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# Economic analysis of educational efficiency in Morocco : An application of the DEA method

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**Abstract:** This paper analyzes the educational efficiency of 81 provincial delegations (DMU) of the Ministry of National Education (MNE) using the non-parametric method of Data Envelopment Analysis (DEA). The outputs and inputs used to measure efficiency pertain to the academic years 2014-2015 and 2020-2021. The results show that the average efficiency score slightly decreased between 2014-2015 and 2020-2021, going from 0.878 to 0.874. However, the number of efficient DMUs, which was 12 in 2014-2015, remained unchanged in 2020-2021. Furthermore, the number of DMUs with an efficiency score above the average increased during this period, going from 31 to 34. The analysis of the results also highlights that the average size of inefficient DMUs is smaller than the average size of efficient DMUs. This indicates that reducing the size of schools does not necessarily lead to an improvement in their efficiencies, as smaller institutions might face a situation of underutilizing the resources at their disposal.

**Keywords:** Educational efficiency, Technical efficiency, DMU, DEA, Input, Output, Returns to scale.

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## 1. Introduction

Education is considered one of the essential challenges of contemporary societies, where intangible investment plays a crucial role. The theory of human capital stipulates that education is an investment that enhances the productivity of those who benefit from it (Tan, 2014; Drábek et al. 2017; World Bank, 2019).

Indeed, education undeniably stands as one of the fundamental pillars in modern societies, where the value of investing in intangible resources is of paramount importance. In this ever-evolving landscape, the theory of human capital emerges as a major theoretical approach, asserting that the act of education is a strategic investment with significant repercussions on individual productivity and, by extension, on the overall development of a society (Becker, 1962; Gillies, 2014).

Investing in education yields significant returns both at the individual and collective levels. Educated individuals are better prepared to seize career opportunities, leading to increased productivity and higher

incomes. Simultaneously, for society as a whole, a focus on education generates a highly skilled workforce capable of contributing significantly to economic development and innovation. Moreover, an educated population is often more inclined to actively participate in civic life, promote collective well-being, and act as a driver of positive change (Blundell et al. 1999; Pelinescu, 2015).
Indeed, investing in education offers substantial long-term benefits for individuals, the economy, and society at large. However, the effectiveness of public intervention in education still falls short when considering the goal of equipping citizens with the ability to sustain themselves through their work. The question of the efficiency of education sparks significant interest for governments in developing economies, as measuring efficiency allows for effective allocation and enables judgments regarding the profitability and returns on education (Teixeira et al. 2016; Deming, 2022).
For this purpose, our study aims to measure and analyze the technical efficiency of educational production at the internal level of 81 provincial directorates (DP) of National Education in Morocco, using the Data Envelopment Analysis (DEA) method. The sample for the study comprised 81 Provincial Directorates (DP) of National Education. The data used pertains to the academic years 2014-2015 and 2020-2021.
For this purpose, the Data Envelopment Analysis (DEA) method is employed, assuming variable returns to scale, to measure and analyze the technical efficiency of educational production at the internal level of the 81 provincial directorates (DP) of the National Education in Morocco. The data has been provided by the Department's Directorate of Strategy, Statistics, and Planning, covering the school years 2014-2015 and 2020-2021.
This study is organized as follows: Section 2 presents a brief literature review. Section 3 introduces the Data Envelopment Analysis (DEA) methodology and data presentation. Then, the interpretation of the results is discussed in section 4. Section 5 concludes.

## 2. Literature review

The deterioration of the education system and fundamental changes impacting the field of education have captured the interest of various stakeholders. They seek to address challenges present at all levels of education, including schools, colleges, high schools, universities, and even continuing education programs. Considering this reality, education, similar to investing in tangible assets, is perceived as an investment in human capital, playing a pivotal role in national development. It is now acknowledged as a profitable endeavor and an essential instrument in shaping public policies (World Bank, 2019; Babbar & Gupta, 2022).
Analyzing the efficiency of an educational or training system involves assessing the extent to which learners manage to reach the set objectives in terms of knowledge and skills in an optimal manner. Efficiency in education can be divided into two forms: internal efficiency and external efficiency (Lockheed & Hanushek, 1994 ; Lamas, 2015).
The internal efficiency of the educational system will be evaluated through the internal performance of each of its constituent levels (Cornali, 2012). Among the primary objectives assigned to it, one is to lead the maximum number of enrolled students in the first year of each cycle to its completion by the end of the cycle, and this should be accomplished within the designated time (This aspect of internal efficiency is often highlighted). Under these conditions, early dropouts during the cycle and high rates of grade repetition are disruptions that act as barriers to achieving this objective. Thus, the fewer repetitions and dropouts there are, the more efficient the system is judged to be. Conversely, high dropout and repetition rates reflect an internal inefficiency of the system (Serdyukov, 2017).
If the analyses targeting the internal efficiency of educational systems broadly concern school processes and the functioning of educational institutions, by comparing school activities and organizational

methods with the results achieved by students while they are still within the system, aiming to find the most cost-effective situations, then the assessment of the external efficiency of an educational system should lead to measuring the effects of education on educated individuals outside the educational system (Cornali, 2012).

