

**MULTIDIMENSIONAL PATTERNS OF LEARNING IN
HIGHER EDUCATION: AN EVIDENCE-BASED
STATISTICAL ANALYSIS ON THICKNESS**

Patrones multidimensionales de aprendizaje en la educación superior: un análisis estadístico basado en la evidencia sobre la densidad

Patricia Moyota-Amaguaya

Escuela Superior Politécnica de
Chimborazo (ESPOCH), Ecuador.
patricia.moyota@epoch.edu.ec

 <https://orcid.org/0000-0002-0661-2855>

Lina Morales-Rodas

Escuela Superior Politécnica de
Chimborazo (ESPOCH), Ecuador.
lina.morales@epoch.edu.ec

 <https://orcid.org/0000-0002-7779-9039>

María Eugenia Rodríguez-Durán

Escuela Superior Politécnica de
Chimborazo (ESPOCH), Ecuador.

 <https://orcid.org/0000-0002-5721-155X>

Daniel Hernán Millán-Ramos

Escuela Superior Politécnica de
Chimborazo (ESPOCH), Ecuador.
hernan.millan@epoch.edu.ec

 <https://orcid.org/0009-0004-7673-1501>

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ABSTRACT

We examined the multidimensional structure of constructs related to learning in Higher Education (HE) using an integrated statistical analysis. The aim was to understand whether Geertz's concept of depth description can be useful for improving English language proficiency. The model included cognitive, metacognitive, affective, and contextual scales in university students from different academic programs. To this end, we analyzed a set of standardized instruments, bibliographic resources, conceptual understanding, learning strategies, metacognitive regulation, cognitive performance, affective engagement, and demographic factors to measure the perceived improvement in English language proficiency. We collected data using descriptive statistics, distribution analysis, box plots, and pairwise correlation matrices to assess central tendency, as well as the potential for dispersion, skewness, and intervariate relationships. The results revealed heterogeneous distribution patterns, the presence of significant outliers, and non-normal behavior across several scales, particularly within the cognitive and metacognitive dimensions. Moderate and statistically significant correlations were identified between conceptual understanding and metacognitive strategies, as well as between metacognitive and affective dimensions, indicating a structural interdependence between learning processes.

Keywords: Thick description, complexity, multidimensional learning process, Higher Education.

RESUMEN

Examinamos la estructura multidimensional de los constructos relacionados con el aprendizaje en la Educación Superior (ES) mediante un análisis estadístico integrado. El objetivo era comprender si la idea de Geertz sobre la descripción de la profundidad puede ser útil para mejorar la competencia en inglés. El modelo incluyó escalas cognitivas, metacognitivas, afectivas y contextuales en estudiantes universitarios de diferentes programas académicos. Para ello, analizamos un conjunto de instrumentos estandarizados, recursos bibliográficos, comprensión conceptual, estrategias de aprendizaje, regulación metacognitiva, rendimiento cognitivo, compromiso afectivo y factores demográficos para medir la percepción de una mejor absorción del objetivo de competencia en inglés. Recopilamos información estadística descriptiva, análisis de distribución, diagramas de caja y matrices de correlación por pares para evaluar la tendencia central, así como las posibilidades de dispersión, asimetría y relaciones intervariables. Los resultados revelaron patrones de distribución heterogéneos, la presencia de valores atípicos significativos y un comportamiento no normal en varias escalas, particularmente dentro de las dimensiones cognitiva y metacognitiva. Se identificaron correlaciones moderadas y estadísticamente significativas entre la comprensión conceptual y las estrategias metacognitivas, así como entre las dimensiones metacognitivas y afectivas, lo que indica una interdependencia estructural entre los procesos de aprendizaje.

Palabras claves: Derechos reproductivos, infertilidad, técnicas de reproducción asistida, igualdad y no discriminación, diversidad familiar.

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INTRODUCTION: BLENDED/ HYBRID EDUCATIONAL STRATEGIES IN SRL

In recent years, the study of self-regulated learning (SRL) and metacognitive processes in HE has gained significant attention due to the rapid expansion of digital and hybrid learning environments. In the first hand, contemporary research highlights that effective learning in HE is strongly associated with students' ability to regulate cognitive, motivational, and behavioral processes during blending activities (Broadbent, 2017):

"For this reason, blended learning, if done well, may combine the benefits afforded by online technologies, with structure and social aspects of face-to-face time, to give an overall richer experience (Van Doorn & Van Doorn, 2014). A blended learning environment provides flexibility, but orientates students to a specific time and location each week to attend on-campus classes. It also allows students to customise their learning, while teaching staff are still able play a pivotal role in providing structure, organisation, scaffolding, and time management to the learning experience for students (Aldhafeeri, 2015, Artino and Jones, 2012)" (Broadbent, 2017).

These processes highlight that, in online and hybrid learning contexts, students should assume greater responsibility for managing their learning strategies and engagement. And this is the reason why SRL could be the ideal framework to hybrid/blended learning.

