Journal of Engineering Science and Technology
Vol. 17, No. 2 (2022) 1105 - 1118

EFFICIENCY OF ACADEMIC ENGINEERING PROGRAMS IN COLOMBIA: AN APPROACH THROUGH DATA ENVELOPMENT ANALYSIS

ENRIQUE DELAHOZ-DOMINGUEZ[1], ADEL MENDOZA-MENDOZA[2,*], DELIMIRO VISBAL-CADAVID[3]

[1]Department of Industrial Engineering, Universidad Tecnológica de Bolívar, Cartagena, Colombia
[2]Department of Industrial Engineering, Universidad del Atlántico, Puerto Colombia, Colombia
[3]Department of Industrial Engineering, Universidad del Magdalena, Santa Marta, Colombia
*Corresponding Author: adelmendoza@uniatlantico.edu.co

Abstract

The purpose of this research is to assess the educational quality based on academic efficiency using three distinct data development analysis models, with the Engineering programs in Colombia serving as decision-making units. The research is evaluative in nature and is divided into four phases: 1) context analysis, 2) database development and adequacy assessment (DEA), 3) exploratory data analysis, and 4) outcome analysis. The results indicate that 14.3%, 29.8%, and 88.7%, respectively, of the engineering programs analysed are efficient for the CCR, BCC, and FDH models. What is novel in this study is the inclusion of end-of-high-school standardized exam results as input variables for the DEA model, as well as end-of-college exam results. Thus, the concept of quality and efficiency may be articulated, implying that colleges with the highest efficiency levels have a larger capacity for human resource transformation. The findings demonstrate how universities with high-quality certification achieve higher levels of efficiency. The proportion of efficient universities with excellent accreditations is 65 percent, 67 percent, and 78 percent, respectively, for CCR, BCC, and FDH. The study's primary contribution is the establishment of an analytical framework for evaluating university degrees that enables the identification and quantification of each degree's strengths and limitations, so serving as a tool for making objective educational decisions.

Keywords: Analytics, DEA, Efficiency, Higher education institutions.

1. Introduction

There is currently a wide range of universities worldwide, which, added to the facilities offered by information technologies to study online, raise competitiveness among universities, and attract and retain qualified students is becoming more complicated [1, 2]. This competence benefits society because it obliges higher education institutions to offer quality services and respond adequately to society's expectancies. So, it is possible to ensure highly skilled professionals fit the labour market needs [3]. So much so, the number of universities that undergo accreditation programs annually has increased in recent years. In this way, it can generate a competitive advantage and attract students [4-6]. Despite the above, both educational institutions and students should have tools that give them a criterion for comparison between universities (in the case of universities) and universities' selection (in students).

Several studies have analysed the quality of education with meta-analysis. It relates the competencies that students acquire and observe their impact on their professional performance, finding that secondary education factors influence higher education performance [6-8]. On the other hand, in the Cyrenne and Chan studied [9] the results of secondary education assessments serve as predictors of higher education outcomes. Traditionally, universities adopt a quality accreditation for evidencing their quality performance achievements. Traditionally, independent agencies are responsible for assessing the universities' capabilities to meet minimums standards in financial resources, student projection, and relationships with society [10, 11]. Conversely, Visbal-Cadavid et al. [12] developed an integrated approach to Machine Learning and DEA, proposing a methodology for forecasting universities' technical efficiency, using academic, financial, and infrastructure variables.

Consequently, in this research, an empirical rational model is developed that takes as input the students' competencies at the end of high school and, as outputs, the professional competencies thereof to estimate the efficiency levels for engineering programs in Colombia. The three DEA estimates three different levels of efficiency: Global, pure, and economical. Finally, this methodology becomes an objective analytical approach to provide critical insights based on data.

2.Theoretical framework

In 1978 the DEA methodology was proposed by Charnes, Cooper, and Rhodes as a non-parametric approach to assessing the performance or efficiency of several organizations (called DMU: Decision Making Unit) in the public and private sector with multiple inputs (resources) and multiple outputs (goods or services). The DEA methodology builds on organizations' existing information on their performance and builds the efficient frontier [13]. Any DMU that is over the border will be efficient otherwise, it will be non-efficient [14]. Thus, the efficiency of a DMU is determined by its ability to transform inputs into desired outputs. On the other hand, it is important to note that the DMU's used must be comparable, so its inputs, such as their outputs, must have homogeneous units [15].