It is noteworthy, in this regard, that this assessment is done retrospectively, given the difficulty of predicting the future returns on investment in human capital and thus the magnitude of the associated risk. In this case, the goal is to determine whether these individuals are socially disciplined in terms of positive and constructive behavior in society (meeting societal objectives), and economically valuable in terms of job quality and wage compensation. Additionally, it aims to ascertain whether these individuals exist in sufficient numbers as educated and skilled professionals to contribute to the country's economic growth (fulfilling the needs of the labor market) (Sutherland et al. 2010).

The areas in which received education can have an influence are traditionally of two types: economic in a narrow sense and social in a broader conception. They can be interpreted in two complementary dimensions: individual on one hand and collective on the other. The intersection of these two perspectives can be illustrated in table 1:

**Table 1:** Areas of influence of education

| | **Social** | **Economic** |
|---|---|---|
| **Individual** | Domain of the family (fertility, health, consumption), participation in civic life, ... | Individual employment opportunities, individual income, individual labor productivity, ... |
| **Collectif** | Population growth, population health, public choice, ... | Unemployment, economic growth, international competitiveness, ... |

**Source**: Prepared by the authors.

The economic aspect of external efficiency leads to highlighting two levels of analysis: the macroeconomic level that pertains to society as a whole, and the microeconomic level that concerns individuals as educated subjects bearing the training provided by the educational system (Goczek et al. 2021).

The macroeconomic aspect of education emphasizes the investment in human capital and, therefore, focuses on its effect on a country's economic growth. Human capital, whose individual choices strongly impact labor market trends, is an integral and essential component of the production factors that contribute to this growth. In this sense, achieving macroeconomic equilibrium is closely correlated with attaining the four objectives of the magic square. According to the literature, these objectives are: (1) achieving economic growth, (2) combating unemployment, (3) controlling inflation, and (4) maintaining balance of payments equilibrium. Therefore, a strong relationship exists between reducing the unemployment rate and economic growth. This means that a low unemployment rate signifies a high employment rate, leading to an increase in demand for goods and services, and consequently, an increase in production to meet this additional demand, which positively impacts economic growth. Another important element that can also impact economic growth is the existence, in terms of educational outputs, of qualified profiles whose productivity will be high and will thus enable competitive gains for businesses.

While the macroeconomic perspective is immediately concerned with systems and their structures, the microeconomic perspective arises from reflections on the system and the policies pursued based on what becomes of individuals who have exited the realm of education and training to enter adult and productive life. In this sense, education economists are interested in the impact of education on individual behaviors regarding health, family planning, migration, information-seeking, and civic behavior. However, the effects that have captured economists' attention the most are those linked to the professional realm. Education is presumed to enhance individuals' professional skills, thus enabling them to be more productive; as a result, they will earn higher incomes due to their education (World Bank, 2019).

Through this approach, economists seek to comprehend individuals' decision-making process concerning investment in human capital. By better grasping this process, the visibility of public decision-makers expands, allowing for more informed decisions on which types of education to curtail, develop, or establish. This also assists families in guiding their children to opt for quality education that brings well-being in terms of wages and the relationship between the field of study and employment specialization. Salary remains the most frequently employed variable by economists. It represents the remuneration for an individual's contribution and facilitates assessing the private returns of education based on the investments undertaken (Ziberi et al. 2022).

Since the seminal paper by Charnes et al. (1978), the application of efficiency models has extended to various sectors, including healthcare (Cordero et al. 2015), water supply (Cherchye et al. 2014), the banking sector (Puri et al. 2017), the public sector (De Witte and Geys, 2013), agriculture (Asmild et al. 2016), and energy (Chen et al. 2017; Hampf et al. 2015). In education, the empirical application of this method faces certain difficulties owing to the complex nature of the production process in this field. This complexity arises from the challenge of comprehensively identifying the outputs (results or products) and inputs (production factors) to account for the multidimensional aspect of education.

One of the early studies that employed the DEA method in education is the one conducted by Bessent et al. (1984), in which the authors assessed the efficiency of 25 public school districts in the state of Texas. They used 6 inputs, namely: the average number of minutes per day devoted to teaching mathematics, the average number of minutes per day allocated to language instruction, the average pedagogical expenses ($) per student in the school, the number of teachers per 100 students, the average percentage of regular teaching staff present each day, and the average percentage of students present each day. Their measure of the output is based on the basic skills objectives adopted by the Texas State Board of Education in 1979. A standardized test that is administered annually to each third, fifth, and ninth-grade student to determine the mastery of basic skills. The results obtained revealed a positive trend: the number of school districts considered efficient increased from 52 in 1981 to 71 in 1983. This increase demonstrates a significant improvement in how districts utilized their resources to achieve their educational objectives. Furthermore, the overall efficiency average increased from 93.4% in 1981 to 98.1% in 1983, highlighting a notable progress in the efficient utilization of resources in these school districts.

