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Academic efficiency of engineering university degrees and its driving factors. A PLS-DEA approach

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Abstract. This research develops an academic production function for the educational process of industrial engineers in Colombia. The proposed function objectively analyses the relationships between the academic competencies obtained in secondary education and the university. The data used correspond to the standardized tests of 4,977 students at the end of high school and university. In the first stage of the model, the structure of the production function was empirically evaluated using a Partial Least Square - Structural Equation Modeling approach. Consequently, in the second stage, the efficiency of the relationships in the academic production function is estimated using Data Envelopment Analysis. The Goodness of Fit index of the empirical model was 0.89, thus, confirming the relationships between the construct's variables. The model validates four transformation relationships and subsequently estimates the efficiency of the interactions in the production function. The average efficiency results of the model in its constant scale are 16.30%, 2.17%, and 5.43%. In conclusion, the model explains the capacity of universities to transform inputs

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(basic competencies of the secondary school) into desired outputs (professional academic competencies). Additionally, the model analyses professional performance from the interactions among academic competencies.

Keywords: efficiency, education, data envelopment analysis, partial least square, structural equation modeling.

JEL Classification: I21

1. INTRODUCTION

Engineering education is widely regarded as a critical aspect of a country's economic and social growth. Therefore, it is essential from a strategic point of view to identify academic efficiency factors that positively impact engineering learning. Consequently, several studies have shown positive associations between the number of engineering graduates and the development of patents (Bianchi & Giorcelli, 2020; Shambaugh et al., 2017), economic growth (Hoeg & Bencze, 2017; C. I. Jones, 2016), and creation of start-ups (Colombo & Piva, 2020; Suh et al., 2020). Thus, the management of university resources has become increasingly relevant (Long & Siemens, 2014).

Different studies have dealt with measuring efficiency in university institutions, and the Data Envelopment Analysis (DEA) is the most used technique. The DEA is an optimization structure that evaluates the efficiency of decision-making units that interact within a competitive sector. The DEA analysis, also known as frontier analysis, has become the standard for developing processes of comparison, measurement, and evaluation of efficiency in productive organizations. Consequently, different approaches can arise from the point of view of DEA analysis; for example, Cook et al. (2019) evaluate organizational behaviour in the specific context of performance-based incentive plans.

In this research, the Decision Making Units (DMU) are the degrees in engineering which allow for the creation of an academic production function, using the results in national standardized exams of the high school (Saber11) as inputs of the model and the results of the national standardized exams in the university stage (SaberPRO) as outputs. Thus, the efficiency frontier is estimated by conceiving education as a transformation process in which the inputs and outputs interact.

One of the main problems of DEA models is the correct definition of input and output variables. Thus, it is possible to find several studies that use different variables and assume a casuistic relationship between them to calculate efficiency levels in the specialized literature. However, it is vital before analyzing efficiency in the educational context to effectively define and quantify the relationship structure between the input and output variables, so the efficiency analysis becomes an improvement factor depending on the strength or weakness of the relationships between variables.

One of the critical aspects of implementing DEA in a specific context is defining the variables associated with the inputs and outputs of the production function. In other contexts, such as manufacturing or service provision, the production function comprises variables' physical or organizational interaction to create a product or service. However, there is no universal definition of the production function in university education. Therefore, several authors have proposed productive structures for university education based on contexts. For example, Visbal et al. (2017) relate the latent variables of Resources, Quality, Achievement, Access, and Accreditation. From another approach, Gralka et al. (2019) analyze university efficiency based on the results obtained in indexed publications and resources obtained to finance research. The approach of Yang et al. (Yang et al., 2018) to define the function of educational efficiency considers the systematic association of variables for the global evaluation of the efficiency of a university, considering subsequent interactions in a two-stage model. Other studies analyze efficiency in the university environment worldwide (Duan, 2019; Madria et al., 2019; Shamohammadi & Oh, 2019).

This research proposes a production function for the educational process of engineers, adapting the evaluation criteria of the Colombian Ministry of Education. To achieve the empirical validation of the proposed relationship structure between variables, the PLS-SEM (Partial Least Square – Structural Equation Modeling) is implemented using the data of engineering students in Colombia for the year 2018.

2. LITERATURE REVIEW

This research focuses on the measurement of academic efficiency in engineering degrees. Consequently, in the literature, there are two main approaches to estimating efficiency in educational contexts, according to the data structure. First, there is the analysis of efficiency using aggregated data corresponding to educational institutions (universities, colleges) such as DMUs. This approach allows the creation of university rankings (Puertas & Marti, 2019), identification of opportunities for improvement in the organizational aspect (de la Torre et al., 2018), and the creation of latent variables articulating the DEA with the analysis of principal components (Jakaitiene et al., 2018).

The second approach analyses efficiency using data at the individual level (students, teachers) as DMUs (Johnes, 2006; Latin & Sicily, 2018). This type of study allows identifying the significant characteristics to explain the student performance; some studies have shown how the average efficiency levels may differ when using the different approaches according to the data. Table 1 shows the main structure of variables used in previous research to analyze efficiency in an educational environment.

