APPLIED PRODUCTION ANALYSIS TERM PAPER

ANALYSING THE PERFORMANCE OF MANAGEMENT INSTITUTES OF INDIA USING DEA WITH REFERENCE TO THE NIRF RANKING METHODOLOGY

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INTRODUCTION:

Today, pursuing a higher degree in Management is a top choice among the youth in India. An estimated 7395 higher-education institutions offering professional and higher degrees in management are there in India. Of these, 5974 are privately funded, and 1230 are publicly funded. Pursuing a higher degree in Management in this country is mainly motivated by more job opportunities, a high income and career growth. Nevertheless, doing an MBA, PGDM, etc. (the most popular higher degrees in Management) in India is costly. Hence, the return on investment (ROI) is the first criterion for a prospective management student to choose their college. Recently, akin to the popular QS World Ranking framework, MHRD (now MoE) India introduced our own NIRF (National Institutional Ranking Framework) ranking system, ranking higher educational institutions across the country based on various qualitative and quantitative parameters. This makes choosing a university easier. But the question is, are these institutions efficient? There can be many measures of their output and input, but in this paper, we shall discuss the most critical measures that might be responsible for the actual performance of the institute from a public and student perspective. To analyse the efficiency of the management institutes, we use DEA or Data Envelopment Analysis. We consider the placement indicators as output and essential factors such as student-faculty ratio, annual capital expenditure, and annual operational expenditure as inputs. DEA, a data-centric method, evaluates the effectiveness of decision-making units (DMUs) that utilise various inputs to generate multiple outputs. These units encompass various sectors such as healthcare, banking, education, transportation, and telecommunications, as noted in previous studies by Cooper et al. (2000), Nigam et al. (2012), Bhattacharya et al. (1996) and Jadhav and Puri (2012).

To evaluate the efficiency of decision-making units (DMUs), various parametric and nonparametric methods, such as Stochastic Frontier Analysis (SFA) and Free Disposal Hull (FDH) and DEA, can be employed. DEA stands out as particularly well-suited to gauge the effectiveness of non-profit entities since traditional performance indicators like profitability and income may not adequately capture their achievements.

Within DEA, numerous approaches have been developed to assess different aspects of efficiency, including technical efficiency, cost efficiency, revenue efficiency, profit efficiency, scale and mix efficiency. This study has policy implications regarding education expenditure and gives a probable picture of to what extent the NIRF rankings can play a role in the decision-making of prospective management students.

LITERATURE REVIEW:

Previously, many studies have been conducted to analyse the efficiency of educational institutions across the world. The methods and parameters imperatively tend to be diverse but insightful simultaneously. **Shale et al.** (1997) analysed the comparative performance of British higher education institutes. They put forth cost and outcome efficiency ideas for thoroughly understanding the universities' functioning. DEA was employed to examine the two different types of efficiency. Expanding the methodology to encompass 45 British universities unveiled a subset of six institutions that demonstrated sufficiently good performance when subjected to various efficiency assessments. Similar studies were done in the UK by **Johnes** (2006). **Munoz** (2016) assesses the research efficiency of Chilean universities using the DEA approach. The study reveals that only a limited number of Chilean universities demonstrate research efficiency.

Additionally, it uncovers intriguing findings regarding the variations in efficiency levels between traditional and private universities. **Li and Ng** (2000) utilised data from 84 premier Chinese universities to examine the effectuality of the Education Reforms in the mid-1980s. It also focused on the research outcomes of the institutes using the DEA approach. The study observes that while research performance has seen enhancements across different regions, institutions as a collective have maintained inefficiency between 1993 and 1995. Furthermore, the breakdown of group efficiency measures reveals that the 84 principal institutions experienced technical, allocative, and reallocative inefficiencies during the three years analysed. **Türkan and Ozel** (2017) analysed the federal universities' productivity in Turkiye utilising DEA. Using a super-efficiency model, they ranked the universities based on their efficiency scores. **Yang et al.** (2018) analysed 64 Chinese research universities from 2010 to 2013 for their performance and efficiency using a 2-stage DEA model. And put forth various policy implications and recommendations aimed at enhancing the universities' performance. Research indicates that the efficiency scores vary depending on the methodology chosen for evaluation.

