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Artificial intelligence for determining learning strategies in university students

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Background: University students employ various learning strategies that influence their academic success and retention in the educational system. However, those who fail to use these strategies effectively may be at risk of dropping out. In this context, the objective of this study was to determine the learning strategies of students at the Pontifical Catholic University of Ecuador, Santo Domingo campus (PUCESD) using artificial intelligence.

Methods: The research followed a quantitative, correlational, and predictive approach, with a probabilistic sample of 162 students aged 17–24, of whom 29% were male and 71% female, from public, private religious, private secular, and semi-private institutions. Through the ACRA questionnaire, three dimensions were evaluated: cognitive strategies, study habits, and learning support.

Results: The results revealed a structure with adequate internal consistency and structural validity, high-lighting a significant relationship between cognitive strategies and study habits, suggesting a positive interaction between the two to optimize learning.

Conclusions: Artificial intelligence proved effective in identifying patterns in learning strategies. However, it is recommended to adjust certain questionnaire items to enhance its precision and applicability in diverse contexts, thereby facilitating targeted interventions.

KEYWORDS

factor analysis, university student, education evaluation, artificial intelligence, learning method

1 Introduction

In higher education, the study of learning strategies employed by students has gained increasing relevance due to its direct influence on academic performance and the development of fundamental competencies (Gachino and Worku, 2019; Mendo-Lázaro et al., 2018; Salas Velasco, 2014). Research on learning strategies has advanced significantly in recent decades, revealing that university students adopt diverse approaches to manage their learning, ranging from contextual and affective support to the implementation of specific techniques for organizing and retaining knowledge (Hattie and Donoghue, 2016; McDaniel and Einstein, 2020). These approaches, which include planning, self-regulation, goal-setting, and active study methods, are essential for successfully addressing the challenges of higher education (Heikkilä and Lonka, 2006; Russell et al., 2022; Wolters and Brady, 2021). However, recent studies emphasize that not all students access these strategies equitably. While some exhibit advanced self-management and contextual support skills, others struggle to adopt them effectively, which negatively impacts their academic performance (Al-Abyadh and Abdel Azeem, 2022; Harvey et al., 2015; Prinsloo and Slade, 2015).

Despite these advances in identifying learning strategies, substantial challenges persist in personalizing these approaches. The heterogeneity in students' abilities, learning styles, and paces poses difficulties for educational institutions, which often lack precise methods to identify the individual learning profile of each student. This limitation hinders the design and implementation of pedagogical interventions tailored to the specific needs of each student, thereby reducing the effectiveness of teaching-learning processes and, consequently, affecting academic success and competency development (Geletu, 2022; Kamalov et al., 2023).

Artificial Intelligence (AI) emerges as an innovative tool with the potential to transform education through automation and precision in identifying learning patterns (Kumar et al., 2023; Tedre et al., 2021). While some prior studies have explored the use of AI algorithms in education to personalize teaching methods, most of this research has focused on online learning environments or specific applications without comprehensively addressing the learning profiles of students in face-to-face university settings (Kabudi et al., 2021; Zawacki-Richter et al., 2019). This represents a gap in the current literature, as no studies have integrated AI to analyze, systematize, and personalize learning strategies based on individual student characteristics in traditional educational contexts (Bhutoria, 2022).

The relevance of this study lies in its innovative approach to addressing this gap by proposing the use of AI to identify and categorize university students' learning strategies based on their specific characteristics. By applying AI to analyze learning patterns, this study contributes not only to a better understanding of learning preferences and styles (Ezzaim et al., 2024) but also to the design of dynamic and personalized pedagogical interventions tailored to each student's needs, ultimately optimizing academic performance and promoting meaningful learning (Dietrich et al., 2021; Tetzlaff et al., 2021).

Based on this framework, the research question is posed as follows: How can artificial intelligence determine the learning strategies of students at the Pontifical Catholic University of Ecuador, Santo Domingo campus (PUCESD)? This question seeks to explore the potential of artificial intelligence techniques to identify strategic learning patterns that remain undetected by conventional analytical methods, thereby contributing to academic performance enhancement and the personalization of educational processes in university contexts.

In line with this inquiry, the following hypotheses are formulated:

H1. There is a statistically significant relationship between cognitive strategies and study habits among university students, indicating that both dimensions interact complementarily to optimize knowledge acquisition and retention processes.

H2. Learning support strategies, such as emotional regulation, seeking academic assistance, and organizing the learning environment, are positively associated with the use of cognitive strategies, reinforcing learning self-regulation.

H3. The factor loadings of the items from the abbreviated ACRA questionnaire accurately identify the three latent dimensions of learning (cognitive strategies, study habits, and support strategies), supporting the structural validity of the instrument in the Ecuadorian university context.

H4. Sociodemographic variables, such as the type of institution of origin, significantly influence the frequency and quality of learning strategy use, shaping differentiated student profiles.

H5. The application of artificial intelligence algorithms allows for the detection of latent patterns in learning strategies with greater precision than traditional statistical approaches, enabling the development of more relevant, individualized, and evidence-based pedagogical interventions.

To answer this research question and test the proposed hypotheses, this study aims to determine the learning strategies of students at the Pontifical Catholic University of Ecuador, Santo Domingo campus (PUCESD), with the goal of identifying strategic profiles and generating recommendations aimed at designing more effective training actions tailored to students' cognitive and contextual needs.

