

Cluster profiles of active learning and academic engagement in ecuadorian technical education

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ABSTRACT

Most quantitative research on active learning methodologies (ALM) and academic engagement (AE) in higher education compares predefined groups, such as academic programs, using a variable-centered logic that reports average differences between categories the researcher already knows. This study instead asks a person-centered question: do naturally occurring configurations of students exist within a single technical and technological higher education institution, independent of the program they are enrolled in? Using data from 130 students across six academic programs at an Ecuadorian technical and technological higher education institute, hierarchical (Ward's method) and k-means cluster analysis were applied to seven ALM and AE subdimension scores. A three-cluster solution was retained based on silhouette width, the Calinski-Harabasz index, and bootstrap stability (adjusted Rand index = .957 across 200 resamples): a Critically Disengaged profile (n = 13, 10.0%; ALM and AE means near 1.3 of 5), a Moderate-Favorable profile (n = 58, 44.6%; means near 3.9-4.0), and a Highly Engaged profile (n = 59, 45.4%; means near 4.8). Cluster membership was statistically independent of academic program (chi-square = 15.21, df = 10, p = .125) and gender (chi-square = 1.82, df = 2, p = .402), indicating that these profiles cut across, rather than coincide with, the program-based differences documented in a companion comparative study using the same dataset. The findings suggest that a small but identifiable subgroup of students combines low active-learning exposure with low engagement regardless of program, a pattern invisible to between-program comparisons alone, with direct implications for targeted, rather than program-wide, institutional support.

Keywords: Active learning; Academic engagement; Cluster analysis; Person-centered approach; Higher education; Ecuador

1. INTRODUCTION

Two companion studies, using the same dataset examined here, established that an 18-item instrument measuring active learning methodologies (ALM) and academic engagement (AE) among students at an Ecuadorian technical and technological higher education institute has excellent internal consistency but a dominant general factor per scale, and that ALM, though not AE, differs significantly across the institution's six academic programs, with Software Development students reporting the lowest exposure and Automation and Instrumentation students the highest. Both studies, like most of the quantitative research on this topic, adopted what Bergman and Magnusson (1997) term a variable-centered approach: they treated ALM and AE subdimensions, or program membership, as variables whose average relationships and differences across predefined categories are the primary object of analysis.

A variable-centered logic, however, answers a specific kind of question well, how do average scores differ between programs, or how do variables correlate, while answering a different kind of question poorly: whether the students within a program, or across the institution as

a whole, actually fall into qualitatively distinct configurations that a program-level average would obscure. Bergman and Trost (2006) frame this as a genuine methodological choice rather than a mere technical preference: a person-centered approach treats the individual, not the variable or the predefined group, as the unit of analysis, asking which patterns of scores actually co-occur across real students, and how many such patterns exist, rather than assuming from the outset that program membership is the relevant grouping variable.

This distinction has immediate practical stakes for the institution this dataset describes. If, as the companion comparative study found, active-learning exposure differs by program while engagement does not, an administrator might reasonably conclude that only program-level curricular reform is needed, targeted at the lower-scoring programs, and that engagement, being program-invariant, requires no such targeting. A person-centered analysis can test a further, complementary possibility that the program-based comparison cannot address: that a subgroup of students combining low exposure and low engagement exists within the institution regardless of program, a subgroup that program-wide curricular reform would not reliably reach because it is not concentrated in any single program.

This distinction also carries a specific institutional-policy implication for the *Universidad Bolivariana del Ecuador* and comparable technical and technological higher education institutions across the region: if resources for student-support interventions are allocated primarily on the basis of program-level averages, as the companion comparative study's findings might otherwise recommend, a substantial share of the students most in need of support could be systematically overlooked because their program of enrollment does not, on average, appear at elevated risk. A person-centered diagnostic, applied at the level of the individual student rather than the program, is therefore not merely a methodological refinement but a precondition for designing support mechanisms capable of reaching the specific students who need them, regardless of which of the institution's six programs they happen to be enrolled in.

This study is the fourth in a series of independent analyses conducted on the same 130-respondent dataset collected at this institution, each applying a distinct analytic lens to a shared underlying question about active learning and academic engagement. A companion psychometric validation study examined whether the measurement instrument itself behaves as theorized; a companion comparative study examined whether academic programs differ on average; a companion structural-equation study examined whether a specific technological mechanism mediates the relationship between pedagogy and engagement. The present, fourth study completes this analytic sequence by asking whether the individual students who make up this population fall into recurring, qualitatively distinct configurations, a question none of the preceding three studies, each variable-centered by design, was positioned to answer. Read as a set, the four studies illustrate that a single, modestly sized regional dataset, if analyzed through a sufficiently varied set of quantitative lenses, can support a substantially more nuanced and more actionable institutional picture than any one of the four analyses could provide in isolation, a point returned to in the Conclusions.

The purposes of this study are threefold:

- 1) Determine whether naturally occurring, qualitatively distinct configurations (profiles) of active learning methodologies and academic engagement exist among students at this institution, using cluster analysis as a person-centered method.
- 2) Characterize the resulting profiles descriptively and validate their statistical robustness through internal (silhouette, Calinski-Harabasz) and stability (bootstrap)

criteria.

- 3) Test whether profile membership is statistically associated with academic program or gender, to establish whether these profiles are simply a restatement of the program-based differences already documented, or a genuinely complementary, cross-cutting pattern.

The remainder of this article proceeds as follows. Section 2 develops the theoretical framework, contrasting variable-centered and person-centered approaches to studying active learning and engagement and situating this study within the limited Latin American literature on student engagement. Section 3 describes the sample, instrument, and clustering procedure. The Results section presents the cluster solution and its validation. The Discussion section interprets the profiles in relation to the companion studies and the broader literature. The Conclusions section summarizes the study's contribution, limitations, and future research directions.

2. FRAMEWORK

2.1. ACTIVE LEARNING AND ACADEMIC ENGAGEMENT IN TECHNICAL HIGHER EDUCATION

Active learning, understood as instruction that engages students in doing and thinking about what they are doing rather than passively receiving information (Bonwell & Eison, 1991), is strongly supported by evidence such as Freeman et al.'s (2014) meta-analysis of 225 STEM studies, which found active learning raised examination performance and reduced failure rates relative to lecturing. Academic engagement, following Fredricks, Blumenfeld, and Paris's (2004) tripartite model of behavioral, cognitive, and emotional engagement, is the outcome most frequently theorized to follow from active methodologies, a relationship self-determination theory (Ryan & Deci, 2000) explains through classroom conditions that support autonomy, competence, and relatedness. Prince (2004) applied this broad framework specifically to engineering and technical education, the disciplinary context most relevant to the institution studied here.

Almost without exception, the empirical literature reviewed for this study, whether international or specifically Latin American, reports the association between active learning and engagement as a population-level, variable-centered finding: on average, across a sample of students, higher active-learning scores accompany higher engagement scores. This framing implicitly treats the population as sufficiently homogeneous that a single correlation, or a single regression coefficient, adequately summarizes the relationship for every student in the sample. Whether this homogeneity assumption holds, or whether the population instead comprises subgroups for whom the joint level of active learning and engagement differs sharply, as opposed to subgroups for whom the two constructs merely correlate differently, is a question the population-level framing cannot address and that the person-centered approach developed in Section 2.2 is specifically designed to test.

2.2. VARIABLE-CENTERED AND PERSON-CENTERED APPROACHES TO STUDYING STUDENTS

Bergman and Magnusson (1997), writing from developmental psychopathology, articulate what remains the clearest statement of the distinction motivating this study: a variable-centered approach takes the variable as the primary unit of theoretical and analytical interest, asking how variables covary or differ across predefined groups on average, while a person-centered approach takes the individual, and the specific pattern of variables that co-occurs within that individual, as the primary unit of interest, asking which patterns actually exist in a population and how prevalent each is. Bergman and Trost (2006) argue that the two approaches are not competitors but answer complementary questions, and that person-centered methods are particularly valuable when a population is suspected to be heterogeneous in ways that a single average, or a small number of predefined subgroup

averages, would mask. Cluster analysis is the most widely used family of methods for operationalizing a person-centered approach with cross-sectional data of the kind examined here, since it groups individuals directly by the similarity of their full score profile rather than by a category assigned before the data were examined.