Table 1

Summary of the review of the literature

Authors	Latent variables	Manifest variables	Sample size
Colbert et al. (2000)	The number of faculty, Number of students, Faculty to student ratio Average, GMAT score, Number of electives.	5	25 MBA Programs
Johnes (2006)	First and higher degrees, recurrent grants for research, undergraduate and postgraduate students, full-time academic staff, depreciation and interest, expenditure on central libraries and central administration.	9	130 universities in England
Nazarko & Šaparauskas (2014)	Financial, staff, organizational and qualitative aspects	15	19 Polish universities of technology
Lorcu & Bolat (2015)	Public Expenditure on Education, Pupi-teacher ratio, math, reading y science.	8	26 European countries
Galbraith & Merrill (2015)	Academic performance, Burnout measures, control variables	7	350 undergraduate business and economics students
Alabdulmenem (2016)	Faculty, administrators, number of new entrants, number of enrollees, and number of graduates.	5	25 public universities in Saudi Arabia
Visbal-Cadavid et al. (2017)	Resources, Quality, Achievement, Access, Accreditation	17	32 universities
Wolszczak-Derlacz (2017)	Academic staff, total revenue, number of students, publications and graduates.	5	500 HEIs in ten European countries and the U.S
Agasisti et al. (2019)	Teacher ratio, government expenditure, public expenditure, PISA scores.	14	24 countries in Europe
Kalapouti et al. (2020)	Human Capital, Expenditures in Research and Development, Patent applications	8	182 regions in the U.S.

Source: compiled by authors

2.1. Educational production function

The educational production function analyses the interactions of the variables of the educational process with an individual result (Hanushek, 1979). The production function concept's origins are related to the Coleman report (T. H. Jones, 1981), which analyzed the distribution of educational resources according to race or ethnic group. From the economic point of view, production functions allow companies to estimate the technical relationships that govern a productive system to determine the maximum possible result obtained with a certain number of inputs. The industrial processes measure the relationships among activities, resources and outcomes with great precision, enabling the characterization of the deterministic relationships between inputs and outputs. However, educational methods have intangibility, heterogeneity, and variability characteristics that make the function of academic production unknown a priori. On the contrary, their construction relies on the available data; some authors criticize quantitative approaches to estimate educational performance, considering that academic results cannot be adequately measured. However, recent studies show the use of standardized test results to measure students' levels of achievement (Bernal et al., 2020, p. 11; De La Hoz et al., 2021).

Other authors have used alternative measures such as student attitudes, attendance rate, or dropout rates from another approach. Thus, the transformation approach in economic theory is not fully adaptable to education, considering education as a service in which the individual is transformed as a function of time through different educational activities, viewing everyone as a human being, independent and with varying attitudes towards the educational process. Therefore, the academic production function has an objective dimension associated with the factors controllable by educational decision-makers; on the other hand, the subjective dimension relates to motivation, abilities, and interests.

Now, in the literature specialized in educational analysis, it is possible to find different studies where they take other variables and assume a cause-effect relationship between them to calculate efficiency levels. Therefore, the efficiency analysis represents an improvement factor depending on the strength or weakness of the relationships between variables. However, it is essential to effectively define and quantify the relationship structure between the input and output variables before analyzing efficiency in educational contexts.

A key aspect when analyzing efficiency in an educational context is defining the variables associated with the inputs and outputs of the production function. Therefore, this research proposes a production function for the educational process of engineers, articulating the evaluation criteria of the Colombian Ministry of Education. To empirically validate the relationship structure between variables, we applied PLS-PM (Partial Least Square – Path Modeling), articulating the standardized tests for engineering students in Colombia for 2018 with the standardized test results carried out at the end of high school.

3. METHODOLOGY

The empirical methodology of this research is divided into two stages that articulate two models (see Figure 1). The first stage develops the Partial Least Squares – Path Modeling (PLS-PM). The second stage implements the Envelopment Data Analysis (DEA). Before these two stages, the database is built, considering the structure required by the models.

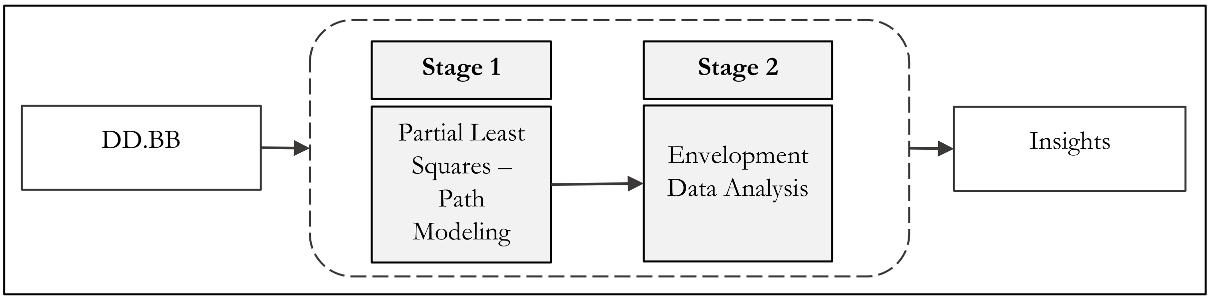

Figure 1. Research methodology
Source: own data

The following stages describe the academic production proposed in this research:

- English, reading and writing skills are transformed into the communication skills of the engineer.
- The skills in science and mathematics in high school are transformed into processes of logical reasoning of the engineer.
- Professional expression is transformed into the professional performance of engineers.
- Logical thinking is transformed into the professional performance of engineers.

Consequently, the educational production function stages generate the following research questions.

RQ1: Does having more excellent communication skills in high school positively impact the professional's communication skills?

RQ2: Do high school skills in science and math positively impact students' logical thought processes?

RQ3: Does professional expression have a positive impact on professional skills?

RQ4: Does logical thinking have a positive impact on professional skills?

The theoretical academic production of engineering education in Colombia will be validated by objective evidence. The four productive interactions will be validated using the PLS-PM technique. Subsequently, the efficiency level for each productive stage will be evaluated using the Data Enveloping Analysis (DEA). Both methods are briefly described in the next section.

3.1. Data

The data source is Mendeley Data Repository, specifically the dataset entitled Data of academic performance evolution for engineering students (Delahoz-Dominguez et al., 2020), which consists of 44 variables of educational and socio-economical information for 12,411 students. The dataset was filtered by Industrial engineering students and aggregated by the university. So, finally, the dataset used for the model consists of 92 universities representing 4977 students. Of the 92 universities studied, 46.25% have a high-quality accreditation.

