International Journal for the Advancement of Counselling (2025) 47:651–676
https://doi.org/10.1007/s10447-025-09606-2

RESEARCH

Assessing The Relationship Among Academic Engagement, Well-being, And Mental Health: Featuring University Students Seeking Support at a Counseling Facility

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Accepted: 13 April 2025 / Published online: 5 May 2025

Abstract
Given the high prevalence of psychological distress and mental health conditions within higher education contexts, identifying potential factors fostering university students' well-being may be pertinent. Academic engagement (AE) appears to play a key role in supporting mental health and buffering psychological issues. This study addressed the association between AE, well-being, and mental health among university students, by focusing on a specific vulnerable sub-population: those who seek support at a university counseling facility. The main objectives were to identify distinct patterns of AE, to examine differences among these patterns, and to explore how they are associated with various psychological well-being and mental health outcomes. Data were collected from 650 students ($M = 23.9$; $SD = 3.2$) attending the counseling facility. Standardized questionnaires were used to measure AE, anxiety, depression, emotion regulation, and psychological distress. Three distinct patterns of academic engagement were identified through a clustering process: Low AE pattern, Moderate AE pattern, and High AE pattern. Multivariate statistical analyses were conducted to examine the associations between these patterns and various well-being and mental health outcomes. Results indicated significant associations between higher levels of academic engagement and improved psychological well-being. Conversely, lower engagement was associated with more severe psychological symptoms and distress. These findings suggest that students' AE should be considered as an integral component of counseling interventions. By highlighting the connection between AE and mental health, this study provides insights for designing effective strategies tailored on students' needs, enhancing mental health and favoring a supportive educational environment.

Keywords Academic Counseling · Academic Engagement · Psychological Well-Being · Mental Health · Psychological Assessment

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The higher education (HE) years coincide with a developmental period bridging late adolescence and early adulthood, marked by unique challenges. Psychological well-being is essential for effectively coping with these demands, which include autonomy seeking, self-determination, self-management, vocational decision making, and the formation of community-based university relationships (Murray & Arnett, 2018). The following sections examine the mental health challenges faced by university students, exploring academic engagement (AE) as a multidimensional construct and analyzing the interplay between AE, well-being, and mental health outcomes, addressing unexplored areas in the literature.

Mental Health Among University Students

Researchers identified several risk factors affecting university students' mental health during this developmental period. For instance, a recent meta-analysis involving a large cohort of undergraduate students ($N = 13{,}790$) revealed an increased risk for depression and suicidality (Sheldon et al., 2021). Similarly, Auerbach et al. (2016) conducted an international survey of 14,000 students across eight countries reported that 35% met the diagnostic criteria for at least one mental health condition within a 12-month period. Furthermore, Zarowski et al. (2024) reported in a literature review of 32 studies conducted during the COVID-19 pandemic significant increases in mental health impairments, including depression, anxiety, and sleep disorders, with female students disproportionately affected. Consistent with these findings, an Italian cross-sectional study reported that approximately 78.5% of students experienced mild to severe psychological distress, with a higher prevalence among females, mirroring trends observed in other Western contexts (Porru et al., 2021).

Among university students, those seeking psychological counseling services constitute a particularly vulnerable subgroup, often experiencing heightened psychological distress compared to their peers (Caldarelli et al., 2024). Counseling services play a critical role in addressing the mental health needs of this population, implementing evidence-based practices to enhance well-being, reduce distress, and support students in navigating academic and personal challenges (Bastianoni et al., 2024). Despite growing recognition of mental health issues within HE, further investigation is needed to identify potential indicators of psychological well-being in this population (Cerolini et al., 2023). Recently, AE has emerged as a promising construct for understanding the experiences of students with diminished well-being (Chaudhry et al., 2024). Thus, further exploration of AE may provide critical insights into the unique characteristics and challenges of students utilizing counseling services, ultimately informing targeted interventions to address their specific needs.

Academic Engagement

AE refers to students' active involvement, commitment, and enthusiasm in the learning process (Alrashidi et al., 2016). It encompasses the capacity to overcome challenges, maintain focus on tasks, and achieve academic goals, manifesting in behaviors such as participation in activities, goal attainment, and respectful conduct (Schaufeli et al., 2002a). Additionally, AE includes cognitive and emotional dimensions, encompassing effective learning strategies, problem-solving skills, and emotional regulation, all driven by intrinsic motivation and a sense of agency (Fredricks et al., 2004; Reeve, 2012).

Social relationships have been shown to play a pivotal role in AE (Li & Xue, 2023), with peer support fostering a sense of belonging, enhancing motivation and cooperation among students (Juvonen et al., 2012). Similarly, positive teacher–student interactions have been found to contribute to a supportive and engaging learning environment (Amerstorfer & von Münster-Kistner, 2021), while external networks, such as family, have been shown to promote safety and connectedness (Wilson et al., 2010; Freda et al., 2016).

Given its multidimensionality, AE is a challenging construct to assess (for a review, see Veiga et al., 2014). Some instruments designed for this purpose, including the Metacognitive Strategies Questionnaire (Wolters, 2004) and the Agentic Engagement Scale (Reeve, 2013), focus on specific dimensions. However, other tools, such as the Engagement vs. Disaffection with Learning Scale (Skinner et al., 2008) and the Utrecht Work Engagement Scale for Students (Schaufeli et al., 2002b), jointly assess behavioral, emotional, and cognitive dimensions. Freda et al. (2023) developed a comprehensive questionnaire capturing six distinct AE dimensions. Given the inherent complexity of AE as a construct, researchers have increasingly adopted a person-centered approach to its measurement, analyzing dimensions collectively, rather than in isolation. By examining the ways in which various AE components interact and form distinct configurations, this perspective provides valuable insights into diverse engagement profiles within the student population.

