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Proposal for the Analysis of the State of Learning in University Students with the Inclusion of ICT in the Classroom

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Abstract: The inclusion of information and communication technologies in education has become a priority for all universities. To meet this need, there are several research works that have dealt with the subject for several decades. However, for its inclusion, the analysis of each institution is necessary since the needs of the university population and the resources for its application change according to each situation. This work seeks to create a method that allows establishing the needs and doubts of students about the use of educational technologies in the classroom without affecting their performance. For this, a process has been designed that identifies learning needs, through the validation of data obtained from surveys and the monitoring of the academic efficiency and learning of a cohort of students. The follow-up includes a period of four years from 2019 to 2022. This follow-up allowed establishing three different realities, in 2019 the academic data was analyzed in a face-to-face education model, from 2020 to 2021 the follow-up was included in a remote model with the use of technologies as a communication channel and in 2022 these were included as a learning component, which marked an in-depth analysis of student performance and how technology affected their learning.

Keywords: analysis of data; e-learning; ICT in the classroom



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1. Introduction

Currently, universities have seen the need to update their educational models and offer the population a student-centered education. This update is mainly due to the experiences left by the pandemic caused by the Coronavirus disease 2019 (COVID 19) [1]. During the pandemic, the different governments established long quarantines and isolation to avoid a higher rate of contagion [2,3]. Therefore, during isolation, universities adopted information and communication technologies (ICT) as a channel to continue their academic activities [4]. Even though universities have presented a high percentage of integration with ICT since before the pandemic, this has not been enough to guarantee learning with its application in the classroom. The best example is online education, having academic models with a high index in the use of ICT, since they base their development on methods and techniques based on ICT to generate knowledge. However, this educational model is among those with a higher percentage of student dropout [5,6].

Based on these experiences, universities consider the use of ICT in an integral way throughout the academic process, which includes a commitment from the technological, administrative, academic, and student areas for its proper functioning. Several reviewed works consider that the integration of ICT in the classroom should generate an enriching experience for students where learning is guaranteed with the use of techniques and tools aligned to the new challenges of society. These works identify the variables that affect learning and limit its proper development in certain sectors of society [7,8]. At the university level, they establish that the new needs of students are not contemplated in a

traditional study model, where learning focuses on the teacher and it is he or she who establishes the learning method, what to learn and how the students should do it.

To identify the needs of students, a group of works has focused on data collection through surveys related to factors such as the academic environment, the economy, the psychological environment, etc. These works seek to obtain the greatest amount of information from the students and subject the data to analysis which allows them to establish which are the factors that have the most incidence in the development of learning [9]. Generally, in these works the identification of the degree of incidence of the factors is carried out by applying statistical models, such as factor analysis. Factor analysis, even though it is a basic statistical model, is widely used due to its effectiveness and the amount of information it generates in a survey. One of its main characteristics is that by means of the Kaiser, Meyer, and Olkin (KMO) calculations and Bartlett's sphericity test, it is possible to identify if the factorial model is adequate and define the validity of the survey to respond to the phenomenon of study [10]. In addition, in the reduction of dimensions it is possible to identify the degree of incidence of each question in the discovery of the feelings of the surveyed population [11].

Another group of works focuses on discovering the needs of the students through the analysis of data on the students' qualifications. To do so, they make use of business intelligence (BI) architectures with the application of data mining algorithms or Big data architectures [12]. Among the main advantages of the application of these architectures is that they can identify patterns in the data and generate knowledge about them [13,14]. In addition, these architectures can extract data from a wide variety of sources and manage large volumes of data. By identifying existing patterns in the data, these can be classified to determine the state of student learning and the impact that each academic activity has on their performance. Data analysis architectures are more robust and can solve various problems of an institution. However, for their applications, it is necessary to have greater economic, technological, and technical resources.

The reviewed works seek to resolve the identification of needs quickly, in such a way that their results contribute to decision-making effectively and efficiently. The methods developed in these works allow identification of the current needs of the students [15,16]. In addition, it is important to consider that after the pandemic and isolation the needs of students have changed. A common example of this is that the pandemic critically affected the economy of several households, which has affected the continuity of the studies of several people or limited the resources available for their learning. Another important factor to establish is the existing motivation by students to use ICT in education [17]. By having this information, universities can establish models of active education, where ICT is considered in the classroom to improve student learning in an interactive environment with technologies [18].

This work took as a source the methods used in the revised works and proposes a data analysis architecture that allow identification of the new needs of students after the pandemic, and, for which purposes, we worked with instruments such as surveys that allowed us to establish the problems and concerns of students in the use of ICT in the classroom [19]. With this information, a data extraction process was applied from the academic sources of the students to later be processed and analyzed through data mining algorithm techniques. The main objective of the analysis was the data of the activities developed in the first quarter of the period 2019 to 2022. These data corresponded to students of a private University in Ecuador and referred to the first part of an educational model where ICTs were applied in the classroom. The results allow the gradual integration of ICT in all university careers and facets and transform its traditional educational model into a model that is aligned with active learning.

2. Materials and Methods

The proposed method for the analysis of academic data was composed of several stages to create a scalable process that allowed constant evaluation and feedback. In Figure 1, the

flowchart that follows the proposed method is presented. This consisted of two phases: the first was responsible for the evaluation of the validity of surveys and the second phase was responsible for the analysis of educational data that allowed identification of the level of learning in each group of students.

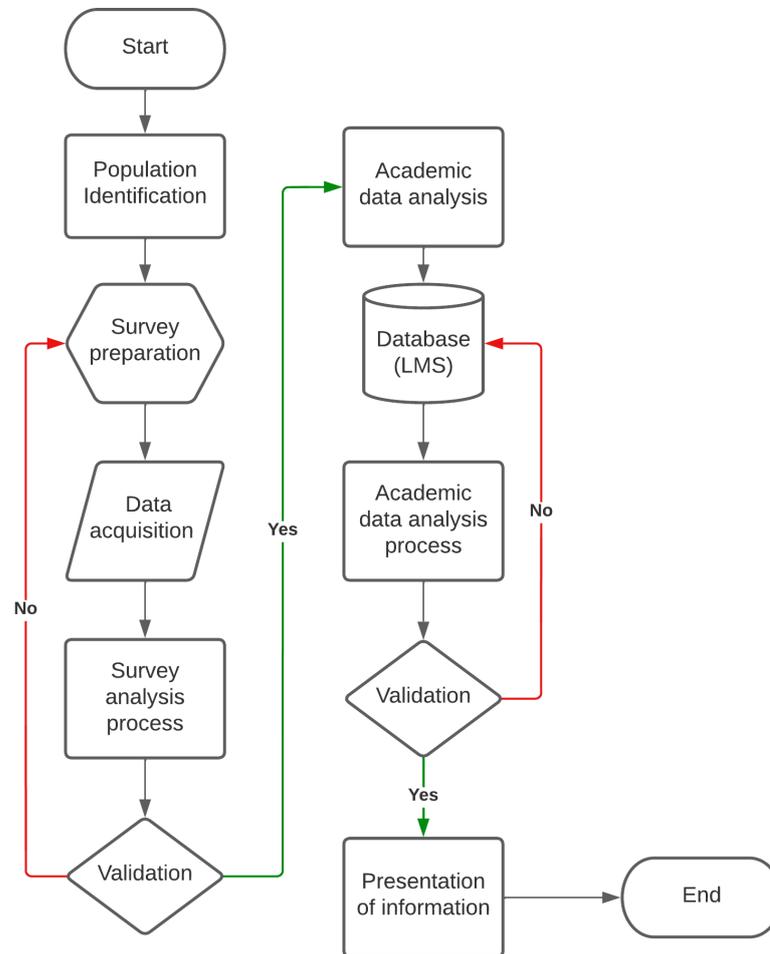


Figure 1. Flowchart for the creation of a survey validation method and data analysis.

2.1. Population Identification

The first phase of the method was responsible for the validation of surveys. The use of these instruments aimed to determine what the feeling of the students was regarding the use of ICT in the classroom [20]. To meet this requirement, it was necessary to comply with an initial step, which focused on identifying the study population. The identification of the population in a survey is very important to determine the statistical reasoning group. The method used to select respondents is known as sampling, where specific groups are identified to draw conclusions and make decisions based on their results.