2 Materials and methods

This study adopts a quantitative, descriptive, and correlational approach, designed to identify the learning strategies employed by first semester university students at the Pontifical Catholic University of Ecuador, Santo Domingo campus (PUCESD). It is a non-experimental, cross-sectional study, as the variables of interest were not manipulated and data were collected at a single point in time.

The study population comprised first-semester students at PUCESD, with a total sample of 162 participants selected through probabilistic sampling. This method ensured representativeness and precision in estimating prevalent learning strategies. Participant distribution by gender included 29.0% men and 71.0% women. Regarding age, the majority of students were between 18 and 19 years old (64.8%), followed by those aged 20–21 years (16.0%), while students over 24 years old represented 4.9%. Additionally, 46.9% of participants graduated from public schools, 17.3% from private religious institutions, 28.4% from private secular institutions, and 7.4% from semi-private institutions.

Data collection utilized the abbreviated ACRA Questionnaire by De la Fuente Arias and Justicia Justicia (2017), a validated instrument that evaluates learning strategies across three major dimensions: cognitive and learning control strategies, learning support strategies, and study habits. The questionnaire was adapted to the Ecuadorian context, maintaining its original four-point Likert scale ranging from 1 = Never or almost never to 4 = Always. This scale captures the frequency with which students employ different learning strategies. Table 1 presents the results of the

TABLE 1 KMO and Bartlett's test for the ACRA instrument.

Measure of sampling adequacy (KMO)	0.811
Bartlett's test of sphericity	$\chi^2 = 2{,}601.516$
Degrees of freedom (df)	946
Significance (p-value)	0.000

TABLE 2 Reliability analysis for learning strategy dimensions in university students.

Learning strategies	Cronbach's alpha	McDonald's omega	Number of items
Cognitive and learning control strategies	0.850	0.851	25
Learning support strategies	0.839	0.837	14
Study habits	0.744	0.749	5
Total	0.912	0.912	44

Kaiser-Meyer-Olkin measure of sampling adequacy and Bartlett's test of sphericity. These indicators assess the suitability of applying factor analysis to the ACRA instrument.

The validation of the ACRA questionnaire in Ecuadorian university students demonstrated robust results, with a KMO index of 0.811 and a significant Bartlett's test (χ^2 = 2,601.516; df = 946; p < 0.001), confirming the suitability of the data for factor analysis. Regarding internal consistency, both Cronbach's alpha and McDonald's omega reached a value of 0.912 for the complete questionnaire, supporting its reliability in alignment with previous studies conducted in Spain. By dimensions, cognitive and learning control strategies achieved an alpha of 0.856, learning support strategies 0.832, and study habits 0.749, reinforcing the structural validity of the instrument and its ability to adequately measure learning strategies in this sample.

Table 2 presents a reliability analysis for the dimensions of the ACRA questionnaire applied to university students, indicating high levels of internal consistency across all evaluated dimensions. The cognitive and learning control strategies dimension achieved a Cronbach's alpha of 0.850 and a McDonald's omega of 0.851, demonstrating excellent reliability across its 25 items. The learning support strategies dimension also showed high internal consistency, with an alpha of 0.839 and an omega of 0.837 for its 14 items. The study habits dimension, comprising 5 items, exhibited a Cronbach's alpha of 0.744 and a McDonald's omega of 0.749, reflecting acceptable reliability. Overall, the complete questionnaire achieved both a Cronbach's alpha and a McDonald's omega of 0.912 across its 44 items, confirming its high reliability and psychometric validation in the context of university students. These results suggest that each dimension consistently and accurately measures the constructs of learning strategies in this population.

Table 3 presents a quantitative exploratory and reliability analysis of the items in the ACRA questionnaire, used to measure learning strategies among university students. The mean responses ranged from 2.27 to 3.44, reflecting a general tendency toward moderate frequency in the use of diverse learning strategies. Cronbach's alpha for each item ranged between 0.908 and 0.912, indicating high internal consistency and supporting the reliability of the questionnaire. These values suggest that the items are coherent and reliably measure the different learning strategies assessed in the sample. Notably, items related to organization and planning, such as time distribution and the use of memorization strategies (items 25 and 39, with means of 3.31 and 2.81, respectively), showed high consistency with the overall construct, suggesting that students prioritize these strategies in their learning processes.

Regarding data processing, the collected information was tabulated and analyzed using SPSS statistical software. Descriptive techniques were initially applied to examine the frequency and distribution of learning strategies according to sociodemographic variables such as gender, age, and type of institution. To assess the internal consistency and structural robustness of the ACRA questionnaire within the Ecuadorian context, reliability analyses were conducted using Cronbach's alpha and McDonald's omega coefficients.

With respect to analytical modeling, generative artificial intelligence techniques were not employed. Instead, non-generative artificial intelligence methods were utilized, specifically the Partial Least Squares (PLS) algorithm, which was operationalized through the Structural Equation Modeling (SEM) approach using the SmartPLS software. This software integrates principles of artificial intelligence for the analysis of multivariate data. It is important to note that SmartPLS is a specialized tool that applies non-generative AI algorithms, designed to estimate complex models with latent variables, even in small samples or with non-normally distributed data. This technique was complemented with plugin-based extensions and tools such as WinEs, enabling the estimation of path coefficients, the assessment of discriminant validity, and the modeling of structural relationships among the three core dimensions of the ACRA instrument: cognitive strategies, study habits, and learning support.

