Digital cognitive tribes in classroom

Tribus digitales cognitivas en el aula

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Keywords
Student tribes; cognitive skills; technological skills

ABSTRACT

The aim of this research was to explore the possibility of conforming types of students, as well as to identify a possible relationship between the educational trajectory and the self-perception of both cognitive and technical skills. The research design was quantitative, transectional correlational. The analysis followed the structural equation model, hierarchical conglomerates and K-means, as well as a Chi-square hypothesis test. The information was collected from 191 university students, and the results showed three types of students that we called: analytical thinkers, progressing learners and technological innovators in addition to identifying a relationship between semester and cognitive skills as techniques. The studies that showed types of students based on cognitive and technical skills are rare and not very conclusive, although they focus on exploring different variables. This study was the first to address skills a priori of self-perceived cognitive and technical skills, as well as a description of the student environment based on different types for the possible application of multimodal courses, in addition to providing a key variable in high and positive self-perception: the semester.

Palabras clave
Tribus de estudiantes; habilidades cognitivas; habilidades tecnológicas

RESUMEN

Este estudio tuvo como propósito explorar la conformación de tipos de estudiantes e identificar una posible relación entre su trayectoria educativa y su percepción en cuanto al nivel de habilidades cognitivas y técnicas. El diseño de la investigación fue de tipo cuantitativo, de corte transeccional correlacional. El análisis siguió el modelo de ecuaciones estructurales, conglomerados jerárquicos y de K-means, así como una prueba de hipótesis de Chi-cuadrada. La información fue recopilada de 191 estudiantes universitarios y los resultados, además de identificar una relación entre el semestre cursado y las habilidades cognitivas y técnicas, mostraron tres tipos de estudiantes denominados: pensadores analíticos, aprendices en progreso e innovadores tecnológicos. Los estudios que evidencian tipos de estudiantes con base en habilidades cognitivas y técnicas, que se centran en explorar diferentes variables, son poco frecuentes y poco concluyentes. Para este estudio se consideró a priori las habilidades cognitivas y técnicas autopercibidas, junto con una descripción del entorno del estudiante y del semestre, una variable clave en la autopercepción alta y positiva para la posible aplicación de cursos en distintas modalidades.

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INTRODUCTION

The new habits of students based on multimedia technological tools and internet connection (for example, the use of mobile phones inside and outside the classroom), have undoubtedly led to changes, opportunities and challenges in the educational field. That is why "constant academic challenges arise about how to address (and take advantage of) the inevitable presence of ICT both in classes and during study time" (Irisarri, 2019, p. 199). Consequently, higher education institutions (HEIs) internationally have glimpsed the changes they must consider adapting to the context that awaits them in the future. These prospective analyses carried out by HEIs before the Covid-19 pandemic already contemplated a strong integration of information and communications technologies (ICT) in educational processes; however, after this global event, the need to consider changes in how to involve technology in formal training processes was accentuated. For this reason, HEIs are seeking to facilitate new knowledge and experiences using new technologies.

Analyzing the way in which university students are grouped helps to glimpse the strategies that would allow a better integration of ICT to train professionals. In response to these challenges, in recent times HEIs have made notable progress in understanding and supporting the multimodal nature of the learning process (Giannakos & Cukurova, 2023), and in contrast to the unimodal model, multimodality allows performing more advanced tasks by incorporating multiple modalities and offering complete representations of information, by taking advantage of the possibility of concentrating information from various sensory sources, which results in better performance in offering a variety of learning activities (Han *et al.,* 2023).

It is a fact that technologies by themselves do not imply changes in the ways of learning, but they do favor the generation of new learning experiences for participants in the training process. Although the advantages of the use of technologies are not in doubt, it is necessary to indicate that the incorporation of ICT poses "new challenges, which implies knowledge, skills, change of attitudes and time [...] [this] has to do with an educational model, which involves teaching-learning processes, institution, students and teachers" (Durán *et al.,* 2017, p. 84). Due to the importance of these skills, it is relevant to identify higher education students by groups to glimpse the strategies that can contribute to the construction of knowledge within the multimodal scheme.

There is renewed interest in assessing students' multimodal compositions, such as reforming educational practices, promoting multiliteracy approaches to learning, and assessing students' understanding and competence. Thus, HEIs seek to review their practices, whether their objectives are more theoretical/philosophical, are aimed at reshaping classroom practice, or focus on ways to measure understanding and development of professional competencies, which is why it is perceived a continuing shift regarding the role of multimodal composition in teaching and learning (Anderson & Kachorsky, 2019). The urgency of facing the problems of learning in the classroom through the use of universally applicable models means that teachers in the classroom have to adapt teaching-learning practices to the average student, which can be frustrating for those who do not go at an average pace, which is called by Trivedi and Pathel (2020, p. 11) as "One size fits all", referring to an educational model applied to everyone.

