster according to their flourishing, anxiety, and depression measures?
    a. **RQ1.1.** How are different demographic groups situated among clusters of engineering students?

Theoretical Framework

This study is guided by the Dual-Factor Model of Mental Health [19], which conceptualizes mental health as comprising two related but distinct dimensions: psychological distress and positive well-being. Under this framework, individuals may exhibit different combinations of distress and flourishing. However, it is important to note that *the absence or lower amount of each does not necessarily imply a higher amount of the other*. We aim to provide a more nuanced understanding of mental health and identify distinct latent profiles that might contribute to both distress and well-being among engineering students.

Methodology

Participants

To conduct this work, we analyzed 37,673 anonymous records from engineering students who completed the Healthy Minds Study (HMS) between 2020 and 2024. The gender composition of the sample was 58.5% male, 37.4% female, 3.0% nonbinary, and 1.2% with missing or other gender identifications (Table 1).

Table 1. Gender composition of engineering students in the Healthy Minds Study, 2020–2024.

Gender Identity	Count	Percent
Male	22,028	58.5%
Female	14,086	37.4%
Non-binary	1,124	3.0%
Missing/Other response	435	1.2%
Total	37,673	100%

Table 2 summarizes the racial composition of engineering student participants. White students represented the largest share of the sample (53.69%), followed by Asian students (23.98%). Smaller proportions identified as Black (5.36%), Multiracial (5.78%), Middle Eastern (2.52%), or Other response (1.88%), and 6.79% were missing race data or self-identified outside the listed categories.

Table 2. Race composition of engineering students in the Healthy Minds Study, 2020–2024.

Race Identity	Count	Percent
White	20227	53.69%
Black	2021	5.36%
Asian	9033	23.98%
Middle Eastern	951	2.52%
Multiracial	2179	5.78%
Other response	703	1.88%
Missing race or self-identified	2559	6.79%
Total	37,673	100%

Measures

The HMS dataset contained measures with excellent validity evidence for the general college student population for factors such as flourishing, anxiety, and depression. We describe each measure further:

- *Flourishing.* We assessed positive well-being using the eight-item Diener Flourishing Scale [20] (henceforth referred to as just "Diener"). Flourishing covers key aspects of life, such as positive relationships, self-esteem, optimism, engagement, and accomplishment. The scale consists of eight items rated on a 7-point Likert scale.
- *Anxiety.* We measured anxiety symptoms with six items from the General Anxiety Disorder (GAD-7) scale [21]. Students indicated how often they experienced anxiety symptoms in the past two weeks on a 4-point scale from "Not at all" to "Nearly every day."
- *Depression.* Depression symptoms were evaluated with the nine-item Patient Health Questionnaire (PHQ-9) [22]. Like the GAD-7, it uses a 4-point scale.

In total, participants responded to 24 survey items: eight flourishing items (Diener), seven anxiety items (GAD-7), and nine depression items (PHQ-9).

Factor Analysis

Although the above measures have established validity evidence with general college populations, we re-evaluated the evidence specifically within the engineering student subsample to ensure construct alignment. To test this functionality, we used a basic two-step factor analysis practice. To reduce the risk of overfitting and strengthen the validity of the evidence, the dataset was randomly split into two halves. Exploratory Factor Analysis (EFA) was conducted in the first subsample, followed by Confirmatory Factor Analysis (CFA) in the second subsample.

Exploratory Factor Analysis (EFA)

EFA was performed to examine the underlying factor structure without imposing a predefined model [23]. Sampling adequacy was evaluated using the Kaiser–Meyer–Olkin (KMO) [24] to check if the sample size and the correlation among items are strong enough to reveal reliable factors, and Bartlett's Test of Sphericity was used to confirm that the correlation matrix was appropriate for factor analysis. We then used parallel analysis to determine the optimal number of factors and applied the *promax* rotation, given the likelihood of correlated constructs [25].

Confirmatory Factor Analysis (CFA)

For the second half, we ran Confirmatory Factor Analysis (CFA) [26] using WLSMV estimation in *lavaan* to test whether the factor structure suggested by EFA provided an acceptable fit. In short, EFA is used to uncover the latent structure, and CFA is used to confirm this structure in an independent subsample.

Clustering Approach & Procedures

Latent profiles were identified using Gaussian Mixture Modeling (GMM), a model-based clustering approach that represents the observed data as a mixture of multivariate normal distributions, with each distribution corresponding to a latent profile [27]. Unlike distance-based clustering, GMM estimates probabilistic membership, which is well-suited for mental health data where profiles may partially overlap and may differ in size, shape, and dispersion [27], [28], [29], [30], [31]. We applied GMM to uncover profiles based on the flourishing, anxiety, and depression factors. All analyses were conducted in R. We conducted GMM using the *mclust* package in R and average scores for flourishing, anxiety, and the two depression subscales (described in Results), which were determined by factor analysis [29].