Patterns of Academic Engagement in the Student Population

Building on the multidimensional framework of AE, several researchers identified distinct configurations of AE dimensions among the student population. For instance, Wilson et al. (2021) distinguished between two configurations among engineering students based on cognitive and emotional dimensions, defining more and less engaged groups. Similarly, Sáenz et al. (2011) identified AE patterns among community college students, highlighting clusters characterized by the frequency of resource utilization (e.g., tutoring) and participation in collaborative learning activities. These patterns were primarily associated with academic behaviors rather than psychological outcomes. More recently, Cano et al. (2024) extended this line of inquiry by exploring configurations of AE and burnout among university students. Their findings revealed significant correlations between these configurations and key factors such as academic satisfaction and learning outcomes.

While these studies have deepened our understanding of AE in the general student population, research has not yet investigated how such patterns manifest in vulnerable groups, such as students seeking psychological counseling. Such research could yield valuable insights, particularly given the empirical evidence linking AE to well-being and mental health outcomes.

Academic Engagement, Well-being, and Mental Health

The literature highlights a bidirectional relationship between AE, well-being, and mental health, showing that poor mental health is significantly associated with absenteeism, diminished academic performance, and reduced participation in university activities (Ishii et al., 2018; Lereya et al., 2019). Depressive symptoms have been shown to negatively correlate with AE, contributing to reduced self-efficacy, diminished learning attitudes, and withdrawal behaviors (Ji et al., 2021; Meeks et al., 2023; Tang & He, 2023). Conversely, students exhibiting higher engagement have been found to report greater life satisfaction, more positive emotions, and lower susceptibility to negative emotional states (Datu et al., 2018; Nelson et al., 2020).

The relationship between anxiety and AE appears less inconsistent. While some studies have found no direct association (Conrad et al., 2023; Landa-Blanco et al., 2024), others have suggested that anxiety symptoms may negatively affect academic outcomes, including achievement, drop-out intentions, and self-perceived competence in academic settings (Asghar, 2014; Brumariu et al., 2022). Emotion regulation has also been identified as a key factor associated with AE. In particular, adaptive strategies such as cognitive reappraisal (CR), which involves the reinterpretation of situations to lessen their emotional impact, have emerged as significant predictors of higher AE among students (Santos et al., 2021). Conversely, expressive suppression (ES)—a strategy that inhibits outward emotional responses—has been linked to poorer well-being outcomes (Dryman & Heimberg, 2018). While some studies have observed an association between ES and lower AE dimensions (Alkharj et al., 2024; Zhoc et al., 2022), others have reported no significant relationship (Beaumont et al., 2023).

In summary, previous research has predominantly addressed the general university student population, giving limited attention to the more vulnerable sub-population of students seeking psychological counseling (Abreu Alves et al., 2022; Amaral & Frick, 2022; Chaudhry et al., 2024). Furthermore, while prior studies have explored particular AE configurations, the associations between these configurations and psychological outcomes in this sub-population remain underexplored (Cano et al., 2024; Saenz et al., 2011; Wilson et al., 2021). Research aimed at addressing this gap could provide critical insights into the interactions between AE, mental health, and well-being, informing interventions tailored to students seeking psychological counseling.

The Present Study

The present study extended the current literature on AE and mental health by exploring the specific sub-population of university students seeking psychological counseling. The primary aim was to identify distinct patterns of AE by clustering students based on their scores across six AE dimensions. This approach aimed at elucidating how different dimensions interact within this population.

The secondary aim was to examine differences in the composition and representation of the identified AE patterns to better understand the diversity of engagement among students seeking psychological counseling. This analysis aimed at uncovering potential subgroups with unique AE profiles and thus distinct needs. Finally, the third aim was to explore the associations between AE patterns and mental health, well-being, and emotion regulation, including psychological distress and the use of emotion regulation strategies.

By integrating these objectives, the study sought to deepen our understanding of the associations between AE and psychological well-being among students seeking psychological counseling. The findings were anticipated to bridge research and practice, offering evidence-based guidance for interventions to enhance academic engagement while improving mental health.

The study received approval from the ethical committee of the Department of Brain and Behavioral Science of University of Pavia and Scuola Universitaria Superiore of Pavia – IUSS (protocol n.115/22).

Methods

The following section outlines the methodological framework adopted in this study. It describes the process of data collection, the measures employed, the characteristics of the sample, and the statistical analyses performed to address the research objectives.

Access to the Counseling Service

Data were collected from June 2023 to June 2024. Students accessed the counseling facility by submitting an online request through the university's platform and signing an informed consent to take part to the survey monitoring psychological profiles of students attending the counseling facility. The survey was entirely anonymous: a unique alphanumeric code was generated for each participant, to ensure data confidentiality. The response rate for the survey was 100%, with no missing data, as completing the survey was a necessary step to continue with the counseling request. However, students could choose to interrupt the process at any time, and completing the survey did not entail any commitment to participate in counseling sessions.

Measures

The survey included five questionnaires assessing academic engagement (AE) dimensions and key areas of psychological well-being and mental health. In the following paragraphs, each questionnaire is described in detail, providing information on its structure, purpose, and scoring.

SInAPSi[1] Academic Engagement Scale (SAES)

SAES consists of 29 items evaluating six dimensions of AE (Freda et al., 2023):

1. Perception of the capability to persist in the university choice: the awareness of possible difficulties and the resources needed to face them (e.g., *I would leave University right away if I had an alternative*). It is associated with drop-out intentions. Items of this dimensions are reversely scored.
2. University value and sense of belonging: the value ascribed to the decision to enroll in the university and the sense of belonging to the academic context (e.g., *University has a great importance in my life*).
3. Value of university course: the recognition of the chosen course's potentialities for one's professional career and personal growth (e.g., *The course of study I'm attending is an opportunity for me*).
4. Integration between the university and relational net: the ability to attain a balance between academic life and personal projects, as well as the sharing of university experiences with external relational networks (e.g., *I discuss with my family about my university path*).
5. Engagement with university professors: the perceived availability, respect, and interest from the faculty members (e.g., *My teachers are interested in my opinions and what I say*).
6. Engagement with university peers: the possibility of building meaningful and supportive relationships with peers in the university context (e.g., *I've made meaningful friends with some college colleagues*).

