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Estimating Added Value in Colombian Higher Education: A Multivariate Approach

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Abstract
In this study we analyse the added value that higher education institutions (HEIs) in Colombia provide to their students, for this we use data from the Saber 11 and Saber Pro tests registered in it. A hierarchical model is used to estimate the difference between the expected and actual performance of students in Saber Pro. Multivariate analysis techniques, such as principal component analysis (PCA) and cluster analysis, are applied to identify and group profiles according to their performance. Finally, data envelopment analysis (DEA) is used to evaluate the efficiency of HEIs in generating added value. The results show that the impact of universities varies according to the competence evaluated.

Keywords: *Value added; higher education; multivariate analysis; educational efficiency.*

1. Introduction

The effect of public policies on education and the quality of the learning obtained by students during their time at a higher education institution highlights the complexity of the educational process (Visbal-Cadavid et al., 2017). According to (Alexander, 2015), the best criterion for measuring the effectiveness of education is the value that education brings to the initial competencies of learners.

In the educational field, value-added models play a relevant role in analyzing the effectiveness of schools and teachers in developing their students' competencies over time (Fernandez & Martinez-Canton, 2019). Value added (VA) is defined as the contribution to students' net progress towards established learning objectives, once other factors outside schools have been isolated, such as students' prior knowledge, social, economic, and family factors, which can contribute to such progress (Zuluaga-Ortiz et al., 2022)

Colombia, on the other hand, is in a privileged position to report the added value of its universities, since it is one of the few countries that evaluates the learning of its students at the end of school through the Saber 11 tests and at the end of university through the Saber Pro tests.

2. Value-added model

The results of the value added by the country's higher education institutions to their students are reported at the INBC level through a hierarchical model, which facilitates the nesting of the data (ICFES, 2019). This model evaluates the difference between the student's estimated performance, based on their initial competencies, and their actual performance in Saber Pro.

Initially, the data from Saber 11 and Saber Pro are crossed, considering students who took both exams within a range of 4 to 8 years. Due to changes in identity documents or other circumstances, a probabilistic cross-check between the two databases is resorted to. To carry out the estimates of value added by INBC, ICFES uses statistical models of parameters varying at more than one level, commonly known as hierarchical or multilevel models.

In the case of value added, the relationships to be estimated are given by the following expression:

$$\widehat{Saber\ pro} = f\ (saber\ 11)$$

That is, it seeks to estimate the individual's score in Saber Pro through the results of Saber 11 in the different competencies that are evaluated in this test, considering the individuals grouped in an INBC.

Subsequently, for each INBC, a comparison neighborhood is defined, to compare the value added by the INBCs that receive similar students in terms of their previous competencies. The reference INBC is compared with those that are part of its comparison neighborhood and we go on to speak of a relative measure of the quality of education, since the added value for the group of similar INBCs is measured (Instituto Colombiano para la Evaluación de la Educación - ICFES, 2022)

3. Information processing

To develop this research work, a descriptive analysis is initially carried out to summarise the data in an organised way and analyse its behaviour. In the second instance, the multivariate statistical technique principal component analysis (PCA) is used to determine the student and university profile generating the best results in the Saber 11 and Saber Pro tests, obtaining principal components that facilitate the interpretation of the data. Subsequently, the cluster analysis technique is used to identify the groups of homogeneous universities. Ultimately, data envelopment analysis is used to estimate the value added by each HEI.

3.1. Description of the data

For the study, students of the Industrial Engineering program are selected first, as it is one of the most offered nationally and in the Caribbean Region. For the development of the research it was not necessary to apply any technique for data collection, the ICFES provides all the information in its records and since 2016 it has been cross-referencing between the Saber 11 and Saber Pro tests.

3.2. Description of the variables

The original database has 40 variables. However, for the purpose of the study, only the variables described in Table 1 are required

Table 1. Variable description

VARIABLE	FULL NAME	DESCRIPTION
MAT_S11	MATHEMATICS - SABER 11	0-100
CR_S11	CRITICAL READING - SABER 11	0-100
CC_S11	CITIZENSHIP SKILLS - SABER 11	0-100
ENG_S11	ENGLISH - SABER 11	0-100
BIO_S11	NATURAL SCIENCES - SABER 11	0-100
CC_PRO	CITIZENSHIP SKILLS – SABER PRO	0-100
WC_PRO	COMUNICACIÓN ESCRITA - SABER PRO	0-100
ENG_PRO	ENGLISH - SABER PRO	0-100
CR_PRO	CRITICAL READING - SABER PRO	0-100
QR_PRO	QUANTITATIVE REASONING - SABER PRO	0-100
INTERNET	INTERNET	YES/NO
COMPUTE R	COMPUTER	YES/NO
SCHOOL_N AT	NATURE OF THE SCHOOL	PRIVATE/PUBLIC
SCHOOL_T YPE	TYPE OF SCHOOL	ACADEMIC/ TECHNICAL/ACADEMIC:

3.3. Aggregated variables

To analyze the added value taking the university as the unit of analysis, it is necessary to create 13 new variables in order to contribute to the description of the profiles.