This distinction also has a specific bearing on how the companion studies' findings should be read in combination rather than in isolation. The companion psychometric validation study, using exploratory factor analysis, asked whether the instrument's items behave as theorized subscales, a variable-centered question about the structure of measurement itself. The companion comparative study asked whether predefined program groups differ on average, a variable-centered question about group differences. Neither study, by design, could answer the question the present study asks whether the population of students, considered individually rather than as members of a predefined program, falls into a small number of recurring configurations. The four studies together therefore illustrate, with a single shared dataset, four genuinely distinct analytic questions that quantitative educational research can ask of the same underlying phenomenon, a point returned to in the Conclusions.

2.3. STUDENT ENGAGEMENT AS A HOLISTIC, POTENTIALLY HETEROGENEOUS CONSTRUCT

Kahu (2013) reviews four dominant perspectives on student engagement, behavioral, psychological, socio-cultural, and holistic, arguing that the holistic perspective, which treats engagement as an emergent state shaped jointly by institutional conditions and individual psychosocial factors, is best positioned to accommodate the possibility that engagement is not evenly distributed across a student population in a way a single mean, or a small number of program means, can capture. Astin's (1984) theory of student involvement and Kuh's (2009) work with the National Survey of Student Engagement both imply, without directly testing, that involvement or engagement varies at the level of the individual student as a function of energy invested, a formulation naturally suited to a person-centered rather than a purely variable-centered test. Tinto's (1993) retention framework adds a practical stake to this heterogeneity: if a subgroup of students combines low engagement with low exposure to the active methodologies theorized to support persistence, that subgroup, rather than the student body, is the population most relevant to targeted retention interventions.

It is worth noting that the holistic perspective Kahu (2013) advocates does not, by itself, specify which analytic method should be used to operationalize engagement's presumed heterogeneity; a holistic conceptual framework is compatible with a person-centered empirical method, as demonstrated here, but is equally compatible with variable-centered methods, such as the group comparisons and mediation analysis reported in the companion studies, that examine heterogeneity indirectly through moderators or subgroup comparisons. The present study's specific contribution is to pair Kahu's (2013) holistic conceptual stance with Bergman and Magnusson's (1997) person-centered empirical stance directly, testing rather than merely asserting that this population's engagement, and its associated active-learning exposure, are heterogeneous in a way a single institutional average would conceal.

2.4. DISCIPLINARY HETEROGENEITY AND THE LIMITS OF GROUP-BASED COMPARISONS

A companion comparative study using this same dataset found that active-learning methodologies differ significantly across the institution's six academic programs, a pattern the study interpreted through Biglan's (1973) and Becher and Trowler's (2001) disciplinary-culture frameworks, with hard-applied-nonlife programs such as Automation and Instrumentation and Automotive Electromechanics reporting higher exposure than Software Development. That comparison, being variable centered by design, necessarily averaged

across all students within each program, which means it cannot address whether a given program's average conceals substantial internal heterogeneity, for instance, whether Software Development's comparatively low average reflects a uniformly moderate experience across its students or a mixture of some students with a favorable experience and others with markedly unfavorable exposure and engagement. The present study's finding that cluster membership is statistically unrelated to program, reported in the Results section, addresses this gap directly and shows that the two analytical strategies, group comparison and person-centered profiling, answer genuinely different, complementary questions rather than one subsuming the other.

It is also worth noting a subtler methodological point that connects this section to Section 2.3 directly: because Biglan's (1973) and Becher and Trowler's (2001) frameworks operate at the level of the discipline or program, they generate predictions about between-program averages, exactly the kind of prediction the companion comparative study tested and partly confirmed. Neither framework, on its own, generates a prediction about within-program heterogeneity, since disciplinary-culture theory is silent on why, within a single program presumably sharing a common disciplinary culture, some students would nonetheless report Critically Disengaged patterns while their classmates in the same courses report Highly Engaged patterns. Explaining this within-program heterogeneity, which this study documents but does not fully explain, most plausibly requires individual-level constructs, such as those emphasized by self-determination theory (Ryan & Deci, 2000) or by Astin's (1984) resource-based account of student involvement, that operate at a level Biglan's (1973) and Becher and Trowler's (2001) frameworks were never designed to address.

2.5. THE LATIN AMERICAN GAP IN STUDENT ENGAGEMENT RESEARCH

Pineda-Báez, Bermúdez-Aponte, Rubiano-Bello, Pava-García, Suárez-García, and Cruz-Becerra (2014), studying 1,906 students across seven Colombian universities, explicitly note that student engagement remains comparatively understudied in Latin America relative to North America and Europe, despite the region's persistent higher-education dropout problems that engagement research elsewhere has helped address. Regionally, Morales-Morgado, Ruiz-Torres, Rodero-Cilleros, Morales-Romo, and Campos-Ortuño (2023) documented the role of digital tools in active-methodology implementation across disciplines, and Pazmiño Carrión (2026), working with a comparable Ecuadorian technological higher education sample, reported a positive association between active methodologies and academic engagement using a multidimensional framework, though, like the great majority of the regional literature, exclusively through a variable-centered, group-average lens. To the authors' knowledge, no published study in the Ecuadorian or broader Latin American technical and technological higher education literature has applied a person-centered, cluster-analytic approach to jointly profiling active learning exposure and academic engagement, a gap this study addresses directly.

This gap is not merely a matter of publication counts; it has methodological consequences for how engagement is typically operationalized in the studies that do exist regionally. Pineda-Báez et al. (2014) themselves adapted the Spanish-language National Survey of Student Engagement (NSSE) for their Colombian sample, a variable-centered instrument designed to compare institutional benchmarks across universities rather than to classify individual students into qualitatively distinct profiles. The broader pattern across the Latin American literature reviewed for this study, including the companion regional studies by Pazmiño Carrión (2026) and Morales-Morgado et al. (2023), is that engagement and active-learning research in the region has imported variable-centered instruments and analytic techniques from the international literature without a parallel adoption of the person-

centered methodological tradition that has existed alongside variable-centered approaches in psychology and educational research internationally since at least Bergman and Magnusson's (1997) foundational statement. The present study's introduction of cluster analysis into this specific regional research line is intended as a small step toward closing that specific methodological gap, alongside the substantive gap Pineda-Báez et al. (2014) identify.

2.6. CLUSTER ANALYSIS AS A PERSON-CENTERED METHOD

Ward's (1963) hierarchical clustering method, which successively merges the pair of clusters producing the smallest increase in within-cluster variance, and MacQueen's (1967) k-means algorithm, which iteratively reassigns observations to the nearest of k centroids, are the two most widely used clustering methods for continuous, multivariate profile data of the kind examined here; a common and recommended practice, followed in this study, is to use Ward's method to inform the choice of the number of clusters and k-means to obtain the final, more computationally refined partition (Bergman & Magnusson, 1997). Determining the appropriate number of clusters is itself a substantive methodological decision rather than a purely mechanical one: Rousseeuw's (1987) silhouette coefficient, which compares each observation's average distance to points in its own cluster against its average distance to points in the nearest neighboring cluster, and Calinski and Harabasz's (1974) variance-ratio criterion, which compares between-cluster to within-cluster dispersion, are two of the most widely used internal validity indices for this purpose, both applied in the present study alongside a bootstrap-based stability check to guard against reporting a solution that, however internally coherent, would not replicate in a new sample drawn from the same population.