Although the proposal of these educational models contemplates the development of cognitive and technological skills, it is still not clear for many HEIs the differential formation that diagnoses the level of capabilities, competencies and even attitudes of the different types of students due to their individual development (García-Cepero *et al*., 2012).[1] Even the lack of uniformity in student performance is highlighted, finding an extensive variation in types of students based on diverse opinions, expectations, abilities and attitudes that some authors have distinguished as *tribes* (Gutiérrez-Martín *et al.,* 2010), so that students with the same interests and approximate levels of development in different skills collaborate in work groups to generate opportunities to develop at similar levels (Trivedi & Patel, 2020).

Studies from the last two decades recognize attempts to identify student traits according to special characteristics, which will help delimit actions and strategies of HEIs to address the special educational needs for each profile. Some research that takes various grouping variables as reference stands out; for example, in Chile, during 2012, groups of students were characterized according to six indicators of academic talent, which produced student profiles based on their cognitive and technical abilities. Among the results, those that carry out construction of the pool of students with outstanding traits, where four types of profiles are indicated:

1) Outstanding: they have higher scores in cognitive skills, academic performance, teacher and peer nomination, self-nomination, as well as perception of ability. However, they have a similar creative imagination to the under-nominees.

2) Under-nominated or invisible: they have high cognitive abilities such as creative imagination, academic performance and self-nomination. This segment stands out for its high perception of ability, but they have average performance in teacher and peer nomination.

[1] This is the case of the Universidad Autónoma de San Luis Potosí (UASLP), the institution where this study is carried out. In its University Model of Comprehensive Training (UMCT), the UASLP (2016) mentions that students must develop the technological-scientific and cognitive-entrepreneurial dimensions, among others.

3) Over-demanded: they have high scores in teacher nomination, but low scores in cognitive abilities such as creative imagination, academic performance, peer nominations, self-nomination and perception of ability.

4) Below the 50th percentile: this segment of students performed below the average of their peers, where they presented lower scores in academic performance and perception of ability (García-Cepero *et al.,* 2012).

Years later, Soler (2014) carried out another analysis of student profiles considering variables such as the intensity of dedication to study, work and attending class, academic performance and future expectations. In total there were four groups:

1) Model students: they dedicate themselves intensely to study, having a dedication regime and high compliance with their academic responsibilities.

2) Misfit students: although they dedicate themselves to studying full-time, their behavior indicates that they do not have a strong connection with their study, interpreted as a disaffection with their career.

3) Working students: they are linked to their studies with greater flexibility because they are students who, in most cases, combine their careers with part-time or full-time work activities.

4) Vocational students: they seek personal development through learning at the university, reviling the aspect of employability, and useful skills for the professional future. They establish a weak commitment to studying to which they dedicate relatively little time, although they approach their career from expressiveness.

By continuing with research that takes the level of digital skills as a variable, the study of typologies carried out by Soria *et al.* (2022) distinguishes three types of middle school students, based on their self-perception on levels of digital competencies and communication skills. The outstanding finding was that the first group with 77 students had a basic level of digital skills, while the second with 157 students showed an intermediate level and the third had 22 students with an advanced level. One of the determining factors in the difference between groups was found in the sociodemographic aspects and origin of the educational institution in which the students are enrolled.

For its part, in the review of the study made by Ríos-Sánchez *et al*. (2018) four types of students were identified based on their levels of ICT-oriented skills:

1) Active style: these profiles are characterized by having advanced skills to follow and apply instructions in tutorials, which allows them to carry out activities effectively.

2) Pragmatic style: this profile shows an ability to build the proposed activities, being able to explore different options, even showing the ability to transfer information, videos and other content between different devices, which is defined as an integrative level of skills.

3) Reflective style: this profile is developed by practicing personal skills, reflected in the final product at an innovative level and the ability to categorize the different elements used for presentations at an integrative level, as well as the ability to put into practice the construction of the activities at an exploratory level.

4) Theoretical style: these profiles usually create digital content for academic activities at an innovative level.

Finally, regarding the relationship between digital skills and engagement in virtual learning, Trivedi & Patel (2020) define five groups of students through a cluster analysis using K-means:

1) Cluster 0: students who demonstrate a poor level of digital competence and, therefore, a weak commitment in their virtual classes.

2) Cluster 1: students who have a high level of digital competence and a high degree of involvement in virtual learning.

3) Cluster 2: students with an average level of digital skills and commitment to virtual learning.

4) Cluster 3: students with poor digital skills, but still demonstrate a high commitment to virtual learning.

5) Cluster 4: students who, despite having high levels of digital competence, do not have a high commitment to their involvement in virtual learning.

However, it is considered that the previous study would have been more interesting if it had included names of the typologies due to their scores in the K-means clusters.