A correct application of the DEA technique requires extensive knowledge of the problem context (market, competition, variables that influence, among others), also, identify the inputs of the DMU's and their respective outputs. Finally, to select the model (CCR, BCC, or one of its variants) and its orientation (input or output) to use. The models used in this article are input-oriented CCR, BCC, and FDH, assuming that their control is possible. In the three models used, those units that are over the efficient border will be efficient.

The main difference between the BCC, CCR, and FDH models is that the efficiency calculated in the CCR model will be less than the efficiency calculated in the BCC model. The CCR model uses overall efficiency, and instead, the BCC model uses technical efficiency. On the other hand, the FDH model is a particular case of DEA, which developed without convexity; unlike the previous two, it generates greater accuracy in measuring efficiency for endogenously fixed inputs. It is effective for measuring economic efficiency [16, 17].

However, Fig. 1 presents the FDH, CCR, and BCC models, and input-oriented. In all three models, DMU's will need to move horizontally to reach the border to be efficient [18], but as mentioned, the scale implemented in each model is different. The global efficiency levels calculated through the DEA models are broken down into Technical Efficiency and Scale Efficiency. This approach makes it possible to identify the sources of inefficiency in the study units, which may be due to the misuse of resources in the production process or the failure to identify critical resources for optimal performance [19]. Thus, global technical efficiency is evaluated through constant returns to scale (CRS) and local technical efficiency through variable returns (VRS). Finally, the scale's efficiency is the relation of constant returns to scale over the variable returns to scale: Efficiency of scale = CRS / VRS.

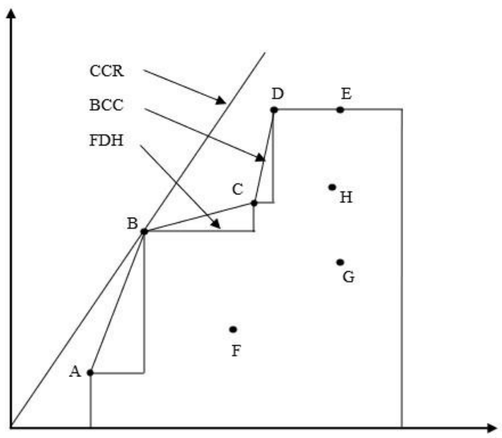

Fig. 1. DEA models [17].

On the other hand, the DEA model solves an optimization problem. The objective function maximizes the reason for its outputs between its inputs, having multiple inputs and outputs. The u_r weights create a virtual output and v_i create a virtual input. Finally, restrictions are those that limit efficiency in the range of 0 and 1 [20].

The models below are in a multiplicative way and are oriented to the inputs as mentioned at the beginning. The CCR-IO and BCC-IO models are the classic tools to develop efficiency analysis in the literature. However, in the context of educational efficiency, the FDH model allows the deviations of inefficient DMUs to be decomposed into explanatory factors, distinguishing between efficiency technique, the correct use of resources, and the use of capacities at scale.

(a) CCR-IO Model

$$\max_{u,v} h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{1}$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad j = 1, \dots, n \tag{2}$$

$$u_r, v_i \geq 0 \qquad r, i = 1, \dots, m \tag{3}$$

(b) BCC-IO Model

$$\max_{u,\mathrm{v},\mathrm{k}} h_o = \frac{u^T y_o + k_o}{v^T x_o} \tag{44}$$

Subject to:

$$\frac{u^T Y_j + k_o}{v^T X_j} \leq 1 \;\; j = 1, \dots, n \tag{5}$$

$$u^T, v^T \geq I\varepsilon \quad i, j = 1, \dots, m \tag{6}$$

$$k_o, free \tag{7}$$

(c) FDH Model

$$\theta^* = \min \theta \tag{8}$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io} \qquad i = 1, \dots, n \tag{9}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \leq y_{ro} \qquad r = 1, \dots, m \tag{10}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{11}$$

$$\lambda_j \epsilon \{0,1\} \;\; j = 1, \dots, n \tag{12}$$

3. Method and materials

This article's development follows a rational scheme as presented in Fig. 2, and Fig. 3 presents the relations between inputs and outputs. To generate the measurement of institutions' academic efficiency, understanding the learning processes' variables is necessary. For this research, the following competencies comprised the DEA model: Math (MAT_S11), Critical Reading (CR_S11), Biology (BIO_S11), English (ING_S11), and Citizen Competences (CC_S11) as the formation resources to acquire the skills of a competent professional, and Critical Reading (CR_PRO), Written Communication (WC_SPRO), Quantitative Reasoning (QR_SPRO), English (ENG_PRO) and Citizen Competences (CC_SPRO) as the achievements achieved of vocational training, defining academic programs according to the university as the decision units (DMU).

