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A Three-Stage Data Envelopment Analysis Approach to Assessing the Performance of Educational Systems

Maryam Nematizadeh[1*], Maryeh Nematizadeh[1]

[1] Department of Basic Science, Technical and Vocational University (TVU), Tehran, Iran

*** Corresponding author email address:** maryam.nematizadeh@yahoo.com

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A B S T R A C T

Assessing the efficiency of education systems is crucial for shaping evidence-based policies and ensuring sustainable human capital development. This study employs a three-stage framework to evaluate Iran's education system from 2005 to 2023, integrating both non-parametric and parametric approaches. In the first stage, Data Envelopment Analysis (DEA) is used to calculate partial efficiency scores for outputs such as primary completion, enrolment, and research productivity. In the second stage, regression analysis investigates the role of contextual variables—including unemployment, youth not in education, employment or training, adjusted savings, and digital access—in shaping efficiency outcomes. Finally, efficiency scores are adjusted and aggregated to produce a comprehensive ranking of performance trends. The findings highlight the varying influence of contextual factors across outputs and provide practical insights for policymakers to improve educational performance and resilience.

Keywords: *Data envelopment analysis, Partial Efficiency, Contextual variable, Regression, Education*

Introduction

Evaluating the performance of education systems is essential for informed policy-making, efficient allocation of resources, and the sustainable development of human capital. In Iran, understanding how public spending, labor participation, and other educational inputs translate into tangible outcomes is particularly important, considering demographic pressures, socio-economic disparities, and technological challenges. However, the complexity of educational processes and the diversity of inputs make it challenging to assess the effectiveness of educational activities accurately.

To address these challenges, scholars have proposed both parametric and non-parametric approaches, each with specific strengths and limitations. Among the non-parametric methods, Data Envelopment Analysis (DEA) has gained wide recognition as a powerful technique for measuring efficiency. Originally introduced by Charnes et al. (1978) and extended by Banker et al. (1984), DEA evaluates multiple inputs and outputs simultaneously without assuming a predefined production function. This flexibility makes it particularly effective for analyzing complex systems such as education, where diverse resources must be translated into varied outcomes.

However, despite its advantages, DEA results may be influenced by hidden or contextual variables—such as economic conditions, unemployment, or digital access—that are not directly observable. Such variables include economic conditions, unemployment among educated individuals, the share of youth not in education, employment, or training, financial investments in education, and access to digital technologies. Accounting for these factors is crucial for obtaining a more accurate understanding of efficiency. Previous studies have shown that combining parametric and non-parametric methods within a multi-stage framework allows for more accurate estimation of contextual effects and yields more realistic results.

This study adopts a three-stage DEA-based approach to assess the performance of Iran’s education system from 2005 to 2023. In the first stage, partial efficiency scores are calculated for each output to identify the contribution of individual outputs to the overall efficiency of each decision-making unit. In the second stage, regression analysis examines the influence of contextual variables on measured efficiency. In the third stage, efficiency scores are adjusted for the effects of contextual factors and used to rank the performance of the education system over time. This comprehensive approach enables a more detailed analysis of educational performance and provides evidence-based policy recommendations.

The remainder of the paper is organized into five sections. Section 2 reviews the relevant literature on educational performance evaluation and the application of DEA. Section 3 describes the research methodology in detail. Section 4 presents and analyzes the results of the efficiency assessment of Iran’s education system, highlighting key strengths, weaknesses, and performance trends. Finally, Section 5 concludes with a discussion of policy implications and recommendations for improving efficiency and optimizing resource allocation in the education sector.

Literature Review

DEA has become one of the most widely used non-parametric methods for evaluating efficiency in the education sector. Ahmad and Khurizan (2024), through a systematic literature review covering studies published between 1992 and 2022, identified institutional performance, departmental evaluation, study program assessment, and higher education management as the principal domains of DEA application in education, highlighting the growing importance of DEA in educational performance measurement. Owing to its ability to simultaneously handle multiple inputs and outputs without requiring a predefined production function, DEA has been extensively applied to assess the performance of educational institutions, national education systems, and public sector programs. As educational systems utilize diverse resources to generate multiple outcomes, DEA provides a suitable framework for measuring performance and identifying opportunities for improvement.

Initial applications of DEA in education focused predominantly on higher education institutions, where universities were treated as decision-making units for evaluating resource utilization and educational outcomes. Zhou and Wang (2009) highlighted the importance of input–output efficiency evaluation in higher education and demonstrated how DEA can support quality improvement and innovation. Li (2011) evaluated the efficiency of human resource utilization in 42 Chinese universities and emphasized the role of scale efficiency in improving educational outcomes and graduate employability. Similarly, Olariu and Brad (2017) assessed Romanian public universities using CRS and VRS DEA models and showed that efficiency indicators can provide useful information for resource allocation and public funding decisions. Karbasian et al. (2016) combined DEA and TOPSIS to evaluate educational departments at Malek-Ashtar University of Technology and stressed the importance of human capital management in educational performance. Kumar and Thakur (2019) further extended DEA applications by employing a dynamic DEA framework to evaluate management education institutions in India and proposed a more objective ranking system based on educational outcomes and resource utilization.