Internal consistency for all the dimensions was Cronbach's $\alpha > 0.70$. Responses are reported on a 5-point Likert-type scale (from 1 = *not at all* to 5 = *very much*). Six separate mean scores are calculated. Each mean score ranges from 0 to 5, with higher values reflecting more positive attribution to that particular dimension. Reliability estimates for scores in this study across all dimensions were as follows: $\alpha = 0.79$ for *Persistence in university choice*, $\alpha = 0.87$ for *University value and sense of belonging*, $\alpha = 0.92$ for *Value of university course*, $\alpha = 0.84$ for *Integration between university and relational network*, $\alpha = 0.88$ for *Engagement with university professors*, and $\alpha = 0.87$ for *Engagement with university peers*.

Generalized Anxiety Disorder—7 (GAD- 7)

The GAD is a broadly used tool in clinical and research settings for screening and assessing generalized anxiety disorder's severity (Spitzer et. al., 2006). Seven questions measure different signs of GAD, such as excessive worry, easy irritation, and

[1] The acronym stands for Services for Active and Participatory Student Inclusion (***Servizi per l'Inclusione Attiva e Partecipata degli Studenti***), referring to the university center of University of Naples, Italy.

nervousness. Item examples are as follows: *Worrying too much about different things*; *Becoming easily annoyed or irritable*. Internal consistency of the tool was Cronbach's $\alpha = 0.92$. Responses range from 0 (Not at all) to 3 (Nearly every day), with a total score going from 0 to 21. Higher scores indicate greater anxiety severity. Continuous score can be categorized into three different levels of anxiety severity. The cut-off points are as follows: 0–4 (minimal); 5–9 (mild); 10–14 (moderate); 15–21 (severe). The reliability estimate for scores on the GAD in this study was $\alpha = 0.81$.

Beck Depression Inventory—II (BDI-II)

The BDI-II is one of the most used instruments for evaluating the severity of depressive symptoms (Cronbach's $\alpha = 0.92$) (Beck et al., 1996). It consists of 21 multiple-choice questions assessing symptoms such as loss of interest, sadness, and guilt. For instance, for *loss of interest*, options are as follows: *I have not lost interest in other people or activities; I am less interested in other people or things than before; I have lost most of my interest in other people or things; It's hard to get interested in anything*. Each item presents a range of responses from 0 to 3, with a maximum total score of 63. Higher scores indicate higher depression severity. Continuous score can be categorized into different depression levels. The cut-off points are as follows: 0–13 (minimal); 14–19 (mild); 20–28 (moderate); 29–63 (severe). The reliability estimate for scores on the BDI-II in this study was $\alpha = 0.89$.

Emotion Regulation Questionnaire (ERQ- 10)

The ERQ-10 is a 10-item scale developed to measure individual tendency to adopt two emotion regulation strategies (Gross & John, 2003): cognitive reappraisal (CR) (e.g., *When I'm faced with a stressful situation, I make myself think about it in a way that helps me stay calm*) and expressive suppression (ES) (e.g., *I keep my emotions to myself*). Cronbach's α consistency coefficients were 0.84 for the Reappraisal scale and 0.72 for the Suppression scale.

Responses are provided on a 7-point Likert-type scale ranging from "strongly disagree" to "strongly agree."

The questionnaire provides two separate total score, with higher score indicating a higher propensity to adopt that specific strategy. CR scale ranged from 7 to 42, while ES scale goes from 7 to 28. The reliability estimates for scores on the ERQ-10 in this study were $\alpha = 0.81$ for cognitive reappraisal and $\alpha = 0.73$ for expressive suppression.

Clinical Outcomes in Routine Evaluation—CORE-OM

The CORE-OM assesses the efficacy of psychological treatments/interventions (Evans et al., 2002). It is also used as a measure of psychological distress in primary and secondary care settings (Barkham et al., 2006). It consists of 34 items on a 5-point frequency scale, from 0 (Not at all) to 4 (Most or all of the time). Internal consistency for the total score assessed in both clinical and non-clinical population was $\alpha = 0.92$. The reliability estimate for scores on the CORE-OM in this study was $\alpha = 0.92$.

The tool covers four domains:

1. Well-being: it explores the overall well-being and satisfaction in life (e.g., *I have felt overwhelmed by my problems*). Internal consistency was $\alpha = 0.74$ in non-clinical population and $\alpha = 0.71$ in clinical population.
2. Problems/symptoms: it concerns emotional, behavioral, or relational problems (e.g., *I have been disturbed by unwanted thoughts and feelings*). Internal consistency was $\alpha = 0.85$ in non-clinical population and $\alpha = 0.87$ in clinical population.
3. Life functioning: it assesses the ability to carry out daily activities, maintain social or work relationships, and engage in social activities (e.g., *I have felt terribly alone and isolated*). Internal consistency was $\alpha = 0.75$ in non-clinical population and $\alpha = 0.77$ in clinical population.
4. Risk: it focuses on risky behaviors, such as self- and other harm (e.g., *I have thought of hurting myself*). Internal consistency was $\alpha = 0.79$ in non-clinical population and $\alpha = 0.77$ in clinical population.

All the domains are problem-scored, meaning that the higher the scores, the more problems the individual is reporting. Well-being domain is interpreted in reverse (higher scores, lower well-being). Possible computable scores for this tool are the total (from 0 to 136), the mean (from 0 to 4), and the clinical (from 0 to 40) ones. Mean scores for each domain (from 0 to 4) can also be analyzed separately. In the validation study on the Italian population, Palmieri and colleagues (2009) reported cut-off values for each domain to discriminate between clinical and non-clinical samples.

Sample

A total of 650 ($M = 23.9$; $SD = 3.2$) university students approached the university counseling facility and completed the online survey. No missing data were observed in the responses. Most participants were female (72.6%) and of Italian nationality (90.6%). Regarding academic programs, 41.4% of students were enrolled in bachelor's degree programs, 26.5% in master's degree programs, and 26.2% in 5- or 6-year degree programs. Additionally, 0.8% of students were attending first- or second-level master's programs, 2.7% were pursuing PhDs, and 2.4% were enrolled in other types of academic programs, including postgraduate schools, single courses, or exchange programs.