3 Results and discussion

The results of the factorial analysis confirm the three-dimensional structure of the ACRA-Abbreviated instrument, which measures learning strategies in university students across three latent dimensions: cognitive strategies, study habits, and learning support strategies. These dimensions provide a robust framework for assessing learning strategies in the university context, offering valuable insights into how students organize, regulate, and support their learning processes.

Figure 1 illustrates the factor loadings of observed variables within each of the latent dimensions of the ACRA-Abbreviated questionnaire. Each item demonstrates a significant loading within its respective dimension, indicating its contribution to the overall construct of learning strategies. The high factor loadings observed in the Cognitive Strategies dimension suggest a strong alignment of items with students' cognitive strategies, such as organization and learning control. Similarly, the Study Habits dimension shows significant loadings, highlighting the importance of personal behaviors and routines in the learning process. Lastly, the Learning Support Strategies dimension exhibits moderate loadings, emphasizing the role of social and emotional support techniques in optimizing university-level learning.

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TABLE 3 Quantitative exploratory analysis and reliability of the ACRA questionnaire items.

Observed variables	Mean	SD	Cronbach's alpha	*N*
1. I create summaries using previously underlined words or phrases.	2.72	0.78	0.911	162
2. I summarize what I studied at the end of each topic.	2.27	0.69	0.912	162
3. I summarize the key points of each section of a topic, lesson, or notes.	2.80	0.80	0.910	162
4. I create outlines using underlined words or phrases from the summaries I've made.	2.67	0.82	0.912	162
5. I dedicate study time to memorizing summaries, outlines, concept maps, etc., focusing on the most important points.	2.56	0.76	0.909	162
6. Before answering an exam, I recall groupings of concepts (summaries, outlines, etc.) I created while studying.	3.10	0.77	0.911	162
7. In books, notes, or other study materials, I underline the most important words, data, or phrases in each paragraph.	3.01	0.82	0.910	162
8. I use underlined content to facilitate memorization.	2.92	0.91	0.910	162
9. I use pencils or pens of different colors to enhance learning.	2.83	1.00	0.912	162
10. I use symbols (exclamation marks, asterisks, drawings), some only intelligible to me, to highlight key information.	2.83	0.90	0.911	162
11. I understand the importance of elaboration strategies, which require establishing relationships among study content.	2.83	0.81	0.910	162
12. I recognize the role of learning strategies that aid memorization using repetition and mnemonics.	2.81	0.79	0.911	162
13. I understand the importance of organizing information through outlines, sequences, diagrams, concept maps, etc.	2.98	0.73	0.909	162
14. I find it helpful to recall mnemonics, drawings, or concept maps I created while studying for exams or assignments.	2.96	0.77	0.910	162
15. I reflect on how I prepare information for oral or written exams (e.g., free association, outlines, drafts).	2.91	0.75	0.909	162
16. For difficult-to-remember information, I look for secondary data to recall the key points.	2.93	0.77	0.909	162
17. Remembering classroom events or other moments of learning helps me recall what I've studied.	3.04	0.73	0.910	162
18. When preparing for oral or written tasks, I recall drawings, images, etc., I created during learning.	3.15	0.74	0.909	162
19. When faced with a problem, I consider known data before attempting an intuitive solution.	2.95	0.84	0.909	162
20. Before starting a written assignment, I create an outline, guide, or plan of topics to address.	2.63	0.80	0.910	162
21. When I lack data for a topic, I generate an "approximate" response by relating it to other subjects I know.	2.83	0.78	0.912	162
22. Before speaking or writing, I think and mentally prepare what I want to say or write.	3.22	0.79	0.908	162
23. To recall information, I first search my memory and then decide if it fits the question or response needed.	3.11	0.66	0.910	162
24. During study, I write or repeat important or difficult-to-remember information several times.	3.19	0.78	0.909	162
25. For dense and difficult content, I reread it slowly to understand better.	3.31	0.77	0.909	162
26. I study to expand my knowledge and expertise.	2.86	0.86	0.910	162
27. I make an effort in my studies to feel proud of myself.	3.26	0.73	0.908	162
28. I motivate myself with encouraging words to stay focused on studying.	3.30	0.81	0.908	162
29. I remind myself that I can exceed my current performance levels in different subjects.	3.38	0.76	0.909	162
30. I use personal resources to manage anxiety that prevents me from concentrating on studying.	2.79	0.76	0.911	162
31. I ensure my study space is free of distractions such as noise, disorder, or insufficient lighting.	3.09	0.91	0.911	162
32. When facing family conflicts, I try to resolve them first to concentrate better on studying.	2.81	0.91	0.911	162
33. I feel motivated by discussing study topics with peers, friends, or family.	2.85	0.90	0.910	162
34. I avoid or resolve conflicts with peers, professors, or family through dialogue.	2.95	0.82	0.910	162
35. I seek help from friends, professors, or family when I have doubts or need to exchange information.	3.18	0.70	0.909	162

(Continued)

TABLE 3 (Continued)

