ASSESSING THE RELATIVE IMPACT OF COLOMBIAN HIGHER EDUCATION INSTITUTIONS USING FUZZY DATA ENVELOPMENT ANALYSIS (FUZZY-DEA) IN STATE EVALUATIONS

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ABSTRACT

This research aims to design a helpful methodology for estimating universities' relative impact on students as a sustainability factor in higher education. To this end, the research methodology implemented a two-stage approach. The first stage involves the relative efficiency analysis of the study units using Fuzzy Data Envelopment Analysis. The second stage consists of a predictive evaluation of the efficiency of the study units. Consequently, among the most relevant results of the research, it is observed that the methodology identifies the institutions that need to strengthen the academic competencies of the industrial engineering program. Additionally, we developed a benchmark analysis called Efficient Route to help inefficient units achieve efficiency, associating efficiency, and sustainability as pillars of higher education processes.

KEYWORDS

Efficiency, higher education, machine learning, predictive evaluation

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Highlights

- *An empirical methodology is presented to evaluate, calculate, and predict the relative contribution under a fuzzy approach.*
- *The evaluation of homogeneous universities allows for correctly determining academic performance and associating efficiency with educational sustainability.*
- *The comparison of equivalent entities yields different average efficiency values for the global analysis.*

INTRODUCTION

Globalisation has catalysed what is now known as the integration of economies, societies, and cultures. Generally, these integrations manifest as global political ideas such as Education for Sustainable Development (Cars and West, 2015). Education for Sustainable Development is an instrument created in December 2002 by the United Nations General Assembly in its resolution 57/254. This instrument aims to provide comprehensive education in values, knowledge, and attitudes for discerning decisions and executing an action plan, considering a country's social, environmental, and economic context.

According to the United Nations, Educational Institutions are vital allies in this educational strategy due to their role as transformers of society through education. Various studies reveal a positive association between economic growth and the number of professionals (Hoeg and Bencze, 2017; Sharma et al., 2018). Meanwhile, Bianchi and Giorcelli (2020) show how countries with higher levels of education have higher levels of innovation, as represented in patent registrations. Corlu and Aydin (2016) demonstrated that science, technology, engineering, and mathematics education increases enterprise creation.

Therefore, it is necessary to overcome the challenges faced by educational institutions in Colombia to provide their students with the best education. The reports from the Organization for Economic Co-operation and Development are alarming, as they indicate the poor academic performance of Latin American countries. Figure 1 shows that Latin American countries rank at the bottom of the list of 79 evaluated countries in the areas assessed by the PISA test. The nation's average score is below the estimated population's average result.

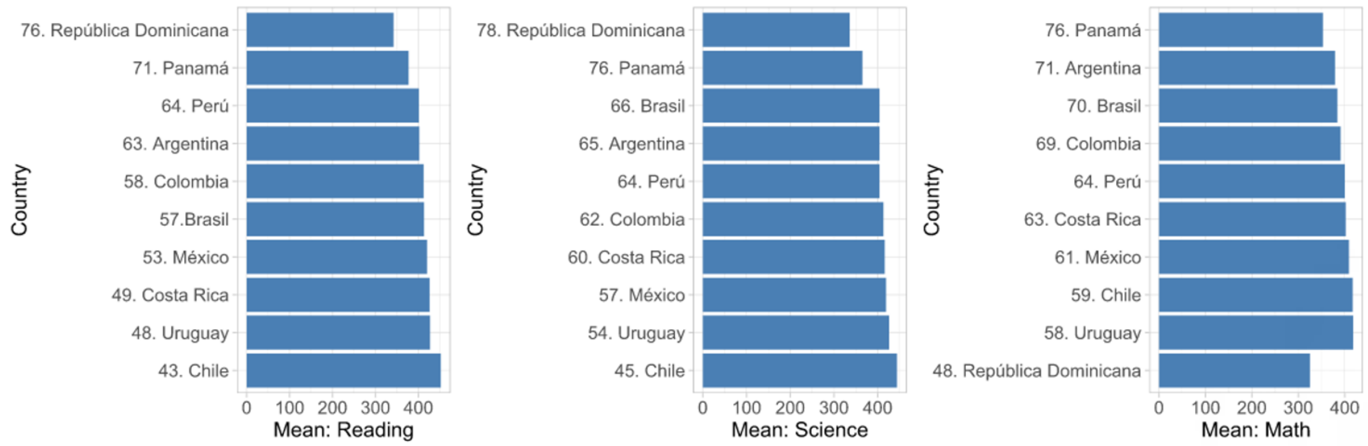

Figure 1: Ranking of PISA evaluation results for the year 2018 (OECD, 2019)

Academic Performance in Higher Education in Colombia

The results of internal assessments conducted in Colombia to evaluate the quality of secondary education confirm the issue of low academic performance (see Figure 2). Since 2016, the average evaluation score administered to students in professional training programs at Higher Education Institutions (IES) in Colombia has been below the value of 150.

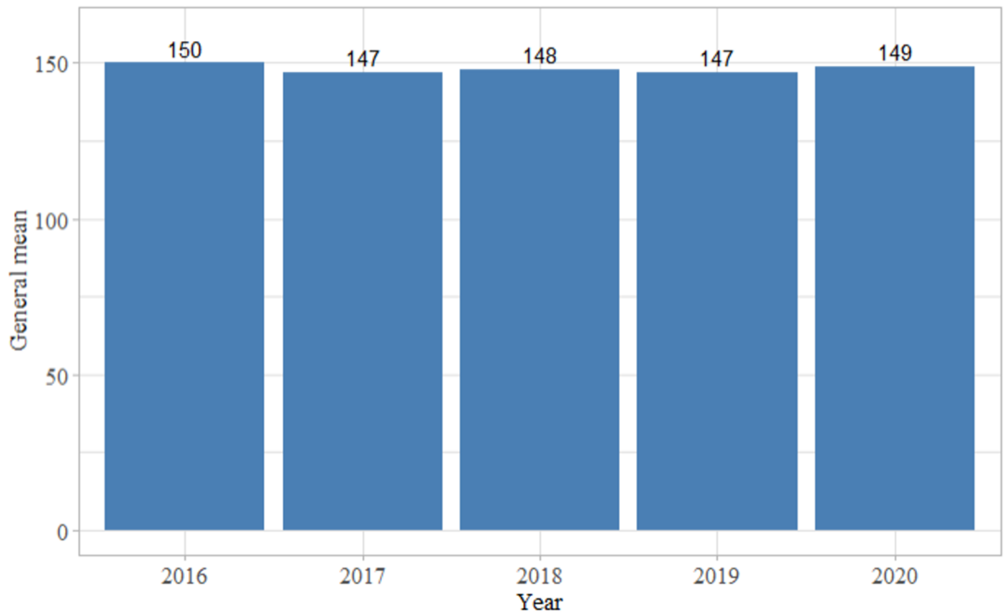

Figure 2: Average of the overall score between 2016 and 2020 (ICFES, 2022)

Previous reports on student academic performance are an issue that must be analysed, addressed, and resolved if the goal set by the United Nations for countries worldwide concerning Education for Sustainable Development is to be met. This is justified through the Sustainable Development Goals (SDGs), a series of targets set by the United Nations to address the world's most pressing global challenges to promote sustainable development worldwide. These objectives cover many areas, from poverty eradication to climate action and quality education (Chankseliani and McCowan, 2021). Specifically, one of the SDGs is Goal 4, which aims to "Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all." Quality education is essential for achieving sustainable development, as it equips individuals with the skills and knowledge required to understand current and future challenges and find innovative solutions (Ferrer-Estévez and Chalmeta, 2021).

In engineering, quality education plays a crucial role in promoting sustainability. Students and professionals in engineering are fundamental in creating sustainable solutions to social, economic, and environmental challenges. Therefore, it is vital that quality education addresses the principles of sustainability and equips students with the necessary skills to design, develop, and manage projects that are socially responsible, environmentally friendly, and contextually appropriate (Kopnina, 2020) Education for Sustainable Development (ESD).