4. Findings

Through the results described below, an analysis can be made of the added value that universities provide to their students in terms of learning.

Table 2. Description of the new variables

VARIABLE	NEW VARIABLE NAME	DESCRIPTION
P_MAT_S11	AVERAGE MATHEMATICS - SABER 11	
P_CR_S11	AVERAGE CRITICAL READING - SABER 11	
P_CC_S11	SOCIAL AND CITIZEN AVERAGES OF THE UNIVERSITY - SABER 11	
P_BIO_S11	AVERAGE NATURAL SCIENCES - SABER 11	
P_ENG_S11	AVERAGE ENGLISH - SABER 11	
P_QR_PRO	AVERAGE QUANTITATIVE REASONING - SABER PRO	
P_CR_PRO	AVERAGE CRITICAL READING - SABER PRO	
P_CC_PRO	AVERAGE CITIZENSHIP COMPETENCIES - SABER PRO	
P_ENG_PRO	AVERAGE ENGLISH - SABER PRO	
P_WC_PRO	AVERAGE WRITTEN COMMUNICATION - SABER PRO	
U_PUBLIC	PUBLIC UNIVERSITY	YES/NO
U_ACREDIT	ACCREDITED UNIVERSITY	YES/NO
P_ACREDIT	ACCREDITED PROGRAM	YES/NO

4.1. Descriptive analysis of the score of industrial engineering students in the different competencies of Saber 11 and Saber Pro.

Through this descriptive analysis, we seek to identify and describe the main characteristics of the study variables and the relationships between them in a summarized way. In addition, it is intended to describe the added value that universities provide in a general way to the students who are part of the study.

The following table compares the scores of Saber 11 and Saber Pro, highlighting greater variability in Saber Pro, which is attributed to the added value of the universities.

Table 3. Descriptive statistics

	Min	Q1	Mediana	Media	Q3	Max	Var
MAT_S11	32	54	60	61,32	68	91	109,74
CR_S11	35	53	59	59,2	65	85	81,75
CC_S11	35	53	58	58,78	65	83	79,72
BIO_S11	34	55	61	61,19	68	89	94,75
ENG_S11	26	49	57	59,9	68	100	186,79
QR_PRO	5	57	79	72	91	100	552,04
CR_PRO	1	36	62	57,83	81	100	765,02
CC_PRO	1	31	60	55,6	81	100	831,45
ENG_PRO	1	47	70	64,42	85	100	659,74
WC_PRO	1	31	57	55,03	80	100	814,28

In Saber 11, the scores are more homogeneous than in Saber Pro. Students enter universities with averages such as 61.32 in mathematics, 59.20 in critical reading, 59.90 in English and similar in other competencies, which allows the starting point to be evaluated before the university impact. In Saber Pro, the highest and lowest averages are in QR_PRO and WC_PRO, respectively. In mathematics, universities add value (from 61.32 to 72.00 on average), but in critical reading and citizenship skills progress is minimal. In English, they generate a notable increase (from 59.90 to 64.42).

4.2. Descriptive analysis of the average of each university in the different competencies of Saber 11 and Saber Pro

This section carries out a descriptive analysis of each university's average in the different competencies of Saber 11 and Saber Pro.

Table 4. Statistical summary of model's variables

	Min	Q1	Mediana	Media	Q3	Max	Var
P_MAT_S11	46,5	54,87	57,93	59,4	61,92	76,14	35,95
P_CR_S11	41	54,62	56,8	57,78	61	68,49	23,5
P_CC_S11	44	54,64	56,96	57,7	60,36	69,12	21,47
P_BIO_S11	48	55,42	58,38	59,43	62,6	73,89	29
P_ENG_S11	45,57	52,11	56,43	57,42	60,97	83,46	54,74
P_QR_PRO	29,5	58,96	68	68,69	77,15	93,44	170,1
P_CR_PRO	25	44,66	53,41	54,46	63,36	82,9	171,52
P_CC_PRO	9	45,55	51,62	52,81	58,85	81,98	161,05
P_ENG_PRO	29,5	48,5	60,02	60,57	70,25	94,18	212,31
P_WC_PRO	15,5	47,49	52	52,77	58,8	76,97	98,41

From the table, it can be seen that the average scores of the universities in the competencies evaluated in Saber Pro are more variable than the average scores in those evaluated in Saber 11; that is, the averages of the universities in each competency of Saber 11 are more homogeneous than in the competencies of Saber Pro.