Analytic Plan

Statistical analyses were carried out through two statistical software packages: JASP and IBM SPSS v.21.

To address the first objective, a hierarchical clustering analysis and k-means models were performed to identify potential distinct AE patterns. SAES six dimensions' mean scores were selected as clustering variables. No missing data were detected, and no deletion has been applied (Cook, 2021). SAES scores were standardized in z-scores to ensure that no feature disproportionately influenced the clustering process (Patel & Mehta, 2011).

Recent guidelines emphasize the importance of sample size relative to the number of clustering variables (Mooi et al., 2018). Dolnicar et al. (2016) suggest a conservative threshold of $n \geq 70 \cdot k$, where k is the number of variables used for clustering. In this study, six dimensions of AE were analyzed ($k = 6$), requiring a minimum sample size of 420 participants to ensure stability and robustness of the clustering solution. With a sample of 650 participants, this study exceeds this threshold, providing sufficient data for reliable cluster identification.

Subsequently, a one-way multivariate analysis of variance (MANOVA) was used to assess differences among the clusters and examine students' characteristics within each group. To conduct this analysis, a power analysis was performed to ensure sufficient statistical power. Specifically, to detect a small effect ($f^2(V) = 0.02$) with a power of 0.90 and a significance level of 0.05, a minimum sample size of 552 participants was required. Using the full sample ($n = 650$) ensured sufficient statistical power for the analysis while preserving the natural distribution of cluster membership. Reducing the sample size could have altered the composition of the clusters, potentially undermining their validity. As noted in the literature, larger samples improve the precision of estimates and results' reliability (VanVoorhis & Morgan, 2007; Lakens, 2022).

Finally, to explore the association among AE, well-being, and mental health outcomes, a one-way MANCOVA was performed. Independent variable was AE patterns and gender was inserted as a covariate. Dependent variables were the scores of the following scales: GAD-7; BDI-II; Cognitive Reappraisal (CR) sub-scale of the ERQ; Expressive Suppression (ES) sub-scale of ERQ; CORE-OM domains (Well-being; Problems; Functioning; Risk). The CORE-OM total score was not included to avoid inflated estimates of the effects, due to the overlap of explained variance between the single domains and total scores (Van den Noortgate et al., 2013).

For both multivariate analyses, the significance level was set at $p < 0.05$ and the Bonferroni correction was applied to multiple comparisons.

Results

This section presents the findings of the statistical analyses, organized to address the study's objectives. Before proceeding with clustering and multivariate analyses, a correlation analysis was conducted to examine relationships among the study's variables. Following this, the identification of AE patterns is described, using hierarchical clustering as an exploratory tool and *k*-means clustering to define the final cluster solution. Subsequently, the distinctiveness of the identified clusters is explored through multivariate analyses, reporting students' characteristics across patterns. Finally, relationships between AE patterns and psychological variables, including well-being and mental health outcomes, are analyzed to examine how they vary across the identified groups. Descriptive statistics investigate differences in symptom severity and psychological functioning across the identified clusters.

Correlation Analysis

A correlation analysis was conducted to examine relationships among the study's variables, including the six AE dimensions and psychological outcomes (e.g., GAD-7, BDI-II, ER1-10 subscales; CORE-OM domains). This preliminary step aimed to assess the strength and direction of these associations and their relevance for further analyses.

Moderate correlations observed among the AE dimensions indicate that these variables are related but not redundant, capturing distinct yet interconnected aspects of academic engagement. Additionally, significant correlations were identified between individual AE dimensions and psychological outcomes, highlighting the potential relevance of these variables for understanding students' psychological functioning. These results provide a basis for investigating how patterns of AE dimensions—representing distinct combinations of the six variables—relate to psychological outcomes. Table 1 reports the Pearson correlation coefficients, with significance levels in brackets.

AE Pattern Identification

To address potential concerns about model assumptions, data were prepared to apply the hierarchical and k-means clustering algorithms (Bardhoshi et al., 2021). Specifically, SAES scores were standardized into z-scores to ensure comparability across variables and to avoid disproportionate influences due to differences in variance. Euclidean distance was chosen as the dissimilarity measure due to its suitability for continuous, standardized variable. Ward's linkage method was employed to minimize within-cluster variance and generate compact clusters. This optimizes the grouping process by merging clusters in a way that results in the smallest possible increase in total within-cluster variance at each step (Murtagh et al., 2014).

Hierarchical clustering was employed as an exploratory method to identify potential grouping structures within the dataset, based on the relationships among SAES scores. This approach was selected to provide a dendrogram (see Fig. 1), displaying visual representation of the relationships among observations. The hierarchical clustering did not establish the final number of clusters but served as a foundational step to suggest possible cluster solutions for k-means analysis (Clatworthy et al., 2005).

Participants were displayed on the horizontal axis of the dendrogram. Each hierarchical structure below a vertical line segment represents a cluster. Vertical lines indicate the distance between merged components forming a cluster: the higher the line at which two cluster merged, the more dissimilar the cluster. A top division indicated a two-cluster solution, with further splits suggesting three and four cluster solutions. To explore these potential alternatives, three k-means cluster analyses

Table 1 Results of correlation analyses

	1	2	3	4	5	6	7	8	9	10	11	12	13
1 Persistence	–												
2 Belonging	0.642***	–											
3.Course value	0.605***	0.694***	–										
4 Integration	0.265***	0.439***	0.331***	–									
5. Peer relationships	0.298***	0.362***	0.362***	0.344***	–								
6. Professor relationships	0.324***	0.361***	0.382***	0.225***	0.267***	–							
7. GAD-7	−0.095*	−0.010	−0.077	−0.033	−0.128***	−0.034	–						
8. BDI-II	−0.281***	−0.156***	−0.231***	−0.264***	−0.301***	−0.087*	0.613***	–					
9. ERQ-10 CR	0.170***	0.181***	0.169***	0.173***	0.137***	0.119*	−0.242***	−0.380***	–				
10. ERQ-10 ES	−0.029	−0.077*	−0.039	−0.227***	−0.175***	−0.066	0.151***	0.250***	0.040	–			
11 Well-being	−0.266***	−0.180***	−0.263***	−0.236***	−0.236***	−0.139***	0.547***	0.709***	−0.353***	0.131***	–		
12 Problems	−0.227***	−0.106***	−0.181***	−0.189***	−0.260***	−0.066	0.696***	0.773***	−0.265***	0.204***	0.740***	–	
13 Functioning	−0.257***	−0.185***	−0.239***	−0.359***	−0.442***	−0.157***	0.470***	0.738***	−0.313***	0.306***	0.641***	0.673***	–
14. Risk	−0.139***	−0.054	−0.039	−0.138***	−0.123***	0.061	0.329***	0.521***	−0.176***	0.105***	0.349***	0.446***	0.411***