Observed variables	Mean	SD	Cronbach's alpha	*N*
36. I feel satisfied when my work is positively valued by peers, professors, or family.	3.44	0.67	0.908	162
37. I encourage and help my peers achieve the best possible outcomes in their school tasks.	3.09	0.83	0.909	162
38. Before studying, I allocate time among all the topics I need to learn.	2.92	0.80	0.909	162
39. Before exams, I create a work plan, allocating time for each topic.	2.81	0.84	0.909	162
40. I try to express what I've learned in my own words instead of repeating it verbatim.	3.28	0.70	0.910	162
41. I strive to learn topics in my own words rather than memorizing them verbatim.	3.22	0.76	0.910	162
42. While studying, I mentally summarize the most important points.	3.36	0.71	0.909	162
43. When starting to study a lesson, I skim through the entire content first.	3.13	0.82	0.911	162
44. While studying a lesson, I take breaks and then review it to learn better.	3.24	0.80	0.910	162

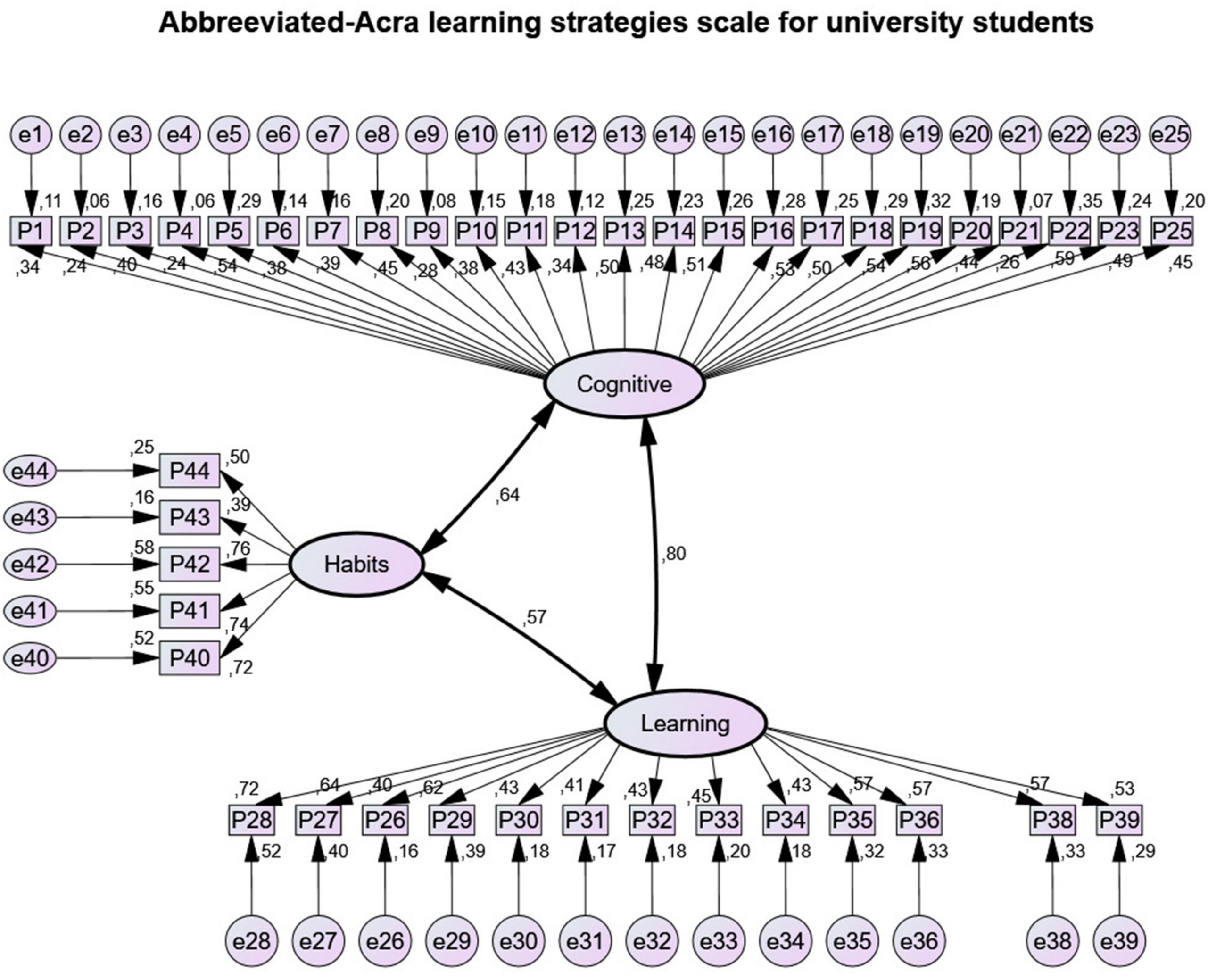

FIGURE 1
Factor loadings of observed and latent variables.

These findings are consistent with previous studies, such as those by Muwonge et al. (2019), which suggest that cognitive strategies, when complemented by learning control and intrinsic motivation, positively impact academic performance. Moreover, study habits and social support strategies have been widely recognized as critical factors in self-managed learning (Boger

TABLE 4 Model fit measures for learning strategies.

Model	CMIN	CMIN/DF	TLI	CFI	RMSEA	AIC
Original	1,477.659	1.644	0.685	0.701	0.063	1,747.659
Interpretation	–	Excellent	Poor	Acceptable	Acceptable	Acceptable
Adjusted	225.075	1.940	0.853	0.875	0.076	333.075
Interpretation	–	1 to 3	>0.700	>0.810	<0.08	–
Cut-off criteria	–	Excellent	Acceptable	Acceptable	Acceptable	Acceptable

CMIN, Chi-square Minimum Value; CMIN/DF, Chi-square Minimum Value divided by Degrees of Freedom; TLI, Tucker-Lewis Index; CFI, Comparative Fit Index; RMSEA, Root Mean Square Error of Approximation; AIC, Akaike Information Criterion.

et al., 2015; Kwarikunda et al., 2022; Morgan et al., 2017). The observed association between the dimensions of Cognitive Strategies and Study Habits with the overall learning construct is consistent with the self-regulation theory proposed by Dunlosky et al. (2013), which posits that effective learning depends not only on the deployment of structured cognitive strategies but also on the establishment of robust study habits that sustain academic engagement and effort over time.

