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LATENT PROFILE MODELING OF SELF-REGULATED LEARNING, MOTIVATIONAL STRATEGIES, DEEP LEARNING TECHNIQUES, AND PERCEIVED ACADEMIC PERFORMANCE AMONG UNIVERSITY STUDENTS

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Abstract:
University students differ substantially in how they regulate learning, maintain motivation, use deep learning techniques, and perceive their academic performance. Identifying these differences can support more targeted academic interventions. This study aimed to identify distinct latent learning profiles based on self-regulated learning, motivational strategies, deep learning techniques, and perceived academic performance, and to examine demographic differences associated with profile membership. A cross-sectional secondary-data analysis was conducted using responses from 1,316 university students from Chile and Ecuador. Nineteen GAEU-1 items were grouped into four learning constructs. Descriptive statistics, Cronbach's alpha, Pearson correlations, latent profile analysis, chi-square tests, Kruskal–Wallis tests, and multinomial logistic regression were performed. Five latent profiles were identified. These ranged from consistently low learning-strategy patterns to highly self-regulated, motivated, and high-performing profiles. All four learning dimensions were positively correlated. Nationality and gender differed significantly across profiles, while age and several other demographic characteristics showed no significant overall differences. Selected demographic predictors were associated with membership in specific profiles. University students demonstrated clear heterogeneity in multidimensional learning patterns. Latent profile modeling provided a useful person-centered framework for identifying students with different academic strengths and support needs.

Keywords: *self-regulated learning; motivational strategies; deep learning; perceived academic performance; latent profile analysis*

1. Introduction

University students are more and more challenged by complex academic tasks, independent study requirements, assessment pressures and varied learning environments. Learning is thus an activity that is not only successful when there is cognitive ability, but also when there is an organization of learning, monitoring and maintenance of learning activities among the students. Students can have varying combinations of learning behaviors even when they are exposed to similar learning circumstances. The study of education data-mining has revealed that learning groups of learners can be clustered into characteristic self-managed learning profiles that show significant heterogeneity in the learning behavior (Araka et al., 2022). These profiles have also been shown by longitudinal evidence to be subject to change as students advance in university (Esnaashari et al., 2023). Self-regulated learning is the active control of learning by planning, monitoring, time management, strategy choice and reflection. Such skills are especially valuable in the higher education where students should be held more accountable in their academic development. Among teacher-education students, there are distinguished profiles of self-regulation, demonstrating varying degrees of organising and controlling their study (Muwonge et al., 2020). Other studies have also found various competency patterns of self-regulated learning in university learners (Schel & Drechsel, 2025). These variations could have an impact on academic perseverance, independence and effectiveness to react to challenging learning conditions.

Motivation strategies are also critical in maintaining effort, persistence and engagement. Learners can depend on personal motivation, hope, future aspirations, and competence-related beliefs to sustain their academic performance in difficult assignments. A study of undergraduates has found varying sets of achievement motivation and metacognitive behavior with respect to academic achievement (Hong et al., 2020). Motivation and self-regulation have also been demonstrated to create a specific learner profile that is associated with learning outcomes (Nie et al., 2024). A study of expectancy-value also proposes that motivational orientations determine the desire to encourage and use self-regulated learning behaviors (Hirt et al., 2022). Deep learning methods are aimed at comprehending, synthesizing and utilizing knowledge, but not memorising information. Such strategies can involve critical reading, summarizing, concept mapping, revising, self-monitoring, and self-studying academic work. University students do not vary in the manner in which cognitive study strategies, and motivational orientations interact, creating significant latent profiles (De Vincenzo and Carpi, 2024). Other related evidence has also associated patterns of teaching and learning strategies with metacognition and motivation of students (Katsantonis, 2025). The deep learning methods can thus reflect a significant aspect of valuable academic learning.