Bootstrap-based stability assessment, in particular, addresses a limitation that internal validity indices such as the silhouette coefficient and the Calinski-Harabasz criterion cannot address on their own: both indices are computed on the same sample used to derive the cluster solution, which means a solution can appear internally coherent by these criteria while still being unstable, in the sense that a different sample of comparable size drawn from the same population might yield a noticeably different partition. Resampling-based stability assessment, of the kind applied in this study through repeated bootstrap resampling and out-of-bag prediction, provides an approximate answer to a question internal validity indices cannot: whether the specific cluster solution reported would be expected to reproduce closely if the study were repeated, a question of direct relevance to any institution considering using a cluster solution of this kind as the basis for resource allocation or targeted intervention, as discussed in the Practical Recommendations section below.

A final methodological point concerns the relationship between the number-of-clusters decision, described in Section 3.4, and the substantive interpretability criterion invoked to justify retaining three clusters over the statistically slightly more cohesive two-cluster solution. Milligan and Cooper's (1985) classic comparative study of thirty internal validity indices for determining the number of clusters, though not the only relevant reference on this question, is broadly consistent with the practice, followed here, of using an internal index such as the silhouette coefficient as one input among several, alongside substantive interpretability and, in this study, external validation against demographic variables and bootstrap stability, rather than as a mechanical, single-number decision rule applied in isolation. This multi-criterion approach to determining the number of clusters is elaborated further in the Results section, where the two-cluster solution's statistical advantage and interpretive limitation are both reported transparently rather than the two-cluster solution being silently set aside.

This transparency principle, reporting a statistically competitive alternative solution alongside the primary retained solution rather than presenting only the final choice as though it were the sole candidate considered, is consistent with broader calls for reproducibility and analytic transparency in quantitative social science research, and is intended to allow readers, and any future researcher attempting to replicate or extend this analysis with new data from the *Universidad Bolivariana del Ecuador* or a comparable institution, to evaluate the number-of-clusters decision on its merits rather than having to take the retained solution on faith.

2.7. CLUSTER ANALYSIS IN EDUCATIONAL RESEARCH: APPLICATIONS AND CAUTIONS

Cluster analysis and other person-centered classification methods have been applied across a range of educational contexts internationally, from identifying at-risk students for early-warning systems in learning analytics to profiling motivational or self-regulation styles among secondary and university students. Across this literature, a recurring methodological caution is that cluster solutions are sensitive to the choice of clustering variables, standardization procedure, linkage method (for hierarchical approaches), and the criteria used to select the number of clusters, which means that a single reported solution, however internally coherent, should ideally be checked against alternative specifications before its substantive interpretation is treated as settled. This caution motivated the robustness checks reported in Section 3.7 and the corresponding results in the Results section, comparing the retained solution against alternative linkage methods and against clustering on each scale separately.

A second recurring caution in this literature concerns sample size relative to the number of clustering variables and the expected size of the smallest cluster. MacCallum, Widaman, Zhang, and Hong's (1999) guidance on sample size in latent-variable and classification contexts, developed originally for factor analysis but broadly applicable to multivariate classification more generally, implies that a cluster as small as the 13-case Critically Disengaged profile identified here approaches the lower bound at which a subgroup's internal structure can be characterized with confidence, even though, as reported in the Results section, this specific subgroup proved highly stable under bootstrap resampling. This tension, between a small cluster's practical importance and the statistical caution its size warrants, is addressed directly in the Limitations subsection of the Conclusions.

A third caution, less frequently discussed than sample size or algorithm sensitivity but equally relevant here, concerns the interpretability of clusters derived from an instrument whose own discriminant validity has been called into question. A companion validation study using this same 18-item instrument reported that exploratory factor analysis identified a single dominant factor per scale rather than the theorized multidimensional structure, raising the possibility that any clustering performed on this instrument's subscale scores is, in effect, clustering on multiple near-redundant measurements of a single underlying disposition rather than on genuinely distinct dimensions. This possibility does not invalidate a cluster analysis of the kind performed here, since even a single well-measured disposition can meaningfully separate a population into low, medium, and high subgroups, but it does mean, as elaborated in the Discussion, that the three profiles identified below should be interpreted as differing in overall level on that disposition rather than in the qualitative shape or configuration of their subscale scores.

2.8. EARLY IDENTIFICATION AND TARGETED INSTITUTIONAL SUPPORT

A person-centered profile such as the Critically Disengaged group identified in this study has a natural application in institutional early-warning and student-support systems, a literature that has grown substantially in higher education internationally as institutions seek to

identify at-risk students before attrition becomes likely, consistent with Tinto's (1993) emphasis on the importance of early, rather than remedial, institutional response. Unlike early-warning systems built primarily on academic performance indicators, such as grades or credit accumulation, a profile built from active-learning exposure and engagement scores, of the kind demonstrated here, could in principle be collected earlier in a student's trajectory, before performance indicators accumulate, offering a potentially faster path to identification. This potential application is discussed further in the Discussion and Conclusions, with the important caveat that a single cross-sectional administration of the kind used in this study is a demonstration of feasibility rather than a validated early-warning instrument ready for institutional deployment.

A further consideration relevant to Latin American technical and technological higher education specifically is that these institutions typically operate with more constrained institutional-research capacity than research-intensive universities, making resource-efficient diagnostic tools particularly valuable. A brief, 18-item self-report instrument of the kind used throughout this series of studies, requiring no specialized software beyond the open-source statistical tools used for the clustering analyses reported here, represents a comparatively low-cost diagnostic relative to the multi-instrument, longitudinal early-warning systems more commonly documented in well-resourced international contexts, a practical consideration directly relevant to whether the approach demonstrated in this study could realistically be adopted by the *Universidad Bolivariana del Ecuador* or similar Ecuadorian institutions operating under comparable resource constraints.

It is important to distinguish, in this context, between the statistical demonstration this study provides and the operational early-warning system such a demonstration might eventually inform. A validated, deployable early-warning tool would typically require, at minimum, evidence that the profile identified predicts a downstream outcome of institutional interest, such as course completion, grade point average, or persistence to the following semester, evidence this study's design, lacking any outcome variable beyond the active-learning and engagement measures used to construct the profiles themselves, cannot provide. The present study therefore should be understood as establishing that stable, cross-program profiles exist and can be identified reliably from a brief instrument, a necessary but not sufficient condition for building the kind of validated early-warning system Tinto's (1993) retention framework would ultimately recommend.

3. METHODOLOGY

3.1. DESIGN

This study used a quantitative, non-experimental, cross-sectional design with a person-centered, exploratory classificatory purpose, applying hierarchical and k-means cluster analysis to identify naturally occurring profiles of active learning methodologies and academic engagement scores.

This design is explicitly complementary to, rather than a replacement for, the designs used in the two companion studies drawing on this dataset. Where the companion validation study used exploratory factor analysis to examine the instrument's internal measurement structure, and the companion comparative study used non-parametric group comparison to examine differences across academic programs, the present study treats the individual student's full profile of scores across all seven ALM and AE subscales as the unit of classification, without reference to program membership, in order to test directly whether meaningful subgroups exist independently of the grouping variable, academic program, that the earlier comparative study had already established as significant for ALM specifically.

3.2. PARTICIPANTS

Participants were 130 students enrolled across six academic programs (Software Development, $n = 28$; Nursing, $n = 25$; Teaching and Educational Innovation, $n = 23$; Automation and Instrumentation, $n = 21$; Automotive Electromechanics, $n = 18$; Business Administration, $n = 15$) at a technical and technological higher education institute in Ecuador, the same sample described in two companion studies using this dataset. Participants were recruited through non-probabilistic convenience sampling and completed an online, anonymous, voluntary questionnaire after providing informed consent.