The application of DEA has gradually expanded beyond universities to regional and national educational systems. Bogetoft et al. (2015) examined upper secondary education efficiency in Nordic and OECD countries and demonstrated that the inclusion of educational quality indicators significantly influences efficiency estimates. Cardoso et al. (2021) evaluated municipal educational systems in Brazil and found that higher educational expenditure does not necessarily lead to higher efficiency. Aparicio and Santín (2022) introduced productivity and performance-gap indices to distinguish between effectiveness and productivity in educational systems. Likewise, Kounetas et al. (2023) investigated secondary school efficiency in Greece and identified substantial opportunities for performance improvement through more effective resource utilization. Using common-weight DEA models, Ucar and Karsak (2024) assessed educational efficiency across OECD countries and emphasized the importance of methodological choices in international comparisons. More recently, Oliveira-Melo et al. (2025) analyzed educational efficiency in 112 countries within the framework of Sustainable Development Goal 4 and concluded that governance quality and effective resource management played a more important role than economic development alone in determining educational efficiency. Similarly, Angelov and Nikolova (2025) reported significant differences in efficiency levels across higher education systems in European Union member states.

Alongside efficiency assessment, several studies have employed DEA to analyze productivity changes and technological progress in education. Rahimian and Soltanifar (2013) applied the Malmquist Productivity Index to Iranian universities and showed that productivity growth is influenced by both technical efficiency change and technological progress. Zhou et al. (2024) used a three-stage DEA–Malmquist framework to evaluate educational science and technology efficiency across Chinese provinces and identified technological progress as the primary source of productivity improvement. Similarly, Ahmad et al. (2025) found that technological change was the main driver of productivity growth among Malaysian public universities. Recent studies have also adopted advanced DEA methodologies to capture the multidimensional nature of educational performance. Ersoy (2021) integrated DEA, super-efficiency analysis, and TOPSIS to evaluate distance education departments in Turkish universities. Sun et al. (2023) proposed a double-frontier parallel DEA model for Chinese higher education systems, while Sharifi et al. (2025) developed a DEA–fuzzy inference framework to incorporate both quantitative and qualitative indicators. Likewise, Zeng et al. (2025) employed a two-stage DEA model to evaluate innovation efficiency in higher education and demonstrated the value of multi-stage approaches for identifying sources of inefficiency.

The growing complexity of educational systems has highlighted the importance of considering contextual and environmental factors in efficiency analysis. Traditional DEA models assume that all decision-making units operate under similar conditions; however, educational performance is often influenced by external factors such as economic conditions, labor market characteristics, technological infrastructure, demographic conditions, and public policies. Ignoring these factors may lead to biased efficiency estimates and misleading conclusions. Consequently, efficiency scores obtained from conventional DEA models may reflect not only managerial performance but also the influence of external operating conditions. To address this issue, Ray (1988) introduced a two-stage framework in which DEA efficiency scores are subsequently analyzed using regression techniques. Wang and Schmidt (2002) discussed the relative merits of one-stage and two-stage approaches, while Simar and Wilson (2007) improved the statistical validity of second-stage analysis through bootstrap and Monte Carlo procedures. Later, Banker and Natarajan (2008) proposed a DEA–OLS framework for estimating the effects of environmental variables on efficiency, and Banker et al. (2019) demonstrated the theoretical consistency of this approach under standard production assumptions. These methodological developments have significantly improved researchers’ ability to distinguish managerial inefficiency from environmental influences and have encouraged the application of multi-stage DEA models in education and other public sectors.

Evidence from Iran remains relatively limited and is concentrated primarily on higher education institutions. Mahdavi (2020) investigated the efficiency of higher education from a sustainable development perspective and reported that improvements in educational productivity contribute positively to long-run economic growth. Arshadi et al. (2022) evaluated the research efficiency of Iranian universities and found significant relationships between DEA efficiency scores and international university rankings. While these studies provide valuable insights into higher education performance, they do not assess the efficiency of the national education system as a whole.

Overall, the existing literature confirms that DEA is a powerful and flexible tool for evaluating educational performance at institutional, regional, and national levels. Nevertheless, three important gaps remain. First, most studies focus on universities, schools, or regional educational units, whereas relatively few examine national education systems over extended periods. Second, although productivity and efficiency analyses are widespread, only a limited number of studies explicitly account for contextual factors through multi-stage DEA frameworks. Third, empirical evidence for Iran is largely restricted to higher education institutions, leaving the performance of the national education system largely unexplored. Therefore, the present study addresses these gaps by employing a three-stage DEA framework to evaluate the performance of Iran’s education system over the period 2005–2023. By incorporating contextual variables into the efficiency assessment process, the study provides a more comprehensive and policy-relevant evaluation of educational performance than conventional DEA approaches.