Determining the Number of Profiles

As an initial diagnostic step, K-means clustering was applied to the standardized indicator scores to examine the within-cluster sum of squares (WSS) across solutions k=1 to 10 and identify an elbow point. The silhouette method was used as a secondary diagnostic to evaluate separation and cohesion across candidate K values (Figure 1). These diagnostics suggested that the three- and four-profile solutions were both plausible, motivating a focused comparison using model-based criteria.

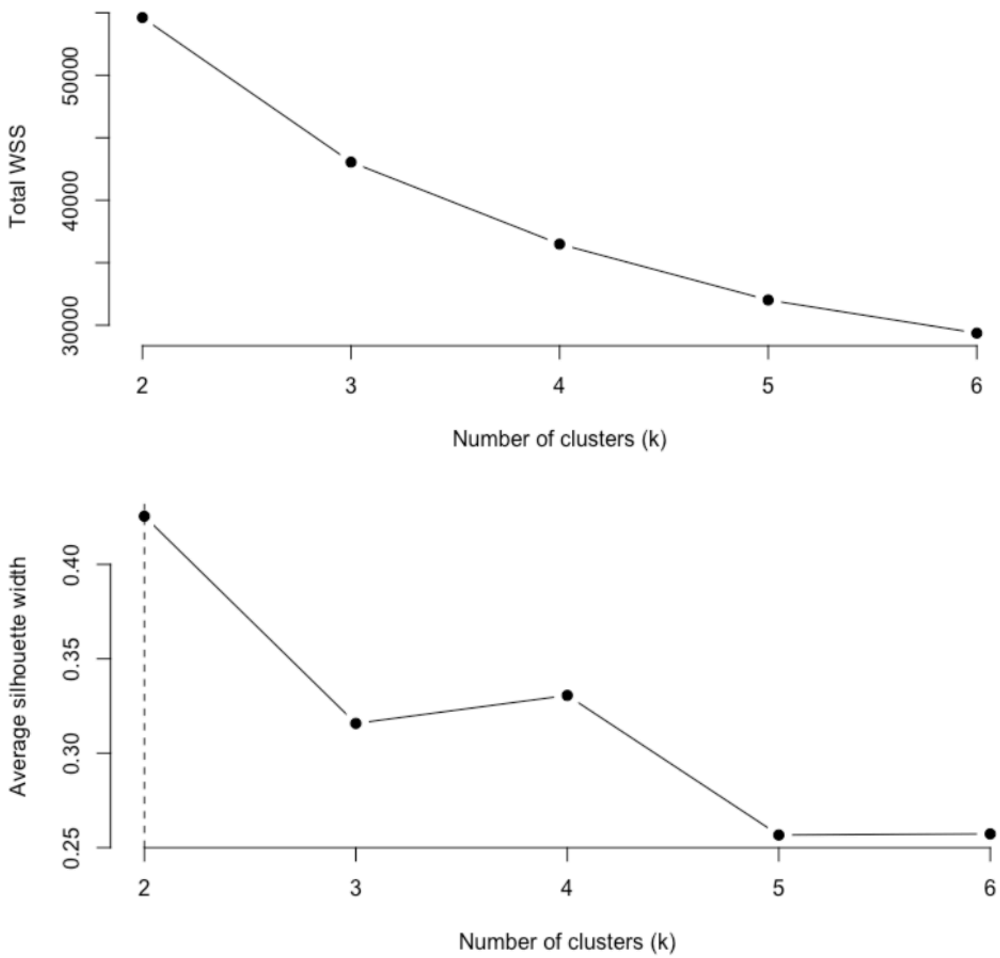

Figure 1. Both three- and four-cluster solutions were plausible; initial clustering diagnostics: (a; above) The elbow plot shows a pronounced reduction in WSS up to k=3, followed by diminishing returns, with additional improvement through k=4. (b; below) Average silhouette analysis supported k=3 and k=4 as viable solutions with reasonable cluster separation; therefore, both were retained for formal model-based comparison.

Cluster Validation

Because three- and four-cluster solutions were plausible based on the diagnostic plots, we compared the Gaussian mixture model in *mclust* for G=3 and G=4 across five covariance parameterizations (VVV, EEE, VEV, VII, EII) [27]. Fraley and Raftery explain the logic of covariance models in the Mixture Model section by describing how each cluster is modeled as a multivariate normal distribution with its own covariance matrix [27]. These models parameterized each cluster covariance matrix via eigenvalue decomposition into volume, shape, and orientation. These covariance parametrizations can be compared by using model selection criteria such as the Bayesian Information Criterion [32]. The comparison between three- and four-cluster solutions in *mclust* was performed by running 1,000 iterations for each solution across five covariance structures: VVV, EEE, VEV, VII, and EII. For each run across each one of the structures, we calculated seven fit measures: Bayesian Information Criterion (BIC), Integrated Completed Likelihood (ICL), Davies–Bouldin index (DB), Akaike information criterion (AIC), partition coefficient (PC), partition entropy (PE), and the Xie–Beni index (XB). The final solution was selected as the model with the maximum BIC among candidates, as is the case with the *mclust* package [33].