3.1.1 Measures

When a student finishes high school in Colombia must take a standardized test called SABER 11, with a measurement scale between zero and one hundred. This test is carried out by the Colombian Institute for the Evaluation of Education (ICFES) to measure the quality of education in schools in Colombia. Table 2 presents the competencies evaluated by the SABER 11 test.

Table 2

Database information

Test section	Variable	Description
Math	M_11	Ability to understand and transform information and plan and execute strategies and solve problems in various contexts.
Citizenship Skills	C_11	Ability to understand, interpret, and evaluate every day and academic texts and understand the meaning of words or phrases.
Critical Reading	R_11	Ability to understand, interpret, and evaluate every day and academic texts and the skills of understanding the meaning of words or phrases.
Social Sciences	S_11	Ability to use fundamental concepts of the social sciences that facilitate the understanding of social, political, economic, cultural and geographical problems and phenomena and basic principles of the Colombian political system.
Science	SC_11	Ability to recognize appropriate questions and procedures, analysis of models describing phenomena, and the ability to use concepts, theories, and models for problem-solving.
English	E_11	Communicative ability in a foreign language from reading, lexicon and grammar tests.

Source: compiled by authors

Similarly, it happens with university students when they have fulfilled more than 70% of the academic subjects of their professional cycle, at this time, undergraduate students must take a knowledge test called SABER PRO that has a measurement scale between zero and three hundred. The SABER PRO is carried out by the (ICFES) to measure the quality of all public or private universities in the country. On the other hand, the exam structure consists of two parts; the first evaluates the generic competencies of every professional, and the second considers the specific competencies of the academic program to which a student belongs. Consequently, for the development of this research, the module on generic and specific competencies of industrial engineering students in Colombia was selected (see Table 3).

Table 3

Information on the database used

Test section	Type	Variable	Description
Writing Communication	Generic	W_PRO	Competence to communicate written ideas regarding a specific topic. In this test, a problem arises, with which the student must develop an argumentative text.
Quantitative Reasoning	Generic	Q_PRO	Every citizen must have mathematical skills, regardless of their profession or trade, in the skills of interpretation and representation, argumentation, formulation and execution in topics such as algebra, calculus, geometry and statistics.
Critical Reading	Generic	R_PRO	Skills to understand, interpret and evaluate texts, understand the meaning of word phrases, relate the parts of a text to give it a global sense, determine whether the author's reasons are convincing and identify arguments and assumptions.
Citizenship Skills	Generic	C_PRO	Knowledge and skills to understand the social environment, its problems and analyze various positions in conflict situations, and skills in argumentation, knowledge, multiperspective and systemic thinking.
English	Generic	E_PRO	Communicative competence in the English language based on reading, lexicon and grammar tests.

Mathematical and statistical thinking	Specific	MST	This competence involves students' ability to understand, analyze and deal with actual or abstract situations with scientific rigor and deal with real or conceptual problems with scientific rigor.
Engineering project formulation	Specific	EFP	Recognition and identification of relevant conditions for the characterization and formulation of projects. Formulation and evaluation of projects. Recognition of the role and disciplinary, social and ethical responsibility as an engineer in a context of professional performance.
Design of production and logistics systems	Specific	DPLS	Production of goods and services. Logistics. Quantitative methods.

Source: compiled by authors

The academic competencies of Saber 11 and Saber PRO are the manifest variables; these are used to estimate the latent variables of the study (see Figure 2).

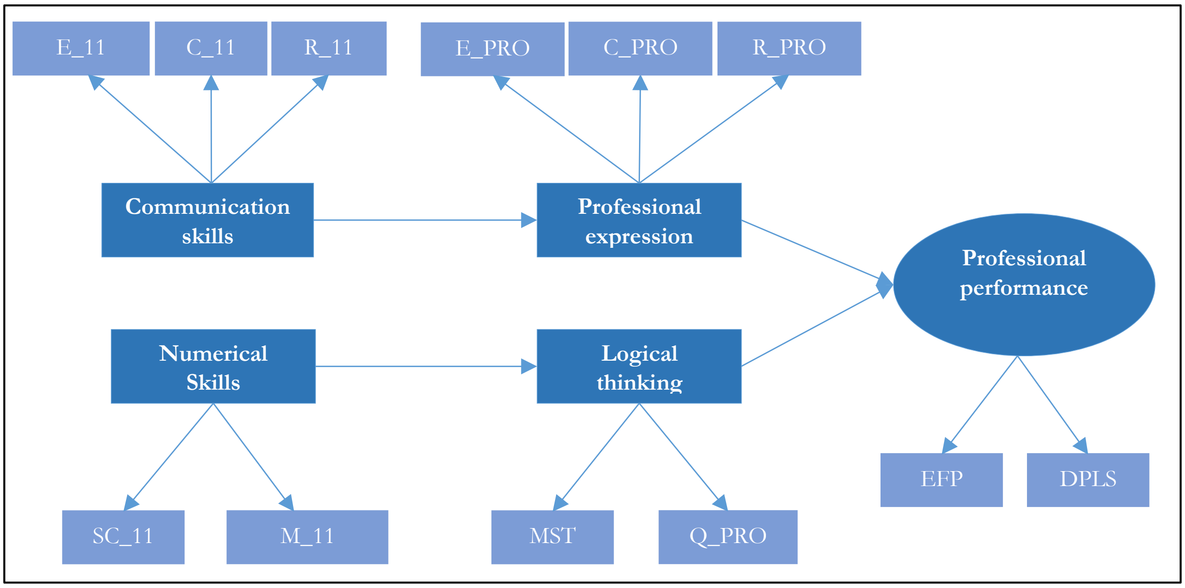

Figure 2. Empirical research model

Source: own data

3.2. Tools and techniques

For the implementation and articulation of the models, the R software was used, the libraries used correspond to deaR (Coll-Serrano et al., 2018) for the Data Envelope Analysis and PLSPM (Sanchez, 2013) for the Partial Least Squares model – Path Modeling.