So, in the other hand, Self-Regulated Learning (SRL) represents one of the most influential theoretical frameworks in contemporary educational research, particularly within HE environments characterized by increasing learner autonomy and the integration of digital technologies in teaching and learning processes. Conceptually, SRL refers to the process through which learners actively plan, monitor, and regulate their

cognitive, motivational, and behavioral processes in order to achieve specific learning goals (Panadero, 2022). This perspective views students as active agents who engage in reflective learning practices, developing metacognitive different skills and self-regulation strategies that significantly influence academic performance.

From a theoretical standpoint, models of SRL are grounded in several conceptual frameworks that explain how learners manage their learning processes. Zimmerman conceptualizes SRL as a cyclical process composed of three main phases: forethought, performance, and self-reflection. During the forethought phase, students set learning goals, select strategies, and establish expectations regarding their performance. In the performance phase, learners apply cognitive strategies while monitoring their progress. Finally, during the self-reflection phase, students evaluate their outcomes and adjust their strategies for future learning activities (Panadero, 2022). This cyclical model has been widely adopted in studies examining learning behaviors in digital and HE contexts.

Within HE, the development of self-regulation skills has become increasingly relevant due to the growing demand for autonomous learning and critical thinking. Numerous studies have demonstrated that students who exhibit higher levels of SRL tend to achieve better academic outcomes, demonstrate stronger intrinsic motivation, and persist longer when facing cognitively demanding tasks (Xu et al., 2022). Furthermore, recent research indicates that self-regulation strategies significantly influence academic performance in online and hybrid learning environments, where students must independently manage their time, attention, and learning resources (Faza & Lestari, 2025).

Contemporary literature also emphasizes the multidimensional nature

of SRL, highlighting the interaction between cognitive, metacognitive, motivational, and emotional factors. In this sense, self-regulated learning extends beyond the application of cognitive strategies and includes complex processes of emotional and motivational regulation that influence students' persistence when engaging with challenging academic tasks (Nyman, 2024). This multidimensional perspective has allowed researchers to gain a deeper understanding of how learners manage their learning processes in increasingly complex and technology-mediated educational environments.

The rapid expansion of digital learning environments has generated increasing interest in the study of SRL within technology-mediated contexts. In particular, learning management systems (LMS), virtual learning platforms, and artificial intelligence-based educational tools have significantly transformed teaching and learning dynamics in HE. These technologies not only expand access to educational resources but also reshape the ways in which students interact with knowledge and regulate their learning processes (Gambo & Shakir, 2021).

In digital learning environments, SRL becomes even more critical because students must independently decide how to structure their study schedules, select appropriate learning resources, and monitor their academic progress. Several studies have shown that success in online learning environments strongly depends on students' ability to develop effective self-regulation strategies, particularly in terms of planning, time management, and metacognitive monitoring (Xu et al., 2022). Without these skills, students may struggle to maintain motivation and successfully complete academic tasks.

The integration of emerging technologies such as artificial intelligence and adaptive learning systems has

also created new opportunities to support the development of self-regulated learning skills. Recent research suggests that AI-based educational tools can provide personalized feedback and adaptive learning support that enhances students' metacognitive strategies (Lan & Zhou, 2025). Consequently, digital technologies are no longer merely platforms for content delivery but also function as intelligent systems capable of supporting reflective and autonomous learning processes. This is a complete new frame to introduce the idea of *thickness* through blending/hybrid strategies.

THICKNESS TO GIVE EPISTEMOLOGICAL DIMENSION TO BLENDING/HYBRID STRATEGIES

The anthropological idea of thickness does not come from statistical and technical studies, nor from studies on formal Education. It was developed by Clifford Geertz and strongly help to found interpretative anthropology, which had an important impact on history, sociology and, which is more important to this argument, to UX/user research. UX/user research adds context and meaning to user behaviors beyond raw data, through thickness, making it more enjoyable and suitable to learning. It emphasizes understanding from the actors' perspectives rather than imposing external theories. These ideas put the center on motivation giving design decisions, based on uncovered people thinking, feelings, and behaviors when interacting with products and services. As it is pretended also in interpretative anthropology, they become assumptions into evidences to intuitive, meaningful, and impactful outputs.

The idea of thickness, as developed by UX/user research, implies to see critically the use of statistics and mathematics in general. So, it relies on a different assumption about how culture works, which is no contradic-

tory to quantitative approaches, but reminds us the very importance on thinking qualitatively about learning as a cognitive process:

"The distinction here is an important one and goes well beyond the narrow view of qualitative as in an open-ended survey question. Rather, studies that are qualitative in nature generate data about behaviors or attitudes based on observing or hearing them directly, whereas in quantitative studies, the data about the behavior or attitudes in question are gathered indirectly, through a measurement or an instrument such as a survey or an analytics tool. In field studies and usability testing, for example, researchers directly observe how people use (or do not use) technology to meet their needs or to complete tasks. These observations give them the ability to ask questions, probe on behavior, or possibly even adjust the study protocol to better meet study objectives. Analysis of the data is usually not mathematical." (Rohrer, 2022).