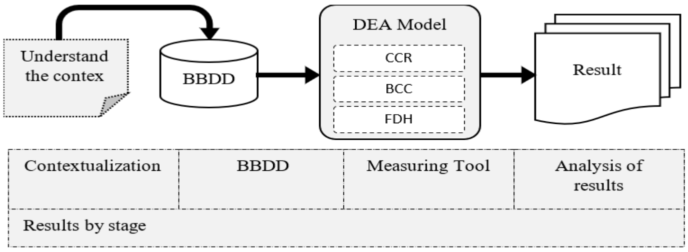

Fig. 2. Investigation methodology.

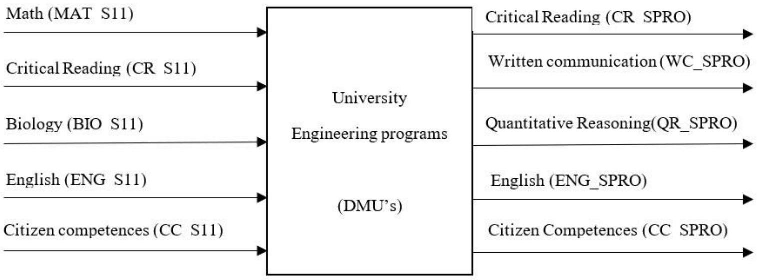

Fig. 3. Rational scheme of the inputs and outputs of the model.

3.1. Population

The database consists of Colombia's SABER 11 (secondary education) status assessment for 2012 and 2013. For a cross-cutting analysis, these results are tracked until their respective 2018 SABER PRO (higher education) status assessment. The database has 12,411 engineering students in mechanical, civil, systems, environmental mechatronics, electrical and electromechanical engineering [21]. The students represent 135 universities and 265 engineering degrees.

In Colombia, the standardized exam results are public and provided by the Colombian Institute for Quality Education (ICFES). On the sample, 31% of the institutions are public, and 44% have a quality accreditation. Each competency's mean results are in Table 1, evidencing how institutions with quality accreditation receive in average students with better results in all the competencies evaluated at high school.

Table 1. Average results aggregated by competencies, funding, and quality accreditation status.

Competencies	Public (31%)	Private (69%)	Quality accreditation (44%)	Non quality accreditation (56%)
Math (S11)	84.03	74.47	82.91	65.37
Critical reading (S11)	69.01	59.16	68.34	48.73
Citizen Competencies (S11)	64.74	56.70	64.81	46.85
English (S11)	69.35	66.67	74.32	52.54
Biology (S11)	55.02	55.09	57.98	48.64
Quantitative Reasoning (SPRO)	178,19	164,58	177,76	161,9
Critical reading (SPRO)	163,77	151,43	163,77	148,85
Citizen competencies (SPRO)	155,96	144,94	156,04	142,61
English (SPRO)	164,2	157,86	172,43	152,03
Written communication (SPRO)	156,26	150,75	156,77	149,35

3.2. Tools and technical

R software [22], the FactomineR multivariate analysis library [23] will be used for the computational analysis of the data for the development of the PCA and the DeaR Envelope Data Analysis library [24]. Also, it should be clarified that to implement this methodology, the DEA measurement structure of the data is shown below in Fig. 4.

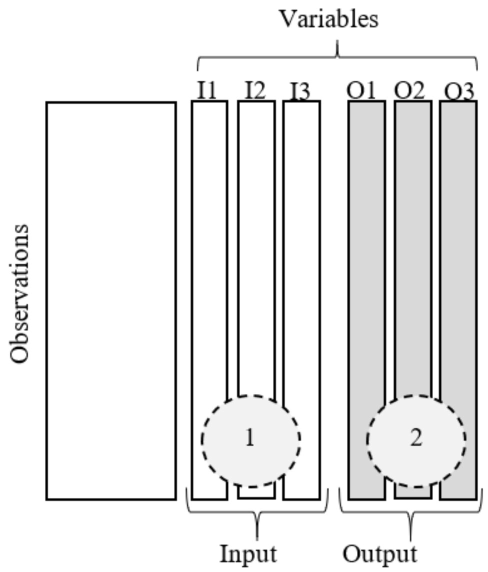

Fig. 4. Structure of the database for the DEA model.

4. Results and Discussion

Table 2 presents the efficiency results delivered by the three DEA models; This contains a sample of the study's DMU, its efficiency score on all three models (CCR, BCC, and FDH), the score for scale efficiency, and final-minded return of scale (RTS). The efficiency results are different due to the assumptions handled by each model, and those are stated in the section of the theoretical framework.