The factorial structure observed in this study further suggests that students who successfully integrate cognitive strategies with organizational habits and emotional support tend to achieve higher academic performance. This finding aligns with the conclusions of Karagiannopoulou et al. (2023), who argue that deep and meaningful learning is closely linked to the integration of multiple strategies and emotional regulation throughout the study process.

The results of the fit measures for the original and adjusted models of the ACRA questionnaire for learning strategies in university students demonstrate significant improvements in model adequacy after adjustments.

Table 4 presents the key fit indices of the model. In the original model, the CMIN/DF index of 1.644 is considered excellent; however, other indices, such as TLI (0.685) and CFI (0.701), reflect unsatisfactory fit, falling below acceptable levels. While the RMSEA of 0.063 and the AIC of 1,747.659 are acceptable, they suggest room for optimization. After adjustments, the adjusted model demonstrates improvements in TLI (0.853) and CFI (0.875), reaching acceptable values closer to the fit standards proposed in the literature. Furthermore, CMIN/DF increased slightly to 1.940, remaining within acceptable ranges, and RMSEA rose slightly to 0.076 but stayed within permissible levels. The AIC showed a significant reduction to 333.075, indicating a more parsimonious and well-fitted model. These findings align with Sahoo (2019), who established that CFI and TLI values above 0.80 indicate acceptable fit, while RMSEA below 0.08 reflects reasonable model fit. The observed improvements in the adjusted model highlight that the adjustments have enabled a more precise and consistent representation of learning strategies (Vianna et al., 2024).

From a theoretical perspective, these results support the proposition by Kryshko et al. (2020) on the importance of cognitive and motivational strategies in academic performance, demonstrating that students employing effective learning strategies achieve better academic outcomes. Additionally, the improved model fit more precisely captures the core components of learning strategies, aligning with the self-regulation theory proposed by Inzlicht et al. (2021), which emphasizes that a well-specified model should encompass both cognitive dimensions and the habitual patterns of personal control and regulatory behavior essential for effective learning.

The regression analysis results show the relationships between specific items of the ACRA questionnaire and the dimensions of learning strategies: cognitive, habits, and learning. These relationships, expressed as regression weights, reflect the extent to which each item contributes to its respective dimension, providing deeper insights into how students apply various strategies in their learning process.

Table 5 presents the regression weights for each item associated with the dimensions of learning strategies. In the cognitive dimension, several items exhibit significant and high regression coefficients ($p < 0.001$), such as P22 (1.78), P19 (1.78), and P24 (1.62), suggesting that these aspects strongly represent cognitive strategies. In the "Learning" dimension, items P28 (1.76) and P27 (1.35) also display high regression weights, indicating their relevance in characterizing learning strategies overall. Finally, in the habits dimension, items P41 (1.12) and P42 (1.06) stand out with high and significant values, reinforcing the importance of structured study habits in the university learning process.

These findings align with previous research emphasizing the importance of cognitive and self-regulation strategies in academic performance. For instance, Theobald (2021) argues that the effective use of cognitive strategies, such as organization and planning, is fundamental to learning self-regulation and academic achievement in university settings. Similarly, Martin et al. (2022) highlight that cognitive strategies and structured habits positively correlate with intrinsic motivation and academic performance, consistent with the high regression weights observed in this dimension.

The statistical significance of the regression weights for most items indicates that these are representative and essential to their respective dimensions, confirming the structural validity of the ACRA model in the university context. According to Sarami and Hojjati (2024), integrating cognitive strategies, study habits, and intrinsic motivation facilitates deeper and more effective learning, as students employing these strategies have greater control over their learning processes and an enhanced ability to address academic challenges. This structural model thus reflects the complexity of learning in higher education, where cognitive strategies are complemented by study habits that contribute to academic success.

The analysis of the standardized factor loadings in the mathematical model reveals the strength of the association between

TABLE 5 Regression weights for learning strategies.