In short, "thickness" in Geertz's model is about depth of interpretation, which gives not just a different technical approach to SRL, but drives us to turn raw observations into rich, culturally grounded explanations. And this what epistemological enriching about ethnographic accounts into behavior. Thick description and interpretation allow deep, overlayed explanations, rather than superficial ones, typically managed by one-way-quantitative tools:

"The concept of culture I espouse, and whose utility the essays below attempt to demonstrate, is essentially a semiotic one. Believing, with Max Weber, that man is an animal suspended in webs of significance he himself has spun, I take culture to be those webs, and the analysis of it to be therefore not an experimental science in search of law but an interpretive one in search of meaning. It is explication I am after, construing social expressions on their surface enigmatical. But this pronouncement, a doctrine in a clause, demands itself some explication.

If you want to understand what a science is, you should look in the first instance not at its theories or its findings, and certainly not at what its apologists say about it, you should look at what the practitioners of it do" (Geertz, 1973, p. 311).

The idea of matching blended/hybrid tools to enhance *thickness* in analysis is supported also by the emergence of Learning Analytics (LA). It can be defined as the collection, measurement, analysis, and interpretation of data generated by learners in digital environments with the purpose of understanding and optimizing learning processes (Heikkinen et al., 2023). This approach enables researchers and educators to analyze large volumes of educational data, including digital activity logs, interactions with learning materials, and patterns of participation in academic activities. This approach is optimal for thickness scopes because, beside the type of blended information, it can help to measure if a multilayer strategy is better by itself than single or simple systems of tools.

One of the major contributions of Learning Analytics is its ability to provide empirical insights into learning processes that were previously difficult to observe directly. Through the analysis of interaction data from digital learning platforms, researchers can identify behavioral patterns associated with different learning strategies and levels of self-regulation (de Barba et al., 2025). This analytical capability allows for a deeper understanding of how students plan, monitor, and regulate their learning activities in digital environments.

In this context, Learning Analytics is optimal to studying SRL from the thickness approach, because it enables real-time observation of learning behaviors based on data generated during academic activities. For instance, learning dashboards based on analytics can provide visual feedback regarding academic progress, allowing students to reflect on their performance and adjust their learning strategies accordingly (Saqr et al., 2023). Such tools facilitate metacognitive reflection and promote more effective self-regulated learning behaviors.

Several empirical studies have demonstrated that educational interventions based on Learning Analytics can significantly improve students' self-regulation skills. For example, experimental research indicates that feedback generated through analytics systems positively influences students' planning behaviors, time management, and monitoring of academic progress (Sun et al., 2024). These findings suggest that Learning Analytics not only enables the analysis of learning processes but also provides opportunities to actively support and improve educational outcomes.

From the thickness point of view, one of the most significant developments in this field involves the use of multimodal learning data to analyze self-regulation processes in real time. These datasets may include interaction logs from digital platforms, behavioral data from online activities, engagement metrics, and even physiological indicators associated with cognitive and emotional processes. The integration of such data sources allows researchers to develop more sophisticated models capable of capturing the dynamic nature of self-regulated learning (de Mooij et al., 2025).

METHODOLOGY

In order to measure the perception of an integrated tool, offering multiple senses to make quantitative approach to the complexity of qualitative tools, we propose a hybrid methodological approach to analyze multidimensional learning patterns in HE environments. The research involved 380 undergraduate university students from different academic programs, ensuring a heterogeneous sample suitable for multivariate educational analysis. Data were collected using a set of standardized instruments designed to measure key learning dimensions, including English proficiency, access to bibliographic resources, conceptual understanding, learning strategies, metacognitive regulation, cognitive

performance, affective engagement, and demographic variables. The analytical process integrated descriptive statistics, exploratory visual analysis (histograms and boxplots), and correlation matrices to examine distributional properties and bivariate relationships among variables. Subsequently, multivariate statistical techniques, including multiple linear regression and principal component analysis, were implemented to identify latent structures and relationships between cognitive, metacognitive, and affective dimensions.

This methodological design is supported by recent studies that highlight the importance of self-regulated learning, metacognitive awareness, and student engagement in HE, particularly in hybrid and technology-mediated learning environments (Broadbent & Poon, 2021; Li & Tsai, 2022; Greene & Azevedo, 2022; Hadwin et al., 2023). Recent empirical evidence also demonstrates that the integration of cognitive and metacognitive processes significantly improves students' academic performance and learning engagement (Jansen et al., 2023; Tauber & Ariel, 2023). Furthermore, emerging research emphasizes the role of learning analytics and artificial intelligence tools in identifying patterns of self-regulated learning, enabling more robust statistical modeling of student learning processes (Li et al., 2024; Alsaiani et al., 2025; Ge et al., 2025). In the context of hybrid and blended learning, several studies indicate that multidimensional analysis of learning behaviors provides valuable insights into the complex interactions between motivation, cognition, and metacognition (Urbina et al., 2021; Lobos et al., 2024; Nyman, 2024). Consequently, this research addresses a significant gap in HE research, namely the limited integration of cognitive, metacognitive, and contextual variables within a unified statistical framework capable of explaining learning patterns in hybrid educational environments.