In another study, Tyagi et al. (2009) applied the DEA method to examine efficiency and its disparities within 348 primary schools in the state of Uttar Pradesh, India. Their methodology considered eight inputs, encompassing various educational resources such as teaching methods, physical infrastructure, supplementary resources, and teacher quality. Additionally, they took into account students' family context, including their parents' education and profession. Regarding the outcomes, these were measured through the average scores obtained by schools in the areas of environmental studies, mathematics, and languages. The findings of their study revealed an average efficiency of 70.58%, with values ranging from 19.44% to 100%. Among the 348 evaluated schools, 67 of them (representing 19.25%) were identified as efficient in their resource utilization to achieve educational outcomes.

On their side, Tsakiridou and Stergiou (2013) undertook an investigation into the level of efficiency in primary education in the northern region of Greece. Their study focused on a sample of 17 primary schools, using three inputs: the school facilities index (including building infrastructure, logistical equipment, full teaching staff), the ratio of teachers to the number of students in the school, and the number of computers accessible to students. Their output represented the average score on the TIMSS test, reflecting students' mathematics test results. They opted for the use of the non-parametric DEA model to assess this efficiency. The obtained results revealed that the average efficiency within the sample stood at 76.26%, with a variation ranging from 40.4% to 100%. This research highlights disparities in how primary schools managed their resources to ensure quality educational provision, with certain schools demonstrating greater efficiency than others in this northern region of Greece.

Di Giacomo and Pennisi (2015) explored the efficiency of primary and secondary schools in the northern, central, and southern regions of Italy. The inputs are related to the human and financial resources of the schools, and the outputs represent their students' mathematics and reading results. By utilizing the DEA method on a sample of over 1000 schools, the authors indicate that there are generally more significant areas for improvement in primary schools than in secondary establishments. However, the potential improvement rate in the south is twice as high as that in the other regions: considering the level of available resources, if all establishments performed as efficiently as the most efficient ones, the efficiency gain would be approximately 36% for primary schools and 28% for secondary establishments.

Yahia & Essid (2019) measured the technical efficiency of secondary education in Tunisia by utilizing data from the Programme for International Student Assessment (PISA) survey conducted in 2015. They employed two inputs: total school enrollment (Number of students) and the total number of teachers (Number of teachers), along with the PISA test score as the output. By adopting the Data Envelopment Analysis (DEA) approach, the authors highlighted that nearly 96.5% of the studied schools were identified as inefficient. This suggests that the resources allocated to secondary education in Tunisia are not fully optimized to achieve optimal educational outcomes. The analysis also revealed a significant opportunity for improvement. On average, the studied establishments could have increased their results by 27% using the same resources available to them. This revelation underscores an untapped potential to enhance the quality of education and academic outcomes by adjusting how resources are utilized.

Cardoso et al. (2021) measured the technical efficiency of municipal educational systems in cities within the state of Rio Grande do Sul, Brazil. The study utilized Data Envelopment Analysis (DEA) focused on output with variable returns to scale (VRS). The assessment included variables measuring the quality of education, student flows, teacher training, school infrastructure, and municipality expenditures. The results indicate that 50% of the sample is technically efficient, with potential for resource utilization improvement within this same group of cities.

## 3. Methodology and data

### 3.1. Theoretical framework of DEA method

The Data Envelopment Analysis (DEA) method is a non-parametric approach based on linear programming that enables the estimation of an empirical production frontier on a sample of observations known as Decision-Making Units (DMUs). This technique originates from the innovative work of Farrell (1957), who drew inspiration from the concept of "resource utilization coefficient" or "technical coefficient" introduced by Debreu (1951).

The DEA methodology operates by evaluating the distance between each decision-making unit and the efficiency frontier. For every observed deviation from this frontier, a measure of efficiency is calculated and assigned. This amounts to assigning an efficiency score, expressed as a number, to each decision-making unit. When a decision-making unit precisely lies on the frontier, its efficiency score equals 1. However, if it falls below the frontier, its efficiency score will be less than 1.

The DEA method is categorized as non-parametric because it enables the construction of an envelope of observations through mathematical programming, without estimating a parameter vector. The essence of the method lies in first identifying the efficient decision-making units in order to build a production frontier through linear or nonlinear interpolation based on these units (Figure 1).