Results

Factor Analysis

The KMO statistic was 0.96, indicating excellent sampling adequacy. Bartlett's Test of Sphericity was highly significant, χ^2= 654130.2, $p < .001$, confirming that the data were appropriate for factor analysis. EFA supported a four-factor solution (literature has demonstrated that PHQ-9 sometimes factors as two separate factors rather than one) that explained approximately 61% of the total variance [30]. EFA was conducted using minimum residual estimation with oblique rotation. Model fit indices indicated a good fit, TLI=0.97, RMSEA=0.05, and RMSR=0.02. Then the structure was validated using maximum-likelihood CFA (Table 3).

Table 3. Factor structure, variance explained, and internal consistency for each (sub)scale.

Factor	Number of Items	Variance %	Cronbach's α
Diener (Flourishing)	Diener item 1-8	23.1	0.92
GAD (Anxiety)	GAD7 1-4, 6-7	17.6	0.91
PHQ_F1 (Depression 1)	PHQ9 1, 3-5, 7	12.7	0.83
PHQ_F2 (Depression 2)	PHQ2_1-2	8.2	0.89

The model (Table 3) showed excellent fit after conducting CFA: CFI=0.994, TLI=0.993, RMSEA=0.032 (90% CI [0.031, 0.032]), and SRMR=0.036. All standardized factor loadings were above 0.59 and statistically significant ($p < .001$). We also checked the reliability of each factor using Cronbach's α. All scales showed internal consistency, with α values ranging from 0.83 to 0.92. After conducting the exploratory factor analysis (EFA), a clear four-factor structure emerged. In addition to distinct factors for flourishing and anxiety, the depression construct is separated into two subscales, which is consistent with prior work showing that PHQ-based depression symptoms can sometimes split into more than one latent dimension [34]. During CFA, items that did not align well with the proposed factor structure were removed to improve model fit and ensure conceptual coherence. The final validated set included 8 Diener items, 6 anxiety items, and 7 depression items distributed across two depression subscales. The retained items for each (sub)scale are summarized in Table 3.

Clustering
The elbow method and silhouette analysis indicated that the optimal number of clusters was k=3 and k=4 (Figure 1). The four-cluster VEV model produced the highest BIC, so it was selected as the final solution.

Figure 2 presents the clustering result of the VEV model across 1,000 runs. Relying on several fit measures rather than a single indicator helps avoid bias in cluster evaluation [28]. Each student was assigned to one of the four clusters from the optimal VEV-covariance GMM solution. Identified profiles were labeled as Cluster 1 ("High Distress"), Cluster 2 ("Mild Distress"), Cluster 3 ("Moderate Distress"), and Cluster 4 ("Low Distress"; Table 4). Cluster 1 comprised 17.5%, Cluster 2 comprised 37.4%, Cluster 3 comprised 32.8%, and Cluster 4 comprised 12.3% of the analytic sample (Table 4). Cluster 1 had the highest average of anxiety and depression scores and the lowest average flourishing score. Cluster 4 showed the opposite pattern, with the lowest anxiety and depression scores and the highest flourishing score. Cluster 3 fell between, with moderate flourishing and elevated anxiety and depression scores. Cluster 2 reflected a mild distress profile, characterized by high flourishing and low-moderate anxiety and depression.