Perceived academic performance is a measurement of the way students assess their competence, progress and achievement. Such perceptions could be affected by confidence, self-efficacy, learning strategies, and perceived academic control. The stress, test anxiety, and performance have also been linked to the profiles of self-regulated learning, meaning that the experiences associated with performance can vary among groups of students (Broks et al., 2024). Academic-performance variability in heterogeneous student populations has also been reported in college students, which validates the application of person-centered models to explain the variation of performance (Li et al., 2026). The four dimensions are conceptually different but are very much interrelated. Self-regulation can reinforce the learning strategies and motivation can maintain the effort necessary to implement the latter. Educational settings have reported relationships between self-regulation and engagement and perceived academic control (Dai et al., 2022) as well as self-regulation profiles and various levels of engagement with online learning (Chen et al., 2025). Self-efficacy and self-regulated strategies have also been linked with academic achievement (Chen et al., 2026).

Traditional variable-centered analyses might not capture subgroups of students with various combinations of these characteristics. Latent profile analysis is a person-centered method of identifying latent groups, which are determined by multidimensional learning patterns. Profiles have been determined in online higher education (Shi et al., 2025), AI-assisted learning (Hu and Zhang, 2025), and at various levels of university education (Esnaashari et al., 2025). Student profile variation may also be due to contextual and institutional factors (Kim et al., 2024).

Although this is increasing, little research has both modeled self-regulated learning, motivational strategies, deep learning methods, and perceived academic performance in a single latent profile framework. As such, the current research was designed to determine unique learning profiles of university students according to these four dimensions and to investigate the demographic variation and predictors related to being a profile member.

Objectives of the study

1.To identify distinct latent profiles of university students based on self-regulated learning, motivational strategies, deep learning techniques, and perceived academic performance.

2.To examine demographic differences and determine the demographic predictors associated with membership in the identified latent learning profiles.

2. Methodology

2.1 Study Design

The quantitative and cross-sectional study design was employed to examine the self-regulated learning patterns, motivational techniques, deep-learning strategies, and perceived academic performance of university students. The analytical approach taken in the study was person-centered since the main aim of the study was to determine groups of students with similar multidimensional learning characteristics. The latent profile modeling was consequently chosen as the main technique, whereby heterogeneous groups of students could be modeled statistically, instead of making the assumption that all students involved were in a single homogeneous learning group.

2.2 Data Source

The data were obtained from the publicly available Mendeley Data repository containing the dataset “Learning Strategies in Higher Education: A Research Dataset” (Ramos-Galarza et al., 2025). There were 1,316 Chilean and Ecuadorian university students as participants of the dataset. The GAEU-1 self-report scale had been used to collect data, with informed consent being obtained. The repository comprised demographic attributes, questionnaire responses that were associated with self-regulated learning, motivational strategy, perceived performance in academics, and deep learning techniques.

2.3 Study Participants and Measurement Instrument

Analytical sample was a group of 1,316 university students aged between 1827 years (Chile and Ecuador). The data on participants was their nationality, gender, age, civil status, parental status, living arrangement, and the type of university they attended. The 19-item GAEU-1 had been used to measure learning characteristics. That is, each item was measured on a five-point Likert scale (1 strongly disagree, to 5 strongly agree). The greater the scores, the more the endorsing of the relevant learning behavior or academic perception.

2.4 Study Variables and Construct Scoring

The items in the questionnaires gave rise to four learning constructs. Self-regulated learning encompassed GA2, GA3, GA4, GA6, GA13, and GA14 whereas motivational strategies encompassed GA7–GA11. GA1, GA5, GA12, and GA15 were perceived academic performance, and the deep learning methods were GA16-GA19. The mean of the respective items of each construct was used as the composite scores. The original one-to-five measurement scale and direct comparison between the learning dimensions were retained in this strategy.

2.5 Data Preparation

Analysis of the data was screened in terms of missing observations, errors of response range and duplicates. The 19 questions in the questionnaire were all answered to make sure that the answers were in the valid one to five Likert range. The learning items did not have any missing values, but there was limited missingness in the chosen demographic variables. Since all the key learning indicators were full-fledged, no imputation was made. Demographic variables were also decoded based on the documentation provided and construct scores were then calculated in order to be used in statistical analysis.

2.6 Statistical Analysis

The data were entered in MS Excel. Categorical attributes were summarized with frequencies and percentages, whereas continuous ones were summarized with means, SD, medians, and ranges. The alpha of Cronbach measured internal consistency, and correlation coefficients were used to measure the relationships between the four dimensions of learning. At least two and up to six profiles in latent profile models were compared based on AIC, BIC, adjusted BIC, entropy, profile size and interpretability. The demographic differences and predictors of profile membership were analyzed by Chi-square tests, Cramer's V, Kruskal-Wallis tests and Multinomial logistic regression. A p value of $p < 0.05$ was established as statistically significant.