In this vein, engineering programs incorporating sustainability into their curriculum raise awareness of the environmental and social impacts of engineering projects. Thus, it teaches students to consider energy efficiency, waste management, responsible use of natural resources, and social equity when designing technical solutions. At the same time, students must also evaluate and communicate the impacts of their projects in terms of sustainability (Chankseliani and McCowan, 2021). Additionally, engineering education can directly contribute to the achievement of several SDGs, such as SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 11 (Sustainable Cities and Communities). By equipping future engineers with knowledge about renewable energies, clean technologies, and sustainable urban design, the groundwork is being laid for more sustainable and resilient development. Therefore, quality engineering education that addresses sustainability principles prepares students to tackle current and future challenges from a responsible and sustainable perspective. Integrating sustainability into engineering education can drive innovation and promote more equitable, resilient, and environmentally respectful development (Avelar et al., 2019) but evolving, field. To conceptualize the phenomenon, accumulated ideas from a total of 193 articles were extracted through a secondary data source, the Web of Science™. The analysis proceeds in two sequential steps. First, the bibliometric analysis identified the networks of co-authorship, periodicals, higher education institutions (HEI).

However, all of this is overshadowed by the context of low performance presented at the beginning of this section. In response to this concern, various authors consider the possible causes of low academic performance, which may include i) the quality assessment approach for educational institutions (OECD, 2019), ii) how variables of interest are analysed (Rodríguez and Huertas, 2016), and iii) differing information on variables that determine academic performance (Pérez, 2019). These causes may also be due to the lack of an educational management tool to analyse student academic information and make accurate decisions regarding academic performance.

The first possible cause of low academic performance contemplates that the quality assessment for educational institutions is obtained by fulfilling three substantive activities (teaching, research, and social outreach or extension) and other specific requirements according to the accreditation requested. Additionally, Duque Oliva and Chaparro Pinzón (2012) consider that quality in education has different focuses: quality as prestige-excellence, quality based on resources, quality as a result, quality as change (added value), quality as an adjustment to purposes, quality as perfection or merit, quality as a program's conformity with prior minimum quality standards through accreditation processes, quality as a cost-value ratio, and quality as suitability for meeting the needs of the recipients or clients.

In Colombia, since 2016, the quality of educational institutions is estimated using the concept of quality as a result, which largely depends on the performance that students from the institution achieve in various evaluations, and quality as change (added value), which is granted based on the influence that the institution has on student performance (ICFES, 2022), it is worth noting that education experts suggest using this approach (Gamboa et al., 2003; Quintero Caro, 2018).

The second cause is that each approach mentioned considers different sets of factors or variables that intervene in educational processes based on an analysis, this makes quality in education a complex concept to define and possibly a multi-dimensional concept with multiple methods for its estimation (Santos et al., 2020) this process requires the development of a theoretical framework in order to analyse the impact of universities' social responsibility strategies on service quality and students' satisfaction with higher education. The present study sought to identify the factors defining students' perceptions of university social responsibility (USR). In the case of quality estimation in Colombia, Pérez (2019) states that the controls carried out on education measure a specific moment of education without considering the evolution of students, evidencing a poor understanding of the situation and, consequently, incorrect solutions to this problem.

The quality of higher education institutions in Colombia is estimated through information from the Saber PRO evaluations (conducted by final-year students in professional programs) (ICFES, 2022). Table 1 presents the variables collected for the evaluation model, and it is observed that they are qualitative; moreover, only the socio-economic information of the student is considered, and no past academic level is taken into account. Therefore, the inferences about the results may not be sufficient to understand current academic performance.

Variable	
Age	Sex
Socio-economic status	Scholarship
Region	Student loan
Type of institution	Head of the household
Tuition fee	Father's education
Hours on the internet	Mother's education
Semester	Public school
Socio-economic level	Private school

Table 1: Survey Variables in the Saber PRO Assessment Used for the Quality Evaluation Model

Lastly, the third cause relates to how variables are analysed, as they are crucial for generating accurate conclusions. According to Rodríguez and Huertas (2016), there are degrees of correspondence between deficient, acceptable, and outstanding academic performance. These authors argue that quality evaluation should consider, for instance, to what extent performance is deficient if an institution exhibits poor academic results. Similarly, if an institution has an acceptable academic performance, to what extent is it considered acceptable? Moreover, if an institution has an outstanding academic performance, to what extent is it considered outstanding?

Considering the challenges above, this research aims to answer the question: What tool should Higher Education Institutions utilise to identify the trajectory (in terms of benchmarking) they should follow to improve their students' academic performance?

LITERATURE REVIEW

Overview of the Colombian Higher Education System

The higher education system in Colombia is characterised by its diverse range of institutions, which include public and private universities, technological institutes, and technical professional institutions (Altbach et al., 2009). The system is governed by the Ministry of National Education, which defines policies and regulations and evaluates and accredits institutions (Ntshoe and Letseka, 2010) and quality assurance, movements have become highly contested issues in the advent of new managerialism1 in higher education. This is because while the notion of quality is critical to institutional autonomy and academic freedom, there are no universal criteria to determine quality in the current conditions of global competitiveness and new managerialism. In this chapter we analyze quality measures and the quality assurance movement in the current global market economy. We investigate ways in which the quality assurance movement has shaped higher education policy and practice and impacted national, regional, and international priorities. The chapter's emphasis is on the following areas: (a. There has been significant growth in higher education enrollment over the past two decades, with a notable increase in private institutions (Barr and Turner, 2013).

Despite the growth of the higher education sector, Colombian higher education institutions (HEIs) face several challenges, such as improving access, equity, and quality (Acosta and Celis, 2014). Moreover, there is a need to enhance teaching and research effectiveness and increase the internationalisation of Colombian HEIs (Navas et al., 2020). On the other hand, the higher education sector also presents opportunities for growth and improvement, such as the potential for collaboration between institutions, innovative teaching and learning methods, and the integration of new technologies (Castro, 2019) dynamics, and actors' interactions, particularly concerning technological innovations. This paper aims to identify some of the most promising trends in blended learning implementations in higher education, the capabilities provided by the technology (e.g., datafication).

State evaluations of higher education institutions play a crucial role in assessing the quality and performance of these institutions, providing valuable information for decision-making processes, and promoting accountability (Shriberg, 2002). State evaluations typically include assessments of teaching, research, community engagement, governance, and management (Abelson et al., 2003). Consequently, national or regional agencies conduct these evaluations and can serve various purposes, such as accreditation, funding allocation, or performance benchmarking (Font, 2002).

In Colombia, state evaluations of higher education institutions are conducted by the National Council for Higher Education Accreditation (CNA) and the Colombian Institute for the Evaluation of Higher Education (ICFES). The CNA is responsible for accrediting institutions based on their compliance with established quality criteria, while the ICFES evaluates the performance of students and programs through standardised tests. These evaluations are a basis for developing national policies and strategies to improve the higher education sector.

Application of Fuzzy Data Envelopment Analysis in Higher Education Performance Evaluation

Fuzzy Data Envelopment Analysis (Fuzzy-DEA) has developed as an essential method for evaluating the performance of higher education institutions, especially when data are imprecise, ambiguous, or subjective. Accounting for the inherent imprecision of input and output characteristics, Fuzzy-DEA has been utilised in several studies to assess the efficiency of higher education institutions in diverse scenarios.

Nojavan et al. (2021) utilised Fuzzy-DEA to evaluate eight higher education institutes in Iran. The study resolved the ambiguity of assessing research quality and its effect on overall efficiency scores by applying fuzzy logic. Their study indicated considerable differences in research efficiency across the examined institutions, shedding light on the aspects contributing to successful research performance.

Similarly, Nazarko and Šaparauskas (2014) applied Fuzzy-DEA to assess the efficiency of university departments, considering the uncertainty associated with the inputs and outputs variables such as number of professors, number of students, equipment and income. Their study found substantial differences in efficiency scores among the university departments, with most institutions operating below their maximum efficiency levels. Their research findings highlighted the need for resource equipment and space improvements to enhance overall performance in the higher education sector.