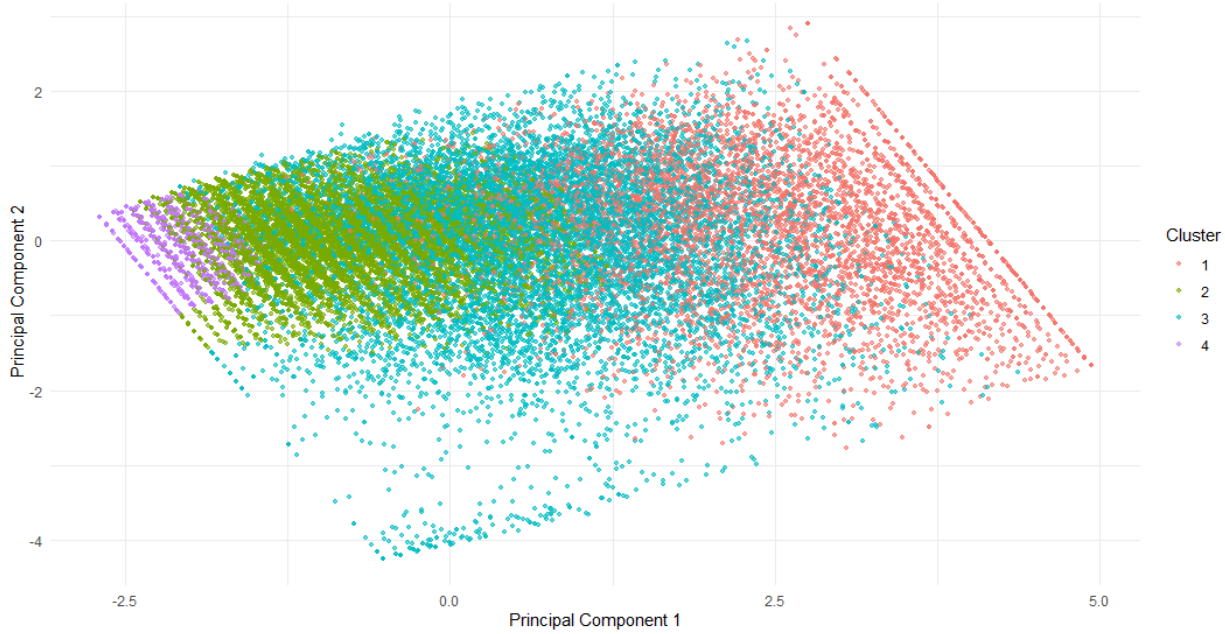

Figure 2. The four-cluster solution consistently achieves the maximum BIC across 1,000 iterations, validating model stability.

Table 4. Mean flourishing, anxiety, and depression scores for each cluster.

#	Name	n	%	Flourishing (Diener)	Anxiety (GAD)	Depression Subscale 1 (PHQ1)	Depression Subscale 2 (PHQ2)
1	High Distress	5,422	17.5	4.37	2.84	3.04	3.87
2	Mild Distress	11,593	37.4	5.78	1.62	1.73	1.94
3	Moderate Distress	10,181	32.8	4.89	2.47	2.53	2.15
4	Low Distress	3,805	12.3	6.34	1.13	1.26	1.00

Demographic Distribution Across Clusters

Tables 5 and 6 summarize the distribution of gender and race across the four identified clusters, respectively. Table 5, supported by Figure 3, shows that males held the largest share of participants. The number of female students was higher in Clusters 1 and 3, which had higher distress compared to Clusters 2 and 4. Similarly, participants who identify as non-binary were more represented in high and moderate distress clusters. Overall, the table demonstrates that gender composition varies across clusters, with higher distress clusters including a higher proportion of women and non-binary participants than lower distress clusters.

Table 5. Gender distribution of participants across four identified clusters (%).

Cluster	Female	Male	Non-binary	Missing/Other
1	44.5	49.7	3.5	2.4
2	34.9	63.6	0.8	0.7
3	43.8	53.2	1.7	1.4
4	26.2	72.9	0.1	0.8

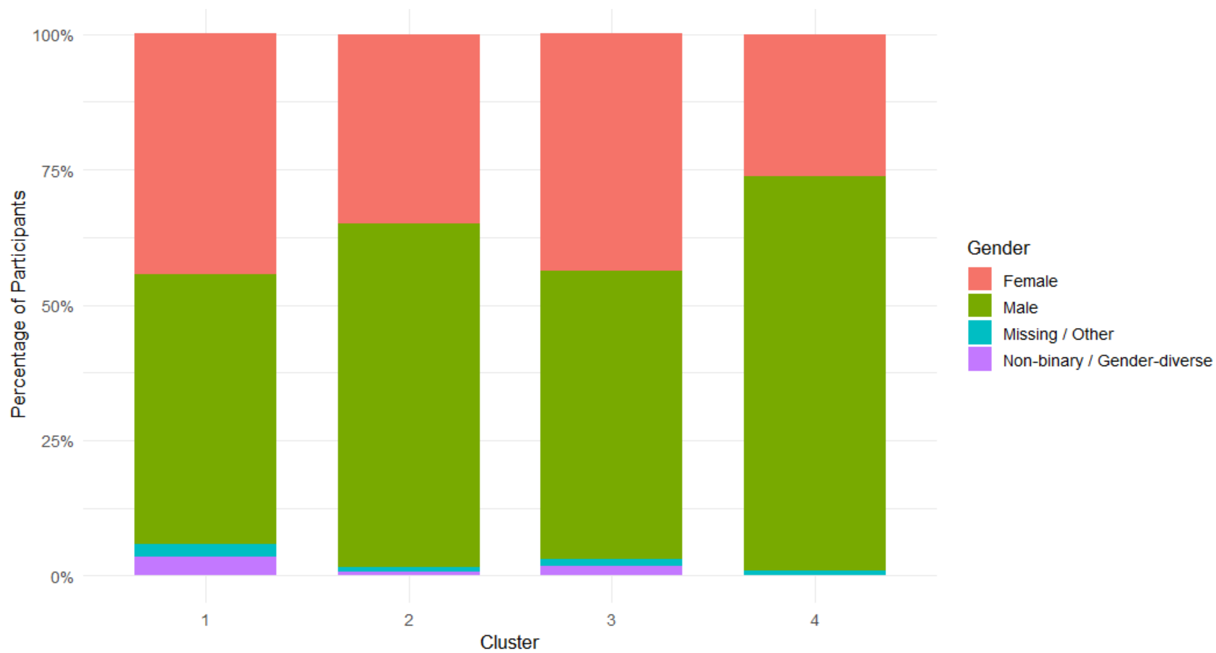

Figure 3. Gender distribution across clusters

Table 6, supported by Figure 4, presents the racial composition of participants across identified clusters. In all clusters, White students comprised the largest proportion of participants, followed by Asian students and multiracial students. Black students represent a smaller share across clusters, and Middle Eastern students remain consistently low. Other categories and missing responses were minimal. Overall, racial composition was broadly similar across clusters, with modest variation. Cluster 3 (Moderate Distress) had a higher proportion of White and multiracial students and a lower proportion of Asian students than the other clusters.