Table 2 lists two new concepts: scale efficiency and RTS. Scale efficiency is the relationship between overall efficiency (CCR) and pure technical efficiency (BCC), this represents the proportion of resources I must use to increase my production.

The value that takes the scale efficiency will indicate its RTS as follows: if the value is equal to 1, the RTS will be constant, this means that for a DMU to increase its level of production (in the context of the article will be the result of the SABERPRO evaluation) it must increase with an equal proportion its resources (in the context of the article will be the result of the assessment SABER11), on the other hand, if it is different from 1 the scale can be increasing or decreasing. If the scale is growing, it indicates that for a DMU to increase its level of production, it will be able to use its resources less portion. Finally, if the scale is decreasing, it indicates that for a DMU to increase its level of production it must use its resources more.

Based on Table 2, the DMU U1 has an efficiency level of 0.896 (not efficient) for the CCR-IO model, 1 (efficient) for the BCC-IO model, and 1 (efficient) for the FDH model, its scale efficiency is 0.896, and its RTS is increasing.

Table 2. Result of the efficiency of the models.

DMU	CCR-IO	BCC-IO	FDH	Scale efficiency	RTS
U1	0.896	1	1	0.896	Increasing
U2	0.882	1	1	0.882	Increasing
U5	1	1	1	1	Constant
U10	1	1	1	1	Constant
U11	0.692	0.962	1.004	0.719	Increasing
U16	0.883	0.963	0.992	0.917	Increasing
U17	0.788	0.948	0.991	0.831	Increasing
U18	0.823	0.975	1	0.844	Increasing
U19	0.752	0.922	0.972	0.816	Increasing
U20	0.725	0.929	1.001	0.780	Increasing
U21	0.792	0.982	1	0.807	Increasing

In summary, although this DMU does not have overall efficiency, it has pure technical efficiency and economic efficiency. Therefore, DMU U1 uses its resources correctly (classrooms, laboratories, books, among others). So, DMU U1 generates more significant outputs (evaluation results) using the same number of resources, but considering administrative aspects (assessments, monitoring, control, methodologies, and strategies), there is a space for improvement. Although DMU U1 efficiently manages the resources, there may be inconsistencies between the outcomes and the objectives. It is essential to mention that DEA results' interpretation is a comparative one concerning the other units within the study. Table 2 summarizes the CCR, BCC, and FDF results, which indicates the percentage of efficient, non-efficient, and super-efficient units of each model.

On the other hand, in addition to delivering efficiency scores, the models predict the objectives that must be met to reach the critical frontier efficiently and, consequently, be an efficient DMU. Table 3 is a sample of four DMU and present the targets for each DEA model. This output corresponds to the targets (goals) that each DMU must achieve in a subject to be over the efficient frontier. For example, DMU U16 in its subject MAT_11 (Math SABER11) must add 3.56 points for the CCR-IO model, 0.34 points for the BBC-IO model, and finally 1.41 points for the HDF model. This variation, as has been mentioned, is due to the nature of each model.

Table 3. Percentage of efficient, non-efficient and super-efficient units.

Model	CCR-IO	BCC-IO	FDH
Efficient	14.3 %	29.8 %	88.7 %
Non-efficient	85.7 %	70.2 %	8.3 %
Super-efficient	0 %	0 %	3 %

Table 4 presents the results globally, which contains the summary of DMU results for each competition considering the models implemented. Table 4 contains the maximum, minimum, average, deviation, and values of each DMU's objectives per academic competency.

The maximum competency value measurement corresponds to the highest value to be increased by a specific DMU of the study to achieve efficiency according to the model used. For example, in the CCR-IO model, The MAT_11 competency (Math SABER11) has a maximum value of 9.56, indicating that to achieve efficiency, a specific DMU must increase this competency score to 9.65. In contrast, the minimum refers to the lowest value that a specific DMU of the study must increase to achieve efficiency. For example, in the HDF model, its QR_PRO (Quantitative Reasoning SABERPRO) competency has a score of 0.04, indicating that to achieve efficiency, a particular DMU of the model must increase to 0.04 to achieve efficiency.

Table 4. Objectives to be achieved by DMU.