For this work, it was considered necessary to select a study population that was truly representative of the entire population [21]. The target population had to be identified and agreed upon by the areas involved in academic and technological pursuits, since, by integrating their knowledge about the students, it was possible to guarantee the results and largely eliminate any feedback that was considered useless for the study. Defining the most significant population made it possible to build a real image of the target sector using the trends of the results. To determine the most significant population, equation 1 was used:

$$n = \frac{N * Z^2 * p * q}{e^2 * (N - 1) + Z^2 * p * q} \tag{1}$$

where:

- N = Population size
- Z = Confidence level (statistical parameter)
- p = Percentage of the population that had the desired attribute
- q = Percentage of the population that did not have the desired attribute
- e = Maximum accepted estimation error

2.2. Survey Preparation

According to the conceptualization of surveys, they are useful to know the attitudes, values, motivations, predispositions, and possible behaviors of many people. Therefore, the instrument is fully valid for the acquisition of data from the most significant population, where the objective is to identify the attitude and predisposition of students towards the use of ICT in the classroom. Once the objective of the survey has been established and with the identification of the sample, its design is passed [22]. To create the structure of the survey, it is important to select the questions to be asked considering the information that you want to obtain. In addition, the information provided on the survey is important, so, therefore, the objective of the research should be included in an initial section.

The next section should include general questions to elicit information from the respondent. This information is important to segment the groups and create a database that allows identifying the population to generate follow-ups and projections of each student group. Generally, the respondents' information is expected to contain their name, age, marital status, educational level, socioeconomic level, etc. This information may vary depending on the purpose of the study or the data available at the university [23,24] the section of questions, these can be open or closed. Open questions give the respondent the option to answer in their own words. In closed questions, the respondent must choose between some of the established answer options. Closed questions have the advantage of being quickly collected and analyzed compared to open questions. Due to its nature, closed questions were used in this work, even in the answer options numerical values were assigned for data analysis. For example, the type of questions that were included in the survey are presented below. In the answers, the values that these represent for the analysis are placed in parentheses. All the questions presented five response options.

- How often do you use information technology in your education?
 - a. Never (1), A few times a day (2), A few times a week (3), Often (4), Every day (5)
- Which of the following activities do you enjoy the most with information technology?
 - a. Entertainment (1), Social media (2), Browsing (3), Education (4), Research (5)

2.3. Data Acquisition

The acquisition of data depends on the tools used for the survey. In several studies this collection is done by physical means, which includes there being a digitization process [25]. In this work, the survey was carried out using technological resources and an online tool, for example, Google Forms or the institution's own tools. Surveys could be included in the learning management system (LMS), which improves data collection and allows surveys to be targeted to target groups.

The extraction of the collected data depends on the tool used, which will generally be found in .xlms or .csv files. If the survey is developed as part of the LMS, the data is accessed from the database, or the download option must be found in the files. To obtain adequate data quality, it is necessary that all questions require a mandatory answer [20]. Configuring the survey in this way does not allow responses to be skipped, which means it is not necessary to create an extensive cleanup and transformation phase. Table 1 presents an example of the type of data obtained from the survey.

Table 1. Example of responses obtained in a traditional survey.

Id	Question 1	Question 2	Question 3	Question 4	Question 5	Question 6
1	40–50	Very difficult	Bass	Never	Any	False information
2	20–30	Very difficult	Medium	Ever	Little	exposure
3	40–50	Easy	Bass	Always	Something	Exposition
4	50–60	Hard	High	Never	Something	Risk
5	50–60	Hard	Medium	Ever	Any	False information

2.4. Survey Analysis Process

The data analysis phase seeks to evaluate the effectiveness of the survey, for which it is necessary to analyze the incidence of each variable in the study phenomenon. The proposed method uses factor analysis for survey validation. This widely used statistical analysis identifies the underlying variables or factors that explain the correlation configuration in a set of observed variables. Factor analysis has as its primary objective to analyze the correlation between a series of variables to discover structures that are not directly observable. The analysis seeks a reduction of the information provided by “p” observed variables with the least loss of information possible.

As main components of the factorial analysis to determine the validity of the survey, we used the correlation matrix. This matrix presents the Pearson correlation values that measure the degree of linear relationship between each pair of variables. Correlation values can be between -1 and +1. However, in practice, the items usually have positive correlations. If the two elements tend to increase or decrease at the same time, the correlation value is positive. In the interpretation of the correlation matrix, the strength and direction of the relationship between two elements or variables is evaluated [26]. A high and positive correlation value indicates that the items measure the same skill or characteristic. Table 2 presents an example of the correlation matrix, where all the elements are highly correlated with each other. Item 1 and Item 2 have a positive linear correlation of 0.903. Item 1 and Item 3 have a positive linear correlation of 0.867, while Item 2 and Item 3 have a positive linear correlation of 0.864. Therefore, these items appear to measure the same characteristic.

Table 2. Example of a correlation matrix with three items and their correspondence values.

		Item 1	Item 2
Correlation	Item 2	0.903	
	Item 3	0.867	0.864

To assess the goodness of fit or adequacy of the data analyzed to a factorial model, two statistics are necessary, namely, the KMO sample adequacy measure and the Bartlett sphericity test. The KMO is an index that compares the magnitude of the observed correlation coefficients with the magnitude of the partial correlation coefficients. Bartlett’s sphericity test tests the null hypothesis that the observed correlation matrix is an identity matrix. If the data comes from a multivariate normal distribution, the Bartlett statistic is approximately distributed according to the chi-square probability model and is a transformation of the determinant of the correlation matrix. If the critical level (Sig.) is greater than 0.05, the null hypothesis of sphericity cannot be rejected and, consequently, it is not possible to ensure that the factorial model is adequate to explain the data. Table 3 presents an example of the values of KMO and Bartlett’s test. KMO establishes the ranges of the coefficients as a significant set, where it is found that, the closer to 1 the value obtained from the KMO test is implies that the relationship between the variables is high. If $KMO \geq 0.9$, the test is very good; notable for $KMO \geq 0.8$; the median for $KMO \geq 0.7$; low for $KMO \geq 0.6$; and very low for $KMO < 0.5$.

Table 3. Example of KMO and Bartlett values to verify partial correlations between variables.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.751
Bartlett’s Test of Sphericity	Approx. Chi-Square	2148.251
	Df	19
	Sig.	0.000

The next component is the total calculation of the explained variance. Table 4 presents an example with values to detail its interpretation. In the analysis of the total percentage of explained variance, it is expected that the minimum accumulated total of the survey explains at least 50% of the phenomenon in some of the components [27]. The example meets this condition, since the variables included in the analysis explain the phenomenon in two components, and the accumulated percentage reaches 56,450%. Therefore, with the results obtained, it is decisive that the instrument can explain the phenomenon.

Table 4. Example of percentage of explained variance.

Component	Initial Eigenvalues			Extraction Sums of Squared Loading		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulate %
1	1.067	36.670	36.670	1.067	36.670	26.670
2	0.998	54.450	51.624	1.987	56.450	56.450
3	0.990	51.757	76.380			
4	0.945	52.360	100.000			

Extraction Method: Principal Component Analysis.

With the results obtained from the analysis, it is possible to determine if the survey responds to the phenomenon under study. If the value of the total calculation of the explained variance is less than 50%, the process performs feedback and goes back to the survey preparation phase. At this stage, the incidence values of the instrument must be identified, and the questions must be reconsidered to be more objective and clarify the answers without any ambiguity. In the opposite case, if the survey can explain the phenomenon under study, the process goes to the next stage.

2.5. Academic Data Analysis

The analysis of academic data has two important factors to consider, the first is the sources that are included in the analysis and the second factor is the type of analysis to be carried out [28]. Data sources can vary and depend on how the information is structured within the organization. For example, several institutions have academic and financial systems, and, in addition to these sources, the analysis can consider the educational platforms available to the university [29,30]. As platforms, the use of LMS stands out, as well as external platforms that can be serious games, interactive rewards applications, etc.