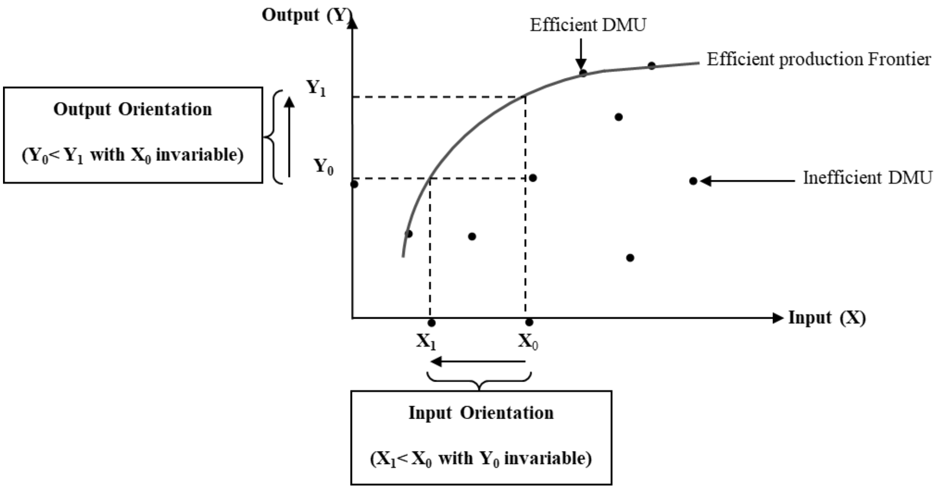


**Figure 1 :** Observations envelopement (1 output and 1 input)

Formally, constructing the production frontier and measuring the efficiency of each production unit (DMU) in relation to this frontier involves finding the optimal values of weights vj and ui that maximize the efficiency of each evaluated unit, while ensuring that all efficiency measures are less than or equal to 1, which corresponds to the efficiency frontier, and under the assumption of constant returns to scale (CCR model ; Charnes et al. 1978). This necessitates solving the following mathematical program N times:

| | |
|---|---|
| $$\begin{cases} Max\ E_m = \dfrac{\sum_{j=1}^{j=J} v_{jm} y_{jm}}{\sum_{i=1}^{i=I} u_{im} x_{im}} \\ \text{S/C} \\ 0 \le \dfrac{\sum_{j=1}^{j=J} v_{jm} y_{jn}}{\sum_{i=1}^{i=I} u_{im} x_{in}} \le 1 \\ (n = 1, 2, \dots N) \\ v_{jm}, u_{im} \ge 0 \end{cases}$$ | – $E_m$ is the efficiency of the mth DMU, with n including m;<br>– $y_{jm}$ is the j[th] output of the mth DMU, $v_{jm}$ being its weight, (j = 1, 2, …, K, …J);<br>– $x_{im}$ is the ith input of the mth DMU, $u_{im}$ being its weight, (i = 1, 2, …, K, …I) ;<br>– $y_{jn}$ is the jth output of the nth DMU, $v_{jn}$ being its weigh;<br>– $x_{in}$ is the ith input of the nth DMU, $u_{in}$ being its weight;<br>– N ≥ max {(J×I) , 3(J+I)} |

However, the fractional form of this program is difficult to optimize. To overcome this difficulty, the problem can be linearized according to two analysis orientations (output and input).

| ***Linearization of the fractional program*** | ***Primal program in matrix form*** | ***Dual program in matrix form*** |
|---|---|---|
| $$\begin{cases} Max\ z = \sum_{j=1}^{j=J} v_{jm} y_{jm} \\ \text{S/C} \quad \sum_{i=1}^{i=I} u_{im} x_{im} = 1 \\ \sum_{j=1}^{j=J} v_{jm} y_{jn} - \sum_{i=1}^{i=I} u_{im} x_{in} \le 0 \quad (n = 1, 2, \dots N) \\ v_{jm}, u_{im} \ge 0 \end{cases}$$ | $$\begin{cases} Max\ z = V_m^t Y_m \\ \text{S/C} \quad U_m^t X_m = 1 \\ V_m^t Y - U_m^t X \le 0 \\ V_m^t\ ,\ U_m^t > 0 \end{cases}$$ | $$\begin{cases} Min\ \ \theta_m \\ \text{S/C} \quad Y_\lambda \ge Y_m \\ X_\lambda \le \theta_m X_m \\ \lambda \ge 0 \end{cases}$$ |

In this problem to be solved N times, θ is a scalar representing the technical efficiency score of the mth decision-making unit ($0 \le \theta \le 1$). If θ = 1, the observed decision-making unit lies on the frontier, meaning it is efficient in the Farrell sense. Conversely, if θ < 1, it reveals the presence of technical inefficiency. λ is a vector (N,1) of constants called multipliers. These indicate how the decision-making units combine to form the frontier against which the mth decision-making unit will be compared. These multipliers are referred to as peers, in reference to the efficient decision-making units that constitute each segment of the efficiency frontier.

| ***Linearization of the fractional program*** | ***Primal program in matrix form*** | ***Dual program in matrix form*** |
|---|---|---|
| $\begin{cases} \quad Min\ z' = \sum_{i=1}^{i=I} u'_{im} x_{im} \\ S/C \quad \sum_{j=1}^{j=J} v'_{jm} y_{jm} = 1 \\ \quad \sum_{j=1}^{j=J} v'_{jm} y_{jn} - \sum_{i=1}^{i=I} u'_{im} x_{in} \le 0 \quad (n = 1, 2, \dots N) \\ \quad v'_{jm}, u'_{im} \ge 0 \end{cases}$ | $\begin{cases} \quad Min\ z' = U'^{t}_{m} X_m \\ S/C \quad V'^{t}_{m} Y_m = 1 \\ \quad V^{t}_{m} Y - U^{t}_{m} X \le 0 \\ \quad V'^{t}_{m}, U'^{t}_{m} > 0 \end{cases}$ | $\begin{cases} \quad Max\ \phi_m \\ S/C \quad Y_{\mu} \ge \phi_m Y_m \\ \quad X_{\mu} \le X_m \\ \quad \mu \ge 0 \end{cases}$ |