DMU	CCR-IO									
	MAT_11	CR_11	CC_11	BIO_11	ENG_11	QR_PRO	CR_PRO	CC_PRO	ENG_PRO	WC_PRO
U16	3.56	0	3.36	2.58	0	0	3.50	0	0	0.03
U17	0	0.85	0	0.75	0	2.38	0.66	5.77	0.00	0
U18	2.26	0	0	0	0	0	0	0	2.34	0
U19	0.82	0	0.22	0	0	0	4.36	0	0	0
DMU	**BCC-IO**									
U16	0.34	0	2.36	1.00	0	0.00	0.00	2.86	0	12.50
U17	0	1.47	0.69	1.72	0	3.53	0.55	6.93	0	0.00
U18	0.04	0.30	0	0	0	0	0	0	0	0.74
U19	0	0	0	0.53	0	0	0	2.96	6.48	0
DMU	**FDH**									
U16	1.41	0	0.86	2.57	2.41	9.33	3.78	8.67	3.78	15.88
U17	0.11	1.80	0	2.44	2.99	8.89	7.89	14.26	13.27	0.30
U18	0	0	0	0	0	0	0	0	0	0
U19	1.96	1.43	0	2.70	2.25	4.60	6.77	13.06	16.05	6.16

On the other hand, the average call measurement corresponds to the mean value that the DMU of the study must increase to achieve efficiency according to the model. For example, in the BCC-IO model, the CR_11 competency (Critical Reading of SABER11) has a value of 0.83, indicating that DMUs in this model on average, must increase to 0.83 to achieve efficiency. Consequently, to complement this measure is presented the deviation, which is the magnitude that captures the distance between each DMU scores in each competition and the overall average by competition.

For example, following the example above, on average the model's DMU should increase to 0.83 with a deviation of 0.99, i.e. the value may increase to 1.82 but this will depend on the observed DMU situation, or may decrease its value, but this is not favourable for the overall test score. Finally, the measurement count corresponds to the number of DMUs that should increase the score according to the competition. For example, in the CCR-IO model in the MAT_11 competency, the DMUs in this model that must increase the score in order for them to become efficient are 143.

In short, a global and unified interpretation of this Table is as follows: We will take as an example the RC_PRO (Quantitative Reasoning SABERPRO) of the HDF model. The results show that 30 DMUs should increase the score by an average of 4.57 with a deviation of 3.45, and there is a critical DMU that should increase its score to 12.72 for reaching the efficient frontier.

Finally, with the models, it is possible to build efficiency ranking based on model references or each model's efficiency. Internally, each model for generating an efficiency score must build a border, and as explained, if a DMU is over the border it is efficient; otherwise, it is not efficient. To build this border, the model compares each DMU and places it at a point within the plane where the border is located; those DMU not on the efficient border will look for the nearest DMU on that border, and this will be known as a reference DMU.

Consequently, in the efficiency ranking based on the number of references, the DMU referenced the most times by non-efficient DMUs will be more efficient. As an example, Table 5 presents the efficiency ranking of the CCR-IO model and contains the DMU, the times it appears as a reference, and the efficient group that belongs (being the first most efficient groups).

Table 5. Summary of objectives to be achieved by models.

Model						**CCR-IO**				
Compe.	**MAT_11**	**CR_11**	**CC_11**	**BIO_11**	**ENG_11**	**QR_PRO**	**CR_PRO**	**CC_PRO**	**ENG_PRO**	**WC_PRO**
Max	9.56	6.57	9.78	8.43	12.05	20.63	22.12	18.32	24.58	42.18
Min	0	0	0	0	0	6.E-11	0	0	0	0
Mean	1.98	1.14	1.65	1.60	1.87	4.49	3.92	4.30	5.78	7.67
Devi.	1.75	1.28	1.48	1.60	2.09	4.93	3.91	4.22	5.70	7.62
Count	143	105	124	103	87	28	124	63	63	115
Model						**BCC-IO**				
Max	7.07	4.74	9.70	8.28	7.24	27.63	24.16	24.29	30.95	52.47
Min	0	0	0	0	0	0	0	0	0	0
Mean	1.04	0.83	1.19	1.21	1.21	2.87	2.95	3.90	4.69	5.96
Devi.	1.50	0.99	1.56	1.51	1.50	5.65	4.40	4.73	5.93	7.00
Count	99	116	62	115	84	27	65	111	66	159
Model						**FDH**				
Max	7.74	6.40	11.69	11.30	11.19	12.72	17.86	20.16	21.03	24.43
Min	0	0	0	0	0	4.E-02	4.E-01	1.E-01	2.E-01	3.E-01
Mean	0.26	0.23	0.14	0.31	0.30	4.57	6.25	8.23	6.70	8.08
Devi.	0.91	0.81	0.87	1.19	1.28	3.45	4.27	5.06	6.19	5.50
Count	245	245	245	245	245	30	30	30	30	30

Table 6 shows the most efficient units, this being an alternative to classifying efficient DMU. If we look at the DMU U74 and U72, these were not taken as a reference, however, for the model if they are efficient.