Aparicio et al. (2019) used Fuzzy-DEA to evaluate the performance of US students and schools participating in PISA (Programme for International Student Assessment) 2015. Their study provided a more robust and comprehensive assessment of educational performance by accounting for the imprecision and subjectivity of input and output factors. The results provide a framework to set the notion of fuzziness in some variables, such as students' socio-economic status or test scores.

In addition to these studies, Fuzzy-DEA has also been used to assess the efficiency of higher education institutions in other countries, such as Phillipines (Mirasol-Cavero and Ocampo, 2021), Taiwan (Liu and Chuang, 2009), and India (Singh et al., 2022). These studies have demonstrated the value of Fuzzy-DEA as a flexible and robust tool for evaluating the performance of higher education institutions, particularly in contexts where data are subject to uncertainty, imprecision, or subjectivity.

In Colombia, the use of Fuzzy-DEA in evaluating the performance of higher education institutions remains restricted, giving a potential for more study and analysis. By introducing fuzzy logic into the DEA framework, the present study attempts to provide a more thorough and nuanced evaluation of the relative contribution of Colombian higher education institutions based on state evaluations. Thus, this study aims to create a tool for educational management to evaluate students' academic performance in the industrial engineering program. Additionally, it is necessary to consider i) the quality assessment approach for educational institutions, ii) how the variables of interest are analysed, and iii) the variables that determine academic performance.

Consequently, it is essential to recognise the research that has been conducted to date in this field. Table 2 presents a summary of the literature review, in which only quantitative research studies were considered due to the focus of this study. Additionally, it is important to note that the identified research has an added-value approach for quality assessment (used in Colombia) due to the implementation of Data Envelopment Analysis models (De La Hoz et al., 2021).

Authors	Variables	Location	Population
Johnes (2006)	Academic scores, number of undergraduate and graduate students, library expenditure (Fuzzy logic approach)	England	130 universities
Nazarko and Šaparauskas (2014)	Financial expenses, faculty, student-to-administrative staff ratio	Poland	19 universities
Do and Chen (2014)	Staff, expenses, university area, credit-hours, publications, and scholarships (Fuzzy logic approach)	Vietnam	18 universities
Galbraith and Merrill (2015)	Academic performance and Burnout measures	United States	350 graduate students in economics and business
Alabdulmenem (2016)	Faculty and administrative staff, number of students, number of graduates	Saudi Arabia	25 universities
Visbal-Cadavid et al. (2017)	Financial resources, quality indicators, accreditations, and achievements	Colombia	32 universities
Wolszczak-Derlacz (2017)	Faculty, total income, number of students, bibliographic production, number of graduates	Europe and United States	500 universities
Aparicio et al. (2019)	PISA 2015 assessment outcomes (Fuzzy logic approach)	PISA Tests	United States
Agasisti et al. (2019)	Faculty, government investment, and PISA results	Europe	24 countries
Kalapouti et al. (2020)	Faculty and administrative staff, spending on research and development, and patents	United States	182 regions
Nojavan et al. (2021)	Outcomes of academic performance evaluations for HEIs (Higher Education Institutions) (Fuzzy logic approach)	Iran	30,000 Iranian students
Aparicio et al. (2021) the so-called plausible values, which are frequently interpreted as a representation of the ability range of students. In this paper, we focus on how this information should be incorporated into the estimation of efficiency measures of student or school performance using data envelopment analysis (DEA)	PISA 2015 assessment outcomes (Fuzzy logic approach)	PISA Tests	72 countries

Table 2: A literature review of papers using the fuzzy data envelopment analysis model

MATERIALS AND METHODS

The current research focuses on three fundamental concepts: Fuzzy Logic, Data Envelopment Analysis, Machine Learning and Methodology.

Fuzzy Logic

The objective of fuzzy logic is to mathematically represent the ambiguity of expressions or events that are observed in everyday life. In other words, the fuzzy numbers represent the uncertainty generated at the borders of the qualifiers (high, medium, low) that describe an event, for example, a student's performance (Rodríguez and Huertas, 2016).

On the other hand, mathematically, a fuzzy set is defined as presented in equation (1).

$$A=\{(x,\mu_A(x))\}, x\in X \tag{1}$$

Thus, the expression $\mu_A(x)$ represents the membership level of x in A and μ_A is the membership function associated with A. The equation defines the level at which each element of X belongs to the fuzzy set; it should be noted that X take values in $R:[-\infty,+\infty]$.

Finally, there exists a series of fuzzy numbers whose usage depends on the event or linguistic variable one wishes to represent. Figure 3 shows the graphical representation of a triangular fuzzy set (a) and another triangular fuzzy set (b). It should be noted that these are the most commonly used sets. The difference lies in the results for the membership function according to the same value of X.

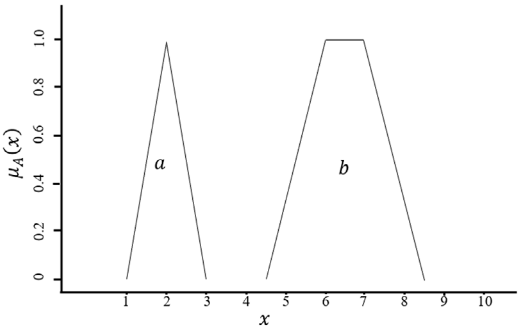

Figure 3: Graphical representation of a triangular fuzzy set (a) and a trapezoidal fuzzy set (b)

Data Envelopment Analysis

The Data Envelopment Analysis (DEA) methodology proposed by Charnes, Cooper, and Rhodes (Charnes et al., 1978) is a non-parametric approach for estimating the relative efficiency of Decision Making Units (DMUs). The outcome of the DEA model is a frontier made up of the most efficient DMUs in the study; it is essential to note that only the DMUs on this frontier are considered efficient.

To construct the DEA model, it is necessary to establish its configuration, which consists of scale return and orientation. First, the scale return can be either constant or variable. It is constant when estimating the system's overall efficiency, which involves understanding all the parts contributing to efficiency outcomes. On the other hand, variable returns are used to observe resource utilisation for each system unit. In other words, this scheme focuses on one aspect of efficiency; therefore, efficiency with variable returns will always be higher than with constant returns.

Additionally, orientation is important for the model's configuration and can be either input-oriented or output-oriented. Input orientation implies that resources or inputs can be reduced to achieve a greater or equal level of outputs. Conversely, an output-oriented model suggests that products or outcomes can be increased using the same input level.

Lastly, equation (2) presents the linear programming model of DEA (León et al., 2003). This model compares the ratio of outputs to inputs. It is worth noting that one DMU will be more efficient than another based on its ability to generate higher output levels with a given input level.

$$
\begin{aligned}
&\min \theta_0 \\
&\textit{Subject to}: \sum_{j=1}^{n} \lambda_j \bar{x}_{ij} \le \theta_0 \tilde{x}_{i0}, i = 1,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j \bar{y}_{rj} \ge \tilde{y}_{r0}, r = 1,\ldots,s \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&\lambda_j \ge 0, j = 1,\ldots,n
\end{aligned} \tag{2}
$$

where, θ_0 is the value of the efficiency of DMU 0, λ_j is the weighting of DMU j, $\bar{x}_{ij}$ is the fuzzy amount of resource i consumed by DMU j, $\tilde{x}_{i0}$ is the fuzzy amount of resource i consumed by DMU 0, $\bar{y}_{rj}$ is the fuzzy amount of output r produced by DMU j, $\tilde{y}_{r0}$ is the fuzzy amount of output r produced by DMU 0, n is the number of DMUs, m is the number of resources, and s is the number of outputs.