No additional participants were recruited specifically for this person-centered analysis; the sample is identical to that used in the two companion studies, which allows this study's cluster solution to be interpreted directly against the program-based and psychometric findings already established for the same 130 students, without the interpretive complications that would arise from comparing results across different samples or data-collection periods. This continuity across all four studies drawing on this dataset is a deliberate design choice, allowing the series to build a cumulative, internally consistent picture of this specific population rather than four unrelated, independently sampled investigations.

3.3. INSTRUMENT

Active learning methodologies and academic engagement were measured with the same 18-item, five-point Likert instrument used in the companion studies, covering four ALM subdimensions, Collaborative Interaction, Learning Autonomy, Problem-Based/Real-Case Learning, and ICT Integration, and three AE subdimensions following Fredricks et al. (2004), Behavioral, Cognitive, and Emotional Engagement. A companion validation study reported excellent reliability for all subscales (Cronbach's alpha between .88 and .98; Cronbach, 1951) though it also found, via exploratory factor analysis, a dominant general factor per scale rather than the full theorized subscale structure, a finding that recommends some caution in treating the seven subscale scores used for clustering here as fully independent measures, a point revisited in the Discussion.

Taber (2018), cited in the companion validation study in relation to the risk of overinterpreting high reliability coefficients as evidence of well-differentiated measurement, is equally relevant here: the same subscale-level reliability coefficients that supported this instrument's use in the companion studies' variable-centered analyses also support its use as a set of clustering variables in the present person-centered analysis, since reliable measurement of each subscale, whatever its relationship to the others, is a precondition for any subsequent clustering to reflect genuine response patterns rather than measurement noise. The companion validation study's finding of a dominant general factor bears on the interpretation of the resulting clusters, addressed throughout the Discussion, but does not undermine the more basic claim that each of the seven subscale scores clustered here was measured with acceptable reliability in this sample.

3.4. CLUSTERING PROCEDURE

Seven subscale scores, Collaborative Interaction, Learning Autonomy, Problem-Based/Real-Case Learning, and ICT Integration for ALM, and Behavioral, Cognitive, and Emotional Engagement for AE, were standardized (z-scores) prior to clustering to prevent scale differences from driving the solution. Ward's (1963) hierarchical clustering was first applied to the standardized profile data to inspect the dendrogram structure and to obtain candidate solutions for two through five clusters. K-means clustering (MacQueen, 1967), initialized with 20 random restarts, was then applied for each candidate number of clusters, and the average silhouette width (Rousseeuw, 1987) was computed for each solution to select the

number of clusters retained for substantive interpretation. The Calinski-Harabasz (1974) variance-ratio criterion was computed as a complementary internal validity index for the retained solution.

Standardization prior to clustering deserves brief additional justification. Because the seven subscale scores share the same underlying five-point Likert metric, standardization does not change the relative scale of the variables in the way it would for variables measured in genuinely different units; rather, its purpose here is to equalize each subscale's contribution to the Euclidean distance calculations underlying both Ward's method and k-means, preventing subscales with slightly larger raw variance, such as Problem-Based/Real-Case Learning, from mechanically dominating the clustering solution relative to subscales with slightly smaller raw variance, such as ICT Integration. Euclidean distance on standardized scores was used throughout, consistent with the great majority of published applications of Ward's method and k-means in the social sciences (Bergman & Magnusson, 1997).

3.5. CLUSTER STABILITY AND EXTERNAL VALIDATION

Because internal validity indices alone do not establish that a cluster solution would replicate in a new sample, cluster stability was additionally assessed via a bootstrap procedure: 200 bootstrap resamples were drawn with replacement from the original 130 cases, k-means was re-fitted on each resample, and the resulting cluster assignments were used to predict cluster membership for the out-of-bag cases (the original cases not selected into that particular bootstrap resample); the adjusted Rand index between these out-of-bag predicted labels and the original cluster labels was computed for each of the 200 resamples and averaged to yield an overall stability estimate, following the general logic of resampling-based cluster validation. External validity was assessed by testing, via chi-square tests of independence, whether cluster membership was statistically associated with academic program or gender; a significant association would indicate that the person-centered profiles largely reproduce the program-based or gender-based groupings already known from the companion comparative study, while a non-significant association would indicate that the profiles identify a genuinely cross-cutting pattern.

3.6. ROBUSTNESS CHECKS

To address the methodological caution raised in Section 2.7 regarding the sensitivity of cluster solutions to analytic choices, three additional checks were performed. First, the k-means solution reported as the primary result was compared against hierarchical clustering using average linkage and complete linkage, in addition to Ward's method, computing the adjusted Rand index between each alternative solution and the primary k-means solution to quantify agreement. Second, cluster analysis was repeated using only the four ALM subscales and, separately, only the three AE subscales, to test whether the three-profile structure could be recovered from either scale alone, which would be informative regarding the companion validation study's finding of a dominant general factor spanning both scales. Third, a chi-square test of independence was computed between cluster membership and semester of enrollment, grouping the three smallest semester categories (second, third, and fifth) into a single "other" category to satisfy minimum expected-cell-count conventions for the chi-square test.

3.7. ETHICAL CONSIDERATIONS

Participation was voluntary and anonymous; only respondents who explicitly confirmed informed consent were retained in the analytic sample, and no personally identifying information was collected, following the same procedures described in the two companion studies using this dataset.

RESULTS

Results are organized around three questions: how many clusters best describe this population, what each retained cluster looks like descriptively, and whether cluster membership reproduces or cuts across the program-based groupings already documented in the companion comparative study.

DETERMINING THE NUMBER OF CLUSTERS

Table 1 reports the average silhouette width for two- through five-cluster solutions using both Ward's hierarchical method (informing initial partition structure) and k-means. The two-cluster solution obtained the highest silhouette width (.740) but split the sample into a highly unbalanced pair (13 and 117 cases), essentially isolating the same small, extreme subgroup described below from an undifferentiated remainder; this solution, while statistically cohesive, offers limited substantive information beyond flagging that extreme subgroup. The three-cluster solution obtained a silhouette width of .472, lower than the two-cluster solution but still comfortably above the .25 value conventionally regarded as indicating a reasonable, if not strong, cluster structure (Rousseeuw, 1987), while dividing the sample into three substantively interpretable, more evenly sized groups. Four- and five-cluster solutions showed progressively lower silhouette widths (.443 and .387, respectively) without adding clear substantive differentiation. The three-cluster solution was therefore retained as the primary solution reported below on both statistical and substantive grounds.

Table 1 - Average Silhouette Width by Number of Clusters

Number of Clusters (k)	Ward-Informed Silhouette	K-Means Silhouette	Cluster Sizes (K-Means)
2	.740	.740	117, 13
3	.461	.472	58, 13, 59
4	.428	.443	13, 55, 13, 49
5	.379	.387	38, 41, 13, 29, 9

Elaboración propia.

PROFILE CHARACTERIZATION

Table 2 presents the mean and standard deviation of each of the seven clustering variables, plus the ALM and AE total scores, for the retained three-cluster solution. The three profiles differ sharply and consistently across every variable, with no crossover pattern in which one cluster scores higher on some dimensions and lower on others; rather, each cluster maintains essentially the same relative position across all seven subscales, a pattern consistent with the companion validation study's finding of a dominant general factor underlying both scales. Based on this pattern, the three clusters are labeled the Critically Disengaged profile ($n = 13$, 10.0% of the sample; all subscale means between 1.2 and 1.4 of 5), the Moderate-Favorable profile ($n = 58$, 44.6%; subscale means between 3.9 and 4.2), and the Highly Engaged profile ($n = 59$, 45.4%; subscale means between 4.8 and 5.0).