3.3. Partial Least Squares – Path Modeling

Partial Least Squares – Path Modeling (PLS-PM) is a statistical methodology that uses linear regression models, structural equations, and multi-table analysis methods. Unlike other models, PLS-PM can graphically represent the relationships of variables studied, allowing to interpret the score it delivers for each relationship built (Law and Fong, 2020). However, the concept of PLS-PM and structural models should not be confused, and the difference lies in the fact that structural models use covariance analysis. At the same time, PLS-PM has a broader application due to the absence of fitting a known statistical distribution

(Ondé & Alvarado, 2018). In the PLS-PM, a variable could be a combination of other variables. Consequently, the PLS-PM quantifies the relationships between variables considering the set of relationships as a system of multiple interconnected linear regressions.

3.4. Partial Least Squares – Path Modeling

Data Envelopment Analysis (DEA) is a tool for analyzing a series of decision-making units (DMU). The DEA tool was proposed in 1978 by Charnes, Cooper, and Rhodes as a non-parametric methodology based on linear programming models; the objective was to study the relative efficiency of a series of decision-making units where there are multiple inputs and outputs (Charnes et al., 1978).

Now, the general idea behind the DEA methodology is that the efficiency of a DMU is determined by its ability to transform inputs into desired outputs. On the other hand, it is essential to remember that the DMUs used must be comparable, so inputs and outputs must have homogeneous units (De La Hoz et al., 2021).

4. EMPIRICAL RESULTS AND DISCUSSION

Before building the models, it is necessary to explore the data and analyze its behaviour. Thus, it is possible to generate more appropriate interpretations. Table 4 presents the information from the observed data set of the study.

Table 4

Statistical data summary

Variable	Test	Average	Deviation	Q3
R_11	Saber 11	57.52	5.41	60.37
C_11	Saber 11	57.45	5.71	60.59
E_11	Saber 11	57.41	7.77	61.11
M_11	Saber 11	59.37	6.40	61.80
SC_11	Saber 11	59.26	5.75	62.44
R_PRO	Saber PRO	53.94	13.43	63.56
C_PRO	Saber PRO	52.52	12.52	60.61
E_PRO	Saber PRO	60.08	15.20	69.54
W_PRO	Saber PRO	52.48	9.48	57.76
Q_PRO	Saber PRO	67.79	13.54	76.70
MST	Saber PRO	133.71	12.99	141.28
DPLS	Saber PRO	147.80	16.50	155.54
EFP	Saber PRO	150.83	14.15	161.76

Source: own data

According to Table 5, the degree of association between the study variables is moderately high; however, due to handling the covariance matrices of the Partial Least Squares model, having correlated data is not a problem.

Table 5

Correlation of study variables

	Saber 11					Saber PRO							
	R_11	C_11	E_11	M_11	SC_11	R_PRO	C_PRO	E_PRO	W_PRO	Q_PRO	MST	DPLS	EFP
R_11	1												
C_11	0,92	1											
E_11	0,85	0,77	1										
M_11	0,91	0,82	0,90	1									
SC_11	0,93	0,85	0,88	0,97	1								
R_PRO	0,90	0,84	0,80	0,87	0,89	1							
C_PRO	0,82	0,80	0,79	0,83	0,85	0,85	1						
E_PRO	0,84	0,75	0,89	0,86	0,86	0,82	0,82	1					
W_PRO	0,64	0,56	0,73	0,64	0,64	0,65	0,70	0,67	1				
Q_PRO	0,89	0,86	0,78	0,87	0,87	0,86	0,83	0,82	0,61	1			
MST	0,84	0,82	0,81	0,87	0,89	0,87	0,88	0,79	0,61	0,86	1		
DPLS	0,84	0,77	0,77	0,83	0,86	0,87	0,78	0,79	0,60	0,83	0,86	1	
EFP	0,81	0,81	0,72	0,77	0,82	0,83	0,83	0,79	0,55	0,87	0,85	0,88	1

Source: own data

The first stage consists of the development of the PLS-PM model. In Figure 3, the final model is presented; the arrows relate the latent variables with the manifest variables and the other latent variables. So, each arrow has an associated coefficient and indicates the direct relationship of one latent variable over the other. Consequently, a global indicator of the model is the Goodness of Fit; this is the geometric mean between the communality and the R2; for this research, it has a value of 0.89, exceeding the minimum value of 0.7 recommended in the literature (Sanchez, 2013).