In this problem to be solved N times, Φ and μ are the counterparts of θ and λ respectively in the previous dual program. Regardless of the chosen orientation for analyzing inefficiency, at the end of solving the previous programs, the following equivalences are found:

$$\mathbf{z^*} = \frac{\mathbf{1}}{\mathbf{z'^*}} \qquad \mathbf{\theta^*} = \frac{\mathbf{1}}{\mathbf{\Phi^*}} \qquad \mathbf{\mu^*} = \left(\frac{\mathbf{1}}{\mathbf{\theta^*}}\right) \times \mathbf{\lambda^*}$$

The assumption of constant returns, as presented above in the CCR model, which leads to the measurement of total efficiency, is not always appropriate. This results in efficiency measures that conflate technical efficiency and scale efficiency. Therefore, to measure efficiency considering variable returns to scale, the CCR model can be modified by adding another convexity constraint that ensures an inefficient firm can only be compared to firms operating on the same scale. Analytically, this involves adding the constraint $\sum_{n=1}^{N} \lambda_n$ 1 to the dual-oriented input problem or the constraint $\sum_{n=1}^{N} \mu_n = 1$ to the dual-oriented output problem in the CCR model.

| ***Dual problem input oriented*** | ***Dual problem output oriented*** |
|---|---|
| $\begin{cases} \quad Min\ \theta_m \\ S/C \quad Y_{\lambda} \ge Y_m \\ \quad X_{\lambda} \le \theta_m X_m \\ \quad \sum_{n=1}^{N} \lambda_n = 1 \\ \quad \text{(ou bien } e^t \lambda = 1 \text{ où } e(N,1) \text{ est vecteur unitaire)} \\ \quad \lambda \ge 0 \end{cases}$ | $\begin{cases} \quad Max\ \phi_m \\ S/C \quad Y_{\mu} \ge \phi_m Y_m \\ \quad X_{\mu} \le X_m \\ \quad \sum_{n=1}^{N} \mu_n = 1 \\ \quad \text{(ou bien } e^t \mu = 1 \text{ où } e(N,1) \text{ est vecteur unitaire)} \\ \quad \mu \ge 0 \end{cases}$ |

### 3.2. Data presentation

The application of the DEA method in the field of education presents certain difficulties linked to the complex nature of the production process in this domain. This stems from the challenge of comprehensively identifying the outputs (results or products) and inputs (production factors) to account for the multidimensional aspect of education.

The current study aims to measure and analyze the technical efficiency of educational production at the internal level of the 81 provincial directorates (DP) of the National Education in Morocco using the non-parametric and multidimensional DEA tool, assuming variable returns to scale. The data has been provided by the Department's Directorate of Strategy, Statistics, and Planning, covering the school years 2014-2015 and 2020-2021. Correction of the identified inefficiency gaps is proposed from both analytical perspectives: reducing inputs or increasing outputs.

The study focuses on estimating the educational efficiency of public primary schools. The data used are aggregated at the level of each provincial directorate. After removing outliers (very low number of students per institution), the sample size of the study comprises 81 provincial directorates.

Technical efficiency is measured using four inputs (teacher-student ratio, administrative staff-student ratio, classroom occupancy ratio, and classroom utilization ratio) on one hand, and three outputs (passing rate, repetition rate, and dropout rate) on the other hand.

**3.2.1. Inputs**

- **Teacher-student ratio :** It is measured by the Teacher/Student Ratio. This ratio helps evaluate the volume of human resources invested in terms of the number of teachers in relation to the total student population. This means that a high number of teachers per student or a low number of students per teacher results in a high teacher-student ratio. This suggests that each teacher tends to a small number of students, providing them with more opportunities to receive individual attention, which can contribute to better long-term results.
- **Administrative Staff Ratio :** It is measured by the Administrative Staff/Student Ratio. This ratio measures the volume of human resources invested in terms of the number of administrative staff members (principals, general supervisors, bursars, etc.) in relation to the total student population. This means that a high number of administrative staff members per student or a low number of students per administrative staff member results in a high administrative staff ratio. This suggests that each administrative staff member tends to a small number of students, providing them with more opportunities to receive their guidance. This will enhance order and discipline in the institution, which can contribute to better long-term outcomes.
- **Classroom occupancy ratio :** It is measured by the Classroom/Student Ratio. This ratio serves to measure both the volume of human resources invested in terms of teachers and the availability of facilities (classrooms, laboratories, and sports fields) to enable students to receive quality education in line with pedagogical standards. It is commonly understood that smaller class sizes allow teachers to focus more on the individual needs of each student and spend less time managing disruptions during classes.
- **Classroom utilization ratio** : It is measured by the Classroom/Class Ratio. This ratio provides an idea of the capacity of a school facility. It has an impact on pedagogical outcomes as the transformation of teaching practices and the emergence of new teaching methods involve the use of new types of small-sized classrooms. In this sense, educational administration must confront the challenge of effectively using classrooms, as the issue sometimes becomes so intricate that it becomes necessary to even modify class schedules and increase the utilization of these rooms.