3. Results

3.1 Participant Characteristics

One thousand three hundred and sixteen Chilean and Ecuadorian university students were included in the analysis. The percentage of females in the sample was 56.69, and males were 43.31. The majority of the respondents were unmarried, no children, lived with their family, and studied at private universities. The average age was 20.45 years and the subject matter was between the ages of 18 and 27 years. As demonstrated in Table 1, the sample consisted of young university students who had rather similar demographic features in both countries that participated.

Table 1. Demographic Characteristics of the Participants

Characteristic	Category	n	%
Nationality	Chile	631	47.95
	Ecuador	685	52.05
Gender	Female	746	56.69
	Male	570	43.31
Civil status	Single	1,273	96.73
	Married	20	1.52
	Divorced	1	0.08
	Common-law	13	0.99
Children	Yes	52	3.95
	No	1,248	94.83
Living arrangement	Alone	93	7.07
	With family	1,086	82.52
	With friends	83	6.31
	With partner/spouse	37	2.81
University type	Private	1,037	78.80
	State	277	21.05

Figure 1 shows the distribution of the selected student characteristics and it is possible to indicate that there are differences in living arrangements and university type among the study population.

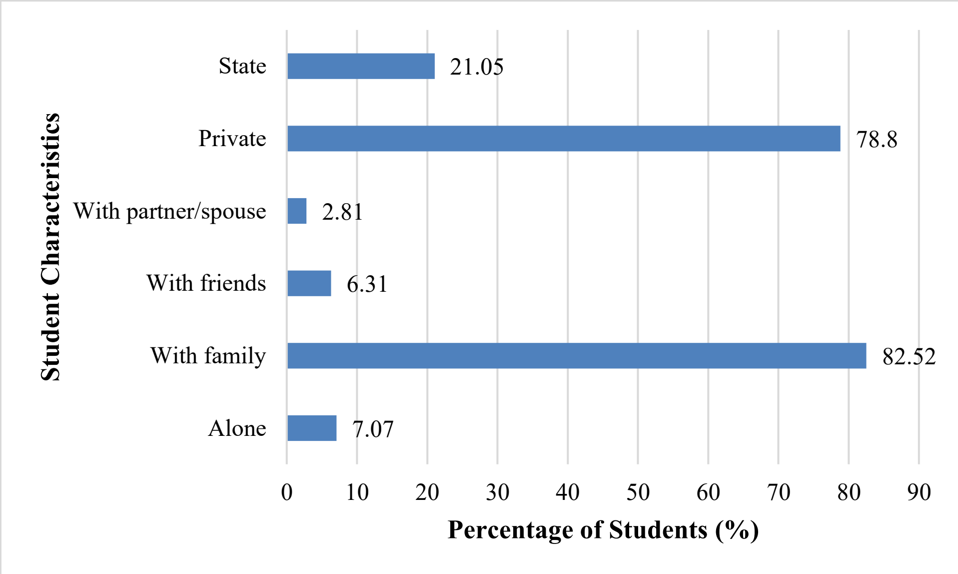

Figure 1. Distribution of Selected Student Characteristics

As Figure 1 indicates, the most common living arrangement was living with family, with very few students living alone, with friends, or with a partner or spouse. In terms of the type of university, the proportion of students in the sample belonging to private-university was significantly higher in comparison with the state-university. On the whole, the distribution reflects that the population of the study was mostly limited by the family-based residence and studying at the private universities.

3.2 Learning Constructs and Reliability

There was generally a high mean score of the four learning dimensions. Motivational strategies were the most highly means, then self-regulated learning, perceived academic performance and deep learning techniques. Self-regulated learning, motivational strategies, and deep learning techniques had an acceptable level of reliability, and perceived academic performance had a relatively poor internal consistency. The alpha values of Cronbach were in the range of 0.610 to 0.793 (as shown in Table 2), which shows that most of the dimensions were satisfactorily consistent to proceed with latent profile analysis.