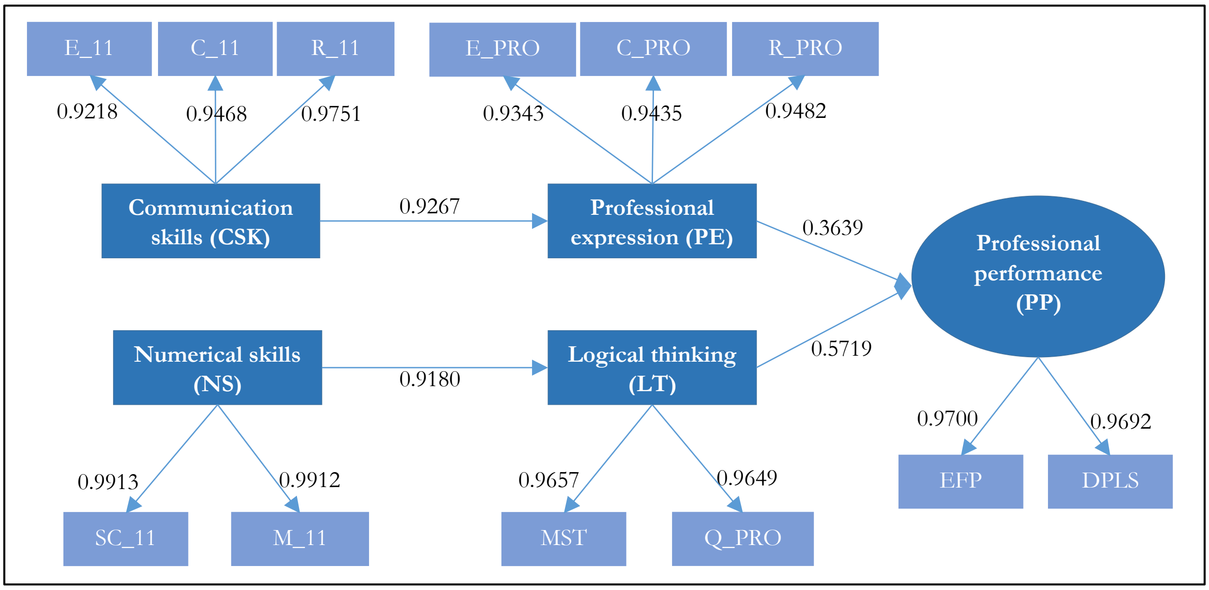

Figure 3. Empirical research final model

Source: own data

Now, Table 6 presents the R-squared (R2), Cronbach's Alpha (C_alpha), Dillon-Goldstein's rho (DG-rho), first eigenvalue (eig_1st), and second eigenvalue (eig_2nd). First, the R2 values of the latent variables have a value greater than 0.6 and the DG-rho and C_alpha values are above 0.7 as suggested in the literature (Sanchez, 2013). Finally, the unidimensionality of the latent variables is evident in the eigenvalues so that the first eigenvalue is much larger than the second eigenvalue for each latent variable.

Table 6

Latent variable performance results

Latent variable	R2	C_alpha	DG-rho	Eig_1st	Eig_2nd
Communication skills	0	0.94	0.96	2.70	0.24
Professional expression	0.86	0.94	0.96	2.66	0.19
Numerical skills	0	0.98	0.99	1.97	0.04
Logical thinking	0.84	0.93	0.96	1.86	0.14
Professional performance	0.85	0.94	0.97	1.88	0.12

Source: own compilation

Consequently, loading indicates the relationship between the manifest and latent variables; considering the literature, it is ideal that this value is more significant than 0.7. On the other hand, the communality is equal to the loading square. Consequently, Table 7 presents the relationship results between the latent variable and their respective manifest variables; this relationship is evaluated using the loading and communality columns, while the redundancy column indicates the ability to predict a new value.

Table 7

Results of the relationship between latent variables

Manifest variable	Latent variable	Weight	Loading	Communality	Redundancy
E_11	Communication skills	0.37	0.98	0.95	0
C_11	Communication skills	0.34	0.95	0.89	0
R_11	Communication skills	0.35	0.92	0.85	0
E_PRO	Professional expression	0.37	0.95	0.89	0.77
C_PRO	Professional expression	0.35	0.94	0.89	0.77
R_PRO	Professional expression	0.35	0.93	0.87	0.75
SC_11	Numerical skills	0.50	0.99	0.98	0
M_11	Numerical skills	0.51	0.99	0.98	0
MST	Logical thinking	0.52	0.97	0.93	0.80
Q_PRO	Logical thinking	0.52	0.97	0.93	0.80
EFP	Professional performance	0.51	0.97	0.94	0.79
DPLS	Professional performance	0.52	0.97	0.94	0.80

Source: own compilation

Consequently, Figure 4 presents the direct and indirect effects among the manifest variables. As can be seen, although Communication Skills are not directly related to Professional Performance, they have an indirect effect. Similarly, the indirect effect of Numerical Skills on Professional Performance is close to the direct effect of Logical Thinking on Professional Performance.

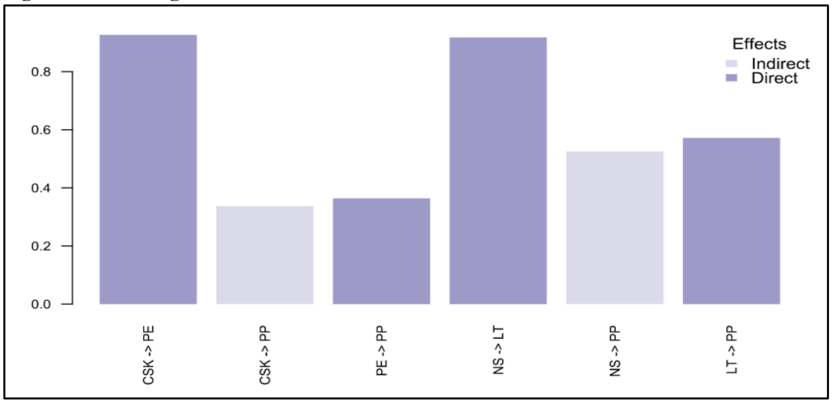

Figure 4. Interaction between variables

Source: own data

Consequently, Table 8 shows the validation of the PLS-PM model for the trajectory coefficients between the latent variables, evidencing that zero is not in the confidence intervals; therefore, the effects of the relationships raised in the model are significant.

Table 8

Validation of the trajectory coefficients of the latent variables

Relation	Original	Mean boot	Std error	Perc.025	Perc.975
CSK → PE	0.93	0.93	0.01	0.90	0.95
PE → PP	0.36	0.36	0.10	0.14	0.57
NS → LT	0.92	0.92	0.02	0.87	0.95
LT → PP	0.57	0.58	0.11	0.33	0.78

Source: own compilation

Finally, the relationship between the manifest and latent variables is verified in the validation stage. Therefore, it is observed in Table 9 that the confidence intervals presented do not include the number zero. Consequently, it is concluded that the relationships between the manifest variables and the latent variables are significant.