**3.2.2. Outputs**

- **Promotion rate (PROM) :** It is calculated by dividing the number of students who passed by the total student population. Ideally, this rate should approach 100%; a high rate signifies a high level of internal efficiency within the education system. This rate disaggregated by year of study helps identify the years of study with low promotion rates. However, this indicator has limitations due to the sometimes required acceptance of averages below ten out of twenty (10/20) as the passing threshold, due to school zoning requirements linked to limited capacity in educational institutions. The success rate is given by the following formula : PROM = ∑ of admissions at the end of the year N / ∑ of students counted on 15/10/N-1.
- **Repetition rate (REP)** : It reflects the level of acquisition of the skills required to progress from one grade to another. High repetition rates indicate problems of internal efficiency within the education system and can be indicative of a poor level of instruction. Thus, they have a negative impact on the school completion rate (the number of years spent in an educational cycle), requiring additional investments in education. When comparing repetition rates across different grade levels, the figures may indicate that repetition rates are higher for certain years, prompting further studies into the causes of the phenomenon and potential remedies. This rate is calculated by dividing the number of students repeating a grade by the total student population. Ideally, repetition rates should

be close to 0%. It is obtained using the following formula : REP = ∑ of repeat students at the end of the year N / ∑ of students counted on 15/10/N-1.

- **Drop-out Rate (DROP) :** School dropout is a phenomenon that has garnered significant interest from governmental and non-governmental education authorities. It is a powerful indicator for shaping public education policies. Ideally, this rate should approach 0% ; a high dropout rate signifies internal efficiency issues within education systems. Comparing rates across different grade levels helps identify the years that policies should prioritize. When calculated over a period (usually the school year), this rate can take negative values. In other words, the number of students who joined the school during this period exceeds the number of students who left. The formula used to calculate the dropout rate is as follows: DROP = 1 - (PROM + REP).

The three outputs above verify the following relationship: **PROM + REP + DROP = 100%.**
To ensure conformity with the requirements of the DEA model, which imposes positive values, and for reasons of output maximization, we have transformed the initial variables to obtain the following new variables: 1/ (REP) and 1/ (DROP+1). Thus, minimizing the repetition rate (REP) and the drop-out rate (DROP) is equivalent to maximizing the following ratios: 1/ (REP) and 1/ (DROP+1) respectively.

## 4. Results and discussion

### 4.1 Efficiency score analysis

The results of the DEA method show that the average efficiency obtained under the assumption of variable scale efficiencies decreased from 0.878 in 2014-2015 to 0.874 in 2020-2021 (Table 2). This suggests that the DMUs could reduce their inputs while maintaining the current level of output or increase their output while keeping their inputs constant by 12.2% in 2014-2015 and 12.6% in 2020-2021. The dispersion around the mean remains relatively low, indicating that variations in inefficiency are relatively minimal compared to the efficiency frontier.
Furthermore, although the average efficiency score slightly decreased between 2014-2015 and 2020-2021, the number of efficient DMUs, which was 12, remained unchanged. Moreover, the number of DMUs with an efficiency score higher than the average increased during this period, going from 31 to 34.

**Table 2:** Descriptive statistics of efficiency scores

| Year | Min | Max | Mean | Standard Deviation | Efficient DMUs | DMUs ≥ average | DMUs < average | Total |
|---|---|---|---|---|---|---|---|---|
| **2014/2015** | 0,7 | 1 | 0,878 | 0,088 | 12 | 31 | 38 | 81 |
| **2020/2021** | 0,6 | 1 | 0,874 | 0,097 | 12 | 34 | 35 | 81 |

**Source** : Authors calculation.

Similarly, it can be observed that the number of efficient DMUs in both 2014-2015 and 2020-2021 amounts to 7 DMUs. This observation highlights that 58% of the efficient DMUs managed to maintain their performance, while 42% (5 DMUs) saw their efficiency decline during this period. However, the number of DMUs that remained inefficient both in 2014-2015 and 2020-2021 reached 69 (Table 3). This observation reflects the persistence of inefficiency over this reference period.

**Table 3:** Matrix of efficient and inefficient DMUs

| 2014-2015 \ 2020-2021 | Efficient DMUs | Inefficient DMUs |
|---|---|---|
| **Efficient DMUs** | 7 | 5 |
| **Inefficient DMUs** | 5 | 69 |

**Source** : Authors calculation.

The analysis of the results highlights that the average size of inefficient DMUs is smaller than the average size of efficient DMUs. This demonstrates that reducing the size of schools does not necessarily lead to the improvement of their efficiencies, as smaller institutions might find themselves in a situation of underutilizing the resources at their disposal (Table 4).