By following the aforementioned works, which offer evidence of different cognitive and technical traits useful to differentiate students, the following research question can be formulated: does identifying student groups formed within the HEIs allow us to glimpse aspects to consider in the development of strategies to implement the educational model with the support of ICT? Table 1 shows the literature review on student typologies, the variables involved in the characterization, as well as the name of the typologies discovered.

Table 1. Student Segment Literature Review

Authors	Typologies	Variables involved
Gutierrez-Martin *et al.* (2010)	Optimistic or pro-ICT student Pessimistic student or anti-ICT Apathetic students Neutral student	Attitudes, communication and information exchange
García-Cepero *et al.* (2012)	Outstanding students Under-nominated students Over-demanded students Average students	Talent pool consisting of intellectual ability, creativity, perception of talents, self-perception of abilities and perception of peers and teachers, as well as demographic categories: gender, age, EI, grade, parents' education and profession, and socioeconomic level
Soler (2014)	Model students Misfit students Working students Vocational students	Dedication to work and study, class attendance, work, social and communication skills, expectations of employability and personal development
Rios-Sanchez *et al.* (2018)	Active Pragmatic Reflective Theoretical	Learning approaches: 1) Active: based on direct experience 2) Reflective: consider observation and data collection 3) Theoretical: based on abstract conceptualization and drawing conclusions 4) Pragmatic: based on active experimentation and seeking practical application Each approach has three levels of performance: exploratory, integrative and innovative.
Carcelen *et al.* (2019)	Unaware/thoughtless Aware/responsible	Type of study (social and experimental sciences), HEI (public or private), the degree of self-control of the smartphone during learning time

Trivedi & Patel (2020)	Cluster 0 Cluster 1 Cluster 2 Cluster 3 Cluster 4	Commitment to virtual learning, digital skills and infrastructure for online learning
Soria *et al*. (2022)	Basic Intermediate Advanced	Levels of self-perception of digital competencies, social and geographical aspects based on the location of the EI

The use of ICT in classrooms is undeniable, in addition to the fact that its contribution to improving teaching-learning processes will depend on variables such as the characteristics of the students regarding their cognitive and technical skills. Based on the previous studies, it is worth asking: do students vary depending on their self-perception of technical and cognitive abilities? Will these differences allow students to be grouped into similar segments?

According to the analyses and variables involved in the formation of student typologies, two lines of study can be established; the first is interpreted as (1) cognitive abilities, shared by research presented in table 1 and other recent authors, such as Salinas *et al*. (2018), who, based on the school instrument, identified the cognitive skills related to learning strategies (memorization and elaboration). Among the metacognitive skills, motivation, self-confidence, self-regulation and performance expectations were identified.

The second line of study is shared by authors such as Ríos-Sánchez *et al*. (2018), who warn about the need for training that integrates (2) technologies with effective teaching strategies and a teaching intervention that facilitates the development of digital skills and their evaluation. This is carried out after analyzing the context and applying the Honey-Alonso learning styles questionnaire, adapted to the context from the version proposed by the authors Honey and Mumford in 1982. In this sense, strategies were implemented to strengthen these competencies from a digital booklet that contains various activities identified by the multivariate analysis method, which focus on learning styles and performance levels, addressing both technical and cognitive aspects.

Recent studies such as that of Aara (2023), consider study habits an integral part of cognitive skills since they significantly influence their ability to learn, understand and reason, therefore, they recommend promoting the improvement of their habits through seminars, interactive sessions and workshops, as well as providing time management skills. The recently documented focus on consumption habits as part of cognitive skills (Iqbal *et al*., 2022) can be useful to identify a level in the evaluation of their autonomy in students' multimodal learning.

On the other hand, the introduction of sociodemographic elements can help to understand the different environments and offer a contextual explanation of the skill levels of the student types sampled. However, the study of Carcelén *et al.* (2019) did not find statistically significant differences between students in the different grades, but they did in terms of disciplinary areas. It was observed that social sciences students tend to check their cell phones more frequently, while engineering and health sciences students use systems to control their use. Social sciences students use the most effective control methods, such as silencing and putting away their cell phones, while engineering or health sciences students keep their cell phones off.

The first group is classified as unaware/thoughtless and is made up of young people who are not very aware of the harm that cell phone use brings, while the second group is called aware/thoughtful, that is, young people who are more aware of the dangers that cell phones bring to academic performance. In addition to the above, students with a longer educational career may present greater cognitive skills and adaptation techniques to multimodal environments.

With the above in mind, two hypotheses are established:

H1: the dimension of the cognitive skills factor is related to the semester taken by higher level students.

H2: the dimension of the technical skills factor is related to the semester taken by higher level students.

Measuring the educational trajectory in the semester allows us to understand the sequence of experiences and academic events experienced by students throughout their educational cycle, in addition to their curricular advancement, which makes it easier to effectively capture their temporal progress through specific semester transitions during their career (Haas & Hadjar, 2020). Sepúlveda (2014) explains that the academic trajectory will be understood as a result of the curricular journey that a student goes through, taking into account the duration of the degree, the regularity of studies and graduation, which allows an understanding of the student's journey through the university.