Recently, in India, some studies have also been done to analyse the efficiency of educational institutions. For example, **Thakur and Kumar (2019)** evaluated the relative performance of Indian HEIs and proposed a comprehensive efficiency measurement that can be generalized to Higher Education Institutions (HEIs) across India. Their research employs dynamic data envelopment analysis (DDEA) as its main analytical method. In order to evaluate the efficiency of institutions, numerous input and output measures have been proposed. In their study, **Bhaskara et al. (2023)** used DEA to evaluate multiple undergraduate departments within a private engineering college in Bengaluru, India, assessing their relative efficiencies over two years (2018–2020). Twelve departments (DMUs) and four variables were chosen for the analysis. The DEA model was constructed using R, and the outcomes were cross-checked against Banxea's Frontier Analysis Tool. The findings revealed that four out of the twelve DMUs exhibited maximum efficiency. In 2015, The MHRD (now MoE) introduced and sanctioned The 'National Institutional Ranking Framework (NIRF)' as a guideline for ranking HEIs in India. The directorate in MHRD established an Expert Committee tasked with identifying crucial parameters for ranking these institutions.
The committee recommended key parameters such as "Graduation Outcomes," "Learning, Teaching, and Resources," Research and Professional Practices," "Perception", and

"Inclusivity and Outreach". Based on the suggestions of the expert committee, a methodology was put forth to rank HEIs (higher education institutions).

In our research, we apply DEA techniques using DEAP software from the University of Queensland to analyse the efficiency of India's top 100 management institutions. Our main focus is whether these institutions can be ranked on the basis of their efficiency scores based on some fundamental parameters often considered by the general public and prospective students. We have discussed this further in detail. Our next goal is to compare their rankings in accordance with our efficiency scores with those of the NIRF ranking in parallel. This will help us to decide to what extent a prospective management student should choose his future college on the basis of NIRF ranks.

First, we begin by describing and explaining the basic DEA models. We then introduce our relevant input and output variables and our dataset. Next, we conduct an isotonicity test, and finally, we give the results of our performance analysis and end the paper with some conclusions and suggestions.

METHODOLOGY:

In this study, we introduce the two fundamental DEA models. First, we have the CCR or Charnes, Cooper and Rhodes model, often called the CCR-DEA model. The concept is as follows:

Consider a set of 'n' DMUs (Decision-making units) (DMU_j; j = 1,2,3,....n). We need to assess their performance or efficiency. Each DMU uses 'i' inputs (i = 1,2,3...,l) and generates 'h' outputs (r = 1,2,....,h). The k^{th} DMU's efficiency score is calculated using the model below:

Model 1- CCR Model:

$$\text{Max } Ek = \left(\sum_{r=1} V_{hk}.y_{hk} \Big/ \sum_{i=1} u_{ik}.x_{ik}\right) \text{ subject to}$$

$$0 <= \left(\sum_{r=1} V_{hk}.y_{hk} \Big/ \sum_{i=1} u_{ik}.x_{ik}\right) <= 1 \quad \forall\ j = 1,2,3.....,n;$$

$$Uik, Vrk, Yrj, Xij >= 0 \quad \forall\ i,r,j$$

Y_{rj} is the quantity of r^{th} output generated by the DMU_j; X_{ij} represents the quantity of the i^{th} input utilised by DMU_j; U_{ik} and V_{rk} are the weights for the i^{th} input and r^{th} output.