The proposed method, due to the nature of the data and the type of sources, focused on extracting data from the LMS. The LMS available to the institution participating in this study centralized the data, which allowed managing a single repository. Once the source and the data were acquired, the type of analysis applied to the data was defined [31]. The type of analysis depends on the information that is required, in robust infrastructures that use analysis models, such as BI or Big data, a new instance must be created that covers the analysis of academic data. The use of these architectures is conditioned by the volume of data to be analyzed. With this consideration, the use of Big data architecture was not adequate since it is not common for universities to have such large volumes of data that they require the use of Big data [32]. The opposite occurs with a BI. This architecture is adaptable to the needs of educational institutions and several of them already have this type of architecture. If this is the case, it is necessary to create a new flow for uploading data to a new Data mart. The advantage of using a multidimensional basis is the use of online analytical processing (OLAP) tools. By generating OLAP cubes it is possible to obtain information about the object of study in a fast and simplified way [33].

In addition to these possibilities, there is another smaller scenario, where the application of techniques such as data mining is applied directly to the data. These scenarios are common when required to respond to a phenomenon that is not redundant. For example, if the analysis requires identifying the use of ICT in the use of a procurement process, this is done on a single occasion. In this case, it was not recommended to use a BI or Big data process, since its implementation requires a lot of resources and since it is not a repetitive process, and the costs do not represent the benefits to be obtained. In this case, it was necessary to propose a personalized model that met the needs of the phenomenon and that guarantees the results. This process could be carried out by means of educational data mining (MDE) techniques and algorithms. The MDE explores the academic databases and improves the segmentation of the student population according to the patterns that they present in their academic performance. By analyzing the relationships between parameters, such as age, gender, qualifications, etc., it is possible to guess their behavior and generate personalized educational plans that reduce problems, such as desertion and poor academic quality.

2.6. Academic Data Analysis Process and Presentation of the Information

In the analysis process phase, the data obtained from the record of qualifications stored in the available academic sources is included, which depends on each university. In general, it is advisable to take the data from the LMSs that have their own grade books. By using this data source, it is possible to identify the performance of the students for each activity, and, in addition, it is necessary to include the data corresponding to the assessment of learning [34,35]. Generally, this assessment corresponds to integrative activities and does not require a numerical rating. This means that the integrative activity can include categories such as insufficient, fair, good, and very good. When creating the categories, students must develop the activity considering several criteria that correspond to a rubric. For example, a rubric can include criteria such as innovation, approaches, methodologies, problem solving, etc. The data obtained in learning are contrasted with factors such as academic efficiency, this being the factor that is considered for the approval of a partial or a course that the student takes [36]. Academic effectiveness does not necessarily mean that the student learned a subject. On the contrary, other factors may be involved that require a more granular analysis. If the questions raised are not addressed with data analysis the process returns to the database stage to integrate new sources until they answer the research questions, generating a feedback loop. For the presentation of the information, the use of tools such as Power BI, Tableau, Excel, etc. is considered. With the use of these tools, it is possible to transmit the knowledge acquired in the data analysis graphically. Control boards, dashboards and pivot tables allow information to be presented clearly and concisely for effective decision-making.

3. Results

For the presentation of results, the method was applied in a case study to determine the feeling of the students regarding the use of ICT in their learning environment. To do so, a survey was designed, and the results were analyzed to determine the validity of the instrument and the incidence value of each question in relation to the study phenomenon. The results obtained on the experience and use of technological resources identified the acceptance and motivation present in the students before the migration from a traditional educational model to an educational model integrated by ICT. In the second stage of the case study, the analysis of the educational data of a faculty that had integrated ICT as a main component in learning was conducted and the results reflected as part of an educational model aligned to active learning was carried out.

3.1. Population Identification

The population was defined by the university that participated in this study; this university is part of higher education in Ecuador. The university is private, which means

that the financing is entirely its own and does not depend on the state. In universities with their own financing, they have the advantage that the application of projects and studies, such as the one developed, do not go through extremely bureaucratic processes, which facilitates their execution. The segmentation of the population considered the total university population of 9400 students and 1500 people teachers and administrative staff. This total population was divided into five faculties, which consisted of several careers offered in person to students. Most careers are made up of eight academic terms, each lasting 16 weeks. The university had considered updating its educational model and methods to include ICT in an environment aligned with active learning. For this reason, a prototype plan had been implemented where a faculty participated with all its careers. The faculty was from the area of administrative sciences and consisted of 5 careers where the number of students was 2800 students, which represented 30% of the total population. This faculty, like the entire university in the pandemic, was forced to continue its academic activities remotely. Therefore, the students had already had some experience in using platforms such as LMS, video conferencing, etc.

For the first stage of the analysis, where the identification of students' feelings towards ICT in education was proposed, the entire population was considered. However, to validate the survey, there needed to be a minimum number of responses. To determine the minimum number of answers, the calculation of the most representative population with equation 1 exposed in the method was used. The values to work with were:

N: 2800

Z: 1.960

P: 50.00%

Q: 50.00%

E: 3.00%

As a result, the sample size was 772.85, and, therefore, the minimum number of respondents was 773 students. With this value, the survey could be considered valid, and the results obtained would represent the sentiments of the total population.

3.2. Survey Preparation

For the preparation of the survey, the researchers generally aligned all the questions with a dimension or study variable. For example, if you want to capture people's trends in the use of public transport, the questions must be objectively and clearly aligned to this topic. There are surveys that seek to solve two dimensions, for example, the use of public transport and citizen security. These surveys must be carried out very precisely, since, when developing the questions, they lose objectivity or can confuse the respondents by generating false information. For the development of this case, we worked with a single dimension, which was the use of ICT in education and the questions that were presented to the students were based on this. The guideline to be followed in the design was that a maximum of ten multiple-choice questions be on the topic and a maximum of three general questions provided basic information about the respondent.

Next, three general questions were presented for the identification of the population. These questions could contain answer types Yes/No or multiple choice:

Gender

- a. Man/Woman

Career

- a. Business Administration; Agribusiness; Economy; Business intelligence management; Marketing

Age

- a. Less than 20; 20-25]; 25-30; 30-35; over 35

For the acquisition of information of the study dimension, the following questions were presented:

The Internet has become a tool that allows access to an infinity of information. How often do you use the Internet appropriately for your learning?

- a. Never; Any occasion; Once a week; Regularly; Forever

In what percentage do you consider the influence of ICT favorable in your learning?

- a. 0%; between 20% and 40%; between 40% and 60%; between 60% and 80%; between 80% and 100%

What is the mastery of skills you have in handling ICT?

- a. Null; Superficial; Enough; Okay; Excellent

Do you consider that the use of ICT in class is:

- a. It is an alternative that does not necessarily influence learning; It is a fashion given the technological age in which we live; It is an alternative support tool for teaching; It is an important resource to improve teaching; It is a determining factor in student learning.

Indicate which of the following activities you carry out with the information you obtain with the use of ICT?

- a. Listen; Understand; Extract information; Contrast information; Check information

Which of the following options do you consider to be a problem with the use of information technology in education?

- a. Availability of equipment and materials; Distractions; Motivation; Time optimization; Specialist teachers

Which of the following activities do you enjoy the most with information technology?

- a. Entertainment; Communication; Social networks; Education; Research

Which of the following options do you consider to be a problem with the use of information technology in education?

- a. Decrease in manual skills; Isolation; Information reliability; Inappropriate content; Exposure of personal data

How effective has the learning been with the education tools?

- a. It has not been effective; Slightly effective; Moderately effective; Highly effective

How do you consider doing homework digitally?

- a. Very difficult; Hard; Moderate; Easy; Very easy

Once the survey had been designed with the corresponding questions, it was necessary to identify the execution method. Due to the characteristics and infrastructure available in the university that participated in the study, the implementation was carried out directly in the LMS. This enabled only the faculty of administrative sciences. The student entered the LMS, and it generated a validation. If the student took the survey, they were redirected to the main classroom page. If the student did not take the survey, it redirected him or her to the survey to press for answers. The time for the survey to be developed was a period of seven days.