Table 2. Descriptive Statistics and Internal Consistency of Learning Constructs

Construct	**Items**	**Mean**	**SD**	**Median**	**Minimum**	**Maximum**	**Cronbach's α**
Self-Regulated Learning	6	4.051	0.635	4.167	1.667	5.000	0.782
Motivational Strategies	5	4.111	0.715	4.200	1.000	5.000	0.793
Perceived Academic Performance	4	3.869	0.644	4.000	1.250	5.000	0.610
Deep Learning Techniques	4	3.816	0.779	3.875	1.000	5.000	0.753

3.3 Relationships Among Learning Dimensions

Each of the learning dimensions was positively and significantly correlated with the others. The most significant correlation was found between self-regulated learning and deep learning techniques, then motivational strategies and perceived academic performance. There was a moderate relationship between motivational strategies and perceived academic performance as well as deep learning techniques. All the correlations were statistically significant, with a range of 0.442 to 0.602. The findings showed that the four constructs had connections but were different enough to justify the use of multidimensional latent profile modeling.

Figure 2 also demonstrates the pattern of correlation among the four dimensions of learning with all constructs demonstrating positive relationships.

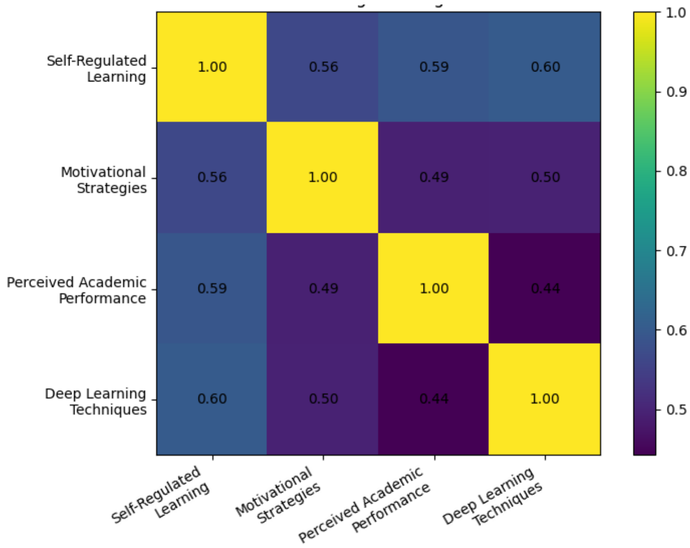

Figure 2. Correlation Heatmap of Learning Dimensions

Figure 2 depicts that the self-regulated learning was most closely correlated with deep learning techniques, then with perceived academic performance. All the relationships were positive which means that higher levels of self-regulation, motivation, perceived performance, and deep learning behaviors were more likely to co-occur among university students.

3.4 Selection of the Optimal Latent Profile Model

AIC, BIC, adjusted BIC, entropy and profile size were used to compare latent profile models of two to six profiles. All the models came together successfully. Even though AIC kept on decreasing as more profiles were added, the five-profile solution had the lowest BIC and maintained a readable minimum profile size. Table 3 also indicates that the entropy and classification quality was also acceptable in the five-profile model. Thus, the five-profile solution was chosen as the best characterization of the heterogeneity of learning patterns among students.

Table 3. Model-Fit Statistics for Latent Profile Solutions

Profiles	**Log-Likelihood**	**AIC**	**BIC**	**Adjusted BIC**	**Entropy**	**Smallest Profile n**	**Smallest Profile %**
2	-6654.084	13342.167	13430.267	13376.266	0.770	606	46.05
3	-6402.185	12856.370	12991.111	12908.521	0.769	248	18.85
4	-6326.292	12722.583	12903.965	12792.787	0.719	185	14.06
5	-6286.118	12660.237	12888.260	12748.493	0.703	104	7.90
6	-6265.178	12636.356	12911.021	12742.665	0.663	88	6.69

3.5 Characteristics of the Five Learning Profiles

There were five student learning profiles identified. The scores of profile 1 were low in all dimensions, but Profile 2 scored very high in self-regulation, motivation, perceived performance, and deep learning. Profile 3 was well-regulated and perceived performance but with relatively low deep learning. Profile 4 also indicated moderate learning features and Profile 5 was a combination of very high motivation, deep learning, and strong self-regulation.