Table 6. Efficiency ranking (CCR-IO model).

DMU	N. of references	Group	DMU	N. of references	Group
U84	150	1	U170	13	19
U238	130	2	U63	12	20
U24	128	3	U90	8	21
U106	93	4	U10	8	21
U240	82	5	U58	7	22
U82	76	6	U137	7	22
U234	68	7	U31	6	23
U253	50	8	U231	5	24
U136	49	9	U191	5	24
U105	48	10	U256	4	25
U173	42	11	U183	4	25
U108	34	12	U135	4	25
U22	33	13	U58	3	26
U126	29	14	U192	2	27
U125	24	15	U64	1	28
U32	22	16	U181	1	28
U229	19	17	U130	1	28
U71	17	18	U74	0	29
U42	13	19	U72	0	29

To rationalize the variations in efficiency's performance, we adjust the efficiency results by the quality accreditation variable (see Table 7). In the results of the global review of each DEA model, a higher proportion of efficient universities can be found in the accredited universities category, with values of 68%, 65%, and 77% for the CCRO-IO, BCC-IO, and FDH models.

Table 7. Efficient DMU's adjusted by quality accreditation.

CCR-O	**Quality Accreditation**	
Efficient	**Not**	**Yes**
Yes	12 (32%)	26 (68%)
Not	137	90
BCC-O	**Quality Accreditation**	
Efficient	**Not**	**Yes**
Yes	27 (35%)	53 (67%)
Not	105 (	80 (43%)
FDH-O	**Quality Accreditation**	
Efficient	**Not**	**Yes**
Yes	102 (23%)	183 (77%)
Not	21 (70%)	9 (30%)

As a recommendation, this type of analysis is of paramount importance for evaluating and controlling educational processes. Each model provides a point of view of what is happening in the case study. The CCR model provides a global efficiency report that translates into how there is synergy between educational resources and the tools, methodologies, and processes implemented to achieve institutional objectives.

The BCC model provides pure technical efficiency information that refers to the efficient use of resources. Finally, the FDH model provides an interpretation of economic efficiency, which refers to a university being more efficient than another (relatively) if it can generate better results in evaluations (outputs) using the same level of academic competencies and educational resources (inputs). This analytical approach is helpful at any educational level, providing objectives insights for planning and improvement. For example, it can support the university and program's decisions to study from the students' point of view. It would be of great help for teachers and educational decision-makers to generate improvement plans around their academic methodologies, tools, and processes implemented because the nature of the analysis is collective and generates a better picture of the educational institution's situation.

Previous research has developed efficiency analyses in educational contexts. For example, the efficiency values of 93% and 98% are obtained for the CCR and BCC levels, respectively, when assessing the Tunisian educational system in 2018 [25]. The authors explain the differences because the non-assumption on the convexity constraint enlarges the feasible region for the CCR model and reduces efficient DMUs compared to the BCC model [26]. Thus, in our research, convexity was not assumed. Therefore this may be one of the causes for differences between efficiency levels.

It is essential to point out that the universities evaluated in this study have different contexts and institutional approaches. Therefore, some of the differences between efficiency levels could be explained by the non-fair comparison of universities with different circumstances. For example, De La Hoz et al. [27] performed a grouping through cluster analysis before evaluating the efficiency through the DEA model, the results show that the CCR efficiency goes from 83% to levels of 93% and 97% when it is measured efficiency between similar institutions.

In our study, there is not a weighting of the relative importance of competencies, which becomes a limitation considering that other authors have shown the importance of incorporating the models' contextual aspects associated with the interests of the decision-makers [28]. Within our research scope, the input variables were not weighted to estimate the impact that high school knowledge has on university performance, in an approach similar to that of Visbal-Cadavid et al. [29] in their study on public universities' efficiency in Colombia.

For future research, it is proposed to involve data corresponding to teaching and student mobility methodologies to better explain the variations in the efficiency results between the institutions. Besides, considering the skills required for an engineer today, it is recommended to weight the input variables according to an expert criterion to associate professional performance with evaluations of the knowledge obtained in high school. Salas-Velasco [30] used Bootstrap DEA to estimate the efficiency of Spanish universities, finding that the traditional calculation of the DEA underestimates the efficiency values. This result is in accordance with our results and is evidence of the need for broaden the spectrum of educational efficiency analysis beyond the CCR-O models.