4.3 Analysis of the main components of the average of each university in the different competencies of Saber 11 and Saber Pro

In this section, an analysis of principal components is carried out with the aim of facilitating the interpretation of the average of each university and characterizing the universities that generate the best results in the saber Pro test based on the accredited program variable.

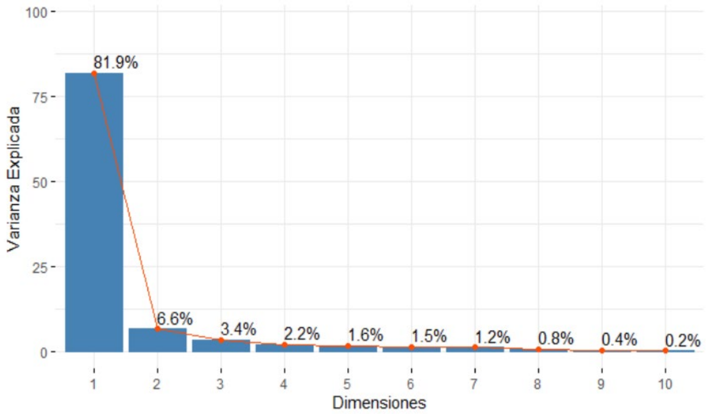

Figure 1. Eigenvalues histogram.

The principal component analysis yields 10 components, of which the first two collect 88.5% of the explained variability. Through the PCA, we analyze the location of the universities concerning the aggregate variable "accredited program". A clear difference is shown between both situations in terms of a score in the first 2 components in a favorable way.

4.4. Cluster analysis of the average of each university in the different competencies of Saber 11 and Saber Pro

In this section, a cluster analysis is carried out to group those universities that are similar in terms of the averages obtained in the Saber 11 and Saber Pro competencies and describe the added value that these provide to their students in a multidimensional way with the help of the components provided by the principal component analysis. Initially, to get an idea of the number of clusters present in the data, a hierarchical algorithm is applied, which in this case is Ward's method, due to its significant advantages, and in particular because it generates more compensated dendrograms (Delahoz-Dominguez et al., 2020); Then, a visual inspection of the obtained dendrogram is performed and a non-hierarchical partition-based algorithm is applied. The result indicates selecting 2 or 3 groups (see figure). The research aims to estimate the multidimensional added value by universities that admit students with similar entry conditions.

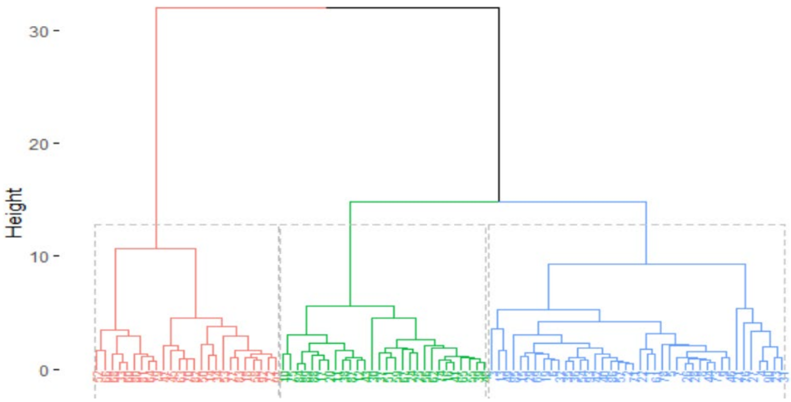

Figure 2. A dendrogram for hierarchical cluster analysis.

Subsequently, we look for the optimal number of clusters from the silhouette method. According to this method, the optimal number of clusters is the one that maximizes the mean of the silhouette coefficient of all observations. Figure 3 shows that the maximum values for the silhouette coefficient are reached at k=2 and k=3.

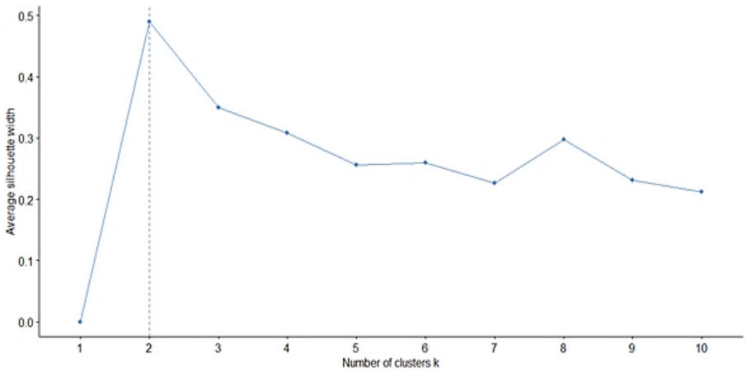

Figure 3. Optimal number of clusters according to the silhouette method.