Table 6. Race distribution of participants across four identified clusters (%).

Cluster	White	Black	Asian	Middle Eastern	Multiracial	Other	Missing/ Self-Identified
1	51.33	4.78	25.45	2.16	8.87	6.05	1.36
2	48	5.3	24.1	3.1	9.7	9.4	0.4
3	58.5	4.3	16.6	2.4	11.6	6.27	0.33
4	51.2	5.7	24.6	2	8	8.1	0.4

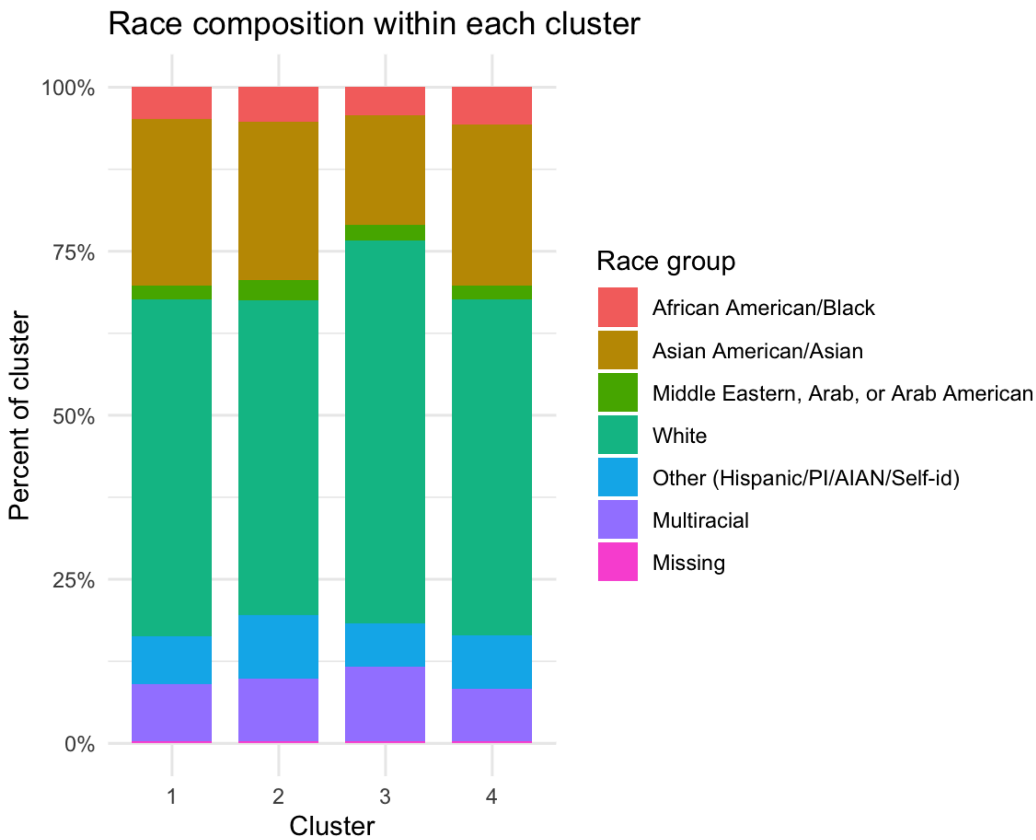

Figure 4. Race composition across clusters

Discussion and Future Work

This study identified four distinct mental health profiles—high, mild, moderate, and low distress—among 37,673 engineering students in the Healthy Minds Study (2020–2024). Measures included the eight-item Diener Flourishing Scale, six GAD-7 items, and seven PHQ-9 items distributed in two subscales. Validity evidence for these measures with engineering students was established using EFA and CFA [31], [35]. Elbow and silhouette methods indicated k=3 and 4 as the optimal values after examining WSS for k=1–10. A Gaussian mixture model (GMM) was then fit, and five covariance structures (VVV, EEE, VEV, VII, and EII) were compared across 1,000 random starts [36], [37], providing strong evidence for a four-cluster solution. Across clusters, meaningful differences emerged in flourishing and mental health symptoms. One cluster showed the lowest flourishing with high anxiety and depression (high distress), whereas another showed the highest flourishing with low anxiety and depression (low distress). The remaining clusters reflected intermediate profiles: mild distress (high flourishing with relatively low-to-moderate anxiety and depression) and moderate distress (moderate flourishing with elevated anxiety and depression). This addresses RQ1 by revealing four latent profiles among engineering students according to their flourishing, anxiety, and depression.