Methodology

This section presents the methodological framework adopted to evaluate the performance and efficiency of Iran's education system. The methodology is designed to provide a comprehensive and robust assessment by integrating both non-parametric and parametric approaches, allowing for the consideration of multiple inputs, outputs, and contextual factors simultaneously. Specifically, the approach is structured into three main steps:

Step 1: Calculating the partial efficiency using the DEA model.

Step 2: Estimating the impact of contextual variables on partial efficiency through a regression model.

Step 3: Ranking the decision-making units.

In the following subsections, each step is described in detail.

❖ ***Step 1: Measuring Partial Efficiency with DEA***

Suppose that there are J DMUs, where each $DMU_j(j = 1,2,\dots,J)$ utilizes inputs $x_{mj}(m = 1,2,\dots,M)$ to produce outputs $y_{rj}(r = 1,2,\dots,R)$. To define the technology set T, the following axioms are assumed:

i) *Inclusion of observations*:

$$\forall j = 1,\dots,J, \left(x_j, y_j\right) \in T.$$

ii) *Strong disposability*:

$$\forall (x,y) \in T;\ \forall x', y' \;\&\; x' \geq x\,, y' \leq y \Rightarrow (x', y') \in T.$$

iii) *Convexity*:

$$(x,y) \in T \;\;\&\;\; (x',y') \in T \Rightarrow \lambda(x,y) + (1-\lambda)(x',y') \in T, 0 \leq \lambda \leq 1.$$

iv) *Minimal extrapolation*:

T is the smallest set satisfying the set of imposed maintained axioms.

Accordingly, the production technology set T can be expressed as follows:

$$\boldsymbol{T} = \{\, (\boldsymbol{x},\boldsymbol{y}): \sum_{j=1}^{J} \boldsymbol{\lambda_j x_{mj}} \leq \boldsymbol{x_m}, \boldsymbol{m} = \boldsymbol{1},\dots,\boldsymbol{M}, \quad \sum_{j=1}^{J} \boldsymbol{\lambda_j y_{rj}} \geq \boldsymbol{y_r}, \boldsymbol{r} = \boldsymbol{1},\dots,\boldsymbol{R}, \quad \sum_{j=1}^{J} \boldsymbol{\lambda_j} = \boldsymbol{1}, \quad \boldsymbol{\lambda_j} \geq \boldsymbol{0}, \boldsymbol{j} = \boldsymbol{1},\dots,\boldsymbol{J}\, \}, \tag{1}$$

Based on this technology set, the Russell efficiency measure for a specific unit DMU_o is computed as (Pastor et al., 1999):

$$RE_o^* = Min \frac{\frac{1}{M}\sum_{m=1}^{M}\alpha_m}{\frac{1}{R}\sum_{r=1}^{R}\beta_r}$$

$$s.t.$$

$$\sum_{j=1}^{J}\lambda_j x_{mj} \leq \alpha_m x_{mo}, m = 1, \dots, M,$$

$$\sum_{j=1}^{J}\lambda_j y_{rj} \geq \beta_r y_{ro}, r = 1, \dots, R, \qquad (2)$$

$$\sum_{j=1}^{J}\lambda_j = 1,$$

$$\beta_r \geq 1, 0 \leq \alpha_m \leq 1, \forall\, m, r,$$

$$\lambda_j \geq 0, \forall j.$$

Here, α_m and β_r represent the input contraction and output expansion factors, respectively. The value RE_o^* indicates the ratio of the average input efficiency to the average output efficiency.

Since this model is nonlinear, it can be linearized using the transformation proposed by Charnes and Cooper (1962). Let $\frac{1}{\frac{1}{R}\sum_{r=1}^{R}\beta_r} = \rho(> 0)$, and set $\beta_r\rho = \tilde{\beta}_r$, $\alpha_m\rho = \tilde{\alpha}_m$, $\lambda_j\rho = \tilde{\lambda}_j$, for all r, m and j. The model can then be equivalently reformulated as follows

$$\widetilde{RE}_o^* = Min \frac{1}{M}\sum_{m=1}^{M}\tilde{\alpha}_m$$

$$s.t.$$

$$\sum_{j=1}^{J}\tilde{\lambda}_j x_{mj} \leq \tilde{\alpha}_m x_{mo}, m = 1, \dots, M,$$

$$\sum_{j=1}^{J}\tilde{\lambda}_j y_{rj} \geq \tilde{\beta}_r y_{ro}, r = 1, \dots, R, \qquad (3)$$

$$\sum_{j=1}^{J}\tilde{\lambda}_j = \rho,$$

$$\frac{1}{R}\sum_{r=1}^{R}\tilde{\beta}_r = 1,$$

$$0 < \rho \leq 1,$$

$$\tilde{\beta}_r \geq \rho, 0 \leq \tilde{\alpha}_m \leq \rho, \forall\, m, r,$$

$$\tilde{\lambda}_j \geq 0, \forall j.$$

Definition 1. DMU_o is efficient if and only if $\widetilde{RE}_o^* = 1$ ($\tilde{\alpha}_m = \tilde{\beta}_r = 1, \forall m, r$); otherwise, it is inefficient.