Consequently, equation (3) presents the DEA model in its version for fuzzy data analysis (León et al., 2003).

$$
\begin{aligned}
&P_T^h \min \theta_0 \\
&\textit{subject to}: \sum_{j=1}^{n} \lambda_j x_{ij} - (1-h) \sum_{j=1}^{n} \lambda_j \alpha_{ij} \le \theta_0 x_{i0} - (1-h)\theta_0 \alpha_{i0}, i = 1,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j x_{ij} + (1-h) \sum_{j=1}^{n} \lambda_j \alpha_{ij} \le \theta_0 x_{i0} + (1-h)\theta_0 \alpha_{i0}, i = 1,\ldots,m \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - (1-h) \sum_{j=1}^{n} \lambda_j \beta_{rj} \ge y_{r0} - (1-h)\beta_{r0}, r = 1,\ldots,s \\
&\sum_{j=1}^{n} \lambda_j y_{rj} + (1-h) \sum_{j=1}^{n} \lambda_j \beta_{rj} \ge y_{r0} + (1-h)\beta_{r0}, r = 1,\ldots,s \\
&\sum_{j=1}^{n} \lambda_j = 1, \\
&h = 0,\ldots,1 \\
&\lambda_j \ge 0, j = 1,\ldots,n
\end{aligned} \tag{3}
$$

where, x_{ij} is the amount of resource i consumed by DMU j, h is the possibility level, α_{ij} is the alpha cut-off level for resource i consumed by DMU j, x_{i0} is the amount of resource i consumed by DMU 0, α_{i0} alpha cut-off level for resource i consumed by DMU 0, y_{rj} is the quantity of output r produced by DMU j, β_{rj} is the betha cut-off level for output r produced by DMU j, y_{r0} is the amount of output r produced by DMU 0, and β_{r0} is the alpha cut-off level for output r produced by DMU 0.

Machine Learning

Two machine learning algorithms are used to support this research's development: Random Forest and Logistic Regression Boosted.

Random Forest

The Random Forest (RF) technique is a supervised machine-learning model and is mainly used for classification (De La Hoz et al., 2021). This model makes use of the democracy criterion, which consists of the creation of multiple responses that will be counted and the final response is classified according to the highest frequency (Louppe, 2014). On the other hand, the main parameters of the RF technique are number of trees (k) and number of variables needed to divide the nodes (m).

Logistic Regression

The Logistic Regression technique proposes the probability ratio (odds). This is the ratio between success and failure in a Bernoulli event. This algorithm predicts the probabilities of success of the diverse levels of the response variable, using the inverse of the logarithm of the probability ratio as a function of the linear predictor.

Boosting Models

The algorithms belonging to the Boosting model family aim to achieve robust and sophisticated predictions from a single model. These algorithms train multiple weak models to generate a robust final model that feeds on information from the weak models (Chen and Guestrin, 2016). This algorithm is also known as a generic and non-specific algorithm, so it is crucial to define the base model (for example, DT, GLMNET, NB, among others) and then it will be improved. This research will apply Boosting to the Logistic Regression model (LogitBoost).

Methodology

The current research is divided into two stages (See Figure 4): efficiency analysis and predictive assessment. In the first stage, fuzzy data analysis is conducted using the technique of Fuzzy Data Envelopment Analysis to estimate the relative efficiency of the Decision-Making Units. Then, in the second stage, a predictive analysis of the efficiency profiles found in the first stage is designed. The results of these two stages allow for generating useful information for decision-making in educational environments.

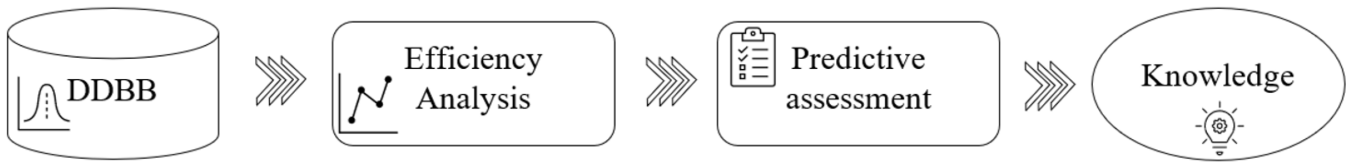

Figure 4: Research methodology (own elaboration)

Data

The data corresponds to the Mendeley's repository of the paper by Delahoz-Dominguez et al. (2020). For the present research, 92 universities (DMUs) are evaluated to summarise the results of the standardised evaluations of high school (Saber 11 - inputs) and university (Saber PRO – outputs) of 4,976 students of the Industrial Engineering program in Colombia (See Table 3). It is important to note that: first, 57% of the institutions evaluated in the database are private. Second, characteristics such as size and age are not homogeneous. And finally, 13.27% of the analysed universities are in socio-economic level 1 (low), 68.37% in level 2 (medium-low), 7.14% in level 3 (medium-high) and 11.22% in level 4 (high).

Variable	Full name	Test	Average	Deviation
MAT_11	Math	Saber 11	61.84	6.96
CR_11	Critical Reading	Saber 11	58.83	5.10
CS_11	Citizenship skills	Saber 11	58.93	5.11
BIO_11	Biology	Saber 11	61.71	6.43
ENG_11	English	Saber 11	58.67	7.50
QR_PRO	Quantitative Reasoning	Saber PRO	73.45	12.33
CR_PRO	Critical Reading	Saber PRO	57.74	12.81
CS_PRO	Citizenship skills	Saber PRO	54.71	11.92
ENG_PRO	English	Saber PRO	62.46	14.72
WC_PRO	Writing Communication	Saber PRO	50.94	8.79
FEP_PRO	Formulation of Engineering Project	Saber PRO	145.84	24.50
ACCP	Academic Program	-	-	-

Table 3: Data summary

On the other hand, for the information analysis, the R software is used (Coll-Serrano et al., 2018; R Core Team, 2013).

RESULTS

Stage 1: Efficiency Analysis

As mentioned, the models used correspond to the two-scale returns of the classic DEA model (CRS Constant, VRS Variable) and scale performance (RTS = CRS/VRS). Table 4 presents the efficiency results of the constant scale model; Table 5 presents the efficiency results of the variable scale model and Table 6 presents the efficiency results of scale performance.

The tables mentioned (4, 5 and 6) contain the level of possibility (h-level or alpha cut), the count of efficient DMUs (Count eff) and the percentage of efficient DMUs, the average (Mean), standard deviation (SD), minimum value (min), quartile one, two and three of the efficiency levels of the DMUs.

Considering the above, Table 4 shows how level h affects efficiency. As the h level increases, the number of efficient DMUs, the average efficiency level, the minimum efficiency value and the quartiles decrease.

On the other hand, although the efficiency model with variable scale return presents a similar behaviour as the model with a constant scale, the efficiency level is higher (see Table 5).

Finally, the model scale performance results equal the constant scale model. This indicates the difficulty that some DMUs could have in achieving the system's overall efficiency, so it is necessary to generate strategies to increase the efficiency of these DMUs.

Consequently, Table 7 presents a non-random sample of the top 10 DMUs for the model with constant scale, variable scale, and scale performance. Table 7 shows a similar efficiency behavior as in the summary tables (4, 5 and 6). For example, for the model with constant scale, no DMU of the sample has crisp efficiency; that is, the DMU is always efficient for the distinct levels of the possibility of h. On the other hand, for the model with variable scale the DMUs U3, U4, U5, U6, U9 and U10 have crisp efficiency. Finally, the efficiency of the scale performance has results comparable to the model with constant scaling; therefore, it does not have DMU with crisp efficiency. It should be noted that for the possibility level $h = 0$, the efficiency scores are always higher than those that would be obtained in the conventional evaluation of the centers of fuzzy triangular numbers ($h = 1$).

h-level	Count eff	Mean	SD	min	Q1	Q2	Q3
0.000	68 (69%)	0.992	0.017	0.911	0.994	1.000	1.000
0.100	59 (60%)	0.990	0.019	0.903	0.990	1.000	1.000
0.200	57 (58%)	0.986	0.023	0.894	0.981	1.000	1.000
0.300	52 (53%)	0.982	0.027	0.883	0.972	1.000	1.000
0.400	43 (44%)	0.977	0.032	0.871	0.960	0.996	1.000
0.500	37 (38%)	0.970	0.038	0.859	0.950	0.990	1.000
0.600	36 (37%)	0.962	0.044	0.836	0.931	0.980	1.000
0.700	31 (32%)	0.953	0.051	0.803	0.913	0.971	1.000
0.800	29 (30%)	0.943	0.058	0.773	0.894	0.961	1.000
0.900	26 (27%)	0.932	0.065	0.745	0.877	0.949	1.000
1.000	20 (20%)	0.921	0.073	0.716	0.857	0.938	0.997