Note: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

were carried out, comparing the models' performance and results' interpretability. Hartigan-Wong algorithm was used with center type set to means, and 25 maximum iterations to ensure stable clustering (Hartigan & Wong, 1979). Table 2 reports the parameters and validation indices of the three models.

The two-cluster solution showed the greatest silhouette and Calinski-Harabasz (CH) index values, indicating the best performing algorithm (Milligan & Coper, 1985). Both the three- and four-cluster solutions had lower Akaike Information Criteria (AIC; Akaike, 1974) and Bayesian Information Criteria (BIC; Stone, 1979), which suggests a better fit for these models. However, the four-cluster solution was associated with lower CH and silhouette indices, indicating reduced cluster quality despite its lower AIC and BIC values. The three-cluster solution provided a good balance between statistical support and practical interpretability, offering a more nuanced differentiation of the student population. Considering both validation indices and results' interpretability, the student population was grouped into three clusters, named *AE patterns*.

AE Pattern Differences

According to the descriptive statistics of the SAES scores in the three clusters (Table 3), Cluster 1 was labelled as *High AE pattern* ($n=202$; $M=23.4$, SD = 0.20), Cluster 2 was labelled as *Low AE pattern* ($n=173$; $M=24.7$, SD = 0.25), and Cluster 3 was labelled as *Moderate AE pattern* ($n=275$; $M=23.7$, SD = 1.19).

Multivariate tests of the one-way MANOVA carried out on the SAES scores showed significant differences among AE patterns (Pillai's trace = 1.004;

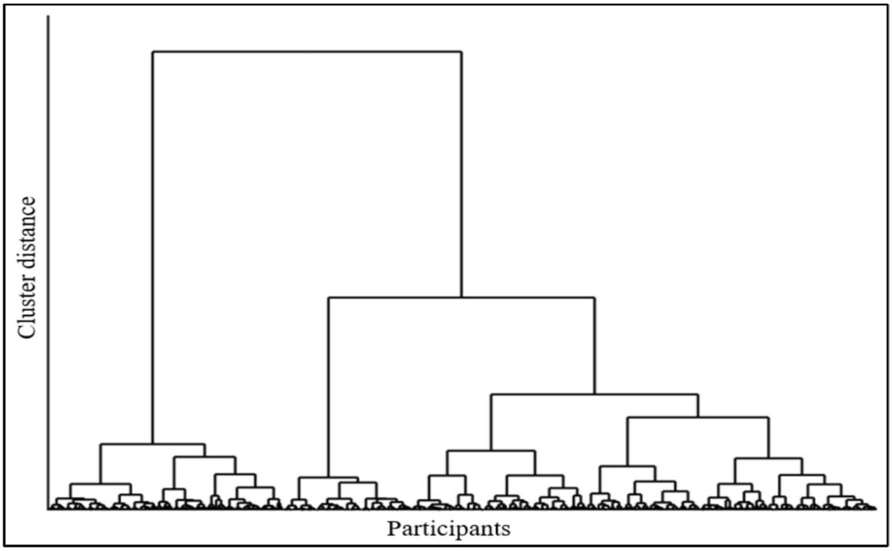

Fig. 1 Dendrogram structure of data

Table 2 Comparisons of k-means models metrics

	Two-cluster model	Three-cluster model	Four-cluster model
AIC	2582.17	2216.31	2152.93
BIC	2635.89	2296.89	2045.48
Silhouette index	0.290	0.200	0.180
Calinski-Harabasz index	338.37	254.26	204.45
Size of each cluster	1 = 301 2 = 349	1 = 202 2 = 173 3 = 275	1 = 165 2 = 152 3 = 148 4 = 185

$F(12,1286) = 108.081$; $p < 0.001$; $\eta_p^2 = 0.502$). Univariate tests revealed significant effects of AE pattern on all dimensions: *Perception of the capability to persist in the university choice* ($F(2,647) = 390.147$; $p < 0.001$; $\eta_p^2 = 0.547$); *University value and sense of belonging* ($F(2,647) = 517.182$; $p < 0.001$; $\eta_p^2 = 0.615$); *Value of University course* ($F(2,647) = 427.052$; $p < 0.001$; $\eta_p^2 = 0.569$), *Integration between the university and relational net* ($F(2,647) = 151.032$; $p < 0.001$; $\eta_p^2 = 0.318$); *Engagement with university peers* ($F(2,647) = 124.697$; $p < 0.001$; $\eta_p^2 = 0.278$); *Engagement with faculty members* ($F(2,647) = 147.488$; $p < 0.001$; $\eta_p^2 = 0.313$). All effect sizes showed a large effect ($\eta_p^2 \geq 0.14$; Richardson, 2011), reinforcing the robustness of the identified clusters. Students in the three AE patterns differed consistently across all engagement dimensions, from academic persistence to relational aspects such as engagement with peers and faculty members.