To calculate the partial efficiency of a specific decision-making unit DMU_o, model (3) is solved by considering all inputs and only one output at a time. Repeating this procedure for each output generates multiple partial efficiency values ($\widetilde{RE}_o^*(y_r): r = 1,2, \dots, R$), each ranging between 0 and 1 (Nematizadeh et al., 2025).

❖ ***Step 2: Regression Model***

In the second stage, the effect of contextual variables (z) on efficiency is examined using the following regression model:

$$\boldsymbol{Log_{10}\left(\widetilde{RE}_o^*(y_r)\right) = \delta_0 + \delta_1 z_{1o} + \cdots + \delta_s z_{so} + \varepsilon_o; r = 1, 2, \ldots, R} \quad (4)$$

where $Log_{10}\left(\widetilde{RE}_o^*(y_r)\right)$ is the logarithm of the partial efficiency score for DMU_o $(o = 1, \ldots, J)$. The coefficients $\delta_s (s = 1, \ldots, S)$ represent the impact of contextual variables on technical efficiency, which can be either positive or negative. Here, δ_0 denotes the intercept and ε_o is the error term.

❖ ***Step 3: Ranking***

To eliminate the influence of contextual variables, adjusted partial efficiency scores are calculated as:

$$\boldsymbol{\widetilde{RE}_o^{New}(y_r) = \widetilde{RE}_o^*(y_r) - (Log_{10}\left(\widetilde{RE}_o^*(y_r)\right) - \delta_0 + \delta_1 z_{1o} + \cdots + \delta_s z_{so} + \varepsilon_o), r = 1, 2, \ldots, R} \quad (5)$$

The average of the adjusted partial efficiency scores

$$\boldsymbol{\varphi_o = \frac{1}{R}\sum_{r=1}^{R} \widetilde{RE}_o^{New}(y_r)\,; o = 1, 2, \ldots, J.} \quad (6)$$

can be considered as a suitable criterion for ranking DMU_o.

Results and Discussion of Findings

This section presents the empirical findings of the study on the Iranian education system over the period 2005–2023. The analysis is structured in three stages. First, the selected variables are introduced together with their descriptive statistics. Second, efficiency scores are estimated using the DEA-based approach, providing insights into the performance trends of the education system across the study period. Finally, regression analysis is applied to assess the influence of contextual factors on the adjusted efficiency scores, allowing for a deeper understanding of the drivers and barriers to efficiency in the Iranian education system.

Indicators and Variables

The study uses data from the World Development Indicators (WDI) database of the World Bank , grouped into inputs, outputs, and contextual variables.

❖ **Input Indicators**

– *Public spending on education as a share of GDP:*

Share of national income allocated to education, reflecting government investment in human capital.

– *Compulsory education, duration (years):*

Number of years of mandatory schooling set by law.

– *Government expenditure on education, total (% of GDP):*

Total government spending on the education sector relative to GDP.

- *Average labor force participation by education level:* Average participation rate of individuals with basic, intermediate, and advanced education in the labor market.

❖ **Output Indicators**

- *Scientific and technical journal articles per million people:*

Number of published research articles, reflecting knowledge production and the performance of higher education.

- *Combined total net enrolment rate, primary, both sexes:*

  Percentage of children of official primary school age enroled in school.

- *Primary completion rate, total (% of relevant age group):*

  Share of students completing the final grade of primary school.

❖ **Contextual Variables**

- *Average unemployment rate by education level:*

  Average unemployment rate among individuals with basic, intermediate, and advanced education.

- *Share of youth not in education, employment, or training:*

  Percentage of the youth population not engaged in school, work, or training.

- *Adjusted savings: education expenditure (% of GNI):*

Education expenditure expressed as part of adjusted net savings, linking education to long-term development.

- *Number of Internet users:*

Percentage of the population with access to the internet, serving as a proxy for digital inclusion in education.

Table 1 presents the summary statistics for the input, output, and contextual variables used in the analysis.