The analysis uses the PAM (Partition Around Medoids) algorithm, where a medoid corresponds to the object of a group that minimizes the mean difference to all the elements in the group. Initially, we work with three groups, obtain the universities that belong to each group and make the representation in two dimensions as shown in Figure 4.

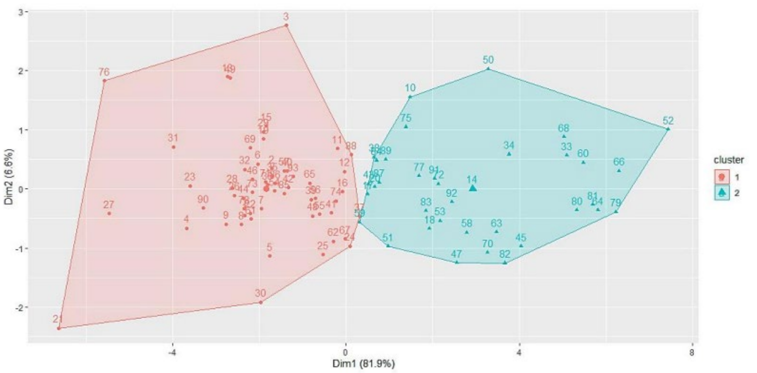

Figure 4. Cluster Analysis visualization

Cluster 1 groups the universities with unfavourable overall scores and favourable or unfavourable written communication scores from Saber Pro. Cluster 2 groups the universities with high overall scores and high and low written communication scores.

4.5. Data Envelopment Analysis

The conceptual scheme that associates the model's input and output variables must be constructed to apply the DEA. The averages of the competencies evaluated in Saber 11 are taken as the model's input variables, and the model's outputs are the averages obtained in Saber Pro.

Based on the data from the universities studied in this research, their efficiency is calculated using the DEA-CCR model, which assumes constant returns to scale (CRS), and the DEA-BBC model, which assumes variable returns to scale (VRS).

Table 5. Summary of the DEA model

Variable	Cluster			
	Group 1		Group2	
	(CRS)	(VRS)	(CRS)	(VRS)
Efficient universities	18(31,58%)	23(40,35%)	17(47,22%)	25(69,44%)
Inefficient universities	39 (68,42%)	34(59,65%)	19(52,78%)	11(30,56%)
Minimum level of efficiency	0,74	0,94	0,89	0,96
Medium efficiency	0,94	0,98	0,98	0,99
Standard deviation	0,06	0,02	0,03	0,01
Number of universities (DMUs)	57	57	36	36

The table presents the efficiency values of all the universities according to the group to which they belong and the DEA model used in each case. Institutions with efficiency values equal to one are classified as efficient, and the rest as "non-efficient." Universities with efficiency values close to 1 (efficiency frontier) are considered close to achieving efficiency, that is, with opportunities for improvement to achieve it.

5. Conclusions

The study showed that the value added by higher education institutions in Colombia varies according to the competence being evaluated; significant improvements were detected in mathematics and English, but little progress in critical reading and citizenship skills. The principal component analysis (PCA) revealed that universities with accredited programs tend to obtain better results in Saber Pro, while the cluster analysis identified different institutional performance profiles. Likewise, the data envelopment analysis (DEA) showed little homogeneity in the educational impact among universities, which highlights a need to strengthen strategies in less developed sectors.

References

Alexander, R. J. (2015). Teaching and learning for all? The quality imperative revisited. *International Journal of Educational Development*, 40, 250-258. https://doi.org/10.1016/j.ijedudev.2014.11.012

Delahoz-Dominguez, E. J., Guillen-Ibarra, S., & Fontalvo-Herrera, T. (2020). Analysis of the quality accreditation in industrial engineering programs and the results in the standardized national tests, in Colombia, Análisis de la acreditación de calidad en programas de ingeniería industrial y los resultados en las pruebas nacionales estandarizadas, en Colombia. *Formacion Universitaria*, 13(1), 127-134.

Fernandez, F. J. I., & Martinez-Canton, A. (2019). Ethics and Transversal Citizenship in the Teaching of Science and Engineering. 2019 IEEE Integrated STEM Education Conference (ISEC), 104-110. https://doi.org/10.1109/ISECon.2019.8881965

Instituto Colombiano para la Evaluación de la Educación - ICFES. (2022). Saber 11 [Dataset]. https://icfes.gov.co/guest/data-icfes

Visbal-Cadavid, D., Martínez-Gómez, M., & Guijarro, F. (2017). Assessing the efficiency of public universities through DEA. A case study. *Sustainability*, 9(8), 1416.

Zuluaga-Ortiz, R., DelaHoz-Dominguez, E., & Camelo-Guarín, A. (2022). Academic efficiency of engineering university degrees and its driving factors. A PLS-DEA approach. *Journal of International Studies*, 15(2).