Johnes and Yu [31] examined the relative efficiency in the production of research of 109 Chinese regular universities in 2003 and 2004, finding that the average global efficiency of the evaluated institutions was 90%, however, this level falls to 80% when student-related input variables are excluded from the model. The level of efficiency is similar to the FDH result of our research (88.7%).

5. Conclusions

Empirical evidence shows as a significant finding that the three DEA models used in this research generate three distinct visions of quality measurement in education. While the CCR model assesses overall system (university) efficiency, the BCC model evaluates technical efficiency (methodologies, metrics, methods), and the FDH model evaluates economic efficiency. Efficiency level results for the CCR, the BBC, and FDH were 14.3%, 29.8%, 88.7%, respectively; these values correspond to the percentage of efficient universities according to each model. On the other hand, each model provides unique and valuable information regarding efficiency levels and improvement targets. However, when analysing the three models conjunctly, the analytical process becomes a methodology for decision-making based on objective data. The evidence shows that quality accreditations seem to be a positive factor in achieving academic efficiency, which is an essential insight for educational decision-makers interested in adopting a quality standard for improvement.

Therefore, the methodology is helpful for universities, students, parents, and teachers. First, this approach helps students and parents choose a quality university that provides the right skills to become a high-profile engineer. Second, it is of great benefit to teachers to steer their classes towards reinforcing other universities' academic levels (Benchmarking) as a reference point. Finally, it is of great help to managers to draw up action plans that reinforce students' lack and reconfiguration of academic contents and teaching approaches. By the way, this methodology is reproducible to other educational fields to assess causalities between skills and performance.

For future research, it is recommended to implement a grouping process to evaluate standard units' efficiency. Consequently, the development of the efficiency models by evaluating the formulated problem's convexity to gain more information on the results could be interesting.

Nomenclatures

i	Index for inputs
j	Index for DMUs
k	Index for outputs
k_o	Variable associated with model convexity
m	Total number of entries considered
n	It is considered n units (j =1, …., n) each of which uses the same inputs (in different quantities) to obtain the same outputs (in different quantities).
s	Number of outputs of the unit
u_r	Virtual output weighting r
v_r	Virtual input weighting r
x_{ij}	Amount of input i consumed by the unit j
x_{io}	Amount of input i consumed by the unit o
y_{rj}	Amount of output r produced by unit j
y_{ro}	Amount of output r produced by unit o

Greek Symbols

λ_j	Semi-positive vector in R^n

Abbreviations

BCC	Banker, Charnes and Cooper model
CCR	Charnes, Cooper and Rhodes model
DMU	Decision-Making Unit
FDH	Free Disposal Hull

References

1. López, C.; Benedito, V.; and León, M.J. (2016). El enfoque de competencias en la formación universitaria y su impacto en la evaluación: La perspectiva de un grupo de profesionales expertos en pedagogía. *Formación Universitaria*, 9(4), 11-22.
2. Numprasertchai, S.; and Poovarawan, Y. (2006). Enhancing university competitiveness through ICT based knowledge management system. 2006 *IEEE International Conference on Management of Innovation and Technology*, Singapore, 1, 417-421.
3. Alvitres, V.; Chambergo, A.; and Fupuy, J. (2014). Formative research and Peruvian university accreditation. *Manglar*, 11(2), 37-48.