Table 9

Validation of the coefficients of the manifest variables

Manifest variable	Latent variable	Original	Mean boot	Std error	Perc.025	Perc.975
E_11	Communication skills	0.98	0.98	0.01	0.96	0.99
C_11	Communication skills	0.95	0.95	0.02	0.91	0.98
R_11	Communication skills	0.92	0.92	0.02	0.89	0.96
E_PRO	Professional expression	0.95	0.95	0.02	0.92	0.97
C_PRO	Professional expression	0.94	0.94	0.02	0.90	0.97
R_PRO	Professional expression	0.93	0.93	0.02	0.91	0.96
SC_11	Numerical skills	0.99	0.99	0.00	0.99	0.99
M_11	Numerical skills	0.99	0.99	0.00	0.99	0.99
MST	Logical thinking	0.97	0.97	0.01	0.95	0.98
Q_PRO	Logical thinking	0.97	0.97	0.01	0.95	0.98
EFP	Professional performance	0.97	0.97	0.01	0.94	0.98
DPLS	Professional performance	0.97	0.97	0.01	0.95	0.98

Source: own compilation

Finally, Table 10 presents the results of the efficiency models. The first model (Model 1) has as input the latent variable Communicative skills, and its output is the latent variable Professional expression. The second model (Model 2) has the latent variable of Numerical skills, and its output is the latent variable of Logical thinking. Finally, the latest model (Model 3) relates the latent variables of Professional Expression and Logical Thinking, and its output is the latent variable of professional performance.

Table 10

Summary of the results of the efficiency models

Measure	Model 1			Model 2			Model 3		
	CRS	VRS	SE	CRS	VRS	SE	CRS	VRS	SE
DMUs Efficient	16.30%	21.74%	16.30%	2.17%	7.61%	2.17%	5.43%	14.13%	5.43%
average	0.85	0.95	0.90	0.88	0.93	0.94	0.92	0.95	0.98
SD	0.11	0.04	0.10	0.05	0.04	0.05	0.04	0.04	0.04
Minimum	0.55	0.88	0.55	0.79	0.85	0.85	0.70	0.76	0.77
Median	0.86	0.95	0.92	0.88	0.93	0.94	0.92	0.95	0.99
Q3	0.97	1.00	0.99	0.92	0.96	0.99	0.95	0.97	1.00

Source: own compilation

Table 11

Summary of the results of the efficiency models

	CSK → PE			NS → LT			PE + LT →PP			Saber 11 Average Scores					
DMU	CRS	VRS	SE	CRS	VRS	SE	CRS	VRS	SE	R_11	C_11	E_11	M_11	SC_11	Saber_11 Overall
U78	1,00	1,00	1,00	0,93	1,00	0,93	0,88	1,00	0,88	69,06	72,35	69,68	75,74	74,24	72,21
U66	0,98	0,98	1,00	0,93	0,99	0,94	0,89	1,00	0,89	69,03	70,76	81,59	73,66	70,52	73,11
U44	1,00	1,00	1,00	1,00	1,00	1,00	0,95	1,00	0,95	67,24	66,36	65,64	67,84	65,72	66,56
U80	0,96	0,96	1,00	0,95	1,00	0,95	0,88	0,95	0,92	69,59	69,44	72,28	72,63	72,03	71,19
U79	1,00	1,00	1,00	0,95	0,96	0,99	0,93	0,99	0,94	66,12	66,28	67,94	71,56	69,74	68,33
U59	1,00	1,00	1,00	0,92	0,94	0,98	0,91	0,97	0,94	67,01	65,64	76,60	72,92	70,59	70,55
U68	1,00	1,00	1,00	0,92	0,95	0,97	0,90	0,96	0,94	65,08	63,67	70,86	70,04	68,63	67,65
U63	1,00	1,00	1,00	0,94	0,95	0,99	0,91	0,95	0,95	66,75	64,54	73,43	72,36	67,39	68,89
U28	1,00	1,00	1,00	1,00	1,00	1,00	0,95	1,00	0,95	52,50	60,50	46,00	53,50	54,50	53,40
U32	1,00	1,00	1,00	0,91	0,92	0,99	0,91	0,97	0,94	65,77	65,19	77,53	70,97	69,14	69,72
U62	0,99	1,00	0,99	0,94	0,94	1,00	0,92	0,97	0,94	65,16	63,92	60,16	69,78	67,89	65,38
U51	1,00	1,00	1,00	0,88	0,91	0,97	0,88	0,92	0,95	69,55	69,08	84,60	78,32	76,09	75,53
U70	0,96	0,97	0,99	0,90	0,91	0,99	0,90	0,93	0,97	65,16	64,10	63,64	68,98	69,12	66,20
U57	0,97	0,97	0,99	0,89	0,90	0,99	0,93	0,95	0,98	63,81	62,19	61,66	64,92	65,70	63,65
U75	0,93	0,98	0,94	0,93	0,93	1,00	0,96	0,98	0,98	58,21	59,43	58,71	59,64	59,79	59,16
U50	0,88	0,92	0,96	0,96	0,97	1,00	0,96	1,00	0,96	59,02	60,40	59,56	61,26	61,23	60,29
U49	1,00	1,00	1,00	0,89	0,89	1,00	0,92	0,95	0,97	62,03	60,91	70,00	63,68	63,90	64,10
U10	1,00	1,00	1,00	0,91	0,91	1,00	0,97	1,00	0,97	56,44	55,44	58,89	61,22	61,78	58,76
U52	1,00	1,00	1,00	0,98	1,00	0,99	1,00	1,00	1,00	63,20	66,00	62,40	58,20	59,80	61,92
U36	0,98	1,00	0,98	0,91	0,92	0,98	1,00	1,00	1,00	56,12	56,59	58,00	57,65	61,12	57,89

Source: own compilation

5. DISCUSSION

As mentioned at the beginning, in the context of university education, there is no universal definition of the production function, as some authors have approached this field from productive structures for university education based on particular contexts (Visbal-Cadavid et al., 2017; Gralka et al., 2019; Yang et al., 2018; Duan, 2019; Madria et al., 2019; Shamohammadi & Oh, 2019). It is there that this research proposes a production function for the educational process of engineers since the results show the adjustment of the proposed production function and prove the existence of relationships between the constructs that compose it.