Table 4: Results of the efficiency model with constant scale

h-level	Count eff	Mean	SD	min	Q1	Q2	Q3
0.000	85 (87%)	0.998	0.006	0.962	1.000	1.000	1.000
0.100	85 (87%)	0.998	0.007	0.957	1.000	1.000	1.000
0.200	82 (84%)	0.997	0.007	0.953	1.000	1.000	1.000
0.300	80 (82%)	0.997	0.008	0.948	1.000	1.000	1.000
0.400	77 (79%)	0.997	0.009	0.943	1.000	1.000	1.000
0.500	71 (72%)	0.996	0.009	0.939	0.999	1.000	1.000
0.600	68 (69%)	0.995	0.010	0.935	0.996	1.000	1.000
0.700	65 (66%)	0.994	0.011	0.931	0.993	1.000	1.000
0.800	63 (64%)	0.993	0.012	0.927	0.989	1.000	1.000
0.900	56 (57%)	0.992	0.013	0.923	0.988	1.000	1.000
1.000	52 (53%)	0.991	0.015	0.919	0.986	1.000	1.000

Table 5: Results of the efficiency model with variable scale

h-level	Count eff	Mean	SD	min	Q1	Q2	Q3
0.000	68 (69%)	0.994	0.014	0.927	0.999	1.000	1.000
0.100	59 (60%)	0.992	0.017	0.918	0.993	1.000	1.000
0.200	57 (58%)	0.989	0.021	0.910	0.989	1.000	1.000
0.300	52 (53%)	0.985	0.025	0.894	0.981	1.000	1.000
0.400	43 (44%)	0.980	0.030	0.879	0.969	0.998	1.000
0.500	37 (38%)	0.974	0.035	0.863	0.955	0.994	1.000
0.600	36 (37%)	0.966	0.042	0.836	0.937	0.984	1.000
0.700	31 (32%)	0.958	0.049	0.803	0.918	0.980	1.000
0.800	29 (30%)	0.949	0.056	0.773	0.900	0.975	1.000
0.900	26 (27%)	0.940	0.064	0.745	0.883	0.966	1.000
1.000	20 (20%)	0.929	0.072	0.716	0.866	0.953	0.998

Table 6: Model scale performance efficiency results

CRS – Level of efficiency										
Level (*h*)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
0.000	1.000	1.000	0.956	0.961	1.000	0.999	0.974	0.911	0.962	0.981
0.100	0.999	1.000	0.949	0.948	1.000	0.993	0.954	0.903	0.955	0.974
0.200	0.989	1.000	0.941	0.934	1.000	0.982	0.935	0.894	0.950	0.968
0.300	0.977	1.000	0.930	0.921	1.000	0.968	0.922	0.883	0.939	0.960
0.400	0.957	0.997	0.912	0.901	0.992	0.955	0.912	0.871	0.928	0.952
0.500	0.938	0.990	0.892	0.870	0.982	0.941	0.900	0.859	0.917	0.942
0.600	0.922	0.983	0.871	0.836	0.964	0.928	0.886	0.842	0.902	0.929
0.700	0.908	0.976	0.849	0.803	0.940	0.913	0.872	0.823	0.884	0.914
0.800	0.892	0.968	0.826	0.773	0.918	0.898	0.855	0.803	0.861	0.898
0.900	0.873	0.957	0.804	0.745	0.896	0.880	0.836	0.782	0.838	0.882
1.000	0.854	0.943	0.781	0.716	0.874	0.859	0.817	0.761	0.816	0.864
VRS - Level of efficiency										
Level (*h*)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
0.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.983	1.000	1.000
0.100	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.983	1.000	1.000
0.200	1.000	1.000	1.000	1.000	1.000	1.000	0.999	0.982	1.000	1.000
0.300	1.000	1.000	1.000	1.000	1.000	1.000	0.997	0.981	1.000	1.000
0.400	1.000	1.000	1.000	1.000	1.000	1.000	0.994	0.980	1.000	1.000
0.500	1.000	1.000	1.000	1.000	1.000	1.000	0.991	0.980	1.000	1.000
0.600	1.000	1.000	1.000	1.000	1.000	1.000	0.989	0.979	1.000	1.000
0.700	1.000	0.998	1.000	1.000	1.000	1.000	0.986	0.978	1.000	1.000
0.800	0.998	0.994	1.000	1.000	1.000	1.000	0.983	0.976	1.000	1.000
0.900	0.994	0.991	1.000	1.000	1.000	0.999	0.980	0.975	1.000	1.000
1.000	0.990	0.987	1.000	0.999	1.000	0.999	0.976	0.973	1.000	0.999
RTS - Level of efficiency										
Level (*h*)	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10
0.000	1.000	1.000	0.956	0.961	1.000	0.999	0.974	0.927	0.962	0.981
0.100	0.999	1.000	0.949	0.948	1.000	0.993	0.954	0.918	0.955	0.974
0.200	0.989	1.000	0.941	0.934	1.000	0.982	0.935	0.910	0.950	0.968
0.300	0.977	1.000	0.930	0.921	1.000	0.968	0.925	0.900	0.939	0.960
0.400	0.957	0.997	0.912	0.901	0.992	0.955	0.917	0.889	0.928	0.952
0.500	0.938	0.990	0.892	0.870	0.982	0.941	0.908	0.877	0.917	0.942
0.600	0.922	0.983	0.871	0.836	0.964	0.928	0.897	0.861	0.902	0.929
0.700	0.908	0.978	0.849	0.803	0.940	0.913	0.884	0.842	0.884	0.914
0.800	0.894	0.973	0.826	0.773	0.918	0.898	0.870	0.823	0.861	0.898
0.900	0.879	0.966	0.804	0.745	0.896	0.881	0.854	0.803	0.838	0.882
1.000	0.863	0.955	0.781	0.716	0.874	0.860	0.837	0.782	0.816	0.865

Table 7: Sample efficiency result for 10 DMUs

Table 8 also generates a concept called fuzzy set of effective units. In this sense, a fuzzy set is represented as the name of the DMU and the value of the maximum level h with which the DMU is still efficient, for example, for the model with constant scale the DMU U1 is efficient for the values h equal to 0, 0.1 and 0.2, then the set is (U1, 0.2).

Model	Effective diffuse assembly
CRS	(U1, 0.2), (U2, 0.4), (U5, 0.3), (U6, 0)
VRS	(U1, 0.8), (U2, 0.7), (U3, 1), (U4, 1), (U5,1), (U6, 1), (U7, 0.3), (U9, 1), (U10, 1)
RTS	(U1, 0.1), (U2, 0.4), (U5, 0.3), (U6, 0.1)

Table 8: Fuzzy set of effective units for 10 DMUs

On the other hand, the advantage of the model is the creation of an efficient route (see Table 9), the path that a non-efficient DMU must follow to become efficient and reach the maximum level of efficiency projected for its group. Two efficient routes were created that correspond to the low-medium efficiency levels (range between the 0th percentile and the 66th percentile of efficiency) and high efficiency (range between the 67th percentile and the 100th percentile of efficiency). For the development of the two routes, all the non-efficient DMUs of the model with constant scale were compared and grouped by efficiency level. Then, the score value of the references between DMUs of the model (lambdas) was observed and ordered from lowest to highest. Finally, DMU sequences were selected more frequently.