Table 1: Summary statistics of data

Indicator type	Variables	Min	Mean	Max	Median	Q1	Q3
Input	Public spending on education as a share of GDP	2.62E+00	3.37E+00	4.60E+00	3.24E+00	2.90E+00	3.78E+00
	Compulsory education, duration	8.00E+00	8.58E+00	9.00E+00	9.00E+00	8.00E+00	9.00E+00
	Government expenditure on education, total	2.62E+00	3.41E+00	4.60E+00	3.24E+00	3.00E+00	3.78E+00
	Average Labor Force Participation by Education Level	4.08E+01	4.39E+01	4.80E+01	4.40E+01	4.21E+01	4.51E+01
Output	Scientific and technical journal articles per million people	9.80E+01	4.32E+02	6.97E+02	4.35E+02	2.93E+02	5.83E+02
	Combined total net enrolment rate, primary, both sexes	9.45E+01	9.69E+01	9.91E+01	9.74E+01	9.56E+01	9.80E+01
	Primary completion rate, total	9.66E+01	1.02E+02	1.11E+02	1.00E+02	9.83E+01	1.06E+02
Contextual variables	Average Unemployment Rate by Education Level	9.58E+00	1.20E+01	1.55E+01	1.22E+01	1.05E+01	1.33E+01
	Share of youth not in education, employment or training, total	2.60E+01	3.22E+01	3.60E+01	3.27E+01	3.12E+01	3.43E+01
	Adjusted savings: education expenditure	2.68E+00	3.62E+00	4.77E+00	3.44E+00	3.28E+00	3.95E+00
	Number of Internet users	5.82E+06	2.90E+07	6.95E+07	1.80E+07	8.10E+06	4.95E+07

Analysis of Partial Efficiency Results

Table 2 presents the partial and adjusted partial efficiency scores of the Iranian education system from 2005 to 2023, alongside the average efficiency (φ_o) and the corresponding ranking of each year. These results allow an assessment of how efficiently the educational system utilizes its inputs—such as public spending on education, compulsory schooling years, total government expenditure, and average labor force participation by education level—to achieve specific outputs. The three outputs considered are: (i) scientific and technical journal articles per million people, reflecting higher education and research performance, (ii) combined total net enrolment rate at the primary level, indicating access to basic education, and (iii) primary completion rate, capturing the success of students in completing the final grade of primary education.

Analysis of partial efficiency for scientific and technical articles shows that the early years (2005–2006) exhibit moderate efficiency, with significant improvement observed from 2011 onward. Peaks in efficiency occur during 2011, 2012, 2014, 2015, and again in 2022–2023, reflecting government investment in higher education, expansion of research centers, and supportive policies for knowledge production. Temporary dips, such as those in 2007, coincide with economic constraints and budgetary fluctuations, which likely affected research funding.

For primary enrolment, efficiency remains relatively high and stable, highlighting effective access to basic education in most years. Slight reductions during 2016–2018 can be linked to demographic shifts, regional disparities, and socioeconomic pressures, including the indirect effects of international sanctions that may have limited school attendance in vulnerable regions.

The primary completion rate demonstrates the most variability. Low efficiency in 2007, 2017, and 2018 reflects challenges such as student dropout due to economic hardship, regional inequalities in school infrastructure, and family-level factors that impede consistent school attendance. Conversely, high efficiency in 2011, 2014, and 2015 aligns with the implementation of targeted educational support programs and increased focus on retention in primary schools.

Overall, the average adjusted efficiency (φ_o) illustrates the combined effect across all outputs. Years 2014, 2015, and 2012 show the highest overall efficiency, while 2007, 2018, and 2006 display the lowest. The ranking results underscore the impact of structural reforms, policy initiatives, and targeted investments on the performance of Iran's education system. Notably, the COVID-19 pandemic (2020–2021) caused minor reductions in efficiency due to school closures and the rapid shift to online learning. However, the adjusted scores suggest a degree of resilience, likely supported by prior digital infrastructure investments and emergency learning strategies. The results highlight that while Iran has achieved significant improvements in education efficiency, continued attention to resource allocation, retention policies, and regional equity remains essential for maximizing system-wide performance.

Table 2: Efficiency results of Iran's Education system

Year	$\widetilde{RE}^*_o(y_1)$	$\widetilde{RE}^*_o(y_2)$	$\widetilde{RE}^*_o(y_3)$	$\widetilde{RE}^{New}_o(y_1)$	$\widetilde{RE}^{New}_o(y_2)$	$\widetilde{RE}^{New}_o(y_3)$	φ_o	Rank
2005	0.8368	1	1	0.8311	0.9588	0.9625	0.9174	13
2006	0.8222	1	0.8725	0.8098	0.9555	0.8800	0.8818	17
2007	0.8043	0.8043	0.8206	0.8193	0.8646	0.8604	0.8481	19
2008	0.8731	0.8731	0.9565	0.8854	0.9089	0.9552	0.9165	15
2009	0.8745	0.8745	1	0.8784	0.8964	0.9802	0.9183	12
2010	0.8916	0.8916	0.99	0.8896	0.8938	0.9787	0.9207	11
2011	1	1	1	0.9692	0.9730	0.9868	0.9764	6