Analyzing school trajectories can constitute a tool to support students to better navigate the curriculum (López *et al.*, 2015), in addition to paying attention to the periods of school career where the student experiences changes (Ortiz, 2015). Nonetheless, it is important to keep in mind that it may be too general to measure the student's educational trajectory considering only the duration of the degree, regularity in studies and graduation. If a comprehensive analysis of a vulnerable population or specific individuals is sought, specific cultural decision-making patterns, individual educational outcomes or vulnerable populations must be considered.

The purpose of this study is to offer a causal model on relationships based on students' self-perception of their technical and cognitive abilities between educational trajectory variables, such as the semester, and, from this, develop student typologies. Therefore, the main research questions are formulated as follows: are students different based on their self-perception of technical and cognitive skills? How would groups of students be formed according to similar characteristics? Is there a direct relationship between the level of cognitive and technological skills and the semester the student is in?

The contributions of this research are: 1) the theoretical study of a growing field of learning and teaching, such as multimodal education and its understanding from the comprehension of different typologies of students due to technological and cognitive enabling factors; and 2) empirical evidence of the semester impact on the self-perception of cognitive and technical skills, as well as the development of different student groups.

METHODOLOGY AND PROCEDURES

Before describing the methodology used, it is relevant to mention, as a reference, the concept of *multimodality* in the context and its integration into the educational model of the HEI where this study is developed. Multimodality is understood as the ability to adapt to educational modality considering the specific characteristics of content, infrastructure conditions, capacities of actors involved and other factors relevant to the training process. This approach attempts to eliminate the rigidity and predetermination that could arise from unimodality, promoting greater educational relevance, flexibility and inclusion (UASLP, 2021).

Taking into account the above, the methodology is based on a quantitative analysis with a cross-sectional approach, since in this study the data was collected at a single moment, in a specific time and with the objective of "describing variables and analyzing their behavior at a given moment" (Müggenburg-Rodríguez & Pérez-Cabrera, 2007, p. 37), and correlational in scope, since it aims to "evaluate the relationship that exists between two or more concepts, categories or variables" (Hernández-Sampieri *et al.,* 2018, p. 97). The sources and instruments for collecting information were primary, and to contrast the hypotheses it was necessary to analyze the relationships between variables, perform hypothesis tests and use the Chi-square test. The sample used corresponds to all students in the educational program of a social sciences discipline, which allows for 100% reliability in the information obtained.

It is essential to specify that the instrument used, titled students' perspective on the conditions for non-conventional modalities (Pérez *et al*., 2022), is designed to evaluate students' self-perception regarding their level of technical and cognitive skills necessary to take classes in non-conventional educational modalities. Likewise, it is important to highlight that the primary objective does not lie in establishing relationships with learning styles, but rather in collecting information to understand in greater depth the level of development of technological and cognitive competencies of students with a view to the incorporation of multimodal spaces in the educational process and identifying typologies of students in the self-perception of these skills. To achieve this, it was necessary to collect primary information through a closed questionnaire, with responses from 191 surveys, corresponding to all students of the bachelor's degree in marketing.

The items describe two dimensions: cognitive and technical. By delving into self-perceived cognitive abilities, this study focuses on aspects such as time management, dedication, self-learning and study habits; this last item, according to recent literature (Iqbal *et al*., 2021), reflects students' learning tendencies, including their ability to engage with academic tasks, their effort and persistence in studying, along with their ability to process and assimilate new information. These habits can significantly influence the way students interact with the study material provided, their ability to concentrate, and success in their academic goals; thus, when evaluating the cognitive dimension of students, the importance of including an evaluation of the self-perceived level of their study habits is taken as a background to have a complete image of their cognitive ability and their preparation for multimodal learning, while perceived technical skills are oriented towards responsibility in digital use and techniques.

The questionnaire prepared by Pérez *et al*. (2022) was replicated in Spanish, where the assessment uses five-position Likert scales: 1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree and 5 = strongly agree. To describe the students' profiles based on their cognitive and technical abilities, information on the current context of each student and their technological qualification was investigated in reference to the semester they are studying; in other words, if they have different electronic devices for classes in non-conventional modalities (tablet, desktop computer, cell phone or laptop), if they are shared with a family member or another person, time they have per day to use those devices for academic activities and the type of internet connection at home and at the university.

In addition, they were asked about the educational digital platforms that they know how to use and if they consider having knowledge and skills for exchange, storage and communication in different applications, as well as for the generation of digital materials in different formats. Additionally, the students gave information about their interest in having some classes offered in these modalities, to take classes in non-conventional modalities, they responded if they have taken courses in these modalities (apart from those offered during the pandemic) and they were asked about the performance considered when taking them, some resolutions of problems in classes, days and ideal time that favored them to take them, advantages they identify when taking these non-conventional modalities and the type of modality that they prefer. This included information about the semester they were in to partially identify the level of educational trajectory.