These findings support the view that student mental health is better represented as heterogeneous profiles rather than a single continuum of distress. The Moderate Distress profile—characterized by moderate flourishing alongside elevated anxiety and depression—suggests that well-being and distress can co-occur. This pattern aligns with a person-centered perspective that conceptualizes well-being as a configuration of psychological functioning rather than a binary distinction between “healthy” versus “at-risk.”

While race composition did not vary significantly across clusters, gender composition did. Males represented the larger group in each cluster; however, the share of women and non-binary participants increased as distress increased. This finding suggests that women and non-binary participants in engineering are more likely to fall into higher-distress profiles, a trend discussed in literature reflecting engineering's cultures of masculinity and difficulty [38]. *These results indicate that demographic differences may reflect not only variation in average symptom level but also differences in membership across distinct mental health profiles*. Further understanding of why, specifically, will be the subject of our future investigation. Particularly, we will investigate which academic, contextual, and institutional conditions are associated with higher or lower flourishing among students and particular demographic groups who show similar levels of anxiety and depression.

Conclusion & Implications

This study used HMS data (2020-2024; N=37,673) guided by a dual-factor view of mental health to identify latent profiles among undergraduate engineering students using flourishing, anxiety, and depression measures. Results reflect the meaningful combination of well-being and distress across four profiles: low distress (high flourishing with low anxiety and depression), mild distress (high flourishing with relatively low-to-moderate anxiety and depression), moderate distress (moderate flourishing with elevated anxiety and depression), and high distress (lower flourishing with high anxiety and depression). This pattern suggests that engineering students vary meaningfully in mental health rather than forming a single, uniform group.

Demographic differences also emerged across profiles: men comprised the largest share in each cluster, but women and non-binary students were disproportionately represented in the moderate and high distress clusters, while missing/other genders remained small. Race differences were comparatively modest overall: White students represented the largest share across clusters, followed by Asian and multiracial students, with smaller proportions of Black and Middle Eastern students and relatively small Other and Missing/self-identified categories. The most notable racial shift occurred in the moderate distress cluster, which had a higher proportion of White and multiracial students and a lower proportion of Asian students relative to other clusters.

The identification of a moderate distress profile provides direct empirical support for the Dual-Factor Model [19] by showing that flourishing and distress can co-occur. The dual-factor profiling results indicate that distress levels alone do not determine students' well-being. For example, one cluster showed low anxiety and depression alongside high flourishing (low distress), whereas another showed elevated (moderate distress) anxiety and depression while still reporting moderate (almost high) flourishing. This pattern suggests that disparities may be reflected not only in differences in average symptom levels but also in variations in representation across distinct mental health profiles.

Recognizing these four mental health groups (high distress, mild, moderate, and low distress profiles) enables more targeted intervention design. The identified profiles in this study can provide a foundation for future research to examine what factors shift well-being within each profile. This work can support the development of strategies that focus not only on distress but also on the role of flourishing and on improving the overall well-being of students in engineering education. This work also suggests that women and non-binary students exhibit higher distress. More structural support is likely needed for these groups. Racial differences were comparatively modest across clusters, with broadly similar composition across profiles, although the moderate distress cluster included relatively higher proportions of White and multiracial students and a lower proportion of Asian students than other clusters, warranting further investigation of race-related contextual factors.

Limitations

This study has some limitations. First, we used the Flourishing Scale, GAD-7, and PHQ-9, which have strong validity evidence, even among engineering students, as we demonstrate, but they rely on students' self-reports, which may introduce bias or under- or over-reporting of symptoms. Second, although the sample was large, the gender distribution was unequal: 58.5% male, 37.4% female, and 3% non-binary students. As a result, conclusions about non-binary students should be interpreted with caution due to limited statistical power.

References

[1] C. J. Wright, S. A. Wilson, J. H. Hammer, L. E. Hargis, M. E. Miller, and E. L. Usher, "Mental health in undergraduate engineering students: Identifying facilitators and barriers to seeking help," *J. Eng. Educ. Wash. DC*, vol. 112, no. 4, pp. 963–986, 2023, doi: 10.1002/jee.20551.

[2] M. D. Whitwer, S. A. Wilson, J. H. Hammer, and B. Gomer, "Mental health and treatment use in undergraduate engineering students: A comparative analysis to students in other academic fields of study," *J. Eng. Educ. Wash. DC*, vol. 114, no. 1, p. n/a, 2025, doi: 10.1002/jee.20629.

[3] A. Danowitz and K. Beddoes, "Mental Health in Engineering Education: Identifying Population and Intersectional Variation," *ALISS Q.*, vol. 65, no. 3, pp. 257–266, 2022, doi: 10.1109/TE.2022.3182626.

[4] S. Wilson *et al.*, "Identifying common perceived stressors and stress-relief strategies among undergraduate engineering students," in *2022 ASEE Annual Conference & Exposition Proceedings*, Minneapolis, MN: ASEE Conferences, Aug. 2022, p. 41009. doi: 10.18260/1-2--41009.