Figure 3 gives the relative size of each of the identified latent profiles showing how students are distributed among the five learning-pattern groups.

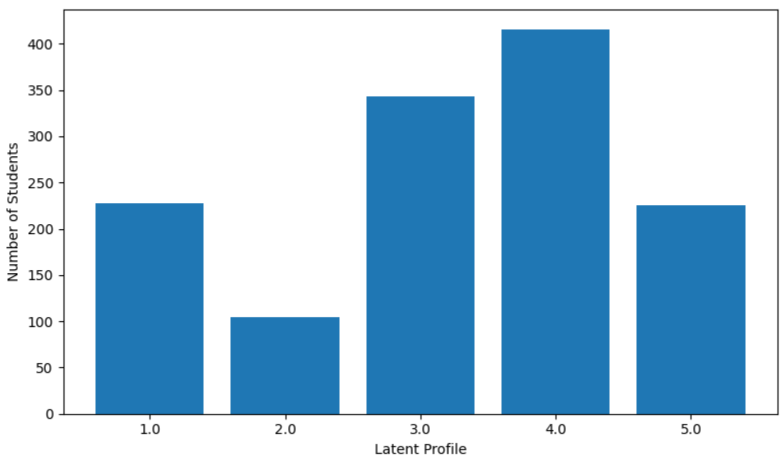

Figure 3. Distribution of Students Across Latent Profiles

Figure 3 indicates that the highest percentage of students was found in Profile 4 then Profile 3. The representation of Profiles 1 and 5 was similar, and Profile 2 was the smallest subgroup. This distribution shows that the moderate and moderately-high learning-pattern profiles were more prevalent than the extreme high-performing profile.

3.6 Demographic Differences Across Learning Profiles

The differences between nationality and gender were statistically significant in the five profiles of latent but the effect sizes were small. There were no significant differences in civil status, parental status, living arrangement, and university type with overall profile membership. There was also no significant difference in age that existed between profiles. The strongest demographic relationship with profile membership was found with nationality as in Table 4, with gender coming in second place. These results show that learning profiles had a weak relationship with demographic aspects in the study population.

Table 4. Demographic Differences Across Latent Profiles

Variable	χ^2 / H	df	p-value	Cramér's V	Result
Nationality	22.065	4	<0.001	0.130	Significant
Gender	10.826	4	0.029	0.091	Significant
Civil status	16.889	12	0.154	0.066	Not significant
Children	0.531	4	0.970	0.020	Not significant
Living arrangement	17.613	12	0.128	0.067	Not significant
University type	8.148	4	0.086	0.079	Not significant
Age†	5.767	4	0.217	—	Not significant

Note: †Kruskal–Wallis H statistic was used for age.

3.7 Predictors of Latent Profile Membership

Multinomial logistic regression revealed that the selected demographic variables were correlated with the data of belonging to certain learning profiles. Male students were less likely to be a part of Profile 2 than was the case with Profile 1. Membership in Profiles 4 and 5 was highly predicted by nationality and the university type was also related to these profiles. Age was not a significant predictor. Table 5 indicated that the overall regression model was statistically significant, but its pseudo-R 2 implied that it could not explain the demographic factors underpinning latent profile membership to an extent.

Table 5. Multinomial Logistic Regression for Latent Profile Membership

Comparison with Profile 1	Predictor	OR	p-value
Profile 2	Age	1.044	0.462
	Male gender	0.524	0.012
	Ecuador nationality	0.762	0.375
	State university	0.883	0.716
Profile 3	Age	1.029	0.508
	Male gender	0.847	0.354
	Ecuador nationality	1.057	0.801
	State university	0.701	0.168
Profile 4	Age	0.984	0.701
	Male gender	1.004	0.983
	Ecuador nationality	0.624	0.023
	State university	0.500	0.004
Profile 5	Age	0.983	0.726
	Male gender	0.844	0.392
	Ecuador nationality	0.444	<0.001
	State university	0.554	0.027

4. Discussion

The current research recognized five different learning profiles of university students in terms of self-regulated learning, motivational strategies, perceived academic performance, and deep learning techniques. The results indicated that there was significant variation in the combination of these learning features by students. Other students showed a pattern of high scores on all dimensions, but some had lower scores in general, or different ratios of strengths and weaknesses. This trend suggests that university students are not to be regarded as a homogenous group and that person-centered analysis can expose learning configurations which might be obscured in traditional methods of averages.