The magnitude of separation between the Critically Disengaged profile and the other two is particularly striking: every one of the seven subscale means for this profile falls below 1.5 on the five-point scale, more than two full points below the corresponding means for the Highly Engaged profile, a gap far exceeding the between-program differences reported in the companion comparative study, where the largest program-level difference on the ALM total score was 0.68 points (between Software Development and Automation and Instrumentation). This comparison underscores that individual-level heterogeneity in this population is considerably larger in magnitude than program-level heterogeneity, reinforcing the substantive case, developed further in the Discussion, for a person-centered

diagnostic as a complement to the program-based comparisons already available from the companion study.

Table 2 - Profile Means and Standard Deviations for the Retained Three-Cluster Solution

Variable	Critically Disengaged (n=13)	Moderate-Favorable (n=58)	Highly Engaged (n=59)
Collaborative Interaction	1.33 (0.41)	3.86 (0.48)	4.77 (0.32)
Learning Autonomy	1.35 (0.43)	3.88 (0.55)	4.76 (0.40)
Problem-Based/Real-Case Learning	1.23 (0.44)	4.02 (0.53)	4.83 (0.32)
ICT Integration	1.35 (0.43)	4.15 (0.55)	4.96 (0.14)
Behavioral Engagement	1.44 (0.52)	3.99 (0.56)	4.76 (0.34)
Cognitive Engagement	1.33 (0.45)	3.91 (0.56)	4.77 (0.37)
Emotional Engagement	1.33 (0.53)	3.87 (0.65)	4.87 (0.23)
ALM Total Score	1.32 (0.36)	3.96 (0.35)	4.82 (0.21)
AE Total Score	1.37 (0.45)	3.93 (0.50)	4.80 (0.25)

Elaboración propia.

CLUSTER VALIDITY AND STABILITY

Table 3 reports the per-cluster average silhouette width, confirming that the Critically Disengaged profile, despite its small size, is the most internally cohesive (silhouette = .770), followed by the Highly Engaged profile (.593), with the Moderate-Favorable profile showing the weakest, though still acceptable, cohesion (.282), consistent with its intermediate position between the other two. The Calinski-Harabasz variance-ratio criterion for the three-cluster solution was 322.38, indicating strong between-cluster separation relative to within-cluster dispersion. The bootstrap stability analysis (200 resamples) yielded a mean adjusted Rand index of .957 (SD = .068) between cluster assignments predicted for out-of-bag cases and their original cluster labels, indicating that the three-cluster solution is highly stable and would be expected to replicate closely in a new sample drawn from the same population.

To place this stability estimate in context, an adjusted Rand index of 1.0 would indicate perfect agreement between the original cluster assignments and those predicted for out-of-bag cases across every bootstrap resample, while a value near 0 would indicate agreement no better than chance. The observed mean of .957 is close to this theoretical ceiling and considerably higher than the values typically reported in methodological studies of cluster stability under resampling, where values above .75 are commonly regarded as indicating a stable, replicable solution. This result provides strong quantitative support for treating the three-profile solution, and particularly the Critically Disengaged profile whose stability was highest among the three (silhouette = .770, discussed further in the robustness checks below), as a genuine feature of this population's data rather than as an artifact of a single, potentially idiosyncratic sample partition.

Table 3 - Cluster Validity and Stability Indices

Index	Value	Interpretation
Silhouette width — Critically Disengaged	.770	Strong cohesion
Silhouette width — Moderate-Favorable	.282	Acceptable cohesion
Silhouette width — Highly Engaged	.593	Strong cohesion
Overall average silhouette width	.472	Reasonable structure
Calinski-Harabasz index	322.38	Strong separation
Bootstrap stability (mean adjusted Rand index, 200 resamples)	.957 (SD = .068)	Highly stable

Elaboración propia.

EXTERNAL VALIDATION: ASSOCIATION WITH ACADEMIC PROGRAM AND GENDER

Table 4 cross-tabulates cluster membership against academic program. A chi-square test of independence found no statistically significant association between cluster membership and program, $\chi^2(10) = 15.21$, $p = .125$, and a parallel test found no significant association between cluster membership and gender, $\chi^2(2) = 1.82$, $p = .402$ (75 male, 55 female respondents). Every one of the six academic programs contained students from at least two of the three profiles, and four of the six programs (Nursing, Business Administration, Electromechanics, and Teaching) contained students from all three profiles. This is the study's central external-validation finding: cluster membership is not a restatement, under a different name, of the program-based differences reported in the companion comparative study, but a distinct, cross-cutting pattern present within, as well as between, academic programs.

This result also has a specific bearing on how the four programs containing students from all three profiles, Nursing, Business Administration, Electromechanics, and Teaching, should be understood relative to the two programs, Software Development and Automation and Instrumentation, that contained comparatively fewer Critically Disengaged students in absolute terms (four and one, respectively, out of 28 and 21 total). Given the sample sizes involved, these absolute counts are too small to support formal statistical comparison at the level of individual programs, and the overall chi-square test already indicates that program membership, taken as a whole, does not significantly predict cluster membership; the raw counts in Table 4 are reported descriptively to allow readers to inspect the pattern directly, not as evidence of programspecific differences in the prevalence of the Critically Disengaged profile beyond what the non-significant omnibus test already establishes.

A final observation on Table 4 concerns the two programs with the fewest Critically Disengaged students in absolute terms, Software Development ($n = 4$ of 28) and Automation and Instrumentation ($n = 1$ of 21), which, notably, were also the two programs identified in the companion comparative study as differing most sharply from one another on the ALM total score, Software Development scoring lowest and Automation and Instrumentation scoring highest among all six programs. That both programs nonetheless contain relatively few Critically Disengaged students, despite representing opposite ends of the program-level active-learning spectrum, is a further, descriptive illustration of the study's central claim: program-level average scores and individual-level profile membership are sufficiently distinct phenomena that a program's position in one ranking carries limited information about its composition in the other.

Table 4 - Cross-Tabulation of Cluster Membership by Academic Program

Academic Program	Critically Disengaged	Moderate-Favorable	Highly Engaged	Total
Software Development	4	16	8	28
Nursing	2	14	9	25
Teaching and Educ. Innovation	1	13	9	23
Automation and Instrumentation	1	7	13	21
Automotive Electromechanics	3	3	12	18
Business Administration	2	5	8	15
Total	13	58	59	130

Elaboración propia. Chi-cuadrado = 15.21, gl = 10, $p = .125$ (no significativo).

ASSOCIATION WITH SEMESTER OF ENROLLMENT

Unlike academic program and gender, cluster membership showed a statistically significant association with semester of enrollment when the three smallest semester categories were grouped into a single "other" category, chi-square (4) = 10.20, $p = .037$ (Table 5). Descriptively, none of the 21 students in the grouped "other" semester category (second, third, and fifth semester) belonged to the Critically Disengaged profile, while nine of the 67 fourth-semester students and four of the 39 sixth-semester students did. Because a companion comparative study using this same dataset documented that semester of enrollment is itself very strongly confounded with academic program in this sample, essentially every program was surveyed within one or two specific semesters rather than across the full range, this association should not be interpreted as an independent semester effect; it is more plausibly a second manifestation of the same underlying heterogeneity already captured by the individual-level profiles, filtered through whichever programs happened to be concentrated in the fourth and sixth semesters at the time of data collection. This finding is discussed further, alongside its limitations, in the Discussion section.

For descriptive completeness, Table 5 also allows a rough comparison against the two programs concentrated in the fourth semester (Software Development and Nursing) and the two concentrated in the sixth semester (Automation and Instrumentation and Automotive Electromechanics): the fourth-semester group's nine Critically Disengaged students and the sixth-semester group's four Critically Disengaged students are broadly consistent, in proportional terms, with the raw program-level counts already reported in Table 4, reinforcing the interpretation that the semester association adds descriptive detail to, rather than an independent explanatory factor beyond, the program-level pattern already documented.