The model validated four resource transformation relationships and subsequently allowed to calculate of the efficiency for each of the interactions of the academic production function. Now, for 25% of the research universities, the level of efficiency is greater than or equal to 97%, 92% and 95%, for models 1, 2 and 3, respectively. Thus, the level of efficiency of the scale of model 1, 2 and 3, for 50% of the universities is 92%, 94% and 99%, respectively, indicating that the educational processes executed in this 50% of universities, make appropriate use of the basic competencies of the students to generate good professionals, thus demonstrating the efficiency of the academic engineering programs in Colombia.

Considering that the first two DEA models (CSK ~ PE) and (NS ~ LT) respresent the transition from school to university. Thus, establishing the ability of universities to transform inputs (basic competencies of high school education) into desired outputs (basic professional academic competencies). For its part, the third DEA model (PE + LT ~ PP) implies the academic maturity of the student, meaning that the student has developed a level of professional competencies that will determine his professional performance.

For example, the DMU U78 (see Table 11) is efficient for the development of the professional communication skills of engineers; however, it does not make adequate management for the development of logical thinking and professional performance of engineers. For its part, the DMU U44 is efficient for developing communication skills and the logical thinking of engineers and not efficient for developing high professional performance. In another example, the DMU U52 is efficient for developing engineers' logical thinking and professional performance, but it is not efficient for developing their communication skills.

Finally, the DMU U36 (see Table 11), despite having a lower level of entries (basic competencies of Saber 11), is efficient for developing professional skills; this could be due to the university's administrative and academic management processes. On the other hand, the DMU U51, although having a higher level of inputs, is only efficient to develop the logical thinking of engineers, and it is not efficient to develop engineers' communicative and professional skills; this could happen due to the imbalance of the university's educational efforts.

Therefore, the main objective of this research is reached by measuring and identifying the factors of academic efficiency that positively impact engineering learning.

6. CONCLUSION

The present research analyses and validates the relationship between the academic competencies of the baccalaureate and the professional academic competencies of industrial engineers in Colombia. The PLS-PM model had an overall performance in its Goodness of Fit index of 0.89. On the other hand, the values of Cronbach's Alpha and Dillon-Goldstein's rho are higher than 0.7 as recommended in the literature. However, as for the results of the DEA models, it is observed for the CRS 1, 2 and 3 model that 16.30%, 2.17% and 5.43%, respectively are efficient. On the other hand, the percentage of efficient units in the VRS model of pure technical or administrative efficiency is 21.74%, 7.61% and 14.13%, respectively. Finally, the rate of efficient units for the production scale of models 1, 2 and 3 is 16.30%, 2.17% and 5.43%, respectively.

This research contributes to the spectrum of knowledge of tools that estimate efficiency in the educational field. It presents a methodological structure that allows, first, to verify the causal relationships of the empirical model and, finally, to estimate the relative efficiency of each relationship. In this way, the information of the articulated model can be used for decision-making by the actors involved in the educational context of the students (teachers, parents, management, among others). Finally, the proposed methodology is replicable to other areas of knowledge and countries. The key is to identify the factors of comparison between Higher Education Universities (for example, for Colombia, the state evaluations Saber 11 and Saber PRO) and the variables involved in the educational process (academic competencies).

REFERENCES

Agasisti, T., Munda, G., & Hippe, R. (2019). Measuring the efficiency of European education systems by combining Data Envelopment Analysis and Multiple-Criteria Evaluation. *Journal of Productivity Analysis*, 51(2), 105–124. https://doi.org/10.1007/SC_11123-019-00549-6

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*, 10(1), 137. https://doi.org/10.5539/ies.v10n1p137

Bernal, G. P., Villegas, L., & Toro, M. (2020). Saber Pro success prediction model using decision tree based learning. ArXiv.

Bianchi, N., & Giorcelli, M. (2020). Scientific Education and Innovation: From Technical Diplomas to University Stem Degrees. *Journal of the European Economic Association*, 18(5), 2608–2646. https://doi.org/10.1093/jeea/jvz049

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. 1978, 2(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Colbert, A., Levary, R. R., & Shaner, M. C. (2000). Determining the relative efficiency of MBA programs using DEA. *European Journal of Operational Research*, 125(3), 656–669. https://doi.org/10.1016/S0377-2217(99)00275-1

Coll-Serrano, V., Benítez, R., & Bolós, V. (2018). Data Envelopment Analysis with deaR (1.2.0) [Computer software]. Universidad de Valencia. https://CRAN.R-project.org/package=deaR

Colombo, M. G., & Piva, E. (2020). Start-ups launched by recent STEM university graduates: The impact of university education on entrepreneurial entry. *Research Policy*, 49(6), 103993. https://doi.org/10.1016/j.respol.2020.103993

Cook, W. D., Ramón, N., Ruiz, J. L., Sirvent, I., & Zhu, J. (2019). DEA-based benchmarking for performance evaluation in pay-for-performance incentive plans. *Omega*, 84, 45–54. https://doi.org/10.1016/j.omega.2018.04.004