4. Burnett, C.A. (2020). Accreditation sanctions as quality signals in a competitive market for students. *Educational Policy*, 0895904820983034.
5. Netanda, R.S.; Mamabolo, J.; and Themane, M. (2019). Do or die: Student support interventions for the survival of distance education institutions in a competitive higher education system. *Studies in Higher Education*, 44(2), 397-414.
6. Heiskala, L.; Erola, J.; and Kilpi-Jakonen, E. (2021). Compensatory and multiplicative advantages: social origin, school performance, and stratified higher education enrolment in Finland. *European Sociological Review*, 37(2), 171-185.
7. Cerdeira, J.M.; Nunes, L.C.; Reis, A.B.; and Seabra, C. (2018). Predictors of student success in Higher Education: Secondary school internal scores versus national exams. *Higher Education Quarterly*, 72(4), 304-313.
8. Vo, H.M.; Zhu, C.; and Diep, N.A. (2017). The effect of blended learning on student performance at course-level in higher education: A meta-analysis. *Studies in Educational Evaluation*, 53, 17-28.
9. Cyrenne, P.; and Chan, A. (2012). High school grades and university performance: A case study. *Economics of Education Review*, 31(5), 524-542.
10. Delahoz-Dominguez, E.J.; Fontalvo, T.J.; and Fontalvo, O.M. (2020). Evaluation of service quality by means of six sigma in a center of documentary attention in a university. *Formación Universitaria*, 13(2), 93-102.
11. Hanh, N.D. (2020). A review of issues of quality assurance and quality accreditation for higher education institutions and the situation in Vietnam. *Accreditation and Quality Assurance*, 25(4), 273-279.
12. Visbal-Cadavid, D.; Mendoza, A. M.; and Hoyos, I.Q. (2019). Prediction of efficiency in colombian higher education institutions with data envelopment analysis and neural networks. *Pesquisa Operacional*, 39(2), 261-275.
13. Pino, J.; Solís, F.; Delgado, M.; and Barea, R. el C. (2010). Evaluación de la eficiencia de grupos de investigación mediante análisis envolvente de datos (DEA). *Profesional de la Información*, 19(2), 160-167.
14. Ligarda, J.; and Ñaccha, M. (2006). La eficiencia de las organizaciones de salud a través del análisis envolvente de datos: Microrredes de la Dirección de Salud IV Lima Este 2003. *Anales de La Facultad de Medicina*, 67(2), 142-151.
15. Legaz, S.G. (1998). El análisis envolvente de datos como sistema de evaluación de la eficiencia técnica de las organizaciones del sector público: Aplicación en los equipos de atención primaria. *Revista Española de Financiación y Contabilidad*, 27(97), 979-1004.
16. Ebrahimnejad, A.; and Shahverdi, R. (2013). Finding target units in FDH modelby least-distance measure model. *Kybernetika*, 49(4), 619-635.
17. Lim, B.; Lee, K.; and Lee, C. (2014). Free disposal hull (FDH) analysis for efficiency measurement: An update to DEA. *The Stata Journal*, 10(2), 1-8.
18. Domínguez, J.; Fernández, P.; and Martínez-Roget, F. (2005). El análisis envolvente de datos en la construcción de indicadores sintéticos. Una aplicación a las provincias españolas. *Estudios de Economía Aplicada*, 23(3), 715-716.
19. Machmud, A.; Ahman, E.; Dirgantari, P.; Waspada, I.; and Nandiyanto, A. (2019). Data envelopment analysis: The efficiency study of food industry in

indonesia. *Journal of Engineering Science and Technology* (*JESTEC*), 14(1), 479-488.

20. Aparicio, J.; Perelman, S.; and Santín, D. (2020). Comparing the evolution of productivity and performance gaps in education systems through DEA: An application to Latin American countries. *Operational Research*, 1-35.
21. Delahoz-Dominguez, E.; Zuluaga, R.; and Fontalvo-Herrera, T. (2020). Dataset of academic performance evolution for engineering students. *Data in Brief*, 30, 105537.
22. Team, R.C. (2013). *R: A language and environment for statistical computing*. The R Development Core Team, Version 2.6.2 (2008-02-08), R Foundation for Statistical Computing.
23. Lê, S.; Josse, J.; and Husson, F. (2008). FactoMineR: An R Package for multivariate analysis. *Journal of Statistical Software*, 25(1), 1-18.
24. Coll-Serrano, V.; Bolos, V.; and Suarez, R. B. (2019). *deaR: Conventional and Fuzzy Data Envelopment Analysis* (1.1.0) [Computer software].
25. Ramzi, S.; Afonso, A.; and Ayadi, M. (2016). Assessment of efficiency in basic and secondary education in Tunisia: A regional analysis. *International Journal of Educational Development*, 51, 62-76.
26. Banker, R.D.; Charnes, A.; and Cooper, W.W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, 30(9), 1078-1092.
27. De La Hoz, E.; Zuluaga, R.; and Mendoza, A. (2021). Assessing and classification of academic efficiency in engineering teaching programs. *Journal on Efficiency and Responsibility in Education and Science*, 14(1), 41-52.
28. Henriques, C.O.; and Marcenaro-Gutierrez, O.D. (2021). Efficiency of secondary schools in Portugal: A novel DEA hybrid approach. *Socio-Economic Planning Sciences*, 74, 100954
29. Visbal-Cadavid, D.; Martínez-Gómez, M.; and Guijarro, F. (2017). Assessing the efficiency of public universities through DEA. A case study. *Sustainability*, 9(8), 1416.
30. Salas-Velasco, M. (2020). Measuring and explaining the production efficiency of Spanish universities using a non-parametric approach and a bootstrapped-truncated regression. *Scientometrics*, 122(2), 825-846.
31. Johnes, J.; and Yu, L. (2008). Measuring the research performance of Chinese higher education institutions using data envelopment analysis. *China Economic Review*, 19(4), 679-696.