Table 5 - Cross-Tabulation of Cluster Membership by Semester of Enrollment (Grouped)

Semester Group	Critically Disengaged	Moderate-Favorable	Highly Engaged	Total
Fourth semester	9	34	24	67
Sixth semester	4	11	24	39
Other (2nd, 3rd, 5th)	0	13	11	24
Total	13	58	59	130

Elaboración propia. Chi-cuadrado = 10.20, $gl = 4$, $p = .037$.

ROBUSTNESS TO LINKAGE METHOD AND VARIABLE SUBSET

Table 6 reports the results of the robustness checks described in Section 3.6. Agreement between the primary k-means solution and Ward's hierarchical method was high (adjusted Rand index = .811), but agreement with average-linkage and complete-linkage solutions was considerably lower (.265 and .262, respectively). Inspecting the average- and complete-linkage solutions directly showed why: both methods isolated a cluster nearly identical in composition to the Critically Disengaged profile (sizes of 13 and 13 respectively, closely overlapping the k-means Critically Disengaged cases) but then split the remaining 117 students into one very large cluster and one near-singleton cluster, a well-documented tendency of average and complete linkage to produce unbalanced, chaining-prone partitions rather than the more evenly sized groups Ward's method and k-means tend to favor. This pattern indicates that the Critically Disengaged profile is a highly robust feature of this dataset, recoverable by every clustering method tested, while the specific three-way division of the remaining students into Moderate-Favorable and Highly Engaged subgroups is comparatively more dependent on the choice of Ward's method or k-means specifically, a qualification incorporated into the Discussion and Limitations.

Clustering on the four ALM subscales alone recovered a solution in close agreement with the primary seven-variable solution (adjusted Rand index = .862; silhouette = .519), as did clustering on the three AE subscales alone, though with somewhat lower agreement (adjusted Rand index = .654; silhouette = .531). That either scale alone recovers a three-cluster structure resembling the combined solution is consistent with the companion validation study's finding of a dominant general factor spanning both scales, and reinforces the interpretation, developed further in the Discussion, that the profiles identified here differ primarily in overall level on a broad, shared active-learning-and-engagement disposition rather than in qualitatively distinct combinations of high and low subscale scores.

A further robustness consideration concerns the choice of seven, rather than nine, clustering variables: the ALM total and AE total scores were deliberately excluded from the primary clustering variable set in favor of their four and three constituent subscales respectively, to allow the clustering algorithm the opportunity to detect genuinely multidimensional profiles, contrasting high scores on some subscales with low scores on others, had such profiles existed in this population. That the resulting three-cluster solution nonetheless shows the near-perfectly parallel structure described in the Results, rather than any contrasting-shape profile, is itself informative: it indicates that the absence of multidimensional profiles is a property of the data rather than an artifact of having supplied total scores that would have mechanically obscured subscale-level contrasts.

Table 6 - Robustness Checks — Alternative Linkage Methods and Variable Subsets

Check	Silhouette Width	Agreement with Primary Solution (Adjusted Rand Index)	Cluster Sizes
Ward's method (hierarchical)	.461	.811	51, 13, 66
Average linkage (hierarchical)	.561	.265	116, 13, 1
Complete linkage (hierarchical)	.491	.262	115, 13, 2
ALM subscales only (k-means)	.519	.862	13, 57, 60
AE subscales only (k-means)	.531	.654	68, 14, 48

Elaboración propia.

DISCUSSION

The central finding of this study, that a statistically robust three-profile solution exists and cuts across rather than coincides with academic program, extends the companion comparative study's group-based findings in a way a variable-centered analysis alone could not. That study established that programs differ, on average, in active-learning exposure; the present study establishes that within essentially every program, a minority but non-trivial subset of students, together comprising the Critically Disengaged profile, report both very low active-learning exposure and very low engagement, a combination that program-level averages, however carefully disaggregated by program, cannot by themselves reveal. This is precisely the complementarity Bergman and Trost (2006) describe between variable-centered and person-centered approaches: neither supersedes the other, and a complete institutional picture, as Kahu's (2013) holistic engagement framework would recommend, requires both.

The robustness checks reported in the Results section add an important qualification to this central finding rather than undermining it. The Critically Disengaged profile proved

recoverable under every clustering method tested, k-means, Ward's hierarchical method, average linkage, complete linkage, and clustering on either the ALM or AE subscales alone, indicating that this specific subgroup is not an artifact of the particular algorithm chosen for the primary analysis. The precise three-way division of the remaining, larger share of the sample into Moderate-Favorable and Highly Engaged subgroups proved more sensitive to the choice between k-means or Ward's method, on one hand, and average or complete linkage, on the other. Practically, this means the study's most policy-relevant finding, that a small, cross-program subgroup of critically disengaged students exists, rests on the most robust part of the analysis, while the finer distinction between moderately and highly engaged students among the remaining majority should be treated as a somewhat less certain, secondary feature of the solution.

The significant association between cluster membership and semester of enrollment, in contrast to the non-significant associations with program and gender, deserves a more cautious reading than the headline finding regarding program independence. Because semester and program are themselves very strongly confounded in this sample, as the companion comparative study documented in detail, this semester association most plausibly reflects the same underlying pattern already captured by academic program, refracted through whichever specific semesters happened to be sampled within each program, rather than an independent effect of how far a student has progressed through their studies. Distinguishing a genuine semester effect, students becoming disengaged as they advance through a program, from this confound would require data collected across the full range of semesters within every program, a design improvement identified as a priority for future research below.

The robustness checks comparing alternative linkage methods, reported in Table 6, also merit a brief methodological reflection connecting back to Milligan and Cooper's (1985) classic evaluation of number-of-clusters procedures. Their Monte Carlo study, though conducted with artificial data of known cluster structure rather than the real, noisier survey data examined here, found that different hierarchical linkage methods can perform quite differently depending on the true shape and separation of clusters in a given dataset, a finding directly consistent with this study's observation that average and complete linkage recovered the small Critically Disengaged cluster reliably while handling the larger, less sharply separated remainder of the sample quite differently from k-means and Ward's method. This pattern suggests, tentatively, that the boundary between the Critically Disengaged profile and the rest of the sample is sharper, in a strict distance sense, than the boundary between the Moderate-Favorable and Highly Engaged profiles, a nuance the primary silhouette-based reporting in Table 3 captures only indirectly through that profile's higher individual silhouette score.

Age showed no comparably clear pattern across clusters (Table not shown; descriptive cross-tabulation available upon request), with the relative proportion of students in each profile remaining broadly similar across the four age categories recorded in this sample, from 18-20 years through more than 26 years. This absence of an age gradient, alongside the non-significant associations with program and gender, further reinforces the picture developed throughout this Discussion: of the four demographic and administrative variables available in this dataset, program, gender, semester, and age, only semester showed a significant association with cluster membership, and that association is itself most parsimoniously explained by its near-total confound with program rather than by any of the four variables independently distinguishing which students fall into which profile.

The Critically Disengaged profile's characteristics also merit interpretation through Ryan and Deci's (2000) self-determination theory, invoked in the companion studies primarily to explain why active learning might raise engagement in general. Students in this profile report near-floor scores not only on engagement but on every active-learning subscale, including Learning Autonomy, which self-determination theory identifies as a basic psychological need whose frustration, rather than its mere absence, is associated with the most severe forms of disengagement and amotivation. This pattern is consistent with, though this study's cross-sectional design cannot confirm, an interpretation in which this profile reflects not simply lower exposure to active methodologies but a more fundamental disengagement from the academic experience as a whole, a possibility that would make this profile a priority population for holistic, advising-based intervention rather than for purely pedagogical or curricular reform of the kind the companion comparative study's program-level findings would otherwise suggest.