De La Hoz, E., Zuluaga, R., & 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. https://doi.org/10.7160/eriesj.2021.140104

de la Torre, E. M., Casani, F., & Sagarra, M. (2018). Defining typologies of universities through a DEA-MDS analysis: An institutional characterization for formative evaluation purposes. *Research Evaluation*, 27(4), 388–403. https://doi.org/10.1093/reseval/rvy024

Delahoz-Dominguez, E., Zuluaga, R., & Fontalvo-Herrera, T. (2020). Dataset of academic performance evolution for engineering students. *Data in Brief*, 30, 105537. https://doi.org/10.1016/j.dib.2020.105537

Duan, S. X. (2019). Measuring university efficiency: An application of data envelopment analysis and strategic group analysis to Australian universities. *Benchmarking: An International Journal*, 26(4), 1161–1173. https://doi.org/10.1108/BIJ-10-2017-0274

Galbraith, C. S., & 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*, 39(2), 255–277. https://doi.org/10.1080/0309877X.2013.858673

Gralka, S., Wohlrabe, K., & Bornmann, L. (2019). How to measure research efficiency in higher education? Research grants vs. publication output. *Journal of Higher Education Policy and Management*, 41(3), 322–341. https://doi.org/10.1080/1360080X.2019.1588492

Hanushek, E. A. (1979). Conceptual and Empirical Issues in the Estimation of Educational Production Functions. *The Journal of Human Resources*, 14(3), 351–388. https://doi.org/10.2307/145575

Hoeg, D. G., & Bencze, J. L. (2017). Values Underpinning STEM Education in the USA: An Analysis of the Next Generation Science Standards. *Science Education*, 101(2), 278–301. https://doi.org/10.1002/sce.21260

Jakaitiene, A., Zilinskas, A., & Stumbriene, D. (2018). Analysis of Education Systems Performance in European Countries by Means of PCA-DEA. *Informatics in Education*, 17(2), 245–263. https://eric.ed.gov/?id=EJ1195648

Johnes, J. (2006). Measuring teaching efficiency in higher education: An application of data envelopment analysis to economics graduates from UK Universities 1993. *European Journal of Operational Research*, 174(1), 443–456. https://doi.org/10.1016/j.ejor.2005.02.044

Jones, C. I. (2016). Chapter 1—The Facts of Economic Growth (J. B. Taylor & H. Uhlig, Eds.; Vol. 2, pp. 3–69). *Elsevier*. https://doi.org/10.1016/bs.hesmac.2016.03.002

Jones, T. H. (1981). Equal Educational Opportunity Revisited. *Journal of Education Finance*, 6(4), 471–484.

Kalapouti, K., Petridis, K., Malesios, C., & 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,* 294(1), 297–320. https://doi.org/10.1007/s10479-017-2728-4

Law, L., & Fong, N. (2020). Applying partial least squares structural equation modeling (PLS-SEM) in an investigation of undergraduate students' learning transfer of academic English. *Journal of English for Academic Purposes*, 46, 100884. https://doi.org/10.1016/j.jeap.2020.100884

Long, P., & Siemens, G. (2014). Penetrating the fog: Analytics in learning and education. *Italian Journal of Educational Technology*, 22(3), 132–137. https://www.learntechlib.org/p/183382/

Lorcu, F., & Bolat, B. A. (2015). Comparison of secondary education PISA results in European member states and Turkey via DEA and SEM. *Journal of WEI Business and Economics*, 4(3), 7.

Madria, W. F., Miguel, A. S., & Li, R. C. (2019). Quality-Oriented Network DEA Model for the Research Efficiency of Philippine Universities. *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, 596–600. https://doi.org/10.1109/IEEM44572.2019.8978816

Nazarko, J., & Šaparauskas, J. (2014). Application of DEA method in efficiency evaluation of public Higher Education Institutions. *Technological and Economic Development of Economy*, 20(1), 25–44. https://doi.org/10.3846/20294913.2014.837116

Ondé, D., & Alvarado, J. (2018). Scale Validation Conducting Confirmatory Factor Analysis: A Monte Carlo Simulation Study With LISREL. https://doi.org/10.3389/fpsyg.2018.00751

Puertas, R., & Marti, L. (2019). Sustainability in Universities: DEA-GreenMetric. *Sustainability*, 11(14), 3766. https://doi.org/10.3390/su11143766

Sanchez, G. (2013). PLS Path Modeling with R (0.4.9) [R]. https://github.com/gastonstat/plspm

Santín, D., & Sicilia, G. (2018). Using DEA for measuring teachers' performance and the impact on students' outcomes: Evidence for Spain. *Journal of Productivity Analysis*, 49(1), 1–15. https://doi.org/10.1007/SC_11123-017-0517-3

Shambaugh, J., Nunn, R., & Portman, B. (2017). Eleven Facts about Innovation and Patents. *Economic Facts*, 28.

Shamohammadi, M., & Oh, D. (2019). Measuring the efficiency changes of private universities of Korea: A two-stage network data envelopment analysis. *Technological Forecasting and Social Change*, 148, 119730. https://doi.org/10.1016/j.techfore.2019.119730

Suh, S. C., Bandi, H., Kim, J., & Tanik, U. J. (2020). Case Study: STEM Contribution in Indian IT Clusters. In C. Zintgraff, S. C. Suh, B. Kellison, & P. E. Resta (Eds.), STEM in the Technopolis: The Power of STEM Education in Regional Technology Policy (pp. 285–296). *Springer International Publishing*. https://doi.org/10.1007/978-3-030-39851-4_15

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

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*, 46(9), 1595–1605. https://doi.org/10.1016/j.respol.2017.07.010

Yang, G., Fukuyama, H., & Song, Y. (2018). Measuring the inefficiency of Chinese research universities based on a two-stage network DEA model. *Journal of Informetrics*, 12(1), 10–30. https://doi.org/10.1016/j.joi.2017.11.002