Question and factors	Estimate	S.E.	C.R.	*P*
P1 I create summaries using previously underlined words or phrases.	<---	Cognitive	1	-
P2 I summarize what I studied at the end of each topic.	<---	Cognitive	0.61	0.26
P3 I summarize the key points of each section of a topic, lesson, or notes.	<---	Cognitive	1.20	0.37
P4 I create outlines using underlined words or phrases from the summaries I've made.	<---	Cognitive	0.72	0.31
P5 I dedicate study time to memorizing summaries, outlines, concept maps, etc., focusing on the most important points.	<---	Cognitive	1.56	0.42
P6 Before answering an exam, I recall groupings of concepts (summaries, outlines, etc.) I created while studying.	<---	Cognitive	1.05	0.34
P7 In books, notes, or other study materials, I underline the most important words, data, or phrases in each paragraph.	<---	Cognitive	1.27	0.39
P8 I use underlined content to facilitate memorization.	<---	Cognitive	1.52	0.44
P9 I use pencils or pens of different colors to enhance learning.	<---	Cognitive	1.07	0.40
P10 I use symbols (exclamation marks, asterisks, drawings), some intelligible only to me, to highlight important information.	<---	Cognitive	1.28	0.40
P11 I understand the importance of elaboration strategies, which require establishing relationships among study content.	<---	Cognitive	1.34	0.39
P12 I recognize the role of learning strategies that aid memorization using repetition and mnemonics.	<---	Cognitive	1.06	0.34
P13 I reflect on the importance of organizing information using outlines, sequences, diagrams, concept maps, matrices.	<---	Cognitive	1.40	0.39
P14 I find it helpful to recall mnemonics, drawings, or concept maps I created while studying for exams or assignments.	<---	Cognitive	1.43	0.40
P15 I reflect on how I prepare information for oral or written exams (e.g., free association, outlines, drafts).	<---	Cognitive	1.45	0.40
P16 For difficult-to-remember information, I look for secondary data to recall key points.	<---	Cognitive	1.54	0.42
P17 Remembering classroom events or other moments of learning helps me recall what I've studied.	<---	Cognitive	1.37	0.38
P18 When preparing for oral or written tasks, I recall drawings, images, etc., I created during learning.	<---	Cognitive	1.53	0.41
P19 When faced with a problem, I consider known data before attempting an intuitive solution.	<---	Cognitive	1.78	0.48
P20 Before starting a written assignment, I create an outline, guide, or plan of topics to address.	<---	Cognitive	1.32	0.39
P21 When I lack data for a topic, I generate an "approximate" response by relating it to other subjects I know.	<---	Cognitive	0.73	0.30
P22 Before speaking or writing, I think and mentally prepare what I want to say or write.	<---	Cognitive	1.78	0.47
P23 To recall information, I first search my memory and then decide if it fits the question or response needed.	<---	Cognitive	1.27	0.35
P24 During study, I write or repeat important or difficult-to-remember information several times.	<---	Cognitive	1.62	0.44
P25 For dense and difficult content, I reread it slowly to better understand it.	<---	Cognitive	1.38	0.39
P26 I study to expand my knowledge and expertise.	<---	Learning	1.00	
P27 I make an effort in my studies to feel proud of myself.	<---	Learning	1.35	0.31
P28 I motivate myself with encouraging words to stay focused on studying.	<---	Learning	1.76	0.39
P29 I remind myself that I can exceed my current performance levels in different subjects.	<---	Learning	1.40	0.32
P30 I use personal resources to manage anxiety that prevents me from concentrating on studying.	<---	Learning	1.00	0.27
P31 I ensure my study space is free of distractions such as noise, disorder, or insufficient lighting.	<---	Learning	1.11	0.31
P32 When facing family conflicts, I try to resolve them first to concentrate better on studying.	<---	Learning	1.18	0.32
P33 I feel motivated by discussing study topics with peers, friends, or family.	<---	Learning	1.27	0.33
P34 I avoid or resolve conflicts with peers, professors, or family through dialogue.	<---	Learning	1.08	0.29
P35 I seek help from friends, professors, or family when I have doubts or need to exchange information.	<---	Learning	1.25	0.29
P36 I feel satisfied when my work is positively valued by peers, professors, or family.	<---	Learning	1.20	0.28
P37 I encourage and help my peers achieve the best possible outcomes in their school tasks.	<---	Learning	1.40	0.33

(Continued)

TABLE 5 (Continued)

Question and factors	Estimate	S.E.	C.R.	*P*
P38 Before studying, I allocate time among all the topics I need to learn.	<---	Learning	1.39	0.33
P39 Before exams, I create a work plan, allocating time for each topic.	<---	Learning	1.36	0.33
P40 I try to express what I've learned in my own words instead of repeating it verbatim.	<---	Habits	1.00	
P41 I strive to learn topics in my own words rather than memorizing them verbatim.	<---	Habits	1.12	0.14
P42 While studying, I mentally summarize the most important points.	<---	Habits	1.06	0.13
P43 When starting to study a lesson, I skim through the entire content first.	<---	Habits	0.64	0.14
P44 While studying a lesson, I take breaks and then review it to learn better.	<---	Habits	0.79	0.14

S.E, Standard Error; C.R, Critical Ratio; P, Probability Value (P-Value), the arrow (<---) indicates a link between the questions and the factor.

TABLE 6 Standardized factor loadings of the mathematical model.

Questions and factors	Estimate
P16 <--- Cognitive	0.555
P17 <--- Cognitive	0.573
P18 <--- Cognitive	0.586
P19 <--- Cognitive	0.551
P22 <--- Cognitive	0.617
P23 <--- Cognitive	0.565
P24 <--- Cognitive	0.524
P25 <--- Cognitive	0.536
P27 <--- Learning	0.631
P28 <--- Learning	0.736
P29 <--- Learning	0.668
P35 <--- Learning	0.635
P36 <--- Learning	0.622
P37 <--- Learning	0.544
P40 <--- Habits	0.756
P41 <--- Habits	0.788
P42 <--- Habits	0.723

TABLE 7 Covariances of learning strategies.