Name group	Efficiency path	Efficiency level
Path 1	U61 - U48 - U45	[0 - 0.94]
Path 2	U39 - U48 - U69	(0.94 - 1]

Table 9: Efficient paths

The efficient routes are composed of the DMUs of Table 10, each route has an expected increase from the competencies of Saber 11 to the competencies of Saber PRO (Diff). For example, path 1 generates a 14.7% increase in learning outcomes from Saber 11 to Saber PRO. It should be noted that the increase must be gradual, that is, it must first reach the efficiency of the first DMU of the route, then the second DMU and so, until reaching the last DMU of the route, consequently, the DMU that passes through the path will be efficient.

Finally, this section presents the analysis of two population variables: type of institution and socio-economic level. Table 11 presents a summary of the efficiency of public and private institutions.

Similarly, Table 12 shows the efficiency analysis according to the universities' socio-economic level.

Path	DMU	Saber 11						Saber PRO						Diff
		MAT	CR	CC	ENG	BIO	Mean	QR	CR	CC	ENG	WC	Mean	
1	U61	72.96	67.69	67.68	65.50	72.05	77.67	91.53	81.41	77.19	78.72	59.50	69.18	10.9%
	U48	61.88	59.52	61.02	59.74	61.52	70.38	89.32	70.22	55.18	69.94	67.22	60.74	13.7%
	U45	66.08	63.65	62.61	71.69	66.53	77.51	81.07	70.46	71.82	86.75	77.43	66.11	14.7%
2	U39	68.83	64.12	64.36	63.52	66.79	74.50	92.48	74.87	70.96	75.56	58.61	65.53	12.0%
	U48	61.88	59.52	61.02	59.74	61.52	70.38	89.32	70.22	55.18	69.94	67.22	60.74	13.7%
	U69	70.04	65.08	63.67	70.86	68.63	79.28	86.87	74.97	77.97	85.08	71.52	67.65	14.7%

Table 10: Characterisation of efficient paths

University	Count eff			Mean			Standard deviant		
	CRS	VRS	RTS	CRS	VRS	RTS	CRS	VRS	RTS
Private	13	27	13	0.935	0.990	0.944	0.068	0.013	0.065
Public	7	25	7	0.902	0.991	0.910	0.076	0.017	0.076

Table 11: Description of the efficiency of public and private universities

Socio-economic level	Count eff			Mean			Standard deviant		
	CRS	VRS	RTS	CRS	VRS	RTS	CRS	VRS	RTS
L1	2	6	2	0.916	0.985	0.930	0.071	0.019	0.073
L2	10	36	10	0.904	0.991	0.912	0.073	0.015	0.071
L3	2	3	2	0.977	0.993	0.984	0.020	0.007	0.018
L4	6	7	6	0.994	0.996	0.998	0.010	0.007	0.005

Table 12: Description of the efficiency of the university's socio-economic levels

Stage 2: Prediction Analysis

Finally, this stage seeks to suggest a model for predictive evaluation for non-efficient universities in the group analysed. In this sense, the route universities must follow to achieve maximum efficiency is established as a response variable, on the other hand, as predictor variables, the academic competencies of the Saber 11 evaluation and the training program are selected. The construction of the model consists of two stages: training and evaluation. The data is divided into two groups, corresponding to 70% for training and 30% for evaluation. In summary, two models are used for the training phase: Random Forest and LogitBoost. In addition, the cross-validation technique with 10 folds is used in this phase. The results show that the best-performing model is Random Forest (see Table 13).

Model	Metric	AUC	Accuracy	F1	Sensitivity	Specificity
Random Forest	Mean	0.641	0.650	0.725	0.892	0.600
	SD	0.157	0.093	0.072	0.142	0.274
LogitBoost	Mean	0.593	0.571	0.684	0.883	0.300
	SD	0.146	0.145	0.114	0.153	0.222

Table 13: Results of model training

Then, the models are evaluated with 30% of the study population, and their results are benchmarked. However, as in the training phase, in the evaluation phase, it is observed that the Random Forest model performs better (see Table 14).

Model	AUC	Accuracy	F1	Sensitivity	Specificity
Random Forest	0.710	0.700	0.727	0.667	0.800
LogitBoost	0.570	0.577	0.649	0.545	0.800

Table 14: Results of model testing

Finally, to generate additional information to understand the model with the best performance, Table 15 is constructed. Table 15 shows the importance of the variables of the Random Forest model. It is possible to identify that the variable with greater weight is the academic program, followed by English, Mathematics, Biology, Citizenship Skills, and Critical Reading.

Variable	Weight	Variable	Weight
ACCP	0.035	ENG_11	0.025
MAT_11	0.001	CR_11	0.000
BIO_11	0.000	CS_11	0.000

Table 15: Importance of the variables of the Random Forest model

DISCUSSION

Data Envelopment Analysis using fuzzy data offers an interesting approach for creating decision-making tools in the educational field. First, a significant advantage of this tool is its ability to incorporate uncertainty when formulating the evaluation model. Moreover, the results allow for analysing efficiency level changes concerning the decision variable - results not provided by a classical DEA model. In other words, if there is a substantial change from one level h of measurement to another $h+1$, then it can be asserted that the evaluated Decision-Making Unit (DMU) is sensitive to the measurement variable. This could be a persuasive argument for using the fuzzy approach to evaluate education quality using DEA models. It should be noted that it is essential to understand the context to adapt the model to the situation.

On the other hand, multiple efficiency measures allow for the creation of various alternatives within an action framework. That is, decision-makers can establish an h level for a student's academic competencies and then observe the efficiency level and its efficient path (if it is not already efficient). In this vein, one could know a student's efficiency level in advance to create an action plan that improves their level of academic competencies and, consequently, the efficiency of the university.

According to the research results, variations in competency levels cause significant differences in educational institutions' efficiency. Consequently, the efficiency level of a student's basic competencies greatly impacts the university's efficiency level. In other words, even if a university has an excellent training program, the student's competency level can be critical and decisive in determining the university's efficiency.

The findings on the economic aspect analysed complement this. For example, in the present analysis, the socio-economic level of the university is presented as a factor that has a small impact on university academic efficiency. Also, the diversity in efficiency within each socio-economic level suggests that institution-specific strategies, beyond their economic context, are crucial to achieving efficiency in higher education. And finally, the consistent efficiency in specific academic programmes indicates that the focus and quality of educational provision may be more critical than socio-economic status. Considering the above, it is necessary to generate crisply efficient DMUs, meaning that a DMU can be efficient at any level of academic competencies. This implies that higher educational institutions should have a prior plan that contributes to raising the level of academic competencies, not just for the university's efficiency level but also because a student's academic performance significantly determines their future professional performance.

Additionally, it is necessary to compare the present research with similar works. For example, the research by Nazari-Shirkouhi et al. (2020) develops a tool for evaluating academic performance based on an integrated fuzzy multicriteria decision-making approach. Unlike our research, Nazari-Shirkouhi et al. (2020) emphasise using the Fuzzy Decision-Making Trial and Evaluation Laboratory and Fuzzy Analytic Network Process tools to determine the indicators' weight for the model. This creates a robust framework for variable selection and model construction. In contrast, the research by Contreras et al. (2020) implemented classification models (decision tree, KNN, and perceptron) to predict academic performance. A differentiating point in Contreras et al.'s research is the use of data mining methodology for predicting academic performance; however, failing to consider the fuzzy aspect of information could be a weakness.

Similarly, Valdés Pasarón et al. (2018) research develops an empirical model combining qualitative and quantitative characteristics about the education system to estimate education quality. A point in favor of Valdés Pasarón et al.'s research is the addition of qualitative variables to provide more information for training models using the fuzzy approach. On the other hand, the research by Lee et al. (2019) constructs a model for evaluating and analysing e-learning systems through a matrix. In Lee et al.'s research, a differentiating point is avoiding the problem of potential sampling errors and the complexity of collecting fuzzy linguistic data through evaluative matrix systems.

Lastly, it should be noted that this model does not require expensive or specialised software, but can be implemented using standard DEA or linear programming packages. This could greatly assist researchers who are just starting to develop efficiency models.