DMU_k can be termed efficient as per CCR if $E_k = 1$; else, CCR inefficient. The CCR model could be used for two approaches: Input-Oriented and Output-Oriented. This is shown in the table below:

Output maximization multiplier model (Model 2)	Input minimization multiplier model (Model 3)
Max $E_k = \sum_{r=1}^{s} v_{rk} y_{rk}$; subject to, $\sum_{i=1}^{m} u_{ik} x_{ik} = 1$; $\sum_{r=1}^{s} v_{rk} y_{rj} - \sum_{i=1}^{m} u_{ik} x_{ij} \leq 1$; $u_{ik} \geq 0, v_{rk} \geq 0$.	Min $E_k = \sum_{i=1}^{m} u_{ik} x_{ik}$; subject to, $\sum_{r=1}^{s} v_{rk} y_{rk} = 1$; $-\sum_{r=1}^{s} v_{rk} y_{rj} + \sum_{i=1}^{m} u_{ik} x_{ij} \geq 1$; $u_{ik} \geq 0, v_{rk} \geq 0$.
Input oriented CCR model (Model 4)	**Output oriented CCR model (Model 5)**
Min θ_k subject to $x_k\theta_k - \sum_{i=1}^{m} x_{ij}\lambda_{jk} \geq 0$ $\sum_{r=1}^{s} y_{rj}\lambda_{jk} \geq y_k$ $\lambda_{jk} \geq 0, \theta_k$ is unrestricted.	Max η_k subject to, $\sum_{i=1}^{m} x_{ij}\lambda_{jk} \leq x_k$ subject to, $\eta_k y_k - \sum_{r=1}^{s} y_{rj}\lambda_{jk} \leq 0$ $\lambda_{jk} \geq 0, \eta_k$ is unrestricted.

Model 2: BCC Model

The next model we are going to deal with is the BCC model or Banker, Charnes and Cooper model. This is an extended version of the CCR Model. The additional feature of this model is that it adds a convexity constraint, which takes into account the Returns to Scale (RTS). The PTE or Pure Technical Efficiency of each DMU is evaluated using this model. The Model is explained as follows:

For k = 1, 2, 3, ..., n

Min θ_k

Subject to

$$\sum_{j=1}^{n} y_{rj}\lambda_{jk} - s_{rk}^{+} = y_{rk} \quad \forall\ r = 1,2,3\ldots,s;$$

$$\sum_{j=1}^{n} X_{ij}\lambda_{jk} + s_{ik}^{-} = \theta_k X_{ik} \quad \forall\ r = 1,2,3\ldots,m;$$

$$\sum_{j=1}^{n} \lambda_{jk} = 1 \qquad \lambda_{jk} \geq 0 \quad \forall j = 1,2,3\ldots\ldots,n;\ \theta_k \text{ is unconstrained in sign}$$

$$S_{rk}^{+} \geq 0 \quad \forall r = 1,2,3\ldots.s;\ S_{ik}^{-} \geq 0 \quad \forall i = 1,2,,\ldots..,m$$

While CCR works under CRS or Constant Returns to Scale, BCC works under VRS or Variable Returns to Scale. In essence, if we scale all inputs by a factor, such as K, the outputs increase by the same factor, K, i.e. giving a Constant Return to Scale (CRS). In contrast, VRS (Variable Returns to Scale) suggests that upon amplifying all inputs by a factor of K, the resulting increase in outputs might not be proportional, leading to a different scaling factor, Z, where K is not necessarily equal to Z.

If K≤Z, it is called DRS or Decreasing Returns to Scale.

If K≥Z, it is called IRS or Increasing Returns to Scale.

The efficiency score we derive under the CRS assumption is the Overall Technical Efficiency, OTE, or just Technical Efficiency (TE) score. If the value of η_k*=1 for a particular DMU, then the DMU can be termed CCR-efficient, and the respective slacks are 0. Similarly, the efficiency score derived under the VRS is the Pure Technical Efficiency or PTE score. This score reflects how the inputs are organised in the production process, highlighting managerial prowess. A BCC-efficient DMU has the score θ_k*=1 satisfied, and the respective slacks are 0 in the model.