3.3. Data Acquisition

After executing the survey, 2260 surveys were obtained, surpassing the most representative population that, according to the calculation, was established at 773 people. By applying the survey through the LMS, the redundancy of responses from a single user was avoided, which improved the quality of the data obtained. The data obtained from the surveys were text-type answers, just as proposed in its design. The data to be analyzed had to be transformed into numerical values. Table 5 presents a summary of the results obtained. To maintain the format of the document, only 25 records and six columns have been added.

The complete sources are available in the journal repository. Similarly, the headings have been replaced by letters that represent the questions, for example, Q1 = Gender; Q2 = race, etc., and the ID column only presents the identifier of the records obtained, it does not refer to data that needs to be analyzed.

Table 5. Sample of the data obtained from the survey carried out on 2260 students, 6 columns of 14 are maintained to maintain the format of the table.

Id	Question 1	Question 2	Question 3	Question 4	Question 5
1	Men	Business Administration	Between, 20–25	Forever	between 60% and 80%
2	Woman	Economy	Between, 20–25	Never	between 60% and 80%
3	Woman	Marketing	Between, 20–25	Any occasion	between 60% and 80%
4	Men	Business intelligence management	Between, 25–30	Once a week	between 40% and 60%
5	Woman	Economy	Between, 25–30	Never	between 80% and 100%
6	Woman	Marketing	over 35	Regularly	between 40% and 60%
7	Men	Marketing	Between, 25–30	Once a week	between 20% and 40%
8	Woman	Business Administration	Between, 25–30	Forever	between 80% and 100%
9	Woman	Marketing	Between, 20–25	Once a week	between 60% and 80%
10	Woman	Business Administration	Between, 30–35	Any occasion	between 40% and 60%
11	Men	Business intelligence management	over 35	Any occasion	between 80% and 100%
12	Men	agribusiness	over 35	Forever	between 80% and 100%
13	Men	Business intelligence management	Between, 20–25	Regularly	between 60% and 80%
14	Woman	Business intelligence management	over 35	Never	between 60% and 80%
15	Men	Economy	over 35	Once a week	between 40% and 60%
16	Men	Marketing	Between, 30–35	Never	between 20% and 40%
17	Men	agribusiness	Between, 30–35	Regularly	between 40% and 60%
18	Woman	Marketing	Between, 20–25	Forever	between 60% and 80%
19	Woman	Business intelligence management	Between, 25–30	Never	between 20% and 40%
20	Men	Economy	Between, 20–25	Never	between 80% and 100%
21	Men	Business Administration	Between, 30–35	Never	between 20% and 40%
22	Men	Business intelligence management	Between, 20–25	Any occasion	between 40% and 60%
23	Men	agribusiness	Between, 30–35	Regularly	between 60% and 80%
24	Men	Business intelligence management	Between, 25–30	Any occasion	between 20% and 40%
25	Men	Marketing	Between, 20–25	Regularly	between 60% and 80%

Table 6 shows the transformation of the data to be analyzed. The replacement of values was considered maintaining a scale from 1 to 5; these values were configured depending on the degree of importance established in the design. This replacement was done in the order in which the possible answers appeared in the preparation section of the survey. For example, in question two the answer options and their equivalents were:

- Business Administration (1)
- Agribusiness (2)
- Economy (3)
- Business intelligence management (4)
- Marketing (5)

This transformation was carried out in all the questions, except in question one (gender). This question did not enter the analysis. However, it was used to determine important information once the validity of the survey was established. In the table, the first 25 records were considered and, due to the format, they include the 13 questions.

Table 6. Sample of the transformed data from the survey of 2260 students, with 14 columns.

Id.	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13
1	1	1	2	5	4	5	3	5	3	4	1	2	1
2	2	3	2	1	4	4	4	3	5	4	5	3	2
3	2	5	2	2	4	5	2	2	2	3	1	2	3
4	1	4	3	3	3	5	4	5	5	2	5	5	2
5	2	3	3	1	5	1	5	4	4	3	4	4	3
6	2	5	5	4	3	5	4	5	3	4	1	3	5
7	1	5	3	3	2	3	3	3	2	2	5	1	4
8	2	1	3	5	5	3	5	4	5	3	1	5	1
9	2	5	2	3	4	1	2	5	5	3	3	2	3
10	2	1	4	2	3	2	3	4	2	3	4	4	1
11	1	4	5	2	5	3	5	4	3	4	5	5	3
12	1	2	5	5	5	1	3	3	3	2	1	5	3
13	1	4	2	4	4	3	5	5	4	5	2	2	3
14	2	4	5	1	4	4	5	4	4	5	3	3	3
15	1	3	5	3	3	5	3	3	3	2	3	1	4
16	1	5	4	1	2	3	4	2	3	4	2	1	5
17	1	2	4	4	3	4	2	5	5	4	2	1	3
18	2	5	2	5	4	3	3	2	2	2	4	1	1
19	2	4	3	1	2	1	5	4	2	2	2	4	1
20	1	3	2	1	5	2	4	5	5	2	5	4	1
21	1	1	4	1	2	4	3	4	3	5	3	2	3
22	1	4	2	2	3	5	4	2	5	4	4	2	5
23	1	2	4	4	4	5	3	2	5	4	4	4	5
24	1	4	3	2	2	2	4	4	2	4	4	3	4
25	1	5	2	4	4	3	3	2	2	5	2	4	5

3.4. Survey Analysis Process

The validation analysis of the survey was carried out using SPSS, where the reduction of dimensions was applied through the factor. To determine the validity of the survey as an instrument, the analysis focused on the KMO matrix and Bartlett’s test. The results obtained from Table 7 determined that the KMO value was very low. However, the sphericity test indicated that, if Sig. (*p*-value) < 0.05, we accepted H0 (null hypothesis), and, therefore, factor analysis could be applied.

Table 7. KMO values to determine the validity of the survey.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.500
Bartlett’s Test of Sphericity	Approx. Chi-Square	92.281
	df	55
	Sig.	0.001

The following analysis was the one generated in the anti-image matrix of Table 8 that calculated the covariance and correlation to define the relationship between the questions of the survey. When reviewing the diagonals of the covariance, it was expected that the values would be close to 1. In the calculation of the correlation the values of the diagonal must be as close as possible to the resulting KMO, which was 0.5. This condition was met in most of the questions and those that did not reach this value, such as Q4, Q5, Q10 and Q11, were kept under observation in the analysis.

Table 8. Anti-image matrix that identifies the covariance and correlation values for each question.

		Q 4	Q 5	Q 6	Q 7	Q 8	Q 9	Q 10	Q 11	Q 12	Q 13	Q 3	
Anti-image Covariance	Q 4	0.993	0.048	−0.019	0.015	0.046	0.018	0.027	−0.023	−0.002	−0.022	−0.011	
	Q 5	0.048	0.990	−0.056	−0.001	−0.028	0.047	−0.003	−0.021	0.025	−0.015	−0.003	
	Q 6	−0.019	−0.056	0.995	0.006	0.000	−0.003	−0.014	0.001	0.016	−0.026	−0.001	
	Q 7	0.015	−0.001	0.006	0.991	−0.043	−0.039	0.006	−0.006	−0.040	−0.053	−0.002	
	Q 8	0.046	−0.028	0.000	−0.043	0.987	−0.031	0.021	−0.006	0.012	−0.011	−0.076	
	Q 9	0.018	0.047	−0.003	−0.039	−0.031	0.989	−0.040	−0.040	−0.044	0.030	0.010	
	Q 10	0.027	−0.003	−0.014	0.006	0.021	−0.040	0.996	−0.001	−0.004	−0.034	−0.009	
	Q 11	−0.023	−0.021	0.001	−0.006	−0.006	−0.040	−0.001	0.996	−0.013	0.027	−0.003	
	Q 12	−0.002	0.025	0.016	−0.040	0.012	−0.044	−0.004	−0.013	0.994	−0.024	−0.008	
	Q 13	−0.022	−0.015	−0.026	−0.053	−0.011	0.030	−0.034	0.027	−0.024	0.992	−0.005	
	Q 3	−0.011	−0.003	−0.001	−0.002	−0.076	0.010	−0.009	−0.003	−0.008	−0.005	0.994	
	Anti-image Correlation	Q 4	0.487 a	0.048	−0.019	0.015	0.047	0.018	0.027	−0.023	−0.002	−0.022	−0.011
		Q 5	0.048	0.499 a	−0.057	−0.001	−0.028	0.048	−0.003	−0.021	0.025	−0.015	−0.003
Q 6		−0.019	−0.057	0.500 a	0.006	0.000	−0.003	−0.014	0.001	0.016	−0.026	−0.001	
Q 7		0.015	−0.001	0.006	0.519 a	−0.043	−0.040	0.006	−0.006	−0.040	−0.054	−0.002	
Q 8		0.047	−0.028	0.000	−0.043	0.503 a	−0.032	0.021	−0.006	0.012	−0.011	−0.077	
Q 9		0.018	0.048	−0.003	−0.040	−0.032	0.500 a	−0.040	−0.040	−0.044	0.031	0.010	
Q 10		0.027	−0.003	−0.014	0.006	0.021	−0.040	0.475 a	−0.001	−0.004	−0.034	−0.009	
Q 11		−0.023	−0.021	0.001	−0.006	−0.006	−0.040	−0.001	0.488 a	−0.013	0.028	−0.003	
Q 12		−0.002	0.025	0.016	−0.040	0.012	−0.044	−0.004	−0.013	0.526 a	−0.024	−0.008	
Q 13		−0.022	−0.015	−0.026	−0.054	−0.011	0.031	−0.034	0.028	−0.024	0.489 a	−0.005	
Q 3		−0.011	−0.003	−0.001	−0.002	−0.077	0.010	−0.009	−0.003	−0.008	−0.005	0.493 a	