Illustration 1. Multidimensional Patterns of Learning



The fact that similar problems have been treated similarly by marketing, or prediction in political science (Castro Aniyar, 2022), that is, using the source of Geertz's interpretive anthropology to resolve the diagnostic descriptions that still suffer from uni-dimensionality, or insufficient layers of meaning, demonstrates that the appreciation initiated in this manuscript seeks a transdisciplinary understanding that remains valid, or perhaps is today, in times of the dominance of statistical models, even more valid than ever.

Statistical sample

380 students were consulted, 290 males and 90 females from two types of degree programs: Technical Practical (Mechanics, Industrial Engineering, Automotive Engineering, Industrial Maintenance, Electronics and Automation, Telecommunications,

Telematics, Graphic Design, Information Technology, Software, Electricity, Agronomy, Renewable Natural Resources, Forestry Engineering, Tourism, Agribusiness, Animal Husbandry, Veterinary Medicine, Transportation Management, Gastronomy) and Theoretical-Analytical; (Physics, Statistics, Mathematics, Environmental Engineering, Biochemistry and Pharmacy, Chemical Engineering, Chemistry, Business Administration, Accounting and Auditing, Finance, Marketing, Medicine, Nutrition and Dietetics, Health Promotion). This analysis considers ages between 17 and 27.

Variable Analysis

A descriptive analysis of the relationships between the study constructs was performed using confirmatory factor analysis, in order to guarantee and establish the most significant relationships between them. To this end, the scaled transformation of the most relevant questions for each construct was included. In this case, self-perception of the English language was determined as a dependent variable, which allowed for the analysis of the factors that most influence personal knowledge and student willingness to adopt a hybrid learning method. A table was included that presents the survey questions with an abbreviated name, as detailed in Table 1. In addition, the following aspects are considered: English Proficiency, Bibliographic Resources, Connectivity, E. Learning, E. Metacognitive, E. Cognitive, E. Affective, and Demographics in Table 2, configured with the corresponding questions.

Figure1. Questions of the questionnaire

Question	ID
Timestamp	i1
Email Address	i2
Score	i3
1. Age	i4
2. Gender	i5
3. Type of residence	i6
4. Student residence status	i7
5. Higher education institution you belong to	i8
6. Type of degree program	i9
7. Level of English you are studying	i10
8. Identify three problems that cause you difficulty when reading and interpreting English text *	i11
9. Self-perception of your level of English	i12
10. Motivation for reading (English)	i13
11. Have you taken any previous courses or training in the English language?	i14
12. Have you read material in English related to academic topics for your degree subjects?	i15
13. Have you read material in English related to academic topics in your English class?	i16
14. If this type of material has NOT been included in your English class, how often would you like to do so?	i17
15. Which of the following texts do you read most often in English?	i18
16. I have a stable and fast internet connection to carry out my online learning activities.	i19
17. Access to online education improves my independent learning.	i20
18. I find online audiovisual resources crucial to my learning.	i21
19. Access to online material outside of campus allows me to structure my independent learning.	i22
20. I learn more efficiently when I can access online resources using different devices.	i23
21. I find that technological resources improve my ability to learn and understand course content.	i24
22. I learn better when course content includes graphics, diagrams, and explanatory videos.	i25
23. I retain information more effectively when listening to audio explanations or lectures.	i26
24. I prefer hands-on activities and interactive exercises that allow me to experiment with the concepts I have learned.	i27
25. I prefer course content to be presented in a logical and structured, step-by-step manner.	i28
26. I learn more effectively when I study on my own and at my own pace.	i29

27. I prefer to work in groups and discuss topics with other classmates to better understand the content.	i30
28. I ask myself questions about the text I intend to read.	i31
29. I pay attention to bold and italicized text to identify key information.	i32
30. I plan what strategies I will use when reading the text, such as highlighting or taking notes.	i33
31. I review the material briefly to know what the text will be about.	i34
32. When I finish reading, I use a checklist to see how well I understood the text.	i35
33. I manage my reading, that is, I plan the time, place, and tasks to be done.	i36
34. When I read, I decide what to read carefully and what to ignore according to what is requested.	i37
35. I take notes while reading to better understand the text.	i38
36. When the text becomes difficult, I read aloud to understand it better.	i39
37. I use reference materials (e.g., a dictionary) to understand what I read.	i40
38. I read the same text two or more times for better understanding.	i41
39. I deduce the meaning of technical words in English based on the context in which they are used	i42
40. I group technical terms or concepts in English into categories or topics to facilitate learning	i43
41. I use mental images to remember and understand the text	i44
42. I ask the teacher for help when I don't understand something in the text	i45
43. You cooperate with your classmates in a group activity	i46
44. You use relaxation or breathing techniques to reduce your anxiety	i47
45. You talk positively to yourself about your ability to read	i48
46. You take risks to practice the English language	i49
47. You control your nervousness or frustration when faced with a difficult text	i50
48. You reward yourself when you complete a task correctly	i51

Figure 2. Appearance vs. Questions

Appearance	Corresponding Question
English Proficiency	i10 (English level you are studying), i12 (Self-perception of your English level), i14 (Have you taken any previous courses or training in the English language?)
Bibliographic Resources	i15 (Have you read material in English related to academic topics for your degree subjects?), i16 (Have you read material in English related to academic topics in your English class?), i17 (How often would you like to include this type of material in your English class?), i18 (Which of the following texts do you read most frequently in English?)