Bonferroni-adjusted multiple comparisons revealed an ascending trend across the three identified patterns. Students in the Low AE pattern reported the lowest scores across all dimensions, including determination to persist in university, perceived university and course value, sharing of academic experiences, and perceived support from professors and peers. Conversely, students in the High AE pattern reported the

Table 3 Descriptive statistics (mean and SD) of AE dimension in the three patterns

	Low AE pattern (cluster 2)		Moderate AE pattern (cluster 3)		High AE pattern (cluster 1)	
AE dimensions	*M*	*SD*	*M*	*SD*	*M*	*SD*
1. Perception of the capability to persist in the university choice	3.06	0.73	4.27	0.54	4.65	0.45
2. University value and sense of belonging	3.24	0.54	4.12	0.48	4.75	0.32
3. Value of university course	2.92	0.61	3.87	0.54	4.57	0.51
4. Integration between the university and external relational net	2.54	0.96	2.95	0.95	4.12	0.89
5. Engagement with university peers	2.50	0.88	3.01	0.91	3.90	0.84
6. Engagement with faculty members	2.73	0.79	3.01	0.66	3.92	0.72

highest scores, indicating positive evaluations of all the AE dimensions. Students in the Moderate AE pattern showed intermediate scores, falling between the others. Relational dimensions (i.e., university peers, professors, external networks) were always associate with lower scores, especially in the Low and Moderate AE patterns, indicating that social interactions within the academic context appear more challenging to attain.

The three AE patterns differed in demographic and academic characteristics. Students in the Low AE pattern were slightly older ($M=24.7$ years) than those in the Moderate ($M=23.7$) and High AE patterns ($M=23.4$). Male students were more prevalent in the Low AE pattern (46.2%) compared to the Moderate (32.4%) and High AE ones (22.8%). Bachelor's students were most represented in the Low AE pattern (46.2%), while master's enrollment was higher in the Moderate (25.5%) and High AE patterns (28.7%). PhD students were a small minority but slightly more common in the High AE pattern (3.5%) than in the Low AE pattern (1.7%).

Association Between AE Patterns, Well-being, and Mental Health Outcomes

To ensure the appropriateness of the one-way MANCOVA, we evaluated the dependent variables' correlation matrix. The analysis revealed moderate associations among AE dimensions, none of which exceeded the commonly recommended threshold (e.g., >0.09) for multicollinearity (Tabachnick & Fidell, 2013). This suggested that the psychological variables were interrelated but not redundant.

Homogeneity of covariance matrices was assessed by conducting a Box's M test. The test yielded d $M=90.503$, $F(72, 920{,}693.199)=1.234$, and $p=0.086$, indicating no significant violation of the assumption of homogeneity of covariance matrices ($p>0.001$). Pillai's trace was selected as the multivariate test statistic due to its robustness and reliability in cases of unequal group sizes (Tabachnick & Fidell, 2013).

Multivariate tests of the one-way MANCOVA performed on well-being and mental health outcomes showed the significant effect of AE patterns (Pillai's trace $=0.192$; $F(16,1280)=8.489$; $p<0.001$; $\eta_p^2=0.096$) and the effect of the covariate (i.e., gender) (Pillai's trace $=0.091$; $F(8,639)=7.975$; $p<0.001$; $\eta_p^2=0.091$).

Univariate tests showed that AE patterns exerted an effect on the following scales: GAD-7 ($F(2,646)=5.951$; $p=0.003$; $\eta_p^2=0.018$); BDI ($F(2,646)=31.435$; $p<0.001$; $\eta_p^2=0.089$); ERQ-CR ($F(2,646)=13.184$; $p<0.001$; $\eta_p^2=0.039$); ERQ-ES ($F(2,646)=5.650$; $p=0.004$; $\eta_p^2=0.017$); CORE-OM well-being domain ($F(2,646)=31.469$; $p<0.001$; $\eta_p^2=0.089$); CORE-OM problems domain ($F(2,646)=18.982$; $p<0.001$; $\eta_p^2=0.056$); CORE-OM functioning domain ($F(2,646)=47.529$; $p<0.001$; $\eta_p^2=0.128$); CORE-OM risk domain ($F(2,646)=3.748$; $p=0.024$; $\eta_p^2=0.011$). Covariate's effect was found on the scores of the GAD-7 ($F(1,646)=15.767$; $p<0.001$; $\eta_p^2=0.024$); BDI ($F(1,646)=10.905$; $p=0.001$; $\eta_p^2=0.017$); CORE-OM well-being domain ($F(1,646)=32.929$; $p<0.001$; $\eta_p^2=0.049$); CORE-OM problems domain

(F(1,646) = 7.125; p = 0.008; η_p^2 = 0.011): female students reported greater anxiety and depressive symptoms, and less psychological well-being compared to male ones.

Effect sizes for AE patterns ranged from small to large (η_p^2 = 0.011–0.128). The strongest effects emerged for psychological well-being (CORE-OM well-being), functioning (CORE-OM functioning), and depressive symptoms (BDI-II), highlighting a strong link between mental health and the academic context. Anxiety symptoms (GAD-7) and emotion regulation strategies (ERQ-CR, ERQ-ES) showed smaller effects, suggesting these difficulties are common among students seeking counseling and less tied to academic engagement patterns. Despite their lower magnitude, differences across AE pattern remained significant, reflecting distinct psychological profiles. The CORE-OM risk domain had the smallest effect size (η_p^2 = 0.011), possibly reflecting the low prevalence of severe risk-related symptoms in the sample.

Table 4 shows the mean and SD of each scale score in the three AE patterns.

Multiple comparisons with the Bonferroni adjustment showed significant differences across AE patterns for all psychological outcomes. Students in the Low AE pattern reported greater anxiety symptoms compared to those in the Moderate and High AE patterns, with no significant differences between the latter two groups. Similarly, depressive symptoms were most pronounced among Low AE pattern students, followed by those in the Moderate AE pattern, and the lowest in the High AE one.

Regulation strategies also varied across patterns. Students in the High AE pattern employed more frequently CR and less ES compared to students in Low and Moderate AE patterns, which did not differ from each other. Concerning CORE-OM domains, students in the Low AE pattern reported the highest impairments in well-being, problems, and functioning domains, followed by those in the Moderate AE pattern, and those in the High AE one. In the risk domain, the Low AE pattern was associated with a higher score compared to solely High AE pattern.