The Scale Efficiency or SE is reflected by the true size of the DMU and is evaluated as follows:

SE_k (kth DMU) = (OTE of DMU_k)/ (PTE of DMU_k) = (CCR Score of DMU_k)/(BCC Score of DMU_k)

The number of inefficient DMUs that have become efficient in relation to a specific DMU, DMU_k, is known as PC or Peer Count. A peer count of 0 means that the DMU is not efficient, indicating that no other DMU has transitioned from inefficiency to efficiency based on DMU_k.

DATA AND VARIABLES

We have taken data from the top 50 management institutions as DMUs for our research. All data was collected from the official website of the NIRF (MoE-GoI); hence, re-verification was non-essential. We employ two variables for our analysis, namely the (i) Output and (ii) Input variables. We describe these variables below and the rationale behind taking these variables.

Choice of Input and Output Variables:

Choosing the respective input and output variables is at the concerned policy analyst's discretion. Authorities often have varied opinions within the education sector, leading to fluctuations in their preferences for what constitutes an input or an output. In DEA, the selection of input variables for assessing the performance of Decision-Making Units (DMUs) in education is consistently diverse on account of its flexibility. In our current study, we assess the performance of various institutions, defining specific input and output variables for each institute as outlined below:

Input Variables (NIRF):

We have considered a total of 3 input variables for our analysis. We have also explained the rationale behind each of those variables below:

(i) **Student-Faculty Ratio:**

Ensuring a reasonable student-faculty ratio is imperative for any educational institution. Reports from reputable sources like UNESCO and the World Bank indicate that attending smaller schools is advantageous for enhanced class participation. In large classes with

hundreds of students, it becomes challenging for professors to provide individual attention to each student.
Therefore, selecting one of the input variables in our analyses as the Student-Faculty ratio is highly pertinent and aligns well with our research objectives. This can be calculated by dividing the total number of enrolled students by the total number of faculty members in the institution.

(ii) **Annual Capital Expenditure:**
It is imperative that adequate funds be used to function and upgrade facilities in an institution. The annual capex data of each institution for the year 2020-21 was taken. Capex reflects the spending of an institution to revamp or maintain its existing infrastructure or create new facilities. It is well-known that to have an effective teaching-learning process and all-round development of students, physical infrastructure like buildings, residences, labs, sports facilities, etc, are essential.

(iii) **Annual Operational Expenditure:**
Similar to capital expenditure, operational expenditure is the minimum amount that an institution spends to maintain its existing resources and fund its day-to-day operations.
While capex might vary depending upon the plans and creation of new facilities, operational expenditures are necessary to ensure the smooth running of the institute. These may include salaries, expenditure on seminars and workshops, conducting exams and dynamic expenditures like rents, bills, etc.

Output Variables (NIRF):
This is perhaps the most important thing in our analysis. More so because the choice of outputs varies greatly for calculating the efficiency of an institution depending upon the main objective or the basis of evaluating the performance of an institution. In our case, we are evaluating and judging the institutions from the perspective of a prospective student who values Return on Investment (ROI) as his top priority. Hence, we have chosen 2 output variables for our study as follows:

(i) **Median Placement Package:**
The median placement package refers to the remuneration offered by companies visiting the campus to recruit students who will graduate soon. This is perhaps the most important factor which almost all students in India consider before joining any educational institution. More so for a management institution due to the high cost involved. A higher median package is an indicator of the demand for graduates of that institution in the labour market.