It's important to note that this situation presents a significant challenge in terms of optimal resource management. Indeed, if smaller establishments fail to fully exploit the resources available to them, it could potentially result in a waste of these resources. This lack of efficient resource utilization can have repercussions on the overall distribution of limited resources among educational institutions. A better allocation of these scarce resources is essential to ensure optimal efficiency and improved performance of the entire educational system.

**Table 4:** Average DMU size

| Year | Efficient DMUs | Inefficient DMUs |
|---|---|---|
| **2014-2015** | 566 | 416 |
| **2020-2021** | 613 | 436 |

**Source** : Authors calculation.

### 4.2 Inefficiency correction

To address the identified inefficiencies, the DEA method proposes two distinct perspectives: input orientation and output orientation. Regarding input orientation, the obtained results highlight an excess use of the employed resources. This excess is particularly pronounced in the case of administrative staff, where a potential for reduction is identified. This potential represents 14.90% and 12.53% of the total administrative staff used for the years 2014-2015 and 2020-2021 respectively (Table 5).

Several factors could explain this trend. One possible reason is task distribution, which might lead to a disproportionate assignment of teachers to administrative tasks such as assisting in management or handling the school library. This reallocation of teachers could result in an inefficient utilization of their time and skills. Regarding other resources, namely teachers, classrooms, and classroom spaces, potential reductions are also observed. For the year 2014-2015, these reduction potentials are around 5.03% for teachers, 4.68% for classrooms, and 0.24% for classroom spaces. These values increase to 6.53%, 7.60%, and 0.70% respectively for the year 2020-2021.

This analysis underscores the importance of balanced management of human and material resources. It is crucial to take measures to reduce the excess utilization of certain resources while ensuring that the adjustments made do not compromise the quality of teaching and learning. Optimal allocation of resources across different functions and activities of the institution can significantly contribute to the overall improvement of efficiency and educational performance.

To achieve this, it's necessary to consider reallocating human resources (teachers and administrative staff) and material resources (classrooms and classroom spaces) to enhance the outputs of the educational system. This includes the use of these resources to provide support activities for students facing academic difficulties and organizing extracurricular activities (enrichment activities, artistic workshops, theatrical events, pedagogical clubs, etc.) to contribute to the development of psycho-social skills and soft skills. Indeed, strengthening the capacity of human resources is essential by consistently adopting continuous training programs tailored to the needs and innovations of pedagogical approaches and educational technology.

***Table 5:*** Inputs gap

| Statistics | Year | Teacher | Administrative staff | Class | Classroom |
|---|---|---|---|---|---|
| **Min** | **2014-2015** | 0,000 | 0,000 | 0,000 | 0,000 |
| | **2020-2021** | 0,000 | 0,000 | 0,000 | 0,000 |
| **Max** | **2014-2015** | 465,552 | 165,378 | 565,435 | 59,087 |
| | **2020-2021** | 1251,206 | 113,746 | 1364,952 | 163,593 |
| **Mean** | **2014-2015** | 77,077 | 16,129 | 71,161 | 2,598 |
| | **2020-2021** | 112,920 | 13,020 | 128,369 | 8,036 |
| **Standard Deviation** | **2014-2015** | 111,009 | 25,987 | 128,063 | 10,335 |
| | **2020-2021** | 209,106 | 21,899 | 226,417 | 31,816 |
| **Total slacks** | **2014-2015** | 6243 | 1306 | 5764 | 210 |
| | **2020-2021** | 9147 | 1055 | 10398 | 651 |
| **Total initial values** | **2014-2015** | 124110 | 8769 | 123087 | 89441 |
| | **2020-2021** | 140107 | 8417 | 136832 | 92864 |
| **Reduction rate** | **2014-2015** | 5,03% | 14,90% | 4,68% | 0,24% |
| | **2020-2021** | 6,53% | 12,53% | 7,60% | 0,70% |

**Source** : Authors calculation.

Regarding the output orientation, the average number of points to increase for the promotion rate is 0.033 and 0.016 points respectively in 2014-2015 and 2020-2021. The average number of points to decrease for the repetition rate and dropout rate is 2.020 and 0.017 respectively in 2014-2015 and 0.013 and 0.005 in 2020-2021 (Table 6). To implement all these corrections and consequently improve educational production, several measures could be undertaken; these include:

- Ensuring the implementation of differentiated pedagogy in the current teaching model to adapt the teaching/learning process to the differences in learning modes and rhythms among students.
- Operationalizing institutional support by establishing monitoring units in schools, as well as integrated support in curricula.
- Equipping schools with well-stocked school libraries that meet the students' needs in different disciplines.
- Providing schools with didactic materials suitable for the new pedagogical engineering in place (figurines, interactive whiteboards, etc.).
- Widely adopting and operationalizing multimedia classrooms to enable the effective integration of ICT (Information and Communication Technologies in Education) in the teaching/learning process.
- Motivating the human resources in schools to encourage them to improve their productivity.
- Strengthening and expanding social support for schooling (school transportation, meals, financial aid, etc.) to combat dropout and absenteeism.
- Upgrading school infrastructure (especially constructing sanitary facilities, especially for girls, providing clean water, electricity, and internet connectivity).
- Expanding the community school model to fight against school dropout and optimize resource utilization.