Table 4 Descriptive statistics (mean and SD) of scores in the three AE pattern

	Low AE pattern		Moderate AE pattern		High AE pattern	
Scales	*M*	*SD*	*M*	*SD*	*M*	*SD*
GAD-7	13.05	4.46	11.65	4.60	12.00	4.66
BDI-II	26.24	10.25	22.07	10.56	18.12	9.94
ERQ-CR	23.76	7.82	25.39	7.26	27.55	7.01
ERQ-ES	15.79	5.53	15.71	5.57	14.12	5.42
CORE-OM domains						
Well-being	2.83	0.71	2.55	0.75	2.25	0.83
Problems	2.33	0.68	2.10	0.76	1.86	0.80
Functioning	2.09	0.59	1.87	0.62	1.49	0.62
Risk	0.36	0.52	0.26	0.45	0.22	0.45

Descriptive Statistics of Well-being and Mental Health Outcomes

In the Low AE pattern, 2.9% of students exhibited minimal anxiety, 23.1% mild, 32.4% moderate, and 41.6% severe anxiety. Depression levels were minimal in 10.4%, mild in 19.1%, moderate in 31.8%, and severe in 38.7%. Emotion regulation was characterized by frequent use of ES (median score = 16) and limited use of CR (median score = 24). CORE-OM outcomes indicated that most students reported significant impairments in well-being (91.3%), experienced emotional and behavioral problems (90.8%), and functioning difficulties (90.2%). The 38.7% indicated a higher likelihood of engaging in risky behavior.

In the Moderate AE pattern, 6.2% of students exhibited minimal anxiety, 26.9% mild, 37.5% moderate, and 29.5% severe anxiety. For depression, 22.5% reported minimal, 20.7% mild, 33.5% moderate, and 23.3% severe symptoms. CR was more commonly used (median score = 26), while ES scores were more similar to the Low AE group (median score = 16).

CORE-OM outcomes showed that 86.2% of students experienced diminished well-being, 79.6% reported emotional and behavioral problems, 82.5% experienced functioning difficulties, and 29.1% were likely to engage in risky behaviors.

The High AE pattern was associated with the least severe outcomes: 5% of students exhibited minimal anxiety, 27.2% mild, 36.6% moderate, and 31.2% severe anxiety. For depression, 38.1% reported minimal, 25.2% mild, 20.3% moderate, and 16.3% severe symptoms. This group exhibited the highest use of cognitive reappraisal (median score = 28) and the lowest use of expressive suppression (median score = 14). Regarding CORE-OM outcomes, 71.3% of students reported significantly decreased well-being, 66.8% reported emotional and behavioral problems, 62.4% had functioning difficulties, and 25.7% were likely to engage in risky behaviors.

A clear association between AE and decrease in all well-being and mental health outcomes is observed. Students with lower academic engagement are those who showed higher scores in all measures, revealing severe psychological symptoms and distress.

Discussion

Research on students' mental health has expanded significantly in recent years (Porru et al., 2021; Sheldon et al., 2021; Zarowski et al., 2024). However, less attention has been directed towards the associations between academic engagement (AE) patterns and psychological distress, particularly within the sub-population of university students seeking psychological support through counseling facilities. Previous classification studies have focused on the general student population, examining academic or stress-related factors (Cano et al., 2024; Saenz et al., 2011), often without addressing their connections to psychological functioning and symptomatic experience (Wilson et al., 2021).

The current study sought to address these gaps by identifying distinct AE patterns among university students attending counseling facilities, examining the characteristics of these patterns, and exploring their associations with well-being and mental health outcomes. Using hierarchical cluster analysis and k-means modeling across six AE dimensions, students were ecologically grouped into three groups characterized by Low, Moderate, and High AE patterns, respectively. These clusters showed significant differences in both AE dimensions and psychological outcomes, highlighting the diverse needs of students within this population.

Summary of AE Patterns

A clear ascending trend in AE dimensions emerged across the Low, Moderate, and High AE patterns, with distinct characteristics captured through descriptive analysis.

Students with a Low AE pattern showed minimal persistence in university activities, a limited sense of belonging, and a weak recognition of the value of their course. Moreover, AE relational dimensions were particularly impaired, with students reporting limited connections to peers, faculty members, and external communities.

Students in the Moderate AE pattern showed slightly higher scores than their Low AE counterparts, but continued to face academic challenges, particularly in the formation of meaningful relationships with academic and external networks. While they recognized the value of their education to a greater extent, they struggled to achieve social integration.

Students with a High AE pattern exhibited strong persistence in their academic activities, a robust sense of belonging, and a clear recognition of the value of their university studies. Relational dimensions were notably positive, with these students perceiving peers and faculty members as supportive and frequently sharing their academic experiences with external communities and family.

Students' Characterization Across AE Patterns

Socio-demographic and academic characteristics across the AE patterns provided additional insights into the diversity of students within the sample. Male students were more frequently represented in the Low and Moderate AE patterns, suggesting lower levels of AE compared to their female counterparts. However, the overrepresentation of female students in the sample may have limited the robustness of the gender-based comparisons. This finding aligns with previous evidence reporting that female students are more likely to seek psychological support in counseling services (Nam et al., 2010).

Students in the Low AE pattern were slightly older (24.7 years) compared to those in the Moderate (23.7 years) and High (23.4 years) AE patterns. Despite their older age, most students exhibiting a Low AE pattern were enrolled in a bachelor's degree program (46.2%), potentially reflecting delays or interruptions in academic progress due to academic difficulties and decreased well-being. Supporting this, data from the Italian inter-university consortium indicate that 36.4% of university students extend beyond the standard timeframe to complete their degrees (AlmaLaurea, 2024). Conversely, in the present study, students enrolled in advanced degree programs were more prevalent in the Moderate and High AE patterns, likely reflecting greater intrinsic motivation and a stronger sense of belonging compared to undergraduates (Glass & Westmont, 2014; Isiksal, 2010).

Associations Between AE Patterns, Well-being, and Mental Health Outcomes

The multivariate analyses revealed significant associations between AE patterns, well-being, and mental health outcomes.

Students in the Low AE pattern exhibited the greatest levels of anxiety symptoms, consistent with studies showing a negative correlation between AE and anxiety (Asghar, 2014; Brumariu et al., 2022). They also demonstrated the highest prevalence of students with severe depressive symptoms, aligning with research showing that depression diminishes self-efficacy and engagement (Ji et al., 2021; Tang & He, 2023).