Connectivity	i19 (I have a stable and fast internet connection to carry out my online learning activities), i20 (Accessibility to online education improves my independent learning), i21 (I find online audiovisual resources crucial to my learning), i22 (Access to online material outside the campus allows me to structure my independent learning), i23 (I learn more efficiently when I can access online resources using different devices)
Learning Strategies	i24 (I find that technological resources improve my ability to learn and understand course content), i25 (I learn better when course content includes graphics, diagrams, and explanatory videos), i26 (I retain information more effectively when listening to audio explanations or lectures), i27 (I prefer practical activities and interactive exercises that allow me to experiment with the concepts I have learned), i28 (I prefer course content to be presented in a logical and structured way, step by step), i29 (I learn more effectively when I study on my own and at my own pace), i30 (I prefer to work in groups and discuss topics with other classmates to better understand the content)
Metacognitive Strategies	i31 (I ask myself questions about the text I intend to read), i32 (I pay attention to bold and italicized text to identify key information), i33 (I plan what strategies I will use when reading the text, such as highlighting or taking notes), i34 (I review the material briefly to know what the text will be about), i35 (After reading, I use a checklist to see how well I understood the text), i36 (I manage my reading, that is, I plan the time, place, and tasks to be done)
Cognitive Strategies	i37 (When I read, I decide what to read carefully and what to ignore according to what is requested), i38 (I take notes while reading for a better understanding of the text), i39 (When the text becomes difficult, I read aloud to understand it better), i40 (I use reference materials (e.g., a dictionary) to understand what I read), i41 (I read the same text two or more times for better understanding), i42 (I deduce the meaning of technical words in English based on the context in which they are used), i43 (I group technical terms or concepts in English into categories or themes to facilitate learning), i44 (I use mental images to remember and understand the text)
Affective Strategies	i45 (You ask the teacher for help when you don't understand something in the text), i46 (You cooperate with your classmates in a group activity), i47 (I use relaxation or breathing techniques to reduce my anxiety), i48 (I talk positively to myself about my ability to read), i49 (I take risks to practice the English language), i50 (I control my nervousness or frustration when faced with a difficult text), i51 (You reward yourself when you complete a task correctly)
Demographics	i5 (Gender), i6 (Type of Residence), i7 (Student Residence Situation), i9 (Type of Degree), i4 (Age)

Confirmatory factor analysis (CFA)

Confirmatory factor analysis (CFA) was used to analyze and validate the relationships between the observed variables and the previously defined latent factors, which correspond to the key aspects of the study, such as "English proficiency," "bibliographic resources," "connectivity," and "learning strategies," among others. By applying CFA, we seek to confirm that the questions associated with each aspect are grouped appropriately,

which will allow us to verify the proposed theoretical structure.

The prior use of CFA is essential to reduce the dimensionality of the variables and obtain a clearer and more understandable representation of the underlying constructs. This approach will help simplify the analysis by combining highly correlated variables into latent factors, improving interpretation and reducing the complexity of the model. In addition, CFA facilitates the estimation of weights (factor loadings) that indicate the degree of relationship between each observed

variable and its corresponding latent factor. These weights are essential for understanding the relative importance of each variable in the model, allowing us to identify which questions have the greatest influence on each construct and optimizing data analysis.

Scaling by factor loadings

The process of scaling nodes from items is based on calculating a weighted measure for each latent factor, using the standardized factor loadings corresponding to each item. First, the standardized factor loadings for each latent variable are obtained, which indicate the strength and direction of the relationship between the items and the latent variables. Then, for each latent factor, the standardized factor loading of each item is multiplied by its observed value and these results are added together. This procedure provides a scalar value that represents the joint contribution of the items to the measurement of the latent factor.

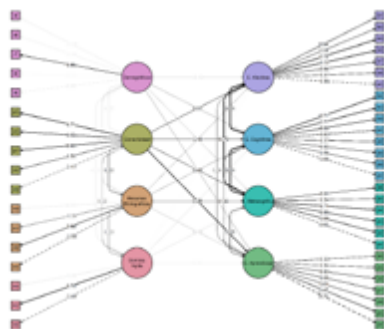
This approach allows for a more accurate representation of the latent variables, as it reflects the underlying relationships between the items and the factors that group them. In addition, obtaining these scalars opens the door to calculating other descriptive statistics, such as the mean, standard deviation, and percentiles, which increases the robustness of the analysis. These additional statistics provide a more detailed view of the distribution and variability of the scalars, which contributes to improving the interpretation and reliability of the model in general. Once the scaling was performed, an exploratory analysis of the scaled variables was carried out, where boxplots, histograms, and a correlation matrix were analyzed, and then a GLM was performed considering English proficiency as the dependent variable.