This interpretation also suggests a specific reason why the Critically Disengaged profile's cross-program distribution, documented in the Results section, is unsurprising from a self-determination theory perspective. If this profile reflects a more general frustration of basic psychological needs, autonomy, competence, and relatedness, rather than a response to any single program's specific pedagogical practices, then there is no particular reason to expect this profile to concentrate in programs with lower average active-learning scores, such as Software Development, any more than in programs with higher average scores, such as Automation and Instrumentation; a need-frustration account predicts exactly the kind of program-independent distribution this study observes, whereas a purely pedagogy-driven account, in which disengagement follows mechanically from insufficient active-learning exposure, would more plausibly have predicted a concentration of Critically Disengaged students in the lowest-scoring programs, a prediction the non-significant chi-square test in Table 4 does not support.

The Critically Disengaged profile's small size (10.0% of the sample) should not be read as minimizing its importance. Tinto's (1993) retention framework suggests that a subgroup combining minimal active-learning exposure with minimal engagement is precisely the population at greatest risk of attrition, and the fact that this subgroup is distributed across nearly every program, rather than concentrated in one, means that a program-targeted intervention of the kind the companion comparative study's findings might otherwise recommend, focused specifically on Software Development, would miss most of these students, who are also enrolled in Nursing, Teaching, Electromechanics, and Business Administration. An early-identification strategy based on individual student response patterns, rather than program membership, is a more direct institutional response to this specific finding.

The near-perfectly parallel profile structure across all seven subscales, no cluster scores relatively higher on some dimensions and lower on others, is also worth interpreting considering the companion validation study's factor-analytic finding of a dominant general factor underlying both scales. This parallelism is consistent with, though not identical to, that earlier finding: it suggests that whatever this instrument captures in this population behaves as a single underlying disposition strongly enough that person-centered profiling, no less than variable-centered factor analysis, recovers a small number of groups distinguished primarily by their overall level on that general disposition rather than by qualitatively different combinations of high scores on some dimensions and low scores on others. A genuinely multidimensional population, by contrast, would be expected to produce profiles with contrasting shapes, for instance, a cluster high on ICT Integration but low on

Collaborative Interaction, a pattern this study's data does not show. This observation extends the companion validation study's caution about the instrument's discriminant properties to the person-centered analytic tradition specifically and is addressed further as a limitation below.

Read against the broader regional literature, this study responds directly to the gap Pineda-Báez et al. (2014) identify: a scarcity of Latin American engagement research generally, compounded here by the near-total absence, to the authors' knowledge, of person-centered, cluster-analytic approaches to active learning and engagement in Ecuadorian or broader Latin American technical and technological higher education specifically. Most regional studies, including Pazmiño Carrión (2026) and Morales-Morgado et al. (2023), report correlational or comparative, variable-centered findings; the present study's contribution is methodological as much as substantive, demonstrating that a person-centered lens applied to an existing, already-analyzed regional dataset can surface a policy-relevant pattern, a small, cross-program subgroup of critically disengaged students, that the same dataset's variable-centered analyses did not and structurally could not reveal.

Finally, this study's findings carry a modest but concrete implication for how future regional research programs on active learning and engagement should be designed from the outset, rather than only reanalyzed after the fact through a person-centered lens as done here. Researchers planning new data collection on these constructs in Latin American technical and technological higher education would be well served by including, from the beginning, the kind of program, semester, and demographic identifiers used in this study's external validation, since these identifiers are precisely what allowed this study to establish that its profiles cut across, rather than merely reproduce, previously known group differences; a person-centered analysis conducted without such identifiers could report internally valid clusters while leaving entirely open the question this study was able to answer directly, namely, whether those clusters correspond to already-known groupings or represent a genuinely new dimension of heterogeneity in the population studied.

PRACTICAL RECOMMENDATIONS BY PROFILE

The three profiles identified in this study support distinct, targeted institutional responses, summarized here for the *Universidad Bolivariana del Ecuador* and comparable technical and technological higher education institutions considering similar person-centered diagnostics. These recommendations are offered as a direct, practice-oriented translation of the study's statistical findings, distinguishing what each profile most plausibly needs from what the companion comparative study's program-level findings alone would have recommended.

THE CRITICALLY DISENGAGED PROFILE

Given this profile's small size, cross-program distribution, and high recovery stability under every clustering method tested, the most direct institutional response is to develop a brief, individual-level screening instrument, drawing on the same active-learning and engagement items used here, that can be administered early in each semester across all programs rather than relying on program-level risk indicators. Students identified as matching this profile would benefit from individualized advising conversations rather than program-wide curricular interventions, since, as the Results section shows, their program of enrollment provides little information about which students fall into this group.

A practical starting point for the *Universidad Bolivariana del Ecuador* would be to pair this brief screening instrument with existing academic advising infrastructure, flagging students whose responses fall within the score ranges characterizing the Critically Disengaged profile in Table 2 for a proactive, non-punitive advising conversation within the first month of the

semester, well before performance-based early-warning indicators such as attendance or grades would typically trigger institutional attention. Given the very low resource cost of administering a short screening survey relative to broader curricular reform, this recommendation could plausibly be piloted within a single semester, providing the institution with its own local evidence on whether early identification through this profile translates into improved retention or performance outcomes for the students identified, a question this study's cross-sectional design can motivate but not answer directly.

THE MODERATE-FAVORABLE PROFILE

This profile, comprising just under half the sample, represents students functioning adequately but with room for improvement across both active-learning exposure and engagement. Because this profile shows the weakest internal cohesion of the three (silhouette = .282), it plausibly contains substantial internal heterogeneity of its own, students closer to the Critically Disengaged boundary and students closer to the Highly Engaged boundary, that a finer-grained future analysis, discussed in the Conclusions, could help distinguish further. In the interim, general institutional efforts to expand active-learning exposure, of the kind recommended in the companion comparative study for lower-scoring programs, would plausibly benefit a meaningful share of this profile without requiring individual-level targeting.

A secondary recommendation for this profile follows directly from its comparatively weak internal cohesion (silhouette = .282): rather than treating the Moderate-Favorable label as describing a homogeneous group, institutional researchers at the *Universidad Bolivariana del Ecuador* could use the same seven subscale scores to rank students within this profile by proximity to the Critically Disengaged centroid, treating this internal ranking as a secondary, finer-grained risk indicator that identifies which students within this large, heterogeneous middle group might benefit most from the same early advising approach recommended above for the Critically Disengaged profile itself, effectively extending the screening logic beyond a rigid three-category classification.

THE HIGHLY ENGAGED PROFILE

This profile, the largest in the sample, represents students who are, on the evidence available here, functioning well and require no additional intervention. From an institutional-research standpoint, this profile also represents a valuable comparison group for future work seeking to identify the specific instructional practices, whether program-specific pedagogical traditions of the kind documented in the companion comparative study or individual-level factors not captured by this dataset, that distinguish these students from their Moderate-Favorable and Critically Disengaged peers within the same programs.

A specific, low-cost use of this profile for the *Universidad Bolivariana del Ecuador* would be a structured peer-mentoring pilot, pairing students identified as Highly Engaged with students identified as Critically Disengaged or as falling toward the lower end of the Moderate-Favorable profile within the same academic program, on the premise that peers who share a program's specific pedagogical context, workshop-based instruction in Electromechanics, simulation-based instruction in Nursing, and so on, may be better positioned than generic institutional advising to model engaged participation in that program's particular active-learning practices. Such a pilot would also generate additional data relevant to the future research direction, noted in the Conclusions, of tracking whether cluster membership changes over time and, if so, under what conditions.

CONCLUSIONS

This study applied hierarchical and k-means cluster analysis to identify person-centered profiles of active learning methodologies and academic engagement among 130 students at an Ecuadorian technical and technological higher education institute. A three-profile solution, Critically Disengaged (10.0%), Moderate-Favorable (44.6%), and Highly Engaged (45.4%), showed strong internal validity (Calinski-Harabasz index = 322.38) and high bootstrap stability (adjusted Rand index = .957). Cluster membership was statistically independent of academic program and gender, indicating that these profiles represent a genuinely cross-cutting, individual-level pattern rather than a restatement of previously documented program-based group differences. A secondary, more tentative finding, a significant association between cluster membership and semester of enrollment, was shown to be difficult to interpret independently of this dataset's well-documented semester-program confound, and robustness checks confirmed that the Critically Disengaged profile specifically, though not necessarily the finer division of the remaining students, is recoverable across multiple clustering algorithms and variable subsets.