(ii) **Placement Percentage:**

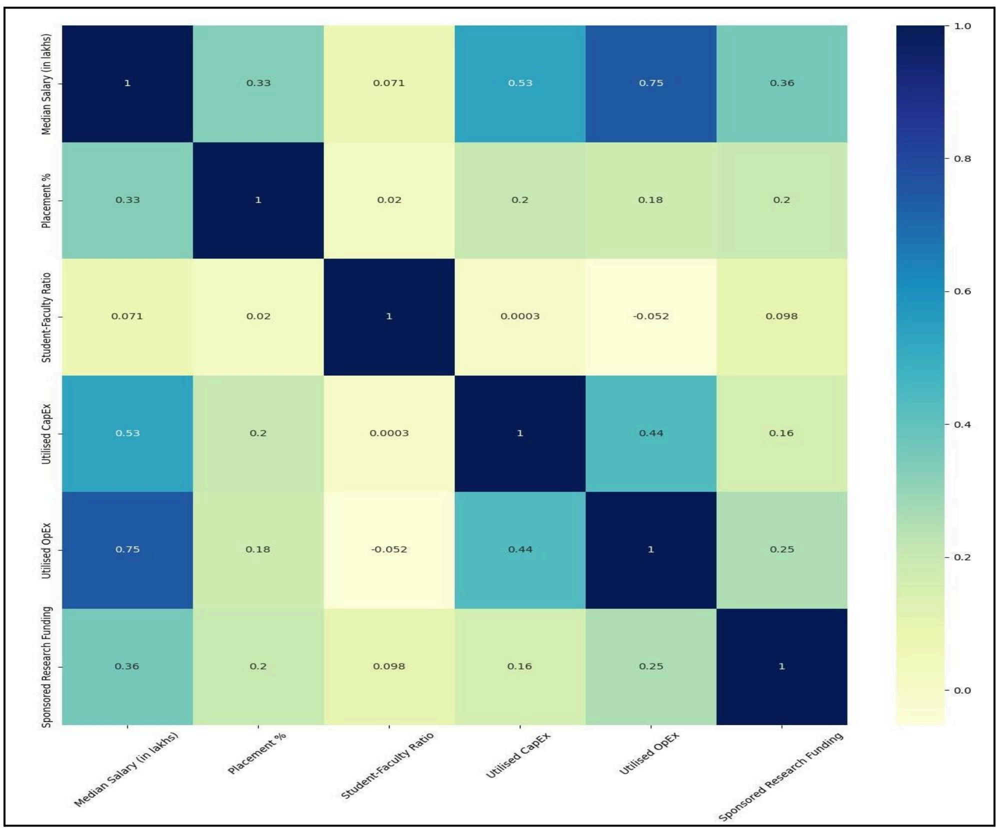
- The placement percentage, the fraction of the enrolled students who get a job offer upon graduation, is another important factor. A higher percentage indicates a higher chance of securing a job offer after graduating from that particular institution. This can be calculated by dividing the number of students placed by the total number of enrolled students in that programme of that institution.

- Several other studies that have studied educational institutions' performance have also considered other factors like research publications, the number of students going for higher studies, patents, and qualitative metrics like public perception (also considered by NIRF). However, we are only focusing on those parameters that form the basis of prospective students' decision-making.

ISOTONICITY TEST

- This test checks the correlation of every variable (both input and output variables) with each other in a matrix format. The test is said to be passed if a positive correlation exists between every pair of variables. Positive correlations also clearly demonstrate that the researcher's choice of input and output variables at the beginning is appropriate.

- As seen from this heatmap, there is a negative correlation between two pairs, both involving the Student-Teacher Ratio variable, thereby failing the test. However, although the correlation is negative, it is not wrong since a lower student-teacher ratio means one teacher has to handle a smaller number of students, resulting in more efficient instruction. If we had reversed the ratio to Teacher-Student, the correlation would have been positive, and the test would have passed. We can say that our Isotonicity test has **failed trivially**.



Performance analysis for input and output-based assessment

TE, PTE, and SE scores have been computed for the top 50 Indian management institutions. The findings are presented in Tables below. An output-oriented DEA approach has been employed to assess the performances of these colleges. However, no discernible general pattern of efficiency score distribution across all institutions has been identified.