a. Measures of Sampling Adequacy (MSA).

Table 9 shows the total explained variance. According to the results obtained, the survey could respond to the study phenomenon in six components with an accumulated percentage of 58,263%. This result allowed defining that the tool was fully valid, and that the data collected could respond to the phenomenon. Therefore, it was possible to analyze the data to identify the influence of each question in relation to the problem posed.

Table 9. Calculation of the total explained variance with two components in an accumulated percentage of 58.263%.

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulate %	Total	% of Variance	Cumulate %
1	1.141	10.372	10.372	1.141	10.372	10.372	1.094	9.944	9.944
2	1.118	10.162	20.535	1.118	10.162	20.535	1.083	9.842	19.786
3	1.069	9.715	30.249	1.069	9.715	30.249	1.079	9.806	29.592
4	1.045	9.502	39.751	1.045	9.502	39.751	1.065	9.684	39.276
5	1.031	9.369	49.120	1.031	9.369	49.120	1.055	9.592	48.869
6	1.006	9.143	58.263	1.006	9.143	58.263	1.033	9.394	58.263
7	0.967	8.788	67.051						
8	0.955	8.686	75.736						
9	0.907	8.250	83.986						
10	0.888	8.072	92.058						
11	0.874	7.942	100.000						

Extraction Method: Principal Component Analysis.

To identify the degree of influence of each question, the matrix of rotated components was generated. Table 10 presents the results obtained from the analysis, where it was expected that there would be only one dimension, since all the questions evaluated a single phenomenon. The generated matrix was composed of six components or factors, where it was observed that only one had three questions, (Q7, Q12 and Q13). For a factor to be given as valid, it had to influence at least three questions, so, in this case, we had other dimensions that did not meet this condition. To improve the existing relationship, the questions that uniquely fed the different factors could be separated.

Table 10. Matrix of rotated components to obtain values for each question and their incidence in 6 components.

	Component					
	1	2	3	4	5	6
Q7	0.701					
Q12	0.527					
Q13	0.485			−0.463		
Q5		0.682				
Q6		0.644				
Q3			0.797			
Q8			0.655			
Q11				0.724		
Q9				0.544		0.343
Q4					0.825	
Q10						0.868

Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization.

In Table 11, the results are presented separating five questions. These were Q2, Q4, Q8, Q10 and Q13. When separating them from the analysis, two factors with greater incidence were obtained, where the questions that had the greatest influence re:

Factor 1 = ICT in the classroom

Q7: Do you consider that the use of ICT in class is:

Q9: Which of the following options do you consider to be a problem with the use of information technology in education?

Q11: Which of the following options do you consider to be a problem with the use of information technologies in education?

Q12: How effective has the learning been with the education tools?

Factor 2 = skills in the use of ICT

Q3: Age

Q5: In what percentage do you consider that the influence of ICT is favorable in your learning?

Q6: What is the domain of skills you have in handling ICT

The questions that have been separated from the analysis have less influence according to the feelings of the students, therefore, these questions should focus on defining a specific factor, such as, for example, development of activities with ICT. Factor analysis allows these relationships to be established and the questions of each survey to be improved to determine the needs of the target population.

Table 11. Matrix of rotated components excluding the questions with less incidence in responding to the phenomenon under study.

	Component	
	1	2
Q9	0.644	
Q12	0.501	
Q7	0.462	
Q11	0.433	
Q3		0.695
Q5		0.684
Q6		0.652

Extraction Method: Principal Component Analysis, Rotation Method: Varimax with Kaiser Normalization.

For this work, the survey was considered adequate as an instrument for data acquisition and the raw results could be presented and related in each sector identified in the survey. For example, the survey was undertaken by 2260 students, of which 953 people were men and there were 1307 women. Table 12 shows the breakdown of students by

major and by gender. In addition, the age ranges of the students are included. These data correspond to the general questions and in this way, it was possible to establish what the feeling of the students regarding the integration of ICT in their education was.

Table 12. Table with general data of the surveyed population, with segmentation by age, gender, and career to which they belong.

Old Students	Business Administration	Agribusiness	Economy	Business Intelligence Management	Marketing	Total
Men	183	189	192	210	179	953
under 20	13	15	14	16	11	69
Between, 20–25	44	41	42	43	35	205
Between, 25–30	36	40	38	58	49	221
Between, 30–35	45	49	60	43	42	239
Over 35	45	44	38	50	42	219
Woman	265	242	253	300	247	1307
under 20	24	17	18	16	9	84
Between, 20–25	64	50	72	73	58	317
Between, 25–30	57	58	66	72	63	316
Between, 30–35	61	47	60	64	63	295
Over 35	59	70	37	75	54	295
Total	448	431	445	510	426	2260

The advantage of the survey results is that they can be presented by question and segmented by age or gender, and everything depends on the objective outlined in the study. The information that was considered relevant in this work corresponded to the questions identified with the greatest influence in the study. With this review, Table 13 presents the results of question 12. The results were not as expected, considering that in 2020 and 2021 ICT was used as a channel to continue education. Therefore, the expected results focused on greater acceptance in the use of ICT. However, if the answers were slightly or moderately then it had not been effective. 929 respondents did not yet accept ICT in education. These results will be contrasted with the analysis of academic data in the following sections.

Q12 = How effective has learning been with ICT in education?

Table 13. Sentiment identified in a survey on the use of ICT in education.

How Effective Has Learning Been with ICT in Education?	Number of Students per Answer
Effective	504
Slightly effective	510
Moderately affective	506
Highly effective	527
It has not been effective	213
Total	2260

3.5. Academic Data Analysis

For the analysis of academic data, the data generated from the students of the 2019 cohort was taken. This segmentation aimed to establish a stage where the students did not use ICT and focused on a purely traditional model, and this period was 2019. The second cut of data had, as a reference, the use of ICT during the pandemic (2020–2021) and finally the data for the period 2022 was added. In this period the university that participated

in this study used ICT with an active learning perspective. In all the periods the data corresponding to the first partial were selected. The university manages the academic period in two partials, each one composed of seven weeks, plus one of evaluation. During the seven weeks, students must develop one activity in class and one autonomously per session; that is, there are 14 activities evaluated, a cumulative evaluation and an integrative work. The integrative work aims to measure the level of learning, this activity is not evaluated through a traditional qualification. This is evaluated by means of indicators, insufficient, regular, good, and very good, even when the teacher adds a grade out of 10, this, to the academic system, is transformed into the criteria. The integrative activity does not influence the passing grade of the course, it focuses on identifying learning.