RELIABILITY, VALIDITY OF MEASUREMENT SCALES AND HYPOTHESIS TESTING

Results interpretation provides information to check that there are no anomalies among the data, in addition to the cumulative percentage of total variance explained, greater than 50% (68.5%). The extraction was carried out through the principal axes method with varimax rotation, which confirms the existence of two factors, one with 38.06% and the second with 30.44% of the total explained variance; this allows us to rule out the existence of a single factor or a dominant factor that represents more than 50% of the data variance, as suggested by Burga (2006).

To ensure the adequacy of sampling, as well as the possibility of factoring the data in a confirmatory analysis, the interpretation of the Kaiser-Mayer-Olkin (KMO) test was used, which was 0.880 for sampling adequacy, the Bartlett's sphericity, which indicates that the Chi-square (x2) is 884.340, with 21 degrees of freedom (df), obtaining a significance of 95% ($p = 0.000$).

The first factor represents the perceived cognitive abilities, which contribute to describing the current context and the technological enablement of the student; specifically, time management, study habits, dedication and self-perceived responsibility to take classes in non-conventional modalities. On the other hand, the second factor is defined through perceived technical skills, where self-learning, digital, and self-perceived technical skills are described to take classes in multiple modalities. Both latent variables (factors) were developed in the instrument of student perspectives on the conditions for non-conventional modalities prepared by Pérez *et al.* (2022), which was the information collection instrument.

To determine both the number of latent variables that explain the variance and covariance of the data, as well as the relationship that these variables have with respect to their errors and the fit of the model, the need arises to perform a confirmatory exploratory analysis, with the objective of giving convergent and discriminant validity to the observable and latent variables (see table 2).

Table 2. Confirmatory factor analysis results

Variable		External loads	a*	ρS **	Composite Reliability	Variance extracted
Latent	Observable					
Perceived cognitive abilities	Self-learning	0.793	0.843	0.844	0.905	0.762
	Dedication	0.865				
	Study habits	0.891				
	Time management	0.818				
Perceived technical skills	Digital	0.886	0.863	0.866	0.907	0.710
	Responsibility	0.827				
	Technical	0.903				

*α: Cronbach's alpha, **ρS: Spearman's rho

Source: own elaboration based on data using LISREL 8.7.

The fit measures show an acceptable model: $x^2 = 152.939$ ($p = 0.000$); NFI = 0.830 and RMSEA = 0.08, which is an acceptable range according to Hu and Bentler (1999). In addition, the discriminant validity of latent variables is evaluated through the root of the extracted variance, where in all cases it is greater than the correlations between constructs. Specifically, the structural diagram proposed in this article is illustrated in Figure 1.

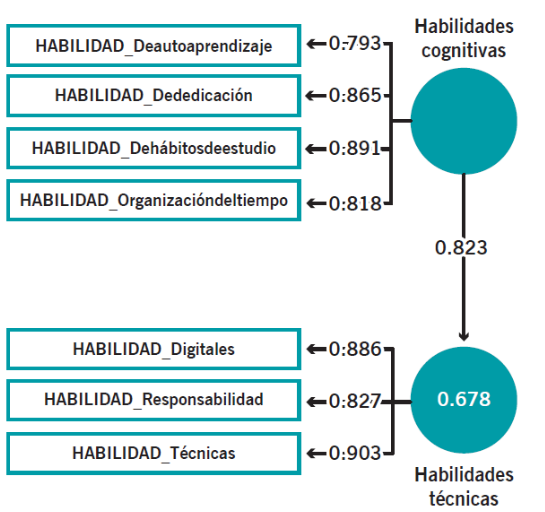

Figure 1. Structural diagram of perceived cognitive and technical skills

Source: own elaboration based on data using LISREL 8.7.

Hierarchical cluster analysis and k-means

Some authors have created groups of students based on their abilities (Gutiérrez-Martín *et al.,* 2010; García-Cepero *et al.,* 2012; Soler, 2014; Rios-Sanchez *et al.*, 2018; Carcelen *et al.,* 2019; Trivedi & Patel, 2020; Soria *et al.*, 2022), and to answer the question of this study: are students different depending on their self-perception of technical and cognitive abilities to adapt to the conditions for non-conventional modalities?, it has been decided to carry out the analysis on a first stage by hierarchical clusters, where the mean used was the squared Euclidean distance with the War clustering method. Consequently, the cluster history was observed, as well as the dendrogram, indicating the optimal point to choose the cluster. The result of the sample for the history of conglomerates obtained a convergence of 190 stages with coefficients between 0 and 7.50 distance values, so they were identified as a possible number of conglomerates between 2-3 groups that are combined from the increase in values in the coefficients. Figure 2 illustrates the difference between stages before student segments become homogeneous or heterogeneous with each other.