CONCLUSION

The present research aimed to design a tool for educational management in a context of uncertainty. To accomplish this, we utilised Data Envelopment Analysis methodology within a framework of uncertainty represented by fuzzy inputs. The research provided a new perspective on evaluating quality in education using DEA models. The designed tool successfully identifies an "efficient path" consisting of universities with standard or ideal efficiency levels, serving as a reference point for universities identified as inefficient to find a path or goal towards increased efficiency. A crucial point in this development is that uncertainty is inherent in every process within the service and production areas. Therefore, the foundation of this research adapts classical DEA models into equivalent "crisp" linear programming formulations.

In addition, the findings show that there is a representation of both public and private efficient universities, with a slightly higher percentage of private universities; however, there is no clear trend indicating that one type of institution (public or private) is more efficient than the other in terms of the academic programmes evaluated. Additionally, some academic programmes, such as Electronic Engineering, Chemical Engineering, Civil Engineering, Mechanical Engineering, and Industrial Engineering, consistently stand out in terms of efficiency, regardless of socio-economic level.

Lastly, this research broadens the scope of knowledge to models that analyse the quality level in education, providing a tool for predictive evaluation under a fuzzy approach. Additionally, future research will consider incorporating Machine Learning models into efficiency evaluation with fuzzy data.

REFERENCES

Abelson, J., Forest, P.-G., Eyles, J., Smith, P., Martin, E. and Gauvin, F.-P. (2003) 'Deliberations about deliberative methods: issues in the design and evaluation of public participation processes', *Social Science & Medicine*, Vol. 57, No. 2, pp. 239–251. https://doi.org/10.1016/S0277-9536(02)00343-X

Acosta, O. and Celis, J. (2014) 'The emergence of doctoral programmes in the Colombian higher education system: Trends and challenges', *PROSPECTS*, Vol. 44, No. 3, pp. 463–481. https://doi.org/10.1007/s11125-014-9310-5

Agasisti, T., Munda, G. and Hippe, R. (2019) 'Measuring the efficiency of European education systems by combining Data Envelopment Analysis and Multiple-Criteria Evaluation', *Journal of Productivity Analysis*, Vol. 51, No. 2, pp. 105–124. https://doi.org/10.1007/s11123-019-00549-6

Alabdulmenem, F. M. (2016) 'Measuring the Efficiency of Public Universities: Using Data Envelopment Analysis (DEA) to Examine Public Universities in Saudi Arabia', *International Education Studies*, Vol. 10, No. 1, pp. 137–143. https://doi.org/10.5539/ies.v10n1p137

Altbach, P. G., Reisberg, L. and Rumbley, L. E. (2009) *Trends in Global Higher Education: Tracking an Academic Revolution*, Trends in global higher education: tracking an academic revolution; a report prepared for the UNESCO 2009 World Conference on Higher Education, Paris, [Online], Available: https://unesdoc.unesco.org/ark:/48223/pf0000183219 [16 Oct 2023]

Aparicio, J., Cordero, J. M. and Ortiz, L. (2021) 'Efficiency Analysis with Educational Data: How to Deal with Plausible Values from International Large-Scale Assessments', *Mathematics*, Vol. 9, No. 13, 1579. https://doi.org/10.3390/math9131579

Aparicio, J., Cordero, J. M. and Ortiz, L. (2019) 'Measuring efficiency in education: The influence of imprecision and variability in data on DEA estimates', *Socio-Economic Planning Sciences*, Vol. 68, 100698. https://doi.org/10.1016/j.seps.2019.03.004

Avelar, A. B. A., da Silva-Oliveira, K. D. and da Silva Pereira, R. (2019) 'Education for advancing the implementation of the Sustainable Development Goals: A systematic approach', *The International Journal of Management Education*, Vol. 17, No. 3, 100322. https://doi.org/10.1016/j.ijme.2019.100322

Barr, A. and Turner, S. E. (2013) 'Expanding Enrollments and Contracting State Budgets: The Effect of the Great Recession on Higher Education', *The ANNALS of the American Academy of Political and Social Science*, Vol. 650, No. 1, pp. 168–193. https://doi.org/10.1177/0002716213500035

Bianchi, N. and Giorcelli, M. (2020) 'Scientific Education and Innovation: From Technical Diplomas to University Stem Degrees', *Journal of the European Economic Association*, Vol. 18, No. 5, pp. 2608–2646. https://doi.org/10.1093/jeea/jvz049

Cars, M. and West, E. E. (2015) 'Education for sustainable society: attainments and good practices in Sweden during the United Nations Decade for Education for Sustainable Development (UNDESD)', *Environment, Development and Sustainability*, Vol. 17, No. 1, pp. 1–21. https://doi.org/10.1007/s10668-014-9537-6

Castro, R. (2019) 'Blended learning in higher education: Trends and capabilities', *Education and Information Technologies*, Vol. 24, No. 4, pp. 2523–2546. https://doi.org/10.1007/s10639-019-09886-3

Chankseliani, M. and McCowan, T. (2021) 'Higher education and the Sustainable Development Goals', *Higher Education*, Vol. 81, No. 1, pp. 1–8. https://doi.org/10.1007/s10734-020-00652-w

Charnes, A., Cooper, W. W. and Rhodes, E. (1978) 'Measuring the efficiency of decision making units', *European Journal of Operational Research*, Vol. 2, No. 6, pp. 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, T. and Guestrin, C. (2016) *XGBoost: A Scalable Tree Boosting System*, In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining - KDD '16 (pp. 785–794), San Francisco, California, USA: ACM Press. https://doi.org/10.1145/2939672.2939785

Coll-Serrano, V., Bolos, V. and Benitez Suarez, R. (2018) *deaR: Conventional and Fuzzy Data Envelopment Analysis*, (Version 1.4.1), España: Universidad de Valencia, [Software], available: https://CRAN.R-project.org/package=deaR [15 April 2023]

Contreras, L. E., Fuentes, H. J. and Rodríguez, J. I. (2020) 'Predicción del rendimiento académico como indicador de éxito/fracaso de los estudiantes de ingeniería, mediante aprendizaje automático', *Formación Universitaria*, Vol. 13, No. 5, pp. 233–246. https://doi.org/10.4067/S0718-50062020000500233

Corlu, M. A and Aydin, E. (2016) 'Evaluation of Learning Gains Through Integrated STEM Projects', *International Journal of Education in Mathematics, Science and Technology*, Vol. 4, No. 1, pp. 20–29. https://dx.doi.org/10.18404/ijemst.35021

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*, Vol. 14, No. 1, pp. 41–52. https://doi.org/10.7160/eriesj.2021.140104

Delahoz-Dominguez, E., Zuluaga, R. and Fontalvo-Herrera, T. (2020) 'Dataset of academic performance evolution for engineering students', *Data in Brief*, Vol. 30, 105537. https://doi.org/10.1016/j.dib.2020.105537

Do, Q. H. and Chen, J.-F. (2014) 'A hybrid fuzzy AHP-DEA approach for assessing university performance', *WSEAS Transactions on Business and Economics*, Vol. 11, pp. 386–397.

Duque Oliva, E. J. and Chaparro Pinzón, C. R. (2012) 'Medición de la percepción de la calidad del servicio de educación por parte de los estudiantes de la uptc duitama', *Criterio Libre*, Vol. 10, No. 16, pp. 159–192. https://doi.org/10.18041/1900-0642/criteriolibre.2012v10n16.1168

Ferrer-Estévez, M. and Chalmeta, R. (2021) 'Integrating Sustainable Development Goals in educational institutions', *The International Journal of Management Education*, Vol. 19, No. 2, 100494. https://doi.org/10.1016/j.ijme.2021.100494

Font, X. (2002) 'Environmental certification in tourism and hospitality: progress, process and prospects', *Tourism Management*, Vol. 23, No. 3, pp. 197–205. https://doi.org/10.1016/S0261-5177(01)00084-X

Galbraith, C. S. and Merrill, G. B. (2015) 'Academic performance and burnout: an efficient frontier analysis of resource use efficiency among employed university students', *Journal of Further and Higher Education*, Vol. 39, No. 2, pp. 255–277. https://doi.org/10.1080/0309877X.2013.858673

Gamboa, L. F., Casas, A. F. and Piñeros, L. J. (2003) 'La teoría del valor agregado: una aproximación a la calidad de la educación en Colombia', *Revista de Economía del Rosario*, Vol. 6, No. 2, pp. 95–116.