The profile (high-performing and highly regulated) in the current study was in line with the past reports that indicated that robust self-regulation is usually associated with desirable motivation and performance-related traits. Yu et al. (2022) also found that there are clear student profiles in which highly emotionally self-efficacious individuals had superior self-regulation, motivation, and academic performance. It was also shown by Sun et al. (2026) that self-regulated learning is interacting with more global psychological traits, such as emotions and mindset, which also supports the interpretation that there is no specific academic behavior that determines successful learning profile but a combination of several processes.

Earlier findings of person-centered variability were also in line with the presence of profiles with uneven combinations of learning characteristics. Wang et al. (2025) found out the heterogeneous reading-to-write and writing strategy profiles that varied in motivation and achievement, which means that students could achieve various learning outcomes when using different strategies. Wang et al. (2023) also indicated the variation in socially regulated learning profiles and association with collaborative learning motivation. These results substantiate the current finding that students may be highly motivated or controlled without the same high-performance of deep-learning behavior or perceived performance. The positive correlations between self-regulated learning, motivational strategies, deep learning techniques and perceived academic performance were also consistent with the earlier studies. According to Xu et al. (2024), self-regulated learning strategies, self-efficacy, and learning engagement were significantly correlated and the motivational and strategic processes are interdependent. Zhang et al. (2026) also demonstrated that the academic performance over time was associated with changes in self-regulated learning strategies. The discovery of a poorer-performing profile in the present study also aligns with the research by Zhang et al. (2022), who established that endangered learning patterns could be observed with the help of behavioral and self-regulatory signs.

The results can have practical implications in the area of higher education as the profiles identified can be used to differentiate students with various learning-support needs. Learners who score low on self-regulation, motivation, or deep-learning can be helped by systematic interventions aimed at time management, reflective learning, goal-setting, and independent-study skills. Uneven students might need more specific assistance addressing the weaker aspect instead of general academic assistance. A profile-based strategy can potentially enable institutions to create more focused learning support as opposed to providing all students with the same intervention. There are a number of restrictions that should be taken into account when interpreting the findings. The research was conducted on cross-sectional secondary data and thus no causal relationships could be drawn. The measures were self-reported and thus could have been affected by the perception bias or social desirability. The perceived academic performance was subjective and did not mirror on objective academic performance. The sample was also narrowed down to university students in two countries and this could be a limitation to generalizability. Moreover, the choice of indicators, model assumptions, and statistical specification can be relied upon to obtain latent profile solutions.

The longitudinal designs that should be employed in future research are used to establish whether students switch learning profiles as time goes by. Perceived performance should be accompanied by objective academic measures of performance like GPA, examination scores, or course completion. External validity would be enhanced with larger and more culturally diverse samples. Additional research in the future may also involve integrating questionnaire measures into digital learning traces, behavioral analytics, or classroom engagement measures. This would enable researchers to study the profile membership development, whether specific interventions can alter students to more adaptive learning patterns, and the most responsive learning dimensions to education support.

5. Conclusion

The current research revealed that the university students had specific learning profiles through self-regulated learning, motivational strategies, deep learning techniques, and perceived performance. Latent profiles identified were five, with the lowest patterns being consistently low in learning-strategy, to highly self-regulated, motivated and high-performing. These dimensions of learning were found to be positively correlated but not always developed among all the students, making the existence of meaningful heterogeneity in the university population a fact. Others had high motivation and self-regulation levels and relatively less deep-learning behavior or perceived performance, which underscores the importance of studying multidimensional learning patterns, as opposed to using the average scores alone. Demographic traits only described a small percentage of profile membership, even though gender, nationality and university type were associated with profile membership. This implies that psychological and strategic attributes associated with learning could be of greater significance than the low-level demographics in differentiating between student groups. The findings favor the latent profile modeling as a handy statistical method of identifying students with varying learning requirements. Such profile data can be used by universities to develop more customized academic support, especially those students who have poorer self-regulation, motivation, or deep-learning strategies. These profiles need to be validated longitudinally in future studies, include objective academic performance, and whether they can be influenced by specific interventions to move to more adaptive learning patterns.

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