[5] S. Panuganti, N. K. Koujel, and J. C. Major, "The role of undergraduate engineering

students' different support networks in promoting emotional well-being: A narrative study," in *2025 Collaborative Network for Engineering & Computing Diversity (CoNECD)*, 2025. Accessed: Apr. 29, 2026. [Online]. Available: https://peer.asee.org/the-role-of-undergraduate-engineering-students-different-support-networks-in-promoting-emotional-well-being-a-narrative-study

[6] K. Robert and J. Leydens, "Dignity and well-being: Narratives of modifying the culture of engineering education to improve mental health among underrepresented STEM students," in *2023 ASEE Annual Conference & Exposition Proceedings*, Baltimore , Maryland: ASEE Conferences, Jun. 2023, p. 43178. doi: 10.18260/1-2--43178.

[7] M. Asghar, A. Minichiello, and S. Ahmed, "Mental health and wellbeing of undergraduate students in engineering: A systematic literature review," *ALISS Q.*, vol. 113, no. 4, pp. 1046–1075, 2024, doi: 10.1002/jee.20574.

[8] F. A. Abidin *et al.*, "Social and psychological determinants of positive mental health in engineering students," *Cogent Psychol.*, vol. 12, no. 1, 2025, doi: 10.1080/23311908.2025.2485753.

[9] S. Khorshid and S. Song, "Work in Progress: Assessing the Need for Mental Health Curricula for Civil, Architecture, and Construction Engineering," in *2023 ASEE Annual Conference & Exposition Proceedings*, Baltimore , Maryland: ASEE Conferences, Jun. 2023, p. 44175. doi: 10.18260/1-2--44175.

[10] D. J. Debnath *et al.*, "The prevalence and risk factors of depression in engineering college students: A cross-sectional study," *Ind. Psychiatry J.*, vol. 32, no. 2, pp. 334–338, 2023, doi: 10.4103/ipj.ipj_5_23.

[11] K. J. Jensen, J. F. Mirabelli, A. J. Kunze, T. E. Romanchek, and K. J. Cross, "Undergraduate student perceptions of stress and mental health in engineering culture," *Int. J. STEM Educ.*, vol. 10, no. 1, pp. 30–23, 2023, doi: 10.1186/s40594-023-00419-6.

[12] G. G. Abulfaraj, R. Upsher, H. M. S. Zavos, and E. J. Dommett, "The Impact of Resilience Interventions on University Students' Mental Health and Well-Being: A Systematic Review," *Educ. Sci.*, vol. 14, no. 5, pp. 510-, 2024, doi: 10.3390/educsci14050510.

[13] H. Perkins *et al.*, "Holistic Wellbeing and Belonging: Attempting to Untangle Stress and Wellness in Their Impact on Sense of Community in Engineering," *Int. J. Community Well-Being*, vol. 4, no. 4, pp. 549–580, Nov. 2021, doi: 10.1007/s42413-021-00149-z.

[14] A. Danowitz and K. Beddoes, "Mental Health in Engineering Education: Identifying Population and Intersectional Variation," *IEEE Trans. Educ.*, vol. 65, no. 3, pp. 257–266, Aug. 2022, doi: 10.1109/TE.2022.3182626.

[15] S. Wilson, K. Wilder, W. Blackburn-Lynch, J. Hammer, and D. Dailey, "ASEE PEER - Investigating mental health distress and help-seeking perceptions in first-year engineering students," 2022. Accessed: Dec. 15, 2025. [Online]. Available: https://peer.asee.org/investigating-mental-health-distress-and-help-seeking-perceptions-in-first-year-engineering-students

[16] K. Beddoes and A. Danowitz, "ASEE PEER - In Their Own Words: How Aspects of Engineering Education Undermine Students' Mental Health," 2022. Accessed: Dec. 15, 2025. [Online]. Available: https://peer.asee.org/in-their-own-words-how-aspects-of-engineering-education-undermine-students-mental-health

[17] M. D. Ahandani, P. Njeck, and O. N. Okoani, "Examining the Effect of Social, Cultural, and Political Factors on the Wellness of International Students in Engineering Doctoral