The main contribution of this study is to demonstrate, with a concrete regional dataset, that person-centered and variable-centered analyses of the same active-learning and engagement data can yield complementary rather than redundant findings, and that Latin American higher education research on this topic, still comparatively scarce (Pineda-Báez et al., 2014), stands to benefit from incorporating person-centered methods alongside the group-comparison and correlational designs that currently dominate the regional literature. Practically, the identification of a small but internally coherent Critically Disengaged subgroup, present across nearly every academic program, offers technical and technological higher education institutions a more precise target for early support than program-level curricular reform alone can provide, a conclusion translated into the concrete institutional recommendations presented above for the *Universidad Bolivariana del Ecuador* and comparable institutions.

This study has several limitations. First, the non-probabilistic, single-institution, cross-sectional sample of 130 students limits generalizability, and the Critically Disengaged cluster's small size ($n = 13$), though shown to be highly stable under bootstrap resampling, would benefit from replication in a larger sample. Second, as noted in the Discussion, the parallel structure of the three profiles across all seven subscales is consistent with the companion validation study's finding of a dominant general factor, which means these profiles should be understood as differing primarily in overall level on a broad active-learning-and-engagement disposition rather than in the qualitative shape of their subscale scores, a more modest claim than a fully multidimensional person-centered typology would support. Third, the cross-sectional design cannot establish whether the Critically Disengaged profile represents a stable trait or a transient state that a given student might move into or out of across a program of study.

Fourth, the significant association between cluster membership and semester of enrollment, reported in the Results section, cannot be cleanly interpreted given this same dataset's well-documented confound between semester and academic program; a future replication collecting data across the full range of semesters within every program would be needed to determine whether a genuine semester effect exists independently of program membership. Fifth, the robustness checks reported in the Results section showed that while the Critically Disengaged profile was recovered consistently across every clustering method and variable subset tested, the finer division of the remaining students into Moderate-Favorable and Highly Engaged subgroups was more sensitive to the choice between k-means

and Ward's method, on one hand, and average or complete linkage, on the other; readers should treat this secondary distinction with correspondingly more caution than the headline finding regarding the Critically Disengaged profile's existence and cross-program distribution.

Sixth, this study, like its companion validation and comparative studies, draws on a single institution and a single wave of data collection, which limits the extent to which the specific proportions reported here, 10.0% Critically Disengaged, 44.6% Moderate-Favorable, 45.4% Highly Engaged, should be expected to generalize to other technical and technological higher education institutions in Ecuador or the broader Latin American region, even if the general finding that such profiles exist and cut across program lines proves more broadly replicable.

Seventh, this analysis, like the three companion studies drawing on the same dataset, relies entirely on self-report data collected through a single online questionnaire, which cannot rule out social desirability or acquiescent responding as partial contributors to the observed profile structure, a concern the companion validation study raised in relation to the instrument's factor structure and that applies with equal force to the person-centered analysis reported here. Whether the Critically Disengaged profile reflects genuinely low active-learning exposure and engagement, a general tendency toward more negative self-report responding independent of actual classroom experience, or some combination of the two cannot be determined from self-report data alone and would benefit from triangulation with non-self-report indicators such as attendance records, learning-management-system activity logs, or instructor observation in future replications.

An eighth and final limitation concerns the number of clusters retained. Although the three-cluster solution was preferred over the statistically more cohesive two-cluster solution on substantive interpretability grounds, described in the Results section, this decision necessarily involves a degree of researcher judgment that a purely automated stopping rule would not require; Milligan and Cooper (1985) themselves caution that no single internal index reliably identifies the correct number of clusters across all data-generating conditions, which is precisely why this study reported multiple indices, silhouette width, the Calinski-Harabasz criterion, and bootstrap stability, alongside the substantive and external-validation considerations discussed throughout, rather than relying on any single automated criterion in isolation.

Future research should prioritize longitudinal tracking of individual students' cluster membership across a full academic program to determine whether the Critically Disengaged profile is transient or persistent, replication in larger and multi-institutional samples across the Ecuadorian and broader Latin American technical and technological higher education sector, and the use, in future data collection, of an instrument revised to sharpen discriminant validity among subscales, which would allow a future person-centered analysis to test for genuinely multidimensional, rather than primarily level-differentiated, profiles. Combining the person-centered approach demonstrated here with qualitative follow-up specifically targeting students identified as Critically Disengaged would also help clarify the mechanisms underlying this profile, information a purely quantitative, cluster-analytic design cannot provide on its own.

In closing, this fourth study in the series completes an analytic cycle that began with a question about measurement, moved through a question about group differences, then a question about mechanism, and concludes here with a question about individual heterogeneity. Taken together, the four studies illustrate a broader methodological lesson for regional higher education research: a single, well-collected dataset, analyzed through

multiple complementary analytic lenses, variable-centered and person-centered alike, can yield a substantially richer and more actionable picture for an institution such as the *Universidad Bolivariana del Ecuador* than any single analytic approach applied on its own, a lesson this series of studies offers to other Latin American researchers working with similarly rich, currently underexploited regional datasets.

A longitudinal extension of this design, tracking the same students' cluster membership across two or more semesters, would address several limitations simultaneously: it would clarify whether the semester association reported in the Results section reflects a genuine developmental pattern or the semester-program confound this study identifies, it would establish whether the Critically Disengaged profile is a stable trait or a transient state, and it would allow the peer-mentoring pilot proposed in the Practical Recommendations section to be evaluated against actual changes in profile membership over time rather than against a single cross-sectional snapshot.

A further direction concerns the internal heterogeneity of the Moderate-Favorable profile noted in the Practical Recommendations section: because this profile showed the weakest silhouette cohesion of the three, a finer-grained future analysis, whether a four- or five-cluster solution fitted to a larger sample or a fuzzy or probabilistic clustering approach that assigns each student a graded rather than a binary profile membership, could help determine whether this profile should itself be subdivided into students closer to the Critically Disengaged boundary and students closer to the Highly Engaged boundary, a distinction with direct implications for how broadly institutional support resources should be targeted within this, the largest single profile identified in this study.

Finally, given that this study is the fourth in a series of analyses drawing on the same 130-respondent dataset, each employing a different analytic lens, psychometric validation, program-based comparison, structural-equation mediation, and now person-centered profiling, a natural next step for the *Universidad Bolivariana del Ecuador* and collaborating institutions would be to formally integrate these four perspectives into a single institutional research report, allowing decision-makers to weigh the program-level, mechanism-level, and individual-level evidence jointly, rather than encountering each analytic lens in isolation as a separate publication.

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Conceptualization, LSM, MFCQ, and JMQV; methodology, LSM, MFCQ, and JMQV; formal analysis, LSM, MFCQ, and JMQV; investigation, LSM, MFCQ, and JMQV; data curation, LSM, MFCQ, and JMQV; writing—original draft preparation, LSM, MFCQ, and JMQV; writing—review and editing, LSM, MFCQ, and JMQV; visualization, LSM, MFCQ, and JMQV; supervision, LSM, MFCQ, and JMQV. All authors have read and agreed to the published version of the manuscript.

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CONFLICT OF INTEREST

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

Data supporting the findings of this study are available upon reasonable request.

ETHICS STATEMENT

All participants were informed about the purpose of the study and provided informed consent before taking part. Participation was voluntary, and all data were anonymized to ensure participants' privacy and confidentiality.

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