The axis evaluated belongs to complementary subjects, for example, office automation, databases, digital tools, etc. In the 2019 cohort, 75 students entered, the follow-up was carried out in the first period of each year, and, therefore, there were 56 activities evaluated by each student corresponding to the periods 2019–2022 and four integrating projects. The activities were evaluated on 10 points. The minimum grade for approval was 6/10 and this was the reference with which the data was analyzed. In addition, the weights of the activities in the corresponding partial had the following distribution:

- Class activities = 25%
- Autonomous activities = 35%
- Evaluation = 40%
- Integrative project = 0%

With the exposed weights, the average is calculated that allows establishing the approval of a course and the integrating project measures the level of learning with which it passes to the next level.

3.6. Information Analysis and Presentation Process

The analysis process seeks to identify the learning level of each group of students. To do so, the average of the activities in the classroom, the average of the activities at home, the partial evaluation, etc. are considered. Table 14 presents the results obtained in 2019. In the first column, the evaluation of learning is presented with the four criteria (insufficient, regular, good, very good). Within each learning category, the range of pass or fail is included, in the second column the number of students is counted for each record evaluated.

Table 14. Analysis of the data obtained from the 2019 period with the establishment of the categories of learning and academic effectiveness.

Learning/Efficiency	Total	Average Activities in Class	Average Autonomous Activities	Average Evaluation	Average Academic Effectiveness
Insufficient	14	5.7	6.2	6.1	6.0
Approve	8	5.7	6.1	8.0	6.7
Fail	6	5.6	6.5	3.7	5.1
Regular	21	5.7	6.1	6.2	6.0
Approve	13	5.9	6.4	7.6	6.8
Fail	8	5.5	5.5	3.9	4.9
Good	18	5.6	6.1	6.8	6.2
Approve	11	5.8	6.7	7.6	6.8
Fail	7	5.4	5.3	5.4	5.3
Very good	22	5.6	5.8	7.0	6.3
Approve	14	6.0	6.4	8.2	7.0
Fail	8	5.1	4.8	5.0	4.9
Total	75	5.7	6.0	6.6	6.1

As mentioned in previous sections, the evaluation period corresponded to the first partial. This condition is important because, even when the results obtained appear in the

condition of passing or failing, this is not necessarily maintained until the end, since the average of the second part has not been evaluated. Therefore, it was found that 46 students passed the midterm by obtaining an effective average grade equal to or greater than 6/10. An unexpected result was that the grades were the factor that determined the approval of a partial and later the approval of a subject. However, this did not imply that the student necessarily learnt a subject. As shown by the results, where, of the 14 students who had reflected insufficient learning, eight passed the midterm with an average grade of 6.7 and only 6 students failed the midterm. All categories had students who passed and failed, with the total number of failed students being 29. When reviewing the very good learning status, it was found that 8 students failed even though their learning level was the highest. The total average of the group in its effectiveness was 6.1, a value that, according to previous analyses and the experience of the academic quality departments, is a normal value in partial 1 in a residential model.

In Figure 2 the data of the previous table is presented graphically. In this it is clearly observed that the categories with the highest incidence in learning were regular with 13 students and very good with 14 students. One of the factors that most influenced student performance was evaluation; this activity was not averaged with another activity and the weight given by the university was 40%. In-class and autonomous activities, in addition to having a lower weight (25% and 35% respectively), were the average of 7 activities in each category.

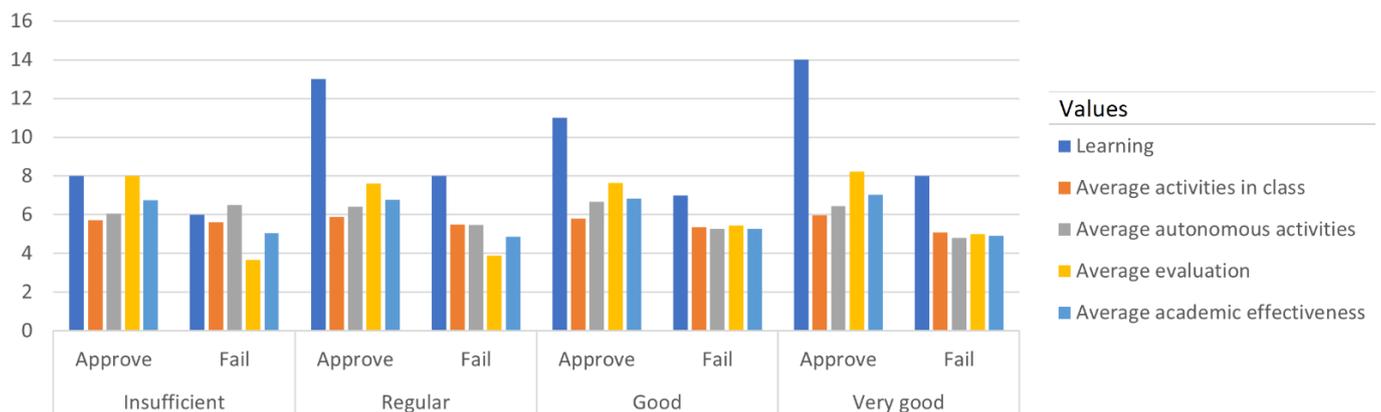


Figure 2. Graph of the trend analysis for the 2019 period.

In Table 15, the total values of the averages of the activities and the total number of students who passed the first part are presented, being the 36 approved and 39 students failed students. This number of students in the failed category rose to 52%, which represented a high value compared to the 2019 period. The average effectiveness dropped two points, standing at 5.9, and the activities that it involved lost between 2 and 4 points. On the other hand, among the expected results, it was found that the number of students who presented a learning between sufficient and regular was 38, of which 20 failed the partial 1. A figure contrary to what happened in the previous year.

Table 15. Analysis of the data obtained from the 2020 period with the establishment of the categories of learning and academic effectiveness.

Learning/Efficiency	Total	Average Activities in Class	Average Autonomous Activities	Average Evaluation	Average Academic Effectiveness
Insufficient	19	5.4	5.8	5.5	5.6
Approve	8	6.8	6.5	7.9	7.1
Fail	11	4.4	5.2	3.7	4.4
Regular	19	5.9	5.9	6.4	6.1
Approve	10	6.3	6.0	8.2	7.0
Fail	9	5.5	5.8	4.4	5.2
Good	21	5.4	5.8	6.3	5.9
Approve	9	5.9	6.2	7.7	6.7
Fail	12	5.0	5.4	5.3	5.2
Very good	16	5.5	5.2	6.6	5.8
Approve	9	5.5	5.4	8.8	6.8
Fail	7	5.4	5.0	3.9	4.6
Total	75	5.5	5.7	6.2	5.9

In Figure 3, the data of the students in the year 2020 is presented. It was in this period that the pandemic began, and the educational modality went from face-to-face to remote. The first striking feature in the figure is that learning decreased drastically. Only the category having regular and very good levels of learning exceeded the number of approved students. In the analysis it was also found that there was a certain relationship between the activities developed in class with the autonomous ones and evaluation remained the factor with the greatest weight in academic effectiveness.

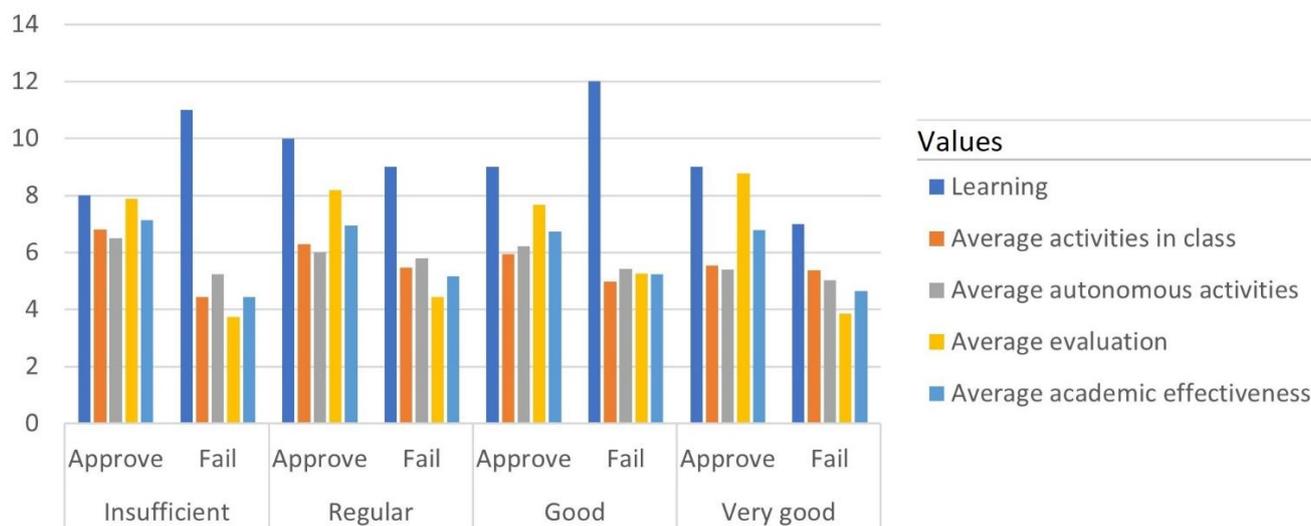


Figure 3. Graph of the trend analysis for the 2020 period.