Programs: A Collaborative Inquiry," in *2025 ASEE Annual Conference & Exposition*, 2025. Accessed: Apr. 28, 2026. [Online]. Available: https://peer.asee.org/examining-the-effect-of-social-cultural-and-political-factors-on-the-wellness-of-international-students-in-engineering-doctoral-programs-a-collaborative-inquiry
[18] H. Oh *et al.*, "The synergy of depression and flourishing/languishing on suicidal thoughts and behaviors: Findings from a national sample of emerging adult students in higher education in the United States," 2024, doi: 10.1371/journal.pone.0309020.
[19] P. J. Greenspoon and D. H. Saklofske, "Toward an Integration of Subjective Well-Being and Psychopathology," 2000.
[20] E. Diener, D. Wirtz, and W. Tov, "New measures of well-being: Flourishing and positive and negative feelings," *Soc Indic Res*, vol. 39, pp. 247–266, Jan. 2010.
[21] S. Rl, K. K, W. Jb, and L. B, "A brief measure for assessing generalized anxiety disorder: the GAD-7," *PubMed*, 2006, Accessed: Dec. 16, 2025. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/16717171/
[22] K. K, S. Rl, and W. Jb, "The PHQ-9: validity of a brief depression severity measure," *PubMed*, 2001, Accessed: Dec. 16, 2025. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/11556941/
[23] W. H. Finch, *Exploratory factor analysis*. in Quantitative applications in the social sciences. Los Angeles, CA: SAGE Publications, Inc., 2020.
[24] B. D. Hill, "The sequential Kaiser-Meyer-Olkin procedure as an alternative for determining the number of factors in common-factor analysis: A Monte Carlo simulation," ProQuest Dissertations & Theses, 2011. Accessed: Dec. 17, 2025. [Online]. Available: https://www.proquest.com/docview/898980750?pq-origsite=primo&accountid=13605
[25] S. Tobias and J. E. Carlson, "Brief Report: Bartlett's Test of Sphericity and Chance Findings in Factor Analysis," *Multivar. Behav. Res.*, vol. 4, no. 3, pp. 375–377, Jul. 1969, doi: 10.1207/s15327906mbr0403_8.
[26] J. M. Roos, *Confirmatory Factor Analysis.* in Quantitative Applications in the Social Sciences. Thousand Oaks: SAGE Publications, Inc, 2021.
[27] C. Fraley and A. E. Raftery, "Model-Based Clustering, Discriminant Analysis, and Density Estimation," *J. Am. Stat. Assoc.*, vol. 97, no. 458, pp. 611–631, Jun. 2002, doi: 10.1198/016214502760047131.
[28] J. Kashihara, Y. Takebayashi, Y. Kunisato, and M. Ito, "Classifying patients with depressive and anxiety disorders according to symptom network structures: A Gaussian graphical mixture model-based clustering," *PloS One*, vol. 16, no. 9, pp. e0256902-, 2021, doi: 10.1371/journal.pone.0256902.
[29] D. Haughton, P. Legrand, and S. Woolford, "Review of Three Latent Class Cluster Analysis Packages: Latent Gold, poLCA, and MCLUST," *Am. Stat.*, vol. 63, no. 1, pp. 81–91, 2009, doi: 10.1198/tast.2009.0016.
[30] L. Boothroyd, D. Dagnan, and S. Muncer, "PHQ-9: One factor or two?," *Psychiatry Res.*, vol. 271, pp. 532–534, Jan. 2019, doi: 10.1016/j.psychres.2018.12.048.
[31] N. Zhang, X. Ren, and Z. Xu, "A latent profile analysis of self-leadership associated with coping styles among general practice students," *Sci. Rep.*, vol. 15, no. 1, pp. 17326–10, 2025, doi: 10.1038/s41598-025-02524-8.
[32] C. Fraley and A. E. Raftery, "Model-Based Clustering, Discriminant Analysis, and Density Estimation," *J. Am. Stat. Assoc.*, vol. 97, no. 458, pp. 611–631, Jun. 2002, doi: 10.1198/016214502760047131.

[33] C. Fraley and A. E. Raftery, “MCLUST: Software for Model-Based Cluster Analysis,” *J. Classif.*, vol. 16, no. 2, pp. 297–306, 2014, doi: 10.1007/s003579900058.

[34] L. Boothroyd, D. Dagnan, and S. Muncer, “PHQ-9: One factor or two?,” *Psychiatry Res.*, vol. 271, pp. 532–534, Jan. 2019, doi: 10.1016/j.psychres.2018.12.048.

[35] R. A. Melendez-Armenta, G. Luna Chontal, and S. G. Garcia Aburto, “Using machine learning to analyze mental health in distance education during the COVID-19 pandemic: an opinion study from university students in Mexico,” *PeerJ Comput. Sci.*, vol. 10, pp. e2241-, 2024, doi: 10.7717/peerj-cs.2241.

[36] N. Yaghmour *et al.*, “Burnout in Graduate Medical Education: Uncovering Resident Burnout Profiles Using Cluster Analysis,” *HCA Healthc. J. Med.*, vol. 5, no. 3, Jun. 2024, doi: 10.36518/2689-0216.1784.

[37] R. Song, F. Pang, H. Jiang, and H. Zhu, “A machine learning based method for constructing group profiles of university students,” *Heliyon*, vol. 10, no. 7, pp. e29181-, 2024, doi: 10.1016/j.heliyon.2024.e29181.

[38] E. Vick, S. A. Wilson, J. H. Hammer, M. Whitwer, and A. N. Gentry, “Engineering student mental health status across gender identities: Analysis of data from the Healthy Minds Study,” in *2025 ASEE Annual Conference & Exposition*, 2025. Accessed: Feb. 22, 2026. [Online]. Available: https://peer.asee.org/engineering-student-mental-health-status-across-gender-identities-analysis-of-data-from-the-healthy-minds-study