Learning strategies	Estimate	S.E.	C.R.	*P*
Cognitive ↔ Learning	0.168	0.036	4.624	***
Habits ↔ Cognitive	0.155	0.035	4.453	***
Habits ↔ Learning	0.130	0.030	4.315	***

Estimate, Coefficient estimate indicating the strength of the relationship between variables; S.E., Standard Error, representing the accuracy of the coefficient estimate; C.R., Critical Ratio, a statistical measure used to test the significance of the estimate (calculated as Estimate/S.E.); P, Probability value, indicating the level of statistical significance of the relationship.
***Indicates a highly significant relationship (P < 0.001).

the questionnaire items and the latent dimensions of learning strategies (Cognitive, Learning, and Habits).

The results in Table 6 show standardized factor loadings that reflect the strength of the association between the items and their respective dimensions, providing a detailed view of the factorial structure of the analyzed instrument. In the cognitive dimension, the values (ranging from 0.524 to 0.617) indicate a moderate association, with item P22 emerging as the most representative of cognitive strategies (0.617). This finding aligns with research highlighting those specific elements within questionnaires are more indicative of cognitive skills, such as problem-solving or critical thinking (Li, 2023).

In the learning dimension, factor loadings range from 0.544 to 0.736, with item P28 showing the strongest association (0.736). This result is consistent with studies identifying key items related to general learning strategies, such as planning and monitoring, which are essential for effective learning (Seli, 2019; Vrieling et al., 2018). The strong representation of item P28 may indicate its relevance for assessing metacognitive competencies within this dimension.

Finally, in the habits dimension, the high factor loadings of items P41 (0.788) and P40 (0.756) emphasize a strong relationship with study habits. These findings align with research underscoring the importance of organized and structured habits for academic success (Aljaffer et al., 2024; Credé and Kuncel, 2008; Muhammad et al., 2023). These items could be interpreted as key indicators for measuring the regularity and quality of study practices.

The results of the covariance between learning strategy dimensions identify the relationship and degree of interdependence among the various strategies used by university students.

In Table 7, covariances are shown between Cognitive and Learning strategies (0.168), Habits and Cognitive strategies (0.155), and Habits and Learning strategies (0.13), all with a high level of statistical significance ($p < 0.001$). The strongest relationship is observed between Cognitive and Learning strategies, suggesting that students who employ cognitive strategies also tend to use learning strategies in a complementary manner. The covariance between Habits and Cognitive strategies indicates that students with good study habits are more likely to apply effective cognitive strategies. Finally, the relationship between Habits and Learning strategies demonstrates moderate interdependence, emphasizing the importance of habits in the overall learning process.

These results align with the self-regulated learning theory of Kuiper and Pesut (2004), which posits that the use of cognitive strategies and the development of study habits are closely related, as both contribute to academic self-regulation. Cognitive strategies,

TABLE 8 Validity measures for the ACRA questionnaire model.

Strategies	CR	AVE	MSV	MaxR (H)	Cognitive	Learning	Habits
Cognitive	0.788	0.318	0.637	0.790	0.564		
Learning	0.807	0.412	0.637	0.814	0.798***	0.642	
Habits	0.800	0.572	0.410	0.803	0.640***	0.539***	0.756

No warnings were reported for this HTMT analysis. The symbols indicate levels of statistical significance as follows: $^{\dagger}p < 0.100$ (marginal significance); $^{*}p < 0.050$ (significant); $^{**}p < 0.010$ (highly significant); $^{***}p < 0.001$ (very highly significant).

such as organizing information and employing memorization techniques, are more effective when supported by consistent study habits, facilitating deeper and more lasting learning (McGuire, 2015; Paas and Sweller, 2012). The relationship between these dimensions is further supported by Saepudin et al. (2024), who emphasize that the development of solid habits is fundamental to the implementation of cognitive strategies and learning regulation.

The significant covariance between learning strategies and study habits also supports Broadbent (2017) deep processing theory, which suggests that students who integrate effective study habits with cognitive strategies are more likely to adopt a deep learning approach, thereby achieving better academic outcomes. This approach implies that students not only memorize information but also seek to understand and apply it, directly linked to the use of well-structured learning strategies and robust study habits. The findings support the design of targeted pedagogical interventions aligned with each learning strategy dimension. These may include cognitive training, structured habit-building programs, and emotional support initiatives. Such actions enable the transition from diagnosis to effective, evidence-based educational practices.

The validity analysis of the ACRA questionnaire model, applied to learning strategies in university students, assesses the accuracy with which the instrument measures the latent dimensions of cognitive strategies, learning, and habits.

Table 8 presents the validity measures for each dimension, including the Composite Reliability (CR), Average Variance Extracted (AVE), Maximum Shared Variance (MSV), and Maximum Reliability (MaxR). The CR values for the Cognitive (0.788), Learning (0.807), and Habits (0.800) dimensions indicate adequate reliability across all dimensions, exceeding the recommended threshold of 0.70 for internal consistency (Boateng et al., 2018). However, the AVE for the Cognitive (0.318) and Learning (0.412) dimensions falls below 0.50, suggesting issues with convergent validity. Discriminant validity is also questionable, as the AVE for the Cognitive and Learning dimensions is lower than the MSV, implying that these dimensions are highly correlated and not clearly distinguished from one another.

To improve convergent validity in the Cognitive dimension, it is recommended to remove item P24, as its presence may reduce the construct's clarity, as indicated by the low AVE value. Similarly, in the Learning dimension, removing item P37 could enhance convergent validity. These adjustments align with the recommendations of Dash and Paul (2021) who suggest that convergent validity is achieved when the AVE exceeds 0.50, and discriminant validity is evident when the AVE is greater than the MSV, which is not the case in this initial model.

TABLE 9 HTMT analysis for learning strategies in university students.