The results from the two-stage model are tabulated below:

INSTITUTE	TE	PTE	SE	RTS	SUP-EFF	NIRF RANK	OUR RANK
IIM-A	0.583	0.982	0.594	DRS	0.58	1	46
IIM-B	0.751	1	0.751	DRS	0.75	2	43
IIM-K	0.552	0.996	0.554	DRS	0.55	3	49
IIM-C	1	1	1	CRS	4.95	4	1
IIT-D	1	1	1	CRS	3.01	5	6
IIM-L	1	1	1	CRS	4.64	6	2
IIM-M	1	1	1	CRS	4.27	7	3
IIM-I	0.757	0.945	0.801	DRS	0.75	8	42
XLRI	1	1	1	CRS	3.88	9	4
IIT-B	0.87	0.87	1	CRS	0.87	10	31
IIM-Raipur	0.954	0.996	0.958	DRS	0.95	11	26
IIM-Rohtak	0.563	0.996	0.565	DRS	0.56	12	48
MDI	1	1	1	CRS	2.98	13	7
IIT-KGP	0.868	1	0.868	DRS	0.87	14	32
IIT-M	1	1	1	CRS	1.84	15	10
IIM-U	1	1	1	CRS	2.62	16	8
SIBM	0.994	1	0.994	DRS	0.99	17	21
IIT-R	1	1	1	CRS	1.77	18	11
IIM-Kashipur	0.93	0.982	0.947	DRS	0.93	19	27
SPJIMR	0.86	1	0.86	DRS	0.86	20	33
NMIMS	0.859	1	0.859	DRS	0.86	21	34
IIM-T	0.886	0.985	0.9	DRS	0.89	22	28
IIT-K	0.971	1	0.971	DRS	0.97	23	22
IIM-Ranchi	1	1	1	CRS	2.05	24	9
Jamia	1	1	1	CRS	1.62	25	14
IIM-S	1	1	1	CRS	3.12	26	5
IIFT	0.847	0.94	0.901	DRS	0.85	27	37
Amity-UP	0.956	1	0.956	DRS	0.96	28	25

INSTITUTE	TE	PTE	SE	RTS	SUP-EFF	NIRF RANK	OUR RANK
IIM-V	0.699	0.862	0.811	DRS	0.70	**29**	**44**
Amrita	1	1	1	CRS	1.12	**30**	**19**
Great Lakes	0.964	0.966	0.998	IRS	0.96	**31**	**24**
LPU	0.429	0.472	0.907	IRS	0.43	**32**	**50**
GIM	0.815	0.996	0.818	DRS	0.82	**33**	**38**
IMI	1	1	1	CRS	1.73	**34**	**12**
NIT-T	1	1	1	CRS	1.65	**35**	**13**
Chandigarh	0.636	0.802	0.794	DRS	0.64	**36**	**45**
MICA	1	1	1	CRS	1.24	**37**	**18**
IMT	0.755	0.996	0.758	DRS	0.76	**38**	**41**
UPES	0.848	1	0.848	IRS	0.85	**39**	**35**
ICFAI	1	1	1	CRS	1.31	**40**	**17**
IIM-J	0.791	1	0.791	DRS	0.79	**41**	**40**
Manipal	0.881	0.989	0.89	DRS	0.88	**42**	**29**
IIM-N	0.802	0.9	0.892	DRS	0.80	**43**	**39**
IIT-ISM	0.568	0.608	0.934	DRS	0.57	**44**	**47**
KJSIMSR	0.964	0.972	0.992	DRS	0.96	**45**	**23**
XIMU	1	1	1	CRS	1.49	**46**	**15**
JIM	1	1	1	CRS	1.08	**47**	**20**
BIMT	0.847	1	0.847	DRS	0.85	**48**	**36**
Thapar	0.877	0.916	0.957	DRS	0.88	**49**	**30**
Anna Uni	1	1	1	CRS	1.48	**50**	**16**

RESULTS

- **Descriptive Statistics**
  Average TE score = 0.96342
  Average PTE score = 0.88154
  Average SE score = 0.91432

- We observe that the inefficient DMUs (**TE score ≠ 1**), which lie above the threshold parameter values, that is, the average scores, tend to perform slightly better than the other inefficient DMUs.