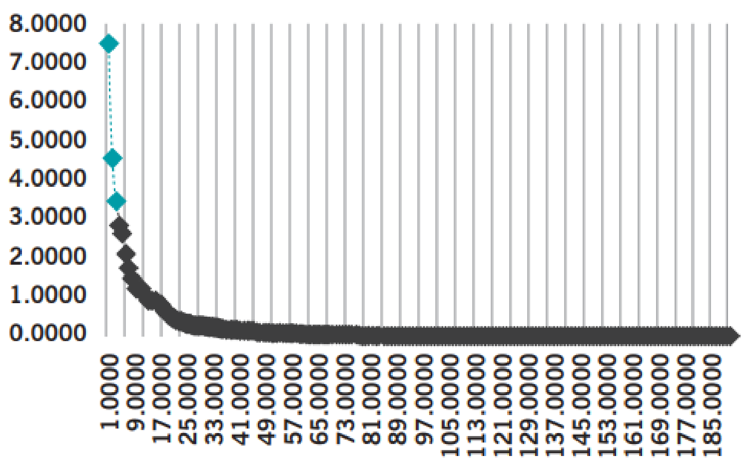

Figure 2. Cluster history results.

Source: own elaboration based on data using SPSS and Microsoft Excel.

By paying special attention to the number of ideal clusters of students, the dendrogram is considered using a final partition of three clusters [a], [b] and [c], which occurs at a similarity level of approximately 15. Now, the clusters are made up of different observations, with [a] being the one with the greatest number of observations (see Figure 3) to the extent that, if the dendrogram were cut at a higher level, there would be fewer final clusters, and if the dendrogram were cut at a lower level, the level of similarity would be higher, but a greater amount of dendrogram would be observed.

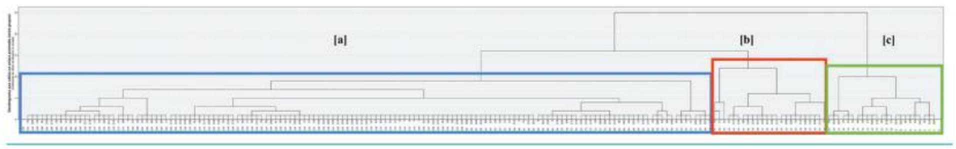

Figure 3. Dendrogram

Source: Adapted from SPSS based on results.

It is necessary to carry out the k-means clustering method by identifying three segments of students as definitive, as well as the number of clusters developed according to their level of perceived abilities, in addition to confirming the correct selection. The results indicate the degree of significance of each factor, group size and position of the final centroids that allow to reaffirm the number of selected clusters. The results of the k-means analysis show three groups, where the first has 69.63% of the total sample, the second obtains 12.57% and the third, 17.8%.

The three groups indicate stability because they exceed 20 members. The significance of the two factors, the result of the analysis of variance (ANOVA), identifies a validity of 95% ($p = 0.000$). Table 3 illustrates the results of the k-means analysis, highlighting that column F describes the variations in the weights of the factors and that cognitive skills are those that provide greater differentiation to student segments.

Table 3. ANOVA results and cluster information

Factor	Final Cluster Center			F	Sig. (95%)
	Analytical thinkers (n = 133)	Apprentices in progress (n = 24)	Technological innovators (n = 34)		
	69.63%	12.56%	17.80%		
Cognitive skills	0.44473	-1.3632	-0.77746	137.95	0.000
Technical skills	0.00327	-1.5100	1.05309	135.611	0.000

Source: own elaboration based on the results using SPSS.

RESULTS

The identification of the types of students was achieved according to the self-perceived levels of cognitive and technical skills, and with the intention of providing a more in-depth description of each group, the profile includes information about the current context, technological enablement, and interest in taking classes in non-conventional modalities.

To answer the research question, it was necessary to distinguish the groups of students by names; this aims to demonstrate aspects of perceived abilities that were emphasized from the scores in the final cluster centers.

In the first profile, students show moderately positive cognitive skills, that is, they perceive themselves as having moderate time management, study habits, dedication and responsibility to take classes in non-conventional modalities, but also with low, although positive, technical skills. It is likely that this group of students perceive themselves as having self-learning, digital and technical skills, to develop classes other than face-to-face ones. This description is called *analytical thinkers*.

In the second profile, students perceive themselves as having negative cognitive and technical skills, that is, they do not consider that they have time management, study habits, dedication or responsibility, nor do they perceive themselves as having self-learning, digital or technical skills to take classes in non-conventional modalities. This group is called *apprentices in progress*.

Finally, in the third profile, students do not perceive themselves as having cognitive skills; it is likely that they do not have time management, study habits, dedication and responsibility to take classes in non-conventional modalities, but they do perceive themselves as having high technical skills. Because of this, they are considered to have self-learning, digital and technical skills, so they are named *technological innovators*.