2012	1	1	1	0.9942	0.9809	1.0023	0.9925	3
2013	0.9562	1	0.9689	0.9563	0.9939	0.9706	0.9736	7
2014	1	1	1	0.9932	0.9964	0.9948	0.9948	2
2015	1	1	0.9914	1.0028	0.9975	0.9932	0.9978	1
2016	0.914	0.9098	0.8993	0.9285	0.9289	0.9192	0.9255	9
2017	0.8708	0.8764	0.8496	0.8829	0.8962	0.8723	0.8838	16
2018	0.8491	0.8654	0.8242	0.8629	0.8873	0.8485	0.8662	18
2019	0.9065	1	0.8689	0.9089	0.9723	0.8711	0.9174	14
2020	0.9383	0.9715	0.8882	0.9300	0.9647	0.8745	0.9231	10
2021	0.9698	0.9771	0.9149	0.9514	0.9704	0.8793	0.9337	8
2022	1	1	0.9402	1.0050	1.0016	0.9482	0.9849	4
2023	1	1	0.9365	1.0084	1.0027	0.9437	0.9849	5

Figures 1, 2, and 3 illustrate the trends in partial and adjusted partial efficiency for the three outputs of the Iranian education system—scientific and technical journal articles per million people (y_1), combined total net enrolment rate in primary education (y_2), and primary completion rate (y_3) —from 2005 to 2023, highlighting how contextual variables influenced performance over time.

In the case of scientific and technical articles, efficiency began at a moderate level in 2005–2007 and showed steady improvement through 2010. A peak period followed in 2011–2015, when performance was close to the maximum. During 2016–2018, partial efficiency declined, but adjusted efficiency remained consistently higher, showing that contextual variables helped compensate for the downturn and highlighted the system's underlying potential. In the following years, particularly after 2019, efficiency returned to high levels, and the adjustment slightly reinforced performance, suggesting that contextual factors continued to enhance the capacity for knowledge production.

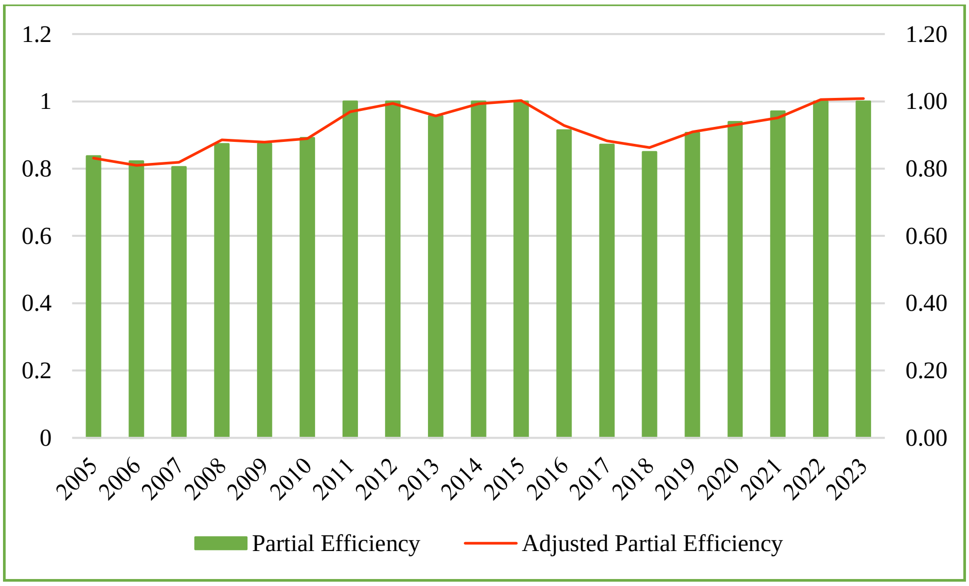

Figure 1: Comparison of Partial and Adjusted Partial Efficiency for y_1

For the primary net enrolment rate, efficiency remained high in most years, though in the early period of 2005–2010 adjusted values were slightly lower, pointing to a negative influence of contextual variables. From 2016 to 2018, partial efficiency declined modestly, but adjusted scores exceeded the partial scores, reflecting the supportive role of contextual factors in cushioning temporary setbacks. Around the COVID-19 pandemic in 2020–2021, adjusted efficiency again fell below partial efficiency, capturing the adverse impact of contextual disruptions. In the final years (2022–2023), both measures converged at peak levels, with contextual variables exerting a reinforcing effect.