In Table 16, the information corresponding to 2021 is presented. In the results it was identified that there were 29 students with an insufficient and regular level of learning. In this period remote communication was maintained. However, the universities began to modify the educational model, focusing it on the needs of students with an adequate use of ICT. In the same way, the number of failed this year began to decrease with 24 students, which was especially important because the activities in class and autonomous activities had improved the average. Therefore, the students in this period found these activities to be important for the highest score, which improved academic effectiveness. In this period, an unexpected result was obtained in the evaluation average, which was higher in the 2020 period, which opens the possibility of generating an analysis model that determines the causes of this change.

Table 16. Analysis of the data obtained from the 2021 period with the establishment of the categories of learning and academic effectiveness.

Learning/Efficiency	Total	Average Activities in Class	Average Autonomous Activities	Average Evaluation	Average Academic Effectiveness
Insufficient	15	6.4	6.5	5.2	6.0
Approve	8	6.7	6.7	7.6	7.1
Fail	7	6.1	6.4	2.4	4.7
Regular	14	6.7	6.8	5.1	6.1
Approve	9	6.8	7.0	6.6	6.8
Fail	5	6.4	6.6	2.6	4.9
Good	25	6.8	6.8	6.6	6.7
Approve	18	6.9	7.0	7.8	7.3
Fail	7	6.8	6.2	3.4	5.2
Very good	21	7.3	7.4	6.1	6.9
Approve	16	7.4	7.6	7.1	7.4
Fail	5	7.0	6.5	3.2	5.3
Total	75	6.9	6.9	5.9	6.5

Figure 4 graphically presents the results found in the 2021 period. In the good and very good learning category, learning was high, and the evaluation punished students who failed. Another important factor to highlight in the results is that there was a certain relationship between classroom and autonomous activities in all learning categories.

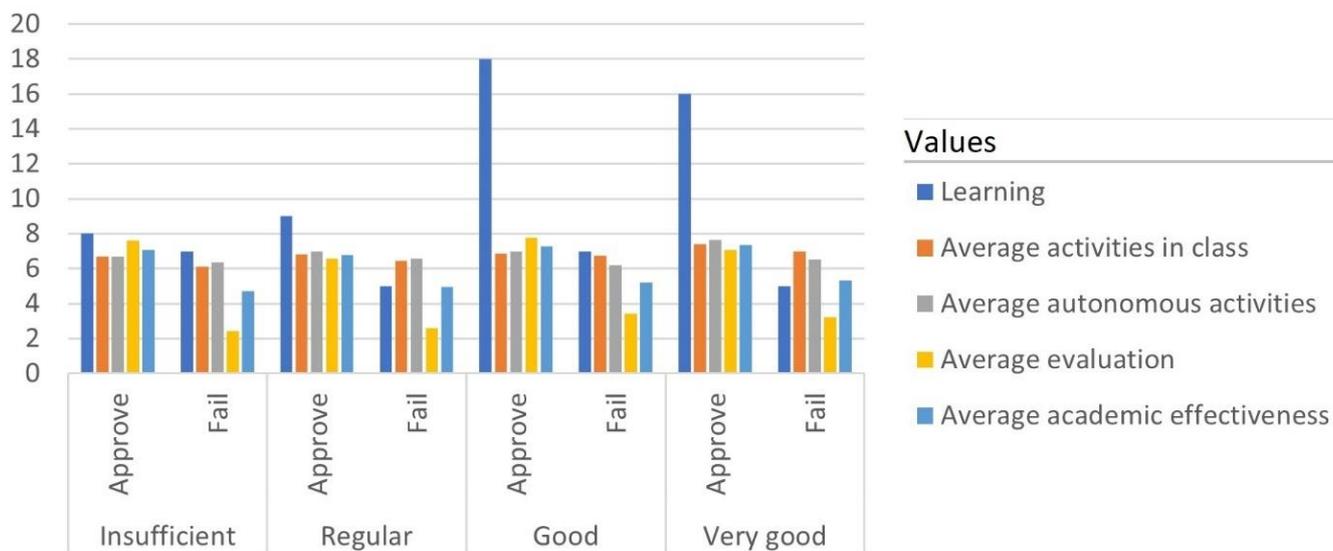


Figure 4. Graph of the trend analysis for the 2021 period.

Table 17 presents the results for the 2022 period, in which the universities returned to attendance. The university that participated in this study in this period integrated ICT directly into its educational model. The activities that they developed in classroom environments and autonomously were the main ones in which ICTs were integrated. According to the results in this period, 63 students passed and 12 failed. The general average of each component was higher than that of the previous periods. In addition, 23 students were categorized with insufficient and regular learning.

Table 17. Analysis of the data obtained from the 2022 period with the establishment of the categories of learning and academic effectiveness.

Learning/Efficiency	Total	Average Activities in Class	Average Autonomous Activities	Average Evaluation	Average Academic Effectiveness
Insufficient	8	7.8	7.6	5.0	6.6
Approve	6	7.8	7.9	5.7	7.0
Fail	2	7.9	7.0	3.0	5.6
Regular	15	7.2	7.1	6.1	6.7
Approve	10	7.4	7.3	7.0	7.2
Fail	5	6.9	6.6	4.4	5.8
Good	22	7.9	7.9	6.9	7.5
Approve	21	7.9	7.9	7.0	7.6
Fail	1	7.4	6.7	4.0	5.8
Very good	30	7.9	7.9	7.1	7.6
Approve	26	8.0	8.0	7.6	7.8
Fail	4	7.0	6.9	3.8	5.7
Total	75	7.8	7.7	6.6	7.3

Figure 5 presents the results for the 2022 period, in which it was observed that the growth trend in learning that began in the previous period was accentuated in the current one. In the very good learning category, there were 26 students, something that had not been seen even in the 2019 period, where a face-to-face model was implemented.

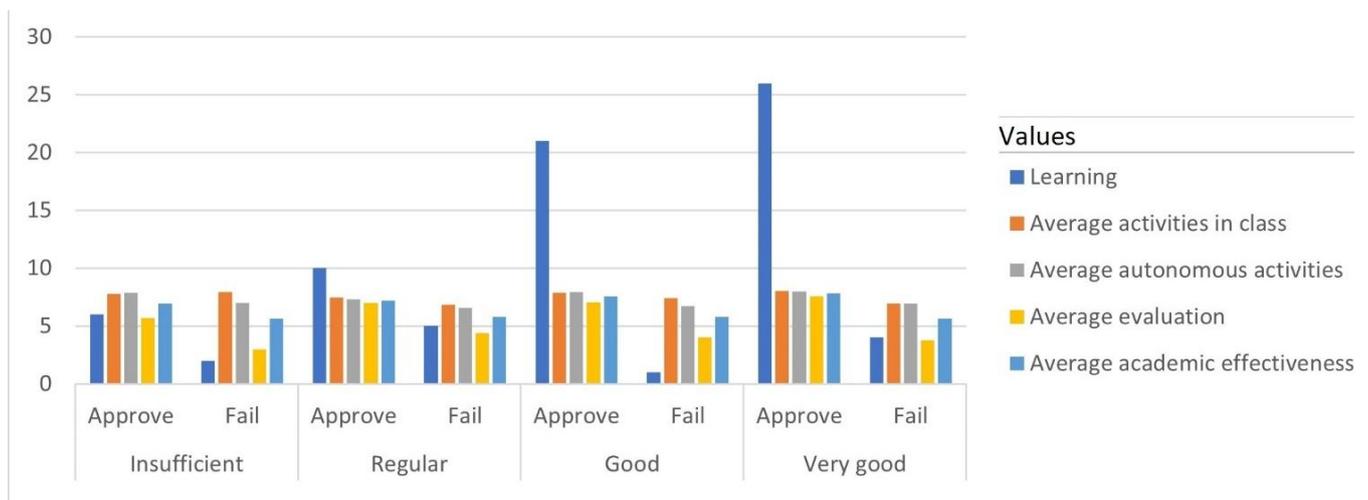


Figure 5. Graph of the trend analysis for the 2022 period.