Hoeg, D. G. and Bencze, J. L. (2017) 'Values Underpinning STEM Education in the USA: An Analysis of the Next Generation Science Standards: VALUES UNDERPINNING STEM EDUCATION', *Science Education*, Vol. 101, No. 2, pp. 278–301. https://doi.org/10.1002/sce.21260

ICFES (2022) *Resultados de la evaluación Saber PRO* [Results of the Saber PRO evaluation], Instituto Colombiano para la Evaluación de la Educación, [Online], Available: https://www.icfes.gov.co/web/guest/acerca-del-examen-saber-pro [26 Oct 2023]

Johnes, J. (2006) 'Data envelopment analysis and its application to the measurement of efficiency in higher education', *Economics of Education Review*, Vol. 25, No. 3, pp. 273–288. https://doi.org/10.1016/j.econedurev.2005.02.005

Kalapouti, K., Petridis, K., Malesios, C. and Dey, P. K. (2020) 'Measuring efficiency of innovation using combined Data Envelopment Analysis and Structural Equation Modeling: empirical study in EU regions', *Annals of Operations Research*, Vol. 294, pp. 297–320. https://doi.org/10.1007/s10479-017-2728-4

Kopnina, H. (2020) 'Education for the future? Critical evaluation of education for sustainable development goals', *The Journal of Environmental Education*, Vol. 51, No. 4, pp. 280–291. https://doi.org/10.1080/00958964.2019.1710444

Lee, T.-S., Wang, C.-H. and Yu, C.-M. (2019) 'Fuzzy Evaluation Model for Enhancing E-Learning Systems', *Mathematics*, Vol. 7, No. 10, 918. https://doi.org/10.3390/math7100918

León, T., Liern, V., Ruiz, J. L. and Sirvent, I. (2003) 'A fuzzy mathematical programming approach to the assessment of efficiency with DEA models', *Fuzzy Sets and Systems*, Vol. 139, No. 2, pp. 407–419. https://doi.org/10.1016/S0165-0114(02)00608-5

Liu, S.-T. and Chuang, M. (2009) 'Fuzzy efficiency measures in fuzzy DEA/AR with application to university libraries', *Expert Systems with Applications*, Vol. 36, No. 2 (Part 1), pp. 1105–1113. https://doi.org/10.1016/j.eswa.2007.10.013

Louppe, G. (2014) *Understanding Random Forests: From Theory to Practice*, [PhD thesis], Ithaca, NY: Cornell University. https://doi.org/10.48550/arXiv.1407.7502

Mirasol-Cavero, D. B. and Ocampo, L. (2021) 'Fuzzy preference programming formulation in data envelopment analysis for university department evaluation', *Journal of Modelling in Management*, Vol. 18, No. 1, pp. 212–238. https://doi.org/10.1108/JM2-08-2020-0205

Navas, L. P., Montes, F., Abolghasem, S., Salas, R. J., Toloo, M. and Zarama, R. (2020) 'Colombian higher education institutions evaluation', *Socio-Economic Planning Sciences*, Vol. 71, 100801. https://doi.org/10.1016/j.seps.2020.100801

Nazari-Shirkouhi, S., Mousakhani, S., Tavakoli, M., Dalvand, M. R., Šaparauskas, J. and Antuchevičienė, J. (2020) 'Importance-performance analysis based balanced scorecard for performance evaluation in higher education institutions: an integrated fuzzy approach', *Journal of Business Economics and Management*, Vol. 21, No. 3, pp. 647–678. https://doi.org/10.3846/jbem.2020.11940

Nazarko, J. and Šaparauskas, J. (2014) 'Application of DEA method in efficiency evaluation of public Higher Education Institutions', *Technological and Economic Development of Economy*, Vol. 20, No. 1, pp. 25–44. https://doi.org/10.3846/20294913.2014.837116

Nojavan, M., Heidari, A. and Mohammaditabar, D. (2021) 'A fuzzy service quality based approach for performance evaluation of educational units', *Socio-Economic Planning Sciences*, Vol. 73, 100816. https://doi.org/10.1016/j.seps.2020.100816

Ntshoe, I. and Letseka, M. (2010) *Quality Assurance and Global Competitiveness in Higher Education*, In L. M. Portnoi, V. D. Rust, & S. S. Bagley (Eds.), Higher Education, Policy, and the Global Competition Phenomenon (pp. 59–71), New York: Palgrave Macmillan US. https://doi.org/10.1057/9780230106130_5

OECD (2019) *Publications - PISA*, Organisation for Economic Co-operation and Development [Online], Available: https://www.oecd.org/pisa/publications/pisa-2018-results.htm [4 Dec 2019].

Pérez, Á. (2019) *¿Por qué la calidad de la educación en Colombia no es buena?*, Semana, [Online], Available: https://www.dinero.com/opinion/columnistas/articulo/por-que-la-calidad-de-la-educacion-en-colombia-no-es-buena-por-angel-perez-martinez/268998 [19 Nov 2019].

Quintero Caro, O. L. (2018) *Efectos de la acreditación de alta calidad en el valor agregado de la educación superior*, [Master tesis], Bogotá: Facultad de Ciencias Económicas y Administrativas, Pontificia Universidad Javeriana. https://doi.org/10.11144/Javeriana.10554.38960

R Core Team (2013) *R: A language and environment for statistical computing*, R Foundation for Statistical Computing, Vienna, Austria, [Software], available: https://www.r-project.org/ [15 Jul 2023]

Rodríguez, M. and Huertas, Y. (2016) 'Metodología para el Diseño de Conjuntos Difusos Tipo-2 a partir de Opiniones de Expertos', *Ingeniería*, Vol. 21, No. 2, pp. 121–137. https://doi.org/10.14483/udistrital.jour.reving.2016.2.a01

Santos, G., Marques, C. S., Justino, E. and Mendes, L. (2020) 'Understanding social responsibility's influence on service quality and student satisfaction in higher education', *Journal of Cleaner Production*, Vol. 256, 120597. https://doi.org/10.1016/j.jclepro.2020.120597

Sharma, P. N., Shmueli, G., Sarstedt, M., Danks, N. and Ray, S. (2018) 'Prediction-Oriented Model Selection in Partial Least Squares Path Modeling', *Decision Sciences*, Vol. 52, No. 3, pp. 567–607. https://doi.org/10.1111/deci.12329

Shriberg, M. (2002) 'Institutional assessment tools for sustainability in higher education: strengths, weaknesses, and implications for practice and theory', *Higher Education Policy*, Vol. 15, No. 2, pp. 153–167. https://doi.org/10.1016/S0952-8733(02)00006-5

Singh, A. P., Yadav, S. P. and Singh, S. K. (2022) 'A multi-objective optimisation approach for DEA models in a fuzzy environment', *Soft Computing*, Vol. 26, No. 6, pp. 2901–2912. https://doi.org/10.1007/s00500-021-06627-y

Valdés Pasarón, S., Ocegueda Hernández, J. M. and Romero Gómez, A. (2018) 'La calidad de la educación y su relación con los niveles de crecimiento económico en México', *Economía y Desarrollo*, Vol. 159, No. 1, pp. 61–79.

Visbal-Cadavid, D., Martínez-Gómez, M. and Guijarro, F. (2017) 'Assessing the Efficiency of Public Universities through DEA. A Case Study', *Sustainability*, Vol. 9, No. 8, 1416. https://doi.org/10.3390/su9081416

Wolszczak-Derlacz, J. (2017) 'An evaluation and explanation of (in)efficiency in higher education institutions in Europe and the U.S. with the application of two-stage semi-parametric DEA', *Research Policy*, Vol. 46, No. 9, pp. 1595–1605. https://doi.org/10.1016/j.respol.2017.07.010