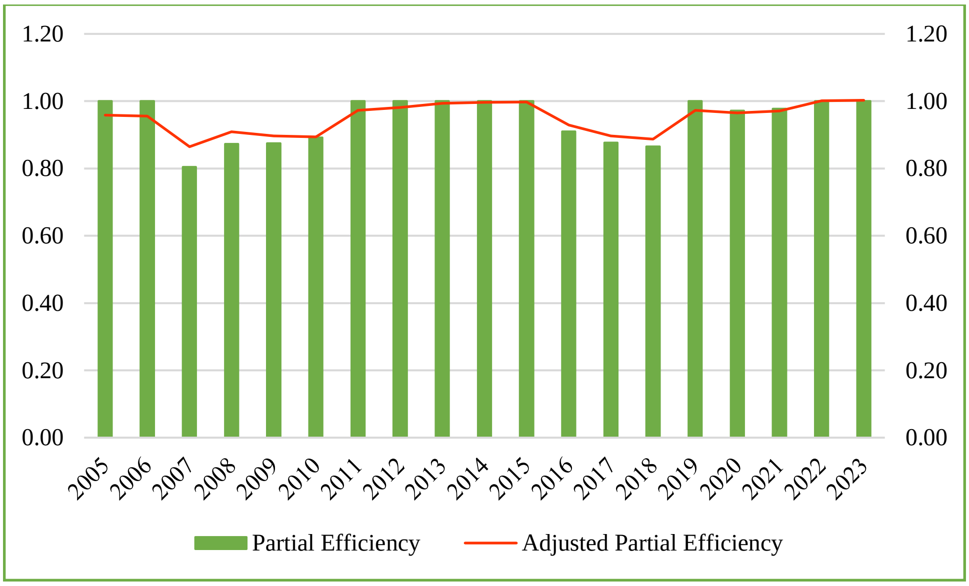

Figure 2: Comparison of Partial and Adjusted Partial Efficiency for y_2

The primary completion rate displayed the most fluctuations. Declines were evident in 2007 and again in 2016–2018, yet in both periods the adjusted values were higher, underscoring the positive role of contextual variables in offsetting weaknesses related to retention and progression. By contrast, during the period 2020–2021 adjusted efficiency fell below partial efficiency, revealing the negative impact of contextual conditions associated with the pandemic. In the most recent years, efficiency improved improvements, and contextual variables contributed positively to sustaining these gains.

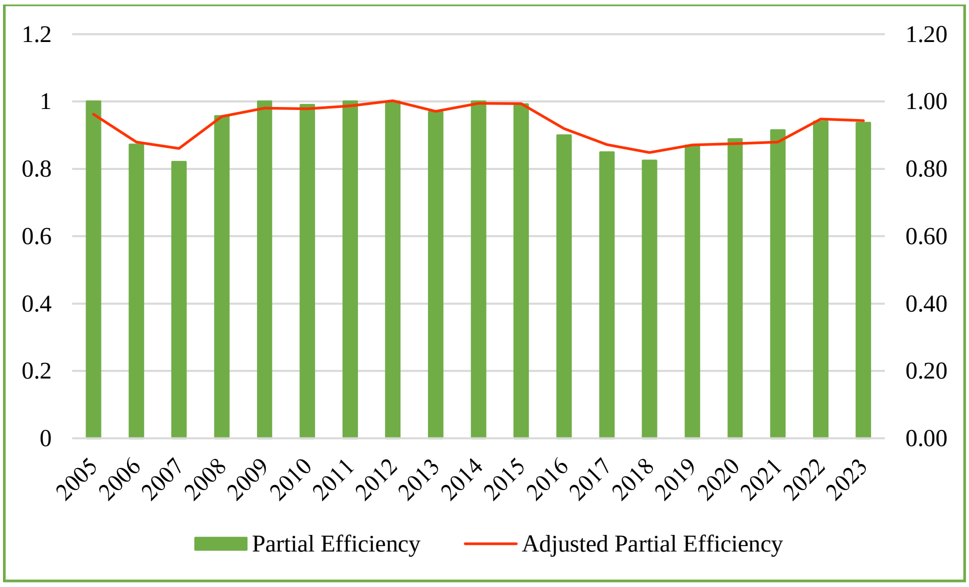

Figure 3: Cmparison of Partial and Adjusted Partial Efficiency for y_3

Regression Analysis of Partial Efficiency Scores

Table 4 presents the regression results for the partial efficiency scores of the Iranian education system, assessing the impact of contextual variables on each of the three output-specific efficiencies. This analysis allows us to examine how socioeconomic and structural factors influence educational performance for different outcomes.

For Partial Efficiency 1, representing the number of scientific and technical journal articles per million people, unemployment among the educated labor force does not have a significant effect ($p =$

0.3313). The share of youth not in education, employment, or training (NEET) has a negative and statistically significant impact (β = -0.0040, p < 0.05), suggesting that disengagement of young people from educational and professional activities can reduce research productivity. Adjusted savings in education expenditure also show a negative and highly significant effect (β = -0.0546, p < 0.001), indicating that increased financial resources alone do not necessarily improve performance without effective management. The number of Internet users has a negative and significant effect as well (β = -5.73E-10, p < 0.01), likely reflecting challenges in online learning and limited capacity of the higher education system to fully leverage digital technologies. The model exhibits high explanatory power (R^2 = 0.8613), explaining approximately 86% of the variation in this output's efficiency.