- Also, there are 26 DMUs with DRS (decreasing returns to scale), especially in the top tier, while 21 are CRS (constant returns to scale). This is ambiguous, as the top institutes receive higher funding and are expected to perform better, but the opposite case is observed.

- Based on our approach, the ranks in green indicate an upward movement and those in red indicate a downward movement. This shows that lower-ranked institutes have achieved a higher ranking, which even opposes public perception. The possible reasons behind this have been further discussed in the conclusion.

- Those DMUs with an **SE score = 1** are observed to have better utilization of resources (Research Funding, CapEx, OpEx) and are operating at an optimal scale size, while those with an **SE score ≠ 1** have a relatively lower efficient resource utilization.

How can inefficient DMUs improve their efficiency?

DEA offers two primary methods to transform an inefficient DMU into an efficient one:

(i) Input reduction: DMU_k's inputs are lowered by keeping its outputs constant.
(ii) Output enhancement: Keep the inputs constant and raise the outputs of the DMU.

The percentage change in inputs and outputs are as follows:

- **Percentage change in m^{th} output of DMU_k** =
  ($\triangle$ $Output_m$ of DMU_k / Actual $Output_m$ of DMU_k) *100

- **Percentage change in p^{th} input of DMU_k** =
  ($\triangle$ $Input_p$ of DMU_k / Actual $Input_p$ of DMU_k) *100

- Where the change($\triangle$) in m^{th} output of DMU is given as =
  Target m^{th} Ouput of DMU_k - True m^{th} Output of DMU_k

- The change ($\triangle$) in p^{th} input of DMU is given as =
  True p^{th} input of DMU_k - Target p^{th} input of DMU_k

CONCLUSIONS AND SUGGESTIONS:

The study's main aim was to evaluate management institutes' performance based on factors generally of concern to prospective students nowadays. This analysis does away with some of the factors considered from a scholarly perspective, i.e. from the viewpoint of academicians and researchers, and analyses them from the perspective of the main stakeholders, that is, the prospective students. DEA certainly allows us to analyse the performance of these institutes by using variables of our choice. In this way, we have re-ranked these universities based on output factors like placement salaries and placement percentage and input factors like Capex, Opex and Student-Faculty ratios.
Further, this can serve as a nice parallel comparison with the existing NIRF ranking. Through our results, we have tried to show that this methodology is not one size fits all and sometimes can be biased.
As can be observed from the results, the rankings of the institutes almost reverse when we change the ranking methodology, that is, by using the DEA approach. For example, the rank of IIM-A slips from 1 to 46. This is ambiguous, as, comparing the output variables of placement % and the median package with other institutes, we can see that it is one of the best. However, the TE score is very low, hence the low ranking. In the previous section, we looked at conventional, theoretical, and straightforward measures for improving the efficiency of institutions by altering inputs and outputs. However, we have also tried to suggest some realistic and adoptable ways in which they might improve their rankings based on their ROI efficiency (as we say).

We propose that the annual funding allocated for every institute, based on a weightage basis, is created based on the past year's performance of that institute for several output factors such as **placement %**, **median package**, etc. This will bring parity among the institutes while ranking, and thus, the rankings will become more efficient.
Another suggestion would be to maintain the scaling across the variables before ranking them. For example, it would be better to scale down the funding values (Research, CapEx, and OpEx, present in 8 figures) due to the presence of decimal values such as the Student-Faculty ratio. We believe that bringing about these changes will greatly enhance the ranking process, which serves as a benchmark for comparing institutes within and across countries and as a reference point for students when choosing their next place of study. Lastly, although we have limited our study to management institutes only, we can extend this idea to other sectors of institutes as well, albeit with slight modifications in the methodology.

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