Emotion regulation strategies also varied across patterns. Students in the High AE pattern predominantly employed cognitive reappraisal —an adaptive strategy linked to improved academic coping and psychological well-being (Butler & De la Paz, 2021). In contrast, students in the Low and Moderate AE patterns relied more heavily on expressive suppression, which is associated with poorer mental health outcomes and reduced academic achievements (Alkharj et al., 2024; Zhoc et al., 2022).

Consistent with previous research, AE was negatively associated with psychological distress (Burgos-Videla et al., 2022; Sharan & Tan, 2008). Students in the Low AE pattern reported the most significant emotional and relational difficulties, significant daily functioning impairment, and the highest likelihood of engaging in risky behaviors. These challenges were progressively less pronounced in the Moderate AE pattern, and least pronounced in the High AE pattern.

Although decreased well-being, emotional difficulties, and risky behaviors were prevalent across the entire sample, students in the High AE cluster reported notably lower levels of psychological distress and reduced engagement in risky behaviors.

Overall, the findings underscore the heterogeneity of students attending counseling facilities, revealing distinct AE patterns associated with varying degrees of well-being and mental health vulnerabilities.

AE and Mental Health: Emerging Insights

The present findings suggest the relevance of AE as a potential indicator of well-being among students seeking counseling support. However, certain considerations must be acknowledged when interpreting the observed associations, and particularly the potential bidirectionality of the relationship between AE and mental health.

Psychological symptoms such as anxiety and depression may contribute to lower AE by undermining students' motivation and reinforcing withdrawal behaviors. Conversely, lower AE may exacerbate these symptoms by diminishing students' feelings of belonging and connectedness to their academic environment (Brumariu et al., 2022; Tang & He., 2023). These mutual influences underscore the interdependence of AE and mental health, highlighting the need for longitudinal studies to explore how these dynamics may evolve over time. Although the current study did not establish causality, the findings suggest that AE may serve as a valuable construct for identifying levels of psychological distress and critical needs among students with decreased well-being.

Another key observation is that, while AE appeared to act as a protective factor against mental health vulnerabilities, it did not entirely shield students from psychological challenges. Indeed, even those in the High AE cluster sought counseling support and reported psychological distress. This finding suggests that the needs of these students may extend beyond academic factors, underscoring the importance of considering individual variability within this complex population to better tailor support interventions.

Practical Implications

The identification of distinct AE patterns provides actional insights for university counseling services, suggesting that early assessments of AE may enable professionals to better understand students' needs and design interventions that effectively address their challenges. For instance, given the observed vulnerabilities across multiple domains among students with Low AE, interventions for these students could focus on fostering adaptive emotion regulation strategies (e.g., cognitive reappraisal) to enhance their coping abilities and academic motivation (Teixeira et al., 2022). Conversely, students with moderate AE may express relational difficulties, suggesting a need for strategies to promote social integration (Douwes et al., 2023). Interventions could focus on strengthening peer connections, improving family relationships, and fostering a sense of belonging within the academic community. Finally, students with high AE may still experience psychological distress, indicating that their needs may extend beyond academic factors. Addressing the underlying sources of this distress in this population while building on their existing strengths could help prevent the escalation of symptoms and mitigate impacts on other areas of well-being.

Limitations and Future Directions

The current findings should be interpreted in light of certain limitations. First, data were collected from a single university in Northern Italy, thereby limiting the generalizability of the results to other organizational or cultural contexts. However, the findings align with broader trends in psychological distress observed among Italian students (Porru et al., 2021).

Second, the study focused on students who submitted an initial request for counseling but did not necessarily proceed to engage in counseling sessions. While this approach allowed for the monitoring of access patterns to the service, it did not account for potential differences among students who started, discontinued, or never began counseling.

Third, sample size warrants consideration. Although the power analysis for the MANOVA indicated that a smaller sample would suffice, the full dataset was retained to better capture naturally occurring patterns. Nevertheless, as noted in the literature, larger samples are essential for improving the precision of estimates and reliability of the results (Lakens, 2022; VanVoorhis & Morgan, 2007).

Another limitation concerns the exclusion of gender as a variable in the clustering process. Given the gender imbalance in the sample, and inconsistent findings regarding gender differences in AE, the incorporation of this variable in the present analysis could have obscured meaningful relationships within data (Eldridge et al., 2006).

Finally, the use of self-report measures may have introduced social desirability and recall inaccuracies. To address this limitation, future research should incorporate alternative methodologies (e.g., behavioral observations, objective data collection) to enhance the robustness and validity of the results.

To expand the current findings and improve generalizability, future studies should consider diverse HE and cultural contexts. Additionally, longitudinal designs may be particularly useful for exploring the directional dynamics between AE and mental health outcomes, as well as changes following counseling interventions. Finally, the inclusion of a wider range of demographic variables and psychological measures could provide a more comprehensive understanding of AE and its implications for the well-being of students with elevated distress and vulnerabilities.

Conclusion

The university years represent a critical developmental stage marked by significant personal and academic challenges, with a high prevalence of mental health issues such as depression, anxiety, and psychological distress. Therefore, the identification of factors that may serve as indicators of students' well-being is essential, and AE, as a multidimensional construct, holds particular promise in this regard. The current findings suggest that, among students seeking counseling support, distinct AE configurations effectively distinguish between mental health and psychological outcomes, providing valuable insight into the role of AE in fostering well-being in HE contexts.

Author Contribution C.G.: study's design; methodology; data processing and analyses; writing and editing; original draft preparation. F.I: data curation and processing; reviewing. D.L.: reviewing and editing; supervision. S.F: reviewing and editing; supervision. L.B.: study's conception and design; supervision; writing; review and editing; funding acquisition. All authors contributed to the article and approved the submitted version.

Funding Open access funding provided by Università degli Studi di Pavia within the CRUI-CARE Agreement.

Data Availability Data presented in this study are available upon request from the corresponding author.

Declarations

Competing Interests The authors declare no competing interests.

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