RESULTS

Confirmatory factor analysis (CFA) results

The model shows a moderate fit, with a significant chi-square ($p < 0.001$), indicating that it does not fit the data perfectly. However, the fit indices suggest a reasonable fit. The CFI (0.874 standard and 0.893 corrected) and TLI (0.862 standard and 0.884 corrected) values are slightly below the recommended threshold of 0.90. Although i19 to i23 (connect), i24 to i30 (learn_est), and i31 to i36 (meet_estcong) show consistent factor loadings. However, the items associated with the latent variable demographics (i5, i6, i7) have low or insignificant factor loadings, suggesting that they do not contribute significantly to this variable.

Figure 3. Items related to their latent variables I¹



Items i5, i6, and i7 were removed from the latent demographic variable, as they did not contribute adequately to the measurement of this variable. In addition, a new confirmatory factor analysis (CFA) was performed without these items to evaluate the structure of the model and improve the fit, obtaining:

¹ In Spanish, language of the researchers. It can be understood.

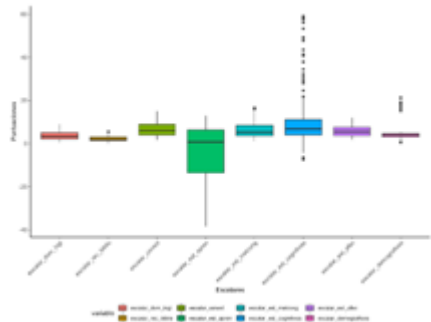
Figure 4. Items related to their latent variables II (improvement)

Results of factorial loadings scaling

This approach allows for a more accurate representation of latent variables, as it reflects the underlying relationships between items and the factors that group them.

English proficiency is relatively homogeneous in the sample, with few individual differences. This suggests a consistent average level among subjects. Likewise, the use of bibliographic resources is stable but limited. Connectivity (digital or academic) also has better scores than the two previous scales and greater heterogeneity, indicating real differences between subjects. Furthermore, this is one of the most problematic scales from a statistical point of view: high heterogeneity in learning styles. On the other hand, metacognitive strategies are relatively well developed and show controlled variability, which is consistent with self-regulated learning processes. Cognitive strategies reflect high differentiation between subjects and the presence of individuals with exceptionally high performance. Likewise, the affective component of learning is stable and consistent, suggesting good overall emotional regulation in the sample. Demographic aspects present a scale

composed of demographic variables, so low variability is to be expected.

Figure 6. Scales and marks of the variables

An exploratory descriptive analysis was conducted on eight scales associated with students' competencies, strategies, and characteristics: English proficiency, use of bibliographic resources, connectivity, learning styles, metacognitive strategies, cognitive strategies, affective strategies, and demographic variables. For each scale, the shape of the distribution, dispersion, presence of outliers, and compliance with normality assumptions were examined using frequency histograms.

The results show substantial heterogeneity in the distribution of scores, suggesting significant differences in the psychometric nature of the scales.

The English proficiency scale showed a unimodal distribution with slight positive asymmetry, with most values concentrated in the low to medium ranges. This pattern indicates a moderate overall level of linguistic competence in the sample, with few subjects scoring high. Similarly, the bibliographic resources scale showed a strong concentration in low values, with marked positive asymmetry and low variability, suggesting limited and homogeneous use of academic sources among participants.

In contrast, the connectivity scale exhibited an approximately normal distribution, with moderate dispersion and well-defined central values. This behavior suggests that the variable has adequate discriminatory power and consistent statistical performance, making it potentially suitable for inferential analysis.

The learning styles scale showed clearly atypical behavior, characterized by a multimodal distribution, strong negative asymmetry, and pronounced extreme values. This pattern suggests the possible coexistence of differentiated subgroups within the sample or problems in the construction of the index, such as the inclusion of uncompensated reverse items. From a psychometric perspective, this scale presents significant risks for direct use in parametric statistical models.

Metacognitive strategies showed a moderate positive asymmetric distribution, with a main concentration in mean values and a tail extending toward high scores. This behavior indicates that, although most students have basic levels of self-regulation, there is a subgroup with advanced metacognitive development.

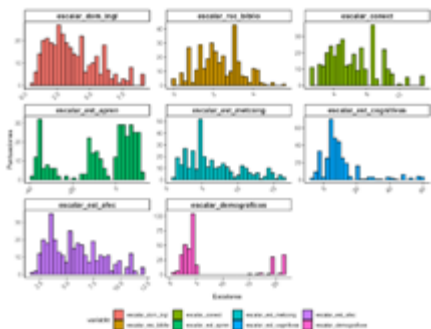
For its part, the cognitive strategies scale showed the greatest dispersion of all the variables analyzed, with extreme positive asymmetry and numerous high outliers. This pattern suggests a high degree of differentiation among participants, possibly associated with levels of expertise or unequal accumulation of complex cognitive skills.