For Partial Efficiency 2, related to the combined total net enrolment rate in primary education, none of the contextual variables show statistically significant effects. This indicates that enrolment at the primary level is largely determined by structural policies and internal school management rather than short-term socioeconomic factors. The explanatory power of this model is relatively low (R^2 = 0.2755), reflecting the limited influence of the selected variables on this outcome.

For Partial Efficiency 3, which measures the primary completion rate, the NEET variable is not significant, but both adjusted savings in education expenditure and the number of Internet users have significant negative effects (p < 0.01 and p = 0.0036, respectively). This suggests that the inefficient allocation of financial and digital resources may hinder the completion of primary education, highlighting the importance of targeted planning and support. The model's explanatory power is moderate (R^2 = 0.5847).

Overall, the regression results indicate that contextual variables affect each output differently. For research output and primary completion, resource management and digital capacity are critical, whereas primary enrolment is primarily influenced by structural educational policies. These findings emphasize that improving efficiency in the Iranian education system requires not only financial investment but also strategic management of resources and effective use of technology.

Table 3: Regression results for partial efficiency scores of Iran's education system

Partial Efficiency	Output 1($\boldsymbol{y_1}$)		Output 2 ($\boldsymbol{y_2}$)		Output 3 ($\boldsymbol{y_3}$)	
Variables	Coefficients	P-value	Coefficients	P-value	Coefficients	P-value
Intercept	0.2667	1.89E-05	0.1217	0.2012	0.0449	0.5178
Unemployment with education	0.0032	0.3313	-0.0056	0.4284	0.0056	0.2970
Share of youth not in education, employment or training, total	-0.0040	0.0297	-0.0003	0.9263	0.0017	0.5339
Adjusted savings: education expenditure	-0.0546	1.39E-05	-0.0164	0.3788	-0.0471	0.0036
Number of Internet users	-5.73E-10	0.0033	-2.59E-10	0.4704	-9.33E-10	0.0030
Multiple R	0.9281		0.5249		0.7647	
R Square	0.8613		0.2755		0.5847	
Adjusted R Square	0.8216		0.0685		0.4661	
Standard Error	0.0138		0.0297		0.0221	

Conclusion and Policy Implications

This study, by evaluating the performance of the Iranian education system from 2005 to 2023 using a three-stage integrated framework, demonstrated that the country's educational performance is significantly influenced by contextual factors. The findings indicate that while financial investment and increased access to digital technologies are necessary, they are not sufficient on their own to improve the system's efficiency. Inefficient resource management, regional inequalities, and unemployment among the educated are among the factors that can offset the positive effects of these investments. To achieve sustainable improvement in educational outcomes—including research output, enrolment rates, and completion rates—policies must shift toward targeted resource management, enhancing the quality of digital infrastructure, and planning for youth employment and skill development. Furthermore, given the varying influence of environmental factors on each output, educational policies should be designed based on robust empirical evidence and tailored to the specific conditions of each region to achieve educational equity and systemic efficiency.

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رویکرد تحلیل پوششی دادههای سه مرحلهای برای ارزیابی عملکرد سیستمهای آموزشی

مریم نعمتی‌زاده[1*]، ماریه نعمتی‌زاده[1]

۱. گروه علوم پایه، دانشکده علوم پایه و عمومی، دانشگاه ملی و مهارت، تهران، ایران

*ایمیل نویسنده مسئول: maryam.nematizadeh@yahoo.com

اطلاعات مقاله

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چکیده

ارزیابی کارایی سیستمهای آموزشی برای شکلدهی سیاستهای مبتنی بر شواهد و تضمین توسعه پایدار سرمایه انسانی بسیار مهم است. این مطالعه از یک چارچوب سه مرحلهای برای ارزیابی سیستم آموزشی ایران از سال ۲۰۰۵ تا ۲۰۲۳ استفاده میکند و رویکردهای ناپارامتری و پارامتری را با هم ادغام میکند. در مرحله اول، از تحلیل پوششی دادهها (DEA) برای محاسبه نمرات کارایی جزئی برای خروجیهایی مانند تکمیل دوره ابتدایی، ثبتنام و بهرهوری تحقیقاتی استفاده میشود. در مرحله دوم، تحلیل رگرسیون نقش متغیرهای زمینهای - از جمله بیکاری، جوانانی که در حال تحصیل، اشتغال یا آموزش نیستند، پسانداز تعدیلشده و دسترسی دیجیتال - را در شکلدهی به نتایج کارایی بررسی میکند. در نهایت، نمرات کارایی تعدیل و تجمیع میشوند تا رتبهبندی جامعی از روندهای عملکرد ایجاد شود. یافتهها، تأثیر متفاوت عوامل زمینهای را در خروجیها برجسته میکند و بینشهای عملی برای سیاستگذاران جهت بهبود عملکرد و تابآوری آموزشی ارائه میدهد.

کلیدواژگان: *تحلیل پوششی دادهها، کارایی جزئی، متغیر زمینهای، رگرسیون، آموزش*

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