In Figure 4, a grouped dispersion is made based on factors where the three clusters of students are highlighted in different colors (blue: analytical thinkers, red: apprentices in progress and green: technological innovators), as well as their score on each factor.

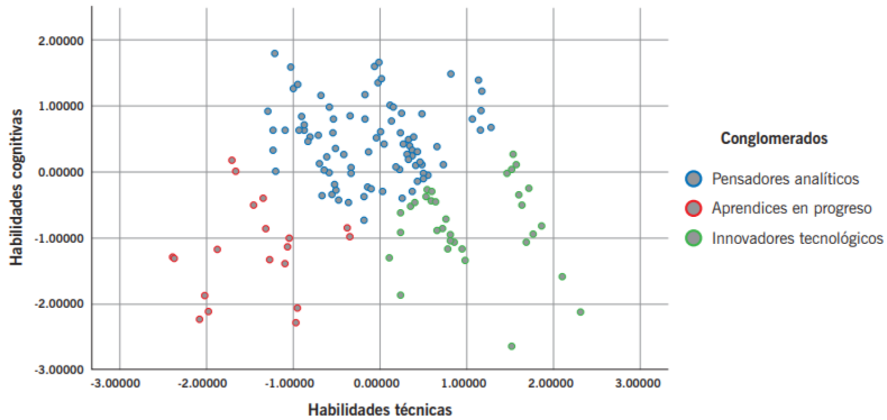

Figure 4. Grouped dispersion of cognitive and technical skills

Source: own elaboration in SPSS based on the data.

Characterization of each group of students

Profile 1. Analytical thinkers

This is the consumer segment with the largest number of students (69.63%) of the total sample; They are concentrated in the first (37.6%), fifth (27.1%) and seventh semester (25.6%). They have electronic devices, mainly cell phones (96.2%) and laptops (87.2%) and, for the most part (56.4%), they do not share these devices. This segment has no restriction on the time they use on electronic devices to carry out academic activities (42.9%), while the internet connection they use to connect to classes at home is Wi-Fi (92.5%) and in their faculty it is through mobile data (64.7%).

The main educational platforms that they know how to use are Moodle (64.7%) and Google Classroom (89.5%), and they have skills and knowledge for the exchange and communication of information, especially through WhatsApp (98.5%), email (95.5%), social media (92.5%) and storage applications, such as Google Drive (67.7%) and OneDrive (60.2%). This profile of students is perceived as having the knowledge and skills to generate digital materials in text (84.2%), audiovisual (69.2%), audio (67.7%) and graphic (57.1%) formats.

Analytical thinkers have not taken courses in unconventional modalities and consider themselves good (51.1%) at performing in courses or classes in unconventional modalities. It is important to emphasize that this profile might be interested in taking some courses that could be offered in different modalities in addition to face-to-face classes (41.4%) and in the morning (75.2%). If they were interested, and did not have an electronic device, it was identified that they would solve it by borrowing computer equipment (31.6%) or purchasing it (28.6%).

Profile 2. Apprentices in progress

The second profile is the group of students with the smallest number of students (12.57%) of the total sample, most of whom are in the first (45.8%) and fifth semester (25%). All students in this segment have a cell phone and the majority have a laptop (79.2%), which in some cases they do not share with their family or with another person (54.2%). Unlike the previous segment, apprentices in progress have a diversified restriction in the availability of daily electronic devices for academic activities, between three and five hours (29.2%) and six to nine hours (25%). Only 37.5% have a Wi-Fi connection at home, while 62.5% connect through mobile data at school.

The platform that they have used the most, and are aware of, is Google Classroom (87.5%), in addition to perceiving themselves as having skills and knowledge for storing information in applications such as Google Drive (50%). Additionally, they perceive themselves as having skills and knowledge for communication and exchange of information through email (91.7%), WhatsApp (87.5%) and social media (79.2%). Likewise, they perceive themselves as having skills and knowledge to generate digital materials in text (83.3%), video (79.2%), audio (70.8%) and graphic (66.7%) formats.

Apprentices in progress have not taken courses in any modality other than face-to-face (75%), and they consider their performance to be good (33%) and average (25%) in courses with non-conventional modalities. To a lesser extent than the segment of analytical thinkers, apprentices in progress also thought that they might be willing to take subjects that were offered in non-face-to-face or mixed modalities (37.5%), and if interested they would opt for a morning schedule (79.2%). However, if there was a problem with having an electronic device, 33.3% would resolve it by going to a university information center (for example, the library).

Profile 3. Technological innovators

This profile has 17.8% of the students in the total sample; they are concentrated in seventh (32.4%), third (26.5%) and fifth semester (26.5%). Most of them have cell phones (97.1%) and laptops (79.4%) as electronic devices for classes in non-conventional modalities. In 70.6% of cases, they do not share these devices with any member of their family and only 32.4% have no time restriction to use them in classes, homework and academic activities. Their main source of internet connection at home is Wi-Fi (88.2%), while at school it is through mobile data (44.1%).