Figure 6 presents the comparison of all the factors included in the analysis throughout the four periods evaluated. The trend lines represent academic effectiveness versus learning. The trend line was stable over time, there were no sharp falls or rises, which was mainly because the students of the 2019 and 2020 periods supported their affectivity in the evaluation considering that it had a weight of 40% of the total. On the other hand, in the period 2021 and 2022 the effectiveness of the students focused with greater emphasis on the development of activities in class and autonomously, these having an additional factor and that is that in these periods the institution focused on the use of ICT in the classroom.

The trend line corresponding to learning was not stable and varied with time. In 2019, learning was low, within a face-to-face modality with a traditional method, that is, learning depending expressly on the teacher. In 2020, learning was even lower than in the previous year, which was specifically due to the beginning of the use of ICT, but in a remote model, marked by the start of the pandemic and in isolation from society. In 2021, the trend began to make positive leaps, considering that there were fewer students with insufficient and

regular learning. The learning level with the highest number of students was focused on the “good” learning category and was even higher than the students who managed to obtain “very good” learning. This period had the characteristic that the use of ICT was already a factor in which students and teachers had already acquired experience and proper use, which improved the level of learning. In the evaluated period of 2022, students with “insufficient” learning decreased considerably and the trend rose to the point that the greatest number of students were at a good and very good level of learning. In this period, learning techniques based on the use of ICT had been applied, where the importance of motivation, research and innovation in the proposed activities was determined. These parameters had even lowered the percentage of interest of students in obtaining higher grades in the evaluation, as their success was focused on the development of classroom and autonomous activities that had been aligned to the use of ICT.

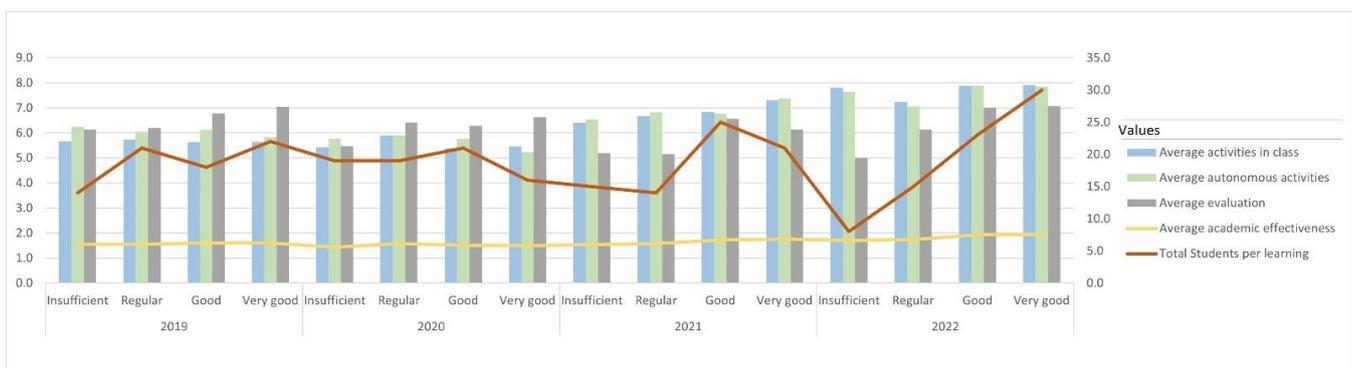


Figure 6. Comparison of the development of activities and registered trends in academic effectiveness and learning in the periods that go from 2019 to 2022.

4. Discussion

In the application of the proposed method, several results have been obtained that were expected as improvement of learning with the inclusion of ICT in the classroom. However, this result was limited by the answers obtained in the surveys where a considerable number of students showed a certain feeling of uncertainty regarding the use of these tools [37,38]. Therefore, it is considered that the method in its two stages is fully applicable to universities that are creating processes to update their educational methods. In the first stage, the validation of surveys is proposed, considering that currently these instruments are the most used in obtaining data that seek to identify the sentiment of an objective population. In the second stage, an analysis of the academic data of a university is proposed to determine the academic effectiveness in relation to student learning.

Reviewed works on the management and analysis of data extracted from surveys do not deal with a statistical model that validates the design of the instrument [39]. Far fewer perform an analysis for each question to identify the degree of incidence in responding to a study phenomenon. The work carried out is not only responsible for the design of the survey, but it does also follow a process that goes from the identification of the problem to its validation [40,41]. In the survey design process, a representative sample is established that must be met as the first filter to validate the information received. This leads to the following difference in relation to the reviewed works, which is validation, for which a statistical method, such as factor analysis, is used. This statistical model can be considered as an old mechanism; however, its results are effective when generating a validation process, through calculations of variance, covariance, etc. This model has even made it possible to identify the incidence of questions in response to the proposed phenomenon [42]. This undoubtedly allows improvement of the instruments used for data acquisition, and this point, in addition, is a strength of the method, since it determines if the questions evaluate the dimension.

The proposed data analysis is related to works that have established data analysis models to determine the effectiveness of the use of ICT in education during COVID-19 [43,44]. However, this proposal considers an analysis where three environments intervene in a period that goes from 2019 to 2022. During these years, the institution that participated in this study went through a face-to-face study modality in 2019 in a traditional way [45,46]. In 2020 and 2021, due to the pandemic, the educational model became remote where ICTs supported education with learning and communication platforms. In the 2022 period, the university-maintained ICTs, but changed the application model and integrated them into the educational method [47,48]. These three scenarios allow a clear vision on the improvement of learning with the use of ICT.

5. Conclusions

The proposed method has been an aid in obtaining and validating information for the university that participated in this study. At present, surveys have become the most used instruments to identify the feelings of people before an object of study. With this precedent, having a process that is responsible for the validity of the survey and how the questions included respond to a phenomenon, is undoubtedly a contribution to the processes of academic quality. In addition, generating test environments that allow an analysis of the functioning of ICT is something that will allow a total inclusion of technologies in the classroom. This is how the different areas of the university that have received the results of this work have considered it.

In the use of computer tools, the advantage of universities is that they have a wide variety of them. This facilitates the implementation of processes capable of analyzing different data sources and generating knowledge for more assertive decision-making. Statistical tools such as SPSS have been used in this work and the Microsoft SQL Integration and Analysis package has been used in the analysis. The versatility of these tools allows them to be integrated into a wide variety of data sources and other tools, which allows the generation of a consolidated and comprehensive process. This advantage can be used to generate continuous processes that are not limited to responding to a single phenomenon. On the contrary, this process be integrated as an academic monitoring tool.

In the results obtained, certain information is easy to detect, and it is not necessary to generate a complicated process. However, this work has the purpose of establishing trends in the effectiveness and learning of students in a period that covers four years. This has been the condition that contributed to our work. During the analysis, the difference between effectiveness and learning was identified. Thus, in the 2019 and 2021 periods, the student data showed that their main objective was to pass the midterm, and, therefore, their efforts were aligned to obtaining the highest grades in the evaluations. On the contrary, in the period 2021 and, especially, in 2022, when the university added ICT as learning instruments, the student's conceptions changed. In these periods, students focused more on the development of activities, both in class and autonomously, in such a way that their learning grew percentagewise. Even in these periods, the performance in the evaluations was leveled with the grades obtained in the other activities, which meant a significant improvement in their learning using ICT.

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