***Table 6:*** Outputs gap

| Statistics | Year | PROM | REP | DROP |
|---|---|---|---|---|
| **Min** | **2014-2015** | 0,000 | 0,000 | 0,000 |
| | **2020-2021** | 0,000 | 0,000 | 0,000 |
| **Max** | **2014-2015** | 0,113 | 6,979 | 0,082 |
| | **2020-2021** | 0,090 | 0,048 | 0,046 |
| **Mean** | **2014-2015** | 0,033 | 2,020 | 0,017 |
| | **2020-2021** | 0,016 | 0,013 | 0,005 |
| **Standard Deviation** | **2014-2015** | 0,031 | 2,029 | 0,021 |
| | **2020-2021** | 0,017 | 0,013 | 0,009 |
| **Average initial values** | **2014-2015** | 0,875 | 0,103 | 0,022 |
| | **2020-2021** | 0,920 | 0,054 | 0,027 |

**Source** : Authors calculation.

## 5. Conclusion

The evaluation of education and training activities has become a necessity today, given that training is a significant investment that forms the foundation of development for all countries. This is why all training authorities are aware of this requirement. Indeed, establishing an evaluation system that provides reliable indicators regarding the quality, appropriateness, and efficiency of the proposed training actions is a pressing matter.

To do so, schools like firms are increasingly concerned with the optimal utilization of their resources (inputs) and the quality of their services (outputs). The present study has emphasized the significance of educational efficiency and its various determinants at both the internal and external levels of the educational system. Additionally, it has advocated for the non-parametric method (DEA) to measure the internal technical efficiency of a sample of 81 provincial departments within the Ministry of National Education, assuming variable scale returns (VRS), during the school years 2014-2015 and 2020-2021. At the conclusion of this study, corrective measures have been proposed to enhance efficiency.

The results of the DEA method reveal that the average efficiency score slightly decreased between 2014-2015 and 2020-2021, shifting from 0.878 to 0.874. However, the number of efficient DMUs (Decision Making Units), which was 12 in 2014-2015, remained unchanged in 2020-2021. Furthermore, the count of DMUs with an efficiency score higher than the average increased during this period, rising from 31 to 34. Similarly, it is observed that the count of efficient DMUs in both 2014-2015 and 2020-2021 amounts to 7 DMUs. This observation highlights that 58% of the efficient DMUs managed to sustain their performance, while 42% (equivalent to 5 DMUs) experienced a decline in efficiency during this period.

The analysis of the results also highlights that the average size of inefficient DMUs is smaller than the average size of efficient DMUs. This demonstrates that reducing the size of schools does not necessarily lead to the improvement of their efficiencies, as smaller institutions could find themselves in a situation of underutilizing the resources at their disposal.

To address the identified inefficiencies, the input orientation highlights an excess use of resources. This excess is particularly pronounced in the case of administrative personnel, where a potential for reduction has been identified. This potential represents 14.90% and 12.53% of the total administrative personnel used in the years 2014-2015 and 2020-2021, respectively.

Regarding the output orientation, the average number of points to be increased for the promotion rate is 0.033 and 0.016 points in the years 2014-2015 and 2020-2021, respectively. The average number of points to be reduced for the repetition rate and dropout rate is 2.020 and 0.017, respectively, in 2014-2015, and 0.013 and 0.005 in 2020-2021.

Despite the criticism that can be directed towards the DEA method, which resides in the fact that the efficiency scores obtained are sensitive to the prior selection of inputs and outputs (the introduction or removal of inputs or outputs leads to a modification of the efficiency scores), this research into efficient educational production and the measures that can lead to the correction of inefficiency gaps have enabled an internal benchmarking among the selected DMUs. They have also provided avenues for reflection for education managers to improve the identified management shortcomings.

However, it does not claim to lead to a completely satisfactory and objective vision due to the constraints and limitations associated with: (1) the choice of the sample; (2) the reliability of available data; (3) the relevance of the different selected inputs and outputs; (4) the measurability of qualitative aspects that influence student learning (the degree of knowledge transformation, the competence of human resources, the impact of the socio-cultural environment, the teaching materials used, the teaching techniques and approaches adopted, student motivation, etc.), and consequently the quality of the assessment of educational efficiency; and (5) the feasibility of the proposed corrective measures in the face of the multi-dimensionality of public management that requires coordination and cooperation, as education is a field where several institutional actors with competing competencies are at play, and they strive to preserve a specific sphere of influence (administration, unions, civil society, etc.).

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