The main platforms they know how to use are Google Classroom (97.1%) and Moodle (70.6%), in addition to perceiving themselves as having knowledge and skills for communication and information exchange through email (100%), social media (94.1%), WhatsApp (94.1%) and

Telegram (55.9%), while in skills and knowledge for data storage, Google Drive (85.3%) and OneDrive (76.5%) stand out. Students in this profile can develop digital materials in text (85.3%), video (76.5%), audio (73.5%) and graphic (61.8%) formats.

A large part of the technological innovators have not taken courses in non-conventional modalities (79.4%), but they consider themselves to have performed well in taking some subjects in this type of modalities (52.9%). This type of student would be interested in taking classes offered in modalities other than face-to-face in the morning (55.9%), and if there are problems due to not having electronic devices, 35.3% would solve it by borrowing computer equipment.

Hypothesis testing

After the cluster analysis to identify the possible existence of types of students, the next step is to respond to the proposed hypotheses. Table 4 shows a strong positive association between the cognitive skills factor and the semester taken by higher education students, where a significance of 0.043 is obtained for H1, on whether there is an association between the cognitive skills factor and the semester, that is, whether there is a relationship between the factor and the semester. This association is 87.3% according to the result of the contingency coefficient, the above is interpreted with the consideration that if students take more semesters, their cognitive abilities increase.

Table 4. Results of associations between variables and factors

Hypothesis: relationships	The contingency coefficient C	Result
H_1 Cognitive skills --> semester	0.873**	Accepted
H_2 Technical skills --> semester	0.873**	Accepted

* $p < 0.05$.

Source: own elaboration based on data using SPSS.

Additionally, H2 results in a positive relationship between the technical skills factor and the semester, that is, in this association of 87.3%, according to the result of the contingency coefficient, the incidence of the semester is high, which can be interpreted that as students complete a higher semester, their technical skills increase, which allows to identify that in their first semesters they have less technical qualification.

DISCUSSION

The objective of the study was to know the existence of different students according to their self-perception on technical and cognitive skills to adapt to the conditions of non-conventional modalities and to analyze the role of the educational trajectory (semester taken) in cognitive and technical skills. Consequently, two hypotheses were proposed that relate cognitive and technical skills to the semester in a positive way, and a question that highlights the levels of self-perception of these skills and descriptive elements of the current context and the technological enablement of the students.

The findings are particularly surprising because no previous research addresses self-perceived technological and cognitive enablement for students' possible adaptation to unconventional environments. Generally, in the application of multimodal environments, the adaptation of the environment is carried out and the enablement is not diagnosed as *a priori* but after the application. As Trivedi and Patel (2020) warn, it is more efficient to develop several versions of training and procedures considering the diverse interests of each type of student, restricting suggestions without losing the ability to personalize groups based on similarities in characteristics.

The characterization of analytical thinkers, apprentices in progress, and technological innovators demonstrates that there are different behaviors of young people at self-perceived levels of cognitive abilities. Two of the three clusters do not feel skilled, and, in the same proportion, they feel between medium and highly capable in the skills. It is possible to relate the above with the studies of Soria *et al.* (2022), Carcelen *et al.* (2019) and Soler (2014), where it is noted that not all students have similar behaviors, highlighting that although they are all HEI students, they are so in different ways.

A greater self-assessment of abilities in relation to the degree they study was considered in a significant way, that is, the higher the semester, the greater the self-perceived abilities will be. In the case of the study of Carcelén *et al.* (2019), this conditions the use of tools such as the smartphone in their learning process, similar to the three clusters that have part or full time of electronic devices to incorporate them into face-to-face classes or mixed modalities, although not all time for some clusters, it is for the majority.

Among the limitations of the study is that it was developed in Mexico, particularly in a context of university students in a socio-administrative educational program. Likewise, the research design uses a cross-sectional sample of students, which limits the study to a specific time frame, making it impossible to generalize the results to times and places other than the one established. Similarly, the availability of the data allows to analyze the educational trajectories in the semesters reported by the students, making it a partial scheme especially for analyzing the academic results of the educational trajectory in broader educational dynamics and time horizons, given the impossibility of following the students over a long period of time.

CONCLUSION

It is necessary to recognize that there are other imperative variables to be examined independently of self-perception, for example, academic performance, skills, participation and engagement in virtual learning. These variables should be investigated during and after the development of multimodal environments in future research. It should also be noted that the relationship between the semester and cognitive and technical skills does not mean causality, so it would be relevant to study the possible explanation of the semester as a mediating or causal variable of the different levels of skills, both cognitive and technical, and exploring variables such as gender, place of origin and other educational programs other than socio-administrative, as well as personality traits that explain in depth the self-assessment of skills for the adaptation of courses in non-conventional modalities.

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