The affective strategies scale exhibited a relatively symmetrical distribution, with controlled dispersion and no severe outliers, indicating stable statistical behavior suitable for comparative analysis. Finally, the demographic variables scale showed a distribution highly concentrated in low values, with some isolated cases of high scores, which is to be expected

given its composite and categorical nature.

Overall, the results show that most scales do not meet the assumption of normality, exhibit significant asymmetries, and, in some cases, influential outliers. These findings have direct implications for the selection of appropriate statistical techniques and analytical models.

Figure 7. Distribution of the data according to variables



Generalized Linear Model (GLM)

This graph shows the distribution and cross-relationship between the scaled aspects, revealing that there is no correlation index higher than 0.6. This allows us to determine and corroborate that the most appropriate method for describing English proficiency is the GLM.

The pair graph combines bivariate scatter plots, univariate density curves, and Pearson correlation coefficients with significance levels, allowing for the simultaneous evaluation of: Direction of the relationship, Magnitude of the effect, Linearity, Presence of outliers, Potential multicollinearity.

A bivariate correlational analysis was performed between the scales of English proficiency, use of bibliographic resources, connectivity, learning styles, metacognitive strategies, cog-

nitive strategies, affective strategies, and demographic variables, using Pearson correlation coefficients. The results were visualized using a pair graph that integrated scatter plots, density functions, and correlation coefficients with significance levels.

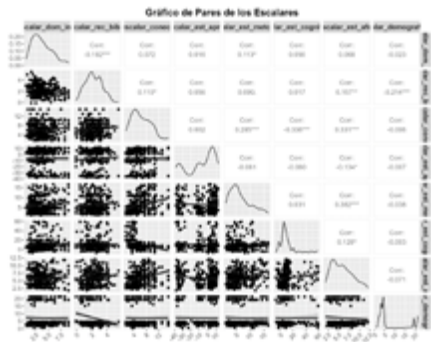
The results showed statistically significant associations, although of small to moderate magnitude. English proficiency was negatively associated with the use of bibliographic resources ($r = -.182, p < .001$) and positively associated with metacognitive strategies ($r = .113, p < .05$). Likewise, the use of bibliographic resources showed positive associations with connectivity ($r = .110, p < .05$) and affective strategies ($r = .157, p < .01$), and a negative relationship with demographic variables ($r = -.214, p < .001$).

Connectivity emerged as a central variable, showing moderate positive associations with metacognitive ($r = .285, p < .001$) and affective ($r = .331, p < .001$) strategies, and a moderate negative relationship with cognitive strategies ($r = -.338, p < .001$). This pattern suggests that access to and use of digital environments is differentially related to different types of learning strategies.

For their part, metacognitive strategies showed a significant positive association with affective strategies ($r = .382, p < .001$), evidencing a functional interrelationship between cognitive and emotional self-regulation. In contrast, the learning styles scale showed weak and barely significant correlations, which limits its explanatory power within the correlational model.

Overall, the results indicate the absence of severe multicollinearity between the variables and support the hypothesis of complex and mediated relationships between the constructs analyzed, rather than direct associations of great magnitude.

Figure 8. Scalar pair graph



The analysis performed using the Generalized Linear Model (GLM) allows us to evaluate how different variables relate to English proficiency. Several models were compared, with the “Best Model” being the one that includes the variables *rec_biblio*, *conect*, *est_metcong*, and *est_cognitivas*, which shows an AIC of 1293.28, a deviance of 959.53, and 326 degrees of residual freedom.

On the other hand, the “Worst Model” includes a greater number of variables, such as *rec_biblio*, *conect*, *est_apren*, *est_metcong*, *est_cognitivas*, *est_afec*, and *demograficos*. This model has an AIC of 1301.74, a deviance of 953.50, and 321 degrees of residual freedom, suggesting that adding more variables does not significantly improve the model fit.

Finally, the “Null Model,” which does not include any predictor variables, has an AIC of 1309.06, a deviance of 1017.33, and 328 degrees of residual freedom, indicating that the model without explanatory variables has the worst fit compared to the other models.

These results support the choice of the “Best Model” as the most appropriate for describing English proficiency, as it has the lowest AIC and a reasonably adjusted deviance, suggesting that the variables *rec_biblio*, *conect*, *est_metcong*, and *est_cognitivas* are those that best explain this domain.