Strategies	Cognitive	Learning	Habits
Cognitive			
Learning	0.819		
Habits	0.655	0.561	

The low convergent and discriminant validity observed in some dimensions is consistent with research highlighting the difficulty of differentiating certain types of learning strategies. For instance, Vermunt (1996) argues that cognitive strategies and learning habits are often interrelated, complicating their clear distinction. Similarly, Nizzolino and Canals (2024) propose that self-regulated learning involves an integration of cognitive strategies and habitual behaviors, which may explain the high tension between these dimensions and the discriminant validity issues in the model.

The Heterotrait-Monotrait Ratio (HTMT) analysis is a critical measure for assessing discriminant validity between the dimensions of a model in this case, the learning strategies of university students evaluated using the ACRA questionnaire.

The HTMT values between the cognitive, learning and habits dimensions, presented in Table 9, demonstrate an adequate level of discriminant validity, with all values below 0.85. However, the coefficient of 0.819 between cognitive and learning suggests potential conceptual overlap, which aligns with studies like Li et al. (2023), highlighting the integration of cognitive strategies within self-regulated learning. This finding corresponds to the theory of Masalimova et al. (2019), which considers these strategies as interrelated components.

On the other hand, the lower HTMT values between habits and the other dimensions (0.655 and 0.561) indicate greater independence of this construct. This suggests that study habits function as support mechanisms in learning, facilitating the implementation of cognitive strategies without being directly integrated into them, consistent with the findings of Wong and Hughes (2023). These results underscore the importance of considering habits as an autonomous factor in the assessment and development of academic competencies.

4 Conclusions

The study achieved its objective of determining the learning strategies of students at the Pontifical Catholic University of Ecuador, Santo Domingo campus (PUCESD), through the application of non-generative artificial intelligence techniques.

Specifically, the Partial Least Squares (PLS) algorithm was employed using SmartPLS software to model the structural relationships among three key dimensions: cognitive strategies, study habits, and learning support. This analytical approach was methodologically transparent and reproducible, addressing the need for clarity in how AI-derived conclusions are reached.

The results confirmed the internal consistency and structural validity of the abbreviated ACRA questionnaire, demonstrating its suitability for evaluating learning strategies in university contexts. A significant relationship was identified between cognitive strategies and study habits, evidencing a functional interdependence between mental regulation processes and academic routines. Furthermore, the factorial analysis revealed adequate loadings across the instrument's three dimensions, although some limitations were noted in the convergent validity of the cognitive and learning support dimensions. Consequently, after evaluating the model's psychometric properties, the structure was refined by excluding items P24 and P37, which strengthened discriminant validity and improved the overall model fit indices.

The integration of artificial intelligence in the study was based on an explicit methodology, utilizing the Partial Least Squares (PLS) algorithm implemented through SmartPLS software. This approach enabled the precise modeling of structural relationships among latent dimensions and provided a clear interpretation of how results were derived, facilitating their understanding and practical use by the educational community. Transparency in the application of AI ensures that educators can trust the traceability of the findings and their relevance for practice.

Moreover, the use of artificial intelligence in this research extended beyond a purely technical or instrumental dimension; it was coherently aligned with the study's pedagogical objectives. This integration made it possible to identify latent patterns in learning strategies, which serve as essential inputs for designing personalized and evidence-based educational interventions. The alignment between AI-generated results and educational goals ensures that the findings are not only methodologically robust but also practically relevant and replicable across diverse educational settings, thereby contributing to the development of an analytical model that is transparent, reliable, and reproducible.

The study's limitations include the need for further adjustments to the ACRA questionnaire to enhance the clarity of certain dimensions and the potential influence of un-considered contextual factors, such as the type of academic programs and the availability of learning resources. These limitations suggest that future research should delve deeper into the personalization of learning strategies using AI, optimizing the ACRA questionnaire for application in diverse educational contexts.

In addition to methodological considerations, it is essential to reflect on the ethical implications of using artificial intelligence in face-to-face educational environments. The use of data-driven models must ensure the protection of students' personal information, respecting the principles of confidentiality and informed consent. Furthermore, the potential for algorithmic bias must be acknowledged, as AI tools may inadvertently reinforce existing inequalities if they are not properly calibrated and validated across diverse populations. Equity in access and outcomes must remain a guiding principle, ensuring that AI-based educational interventions do not disadvantage vulnerable groups. These ethical reflections are fundamental for promoting responsible and inclusive AI.

For future research, it is recommended to expand the sample to other higher education institutions and adopt mixed-method approaches integrating qualitative analysis to gain deeper insights into students' perceptions of their learning strategies. Additionally, examining the impact of AI-based personalized pedagogical interventions on academic performance would contribute to the development of adaptive and student centered teaching models.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

ÁS-G: Conceptualization, Data curation, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing. CO-M: Conceptualization, Formal analysis, Project administration, Writing – original draft, Writing – review & editing. RB-L: Resources, Software, Writing – original draft, Writing – review & editing. TS-E: Investigation, Methodology, Writing – original draft, Writing – review & editing. EH-M: Conceptualization, Methodology, Visualization, Writing – original draft, Writing – review & editing. BB-G: Data curation, Validation, Writing – original draft, Writing – review & editing. LC-B: Resources, Validation, Writing – original draft, Writing – review & editing. JM-C: Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review & editing.

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The author(s) declare that no Gen AI was used in the creation of this manuscript.

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