Figure 9. GLM Result

Modelo	Formula	AIC	Deviance	Residual
Mejor Modelo	escalar_est_apren + esca- lar_demograficos	1293.82	959.53	326
Peor Modelo	escalar_rec_biblio + escalar_ conect + escalar_est_apren + escalar_est_metcong + escalar_est_cognitivas + es- calar_est_afec + escalar_de- mograficos	1301.74	953.50	321
Modelo Nulo	1	1309.06	1017.33	328

DISCUSSION

The statistical analysis of the multidimensional learning scales reveals relevant patterns that contribute to the contemporary understanding of learning processes in HE, particularly within hybrid and technology-mediated educational environments. The distributional analysis derived from histograms and boxplots indicates heterogeneous behavior across the evaluated dimensions, suggesting that students exhibit diverse levels of cognitive processing, metacognitive regulation, and affective engagement, related to different tools and different angles of synchronic analysis. Notably, the learning strategies dimension presents the highest variability and the presence of extreme values, which may indicate substantial differences in students' capacity to regulate their learning processes, in the multidimensional context. This pattern is consistent with current research on self-regulated learning (SRL), which suggests that hybrid learning contexts often intensify disparities in students' strategic learning behaviors due to variations in digital competence, academic preparedness, and motivational regulation (Broadbent, 2023; Greene & Azevedo, 2022; Hadwin et al., 2023). From a theoretical perspective, SRL models conceptualize learning as an iterative process involving cognitive, mo-

tivational, and behavioral regulation, which becomes particularly complex in environments where learners must assume greater autonomy over their learning processes (Panadero, 2022).

The correlation analysis further reveals meaningful relationships among the evaluated learning dimensions, highlighting the interconnected nature of cognitive and metacognitive processes in HE learning environments. The moderate positive correlation observed between conceptual knowledge and metacognitive regulation suggests that students with deeper conceptual understanding are more likely to engage in strategic monitoring, evaluation, and regulation of their cognitive processes. This finding supports recent empirical studies demonstrating that metacognitive regulation plays a mediating role between knowledge acquisition and academic performance, particularly in complex learning environments that require higher-order thinking and self-monitoring skills (Jansen et al., 2023; Tauber & Ariel, 2023). Furthermore, the positive association identified between metacognitive and affective dimensions reinforces the idea that emotional engagement and motivational factors are strongly intertwined with metacognitive control processes. Contemporary research in educational psychology highlights that students who actively regulate their cognition also demonstrate grea-

ter persistence, intrinsic motivation, and emotional investment in learning activities (Nyman, 2024; Panadero, 2022).

Another significant result emerging from the correlation matrix is the relatively weak association between contextual variables—such as bibliographic resources and demographic characteristics—and the core learning dimensions. This observation suggests that the mere availability of academic resources does not necessarily translate into meaningful cognitive engagement or the development of effective learning strategies. Recent studies examining hybrid and blended learning systems emphasize that access to digital or bibliographic resources must be complemented by instructional designs that promote active learning, reflective thinking, and collaborative knowledge construction (Urbina et al., 2021; Viberg et al., 2023). In this regard, the findings reinforce the argument that pedagogical scaffolding and metacognitive guidance are essential elements for fostering deeper learning processes within contemporary HE environments.

The presence of several outliers within the cognitive and metacognitive scales also provides valuable insights into the heterogeneity of student learning behaviors, which favors the central idea of this manuscript. In fact, these extreme observations may represent either highly autonomous learners with advanced self-regulation skills or students who experience substantial challenges in managing their learning processes. Such variability has been widely documented in learning analytics research, which demonstrates that students interacting with hybrid educational systems tend to exhibit highly differentiated learning trajectories (Li et al., 2024; Viberg et al., 2023). The identification of these patterns through multivariate statistical analysis therefore contributes to a more refined understanding of

student learning profiles and supports the development of data-informed educational interventions aimed at improving academic performance and engagement.

Overall, the results of this study reinforce the growing consensus in the international literature that learning in HE should be understood as a multidimensional construct that integrates cognitive, metacognitive, affective, and contextual components. In fact, modern educational research increasingly emphasizes the importance of analytical frameworks capable of capturing these complex interactions through advanced statistical modeling and learning analytics approaches (Ge et al., 2025; Greene & Azevedo, 2022; Viberg et al., 2023). By applying multidimensional statistical techniques, the present study demonstrates that significant relationships among learning variables can be identified, thereby providing empirical evidence that supports the design of more effective pedagogical strategies within hybrid educational environments. This goes on the same Geertz (1973) founding idea, now applied: the thick description in social sciences, related to perceive multidimensional reality of the learning process, drives itself to introduce sense and accuracy.

Finally, this research contributes to addressing a persistent gap in the recent literature concerning the empirical integration of cognitive, metacognitive, and affective dimensions within a unified analytical framework. While numerous studies examine these dimensions independently, fewer investigations adopt a holistic approach that simultaneously considers their interactions through quantitative modeling. By integrating exploratory statistical analysis with multivariate correlation techniques, the present study provides empirical support for contemporary theoretical models of self-regulated learning and highlights the importance of adopting

multidimensional analytical perspectives, like those based on thick descriptions, when investigating student learning processes in HE contexts (Hadwin et al., 2023; Panadero, 2022; Tauber & Ariel, 2023).

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