Article

Evaluating the Performance of Sharif University of Technology Faculties Using Data Envelopment Analysis

Mays Hussein Amin Al-Ameedi[1], Ramzi Taher Abd Al Rdha Altmemy[2], Ameer Abbas Jabbar[3]

[1] Ministry of Education, Babylon Education Directorate, Iraq, Maysameen96@gmail.com

[2] Ministry of Education, Dhi Qar Education Directorate, Iraq, rmzy51076@gmail.com

[3] Ministry of Education, Babylon Education Directorate, Iraq, amyrbasjbar9@gmail.com

Abstract: This study evaluates the relative performance of 12 faculties at Sharif University of Technology using data envelopment analysis (DEA). Three inputs—training or teaching staff, research staff, and student numbers—are assessed against three outputs: published articles, graduates, and academic awards. The assessment uses the efficiency scores and ranks reported in the original case-study table. Faculty 10 attained the highest efficiency score (1.000000), followed by Faculties 5 (0.991365) and 1 (0.971250), whereas Faculty 8 recorded the lowest score (0.579812). The mean reported efficiency was 0.8336. These findings suggest considerable variation in relative input–output performance and identify possible internal benchmarking opportunities. Because the underlying faculty-level input–output observations and full model settings were not supplied, the reported scores are interpreted descriptively rather than independently replicated. The study recommends transparent variable selection, sensitivity analysis, and follow-up assessment to guide academic resource allocation.

Keywords: data envelopment analysis, higher education, faculty efficiency, benchmarking, performance evaluation

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1. Introduction

Universities face increasing pressure to demonstrate the effective use of academic resources while maintaining teaching, research, and societal contributions. Performance measurement in higher education is challenging because teaching and research activities use several types of inputs to produce different outputs [1], [2], [3], [4]. Conventional one-dimensional indicators may obscure these trade-offs and can create misleading rankings across faculties with different workloads and missions [5], [6].

Data envelopment analysis (DEA), introduced by Charnes, Cooper, and Rhodes [7], provides a non-parametric framework for assessing the relative efficiency of comparable decision-making units (DMUs) with multiple inputs and outputs. Subsequent developments permit varying returns to scale and the study of scale inefficiency [8]. Empirical applications to universities demonstrate the practical value of DEA for benchmarking and resource management while stressing the need for suitable and comparable indicators [2], [3], [9].

This study evaluates 12 faculties of Sharif University of Technology using reported DEA efficiency scores. Its objectives are to describe differences in faculty efficiency, identify relative benchmark and improvement candidates, and discuss the implications and limitations of interpreting

DEA-based rankings for academic management. The primary contribution is a transparent interpretation of the existing case-study results rather than a new estimation from unavailable raw observations.

1.1. Literature Review

1.1.1. Efficiency Measurement in Higher Education

Higher education produces joint outputs that cannot be adequately summarized by a single performance indicator. Abbott and Doucouliagos [9] evaluated Australian universities using DEA, demonstrating the relevance of combining teaching and research dimensions. Later reviews document the broad use of efficiency frontiers to evaluate institutions, departments, programs, and other academic activities [1], [2], [3], [4]. Differences in institutional size and academic mission may affect comparison quality and warrant careful DMU selection [5].

1.1.2. DEA Models and Benchmarking

The CCR model assumes constant returns to scale and estimates relative efficiency with weighted input–output ratios [7]. The BCC formulation allows variable returns to scale, distinguishing pure technical from scale-related efficiency [8]. Standard references emphasize that efficient units form a frontier relative to the comparison set, not a universal or causal measure of excellence [10], [11], [12]. Weight restrictions, cross-efficiency, and alternative ranking approaches can reduce ambiguity when many DMUs are efficient [13], [14].

1.1.3. Research Gap and Analytical Focus

Studies of university DEA emphasize sensitivity to indicators, data coverage, heterogeneity, and modeling choices [1], [2], [3], [4], [5], [6]. The present case study uses workforce and enrollment inputs with publication, graduation, and award outputs. The analysis focuses on reported faculty-level efficiency differences and on practical interpretations that remain justified without the original input–output dataset. The guiding research question is: How do the 12 faculties compare in reported DEA efficiency, and what can these differences reasonably suggest for university-level benchmarking.

2. Materials and Methods

This study follows a quantitative, descriptive case-study approach using secondary efficiency results supplied in the original manuscript. The units of analysis are 12 faculties, treated as DMUs. The original manuscript identifies three inputs and three outputs and describes a constrained-weight DEA formulation. However, the faculty-level input and output matrix, the exact weight restrictions, software, return-to-scale assumption, and observation year are not reported. Consequently, no new DEA optimization is claimed here; the reported efficiency scores and rankings are reproduced and analyzed descriptively.

Table 1. Input and output variables used in the DEA assessment

Type	Code	Indicator
Input	I1	Number of staff in the training/teaching department
Input	I2	Number of staff in the research department
Input	I3	Number of students
Output	O1	Number of published articles
Output	O2	Number of graduates
Output	O3	Number of awards won by faculty members

In a standard input-oriented CCR envelopment formulation, efficiency for faculty o may be estimated by minimizing θ subject to $\Sigma j\ \lambda j\ xij \leq \theta xio$ (for each input i), $\Sigma j\ \lambda j\ yrj \geq yro$ (for each output

r), and $\lambda j \geq 0$ [7], [10]. This expression is provided as methodological context; it is not asserted to reproduce the original constrained-weight scores. An explicit equality $\Sigma j\ \lambda j = 1$ would correspond to the variable-returns-to-scale BCC extension [8].

Descriptive evaluation includes the observed rank, mean, range, and performance gaps relative to the frontier score of 1.000. Because the raw input–output values are unavailable, peer weights, slacks, scale efficiency, statistical significance, and causality cannot be computed or inferred.

3. Results

3.1. Reported DEA Efficiency and Rankings

Table 2 reproduces the 12 efficiency estimates and ranks in the submitted manuscript. Faculty 10 was ranked first (1.000000), with Faculties 5 and 1 closely following at 0.991365 and 0.971250. Faculties 8 and 9 displayed the lowest efficiencies (0.579812 and 0.698631, respectively). Faculty 4 recorded 0.726510 and ranked tenth, contrary to the original narrative that characterized it as the least effective faculty.

Table 2. DEA efficiency scores, reported ranks, and calculated gaps to the unit frontier. Source: original manuscript; gaps calculated from supplied scores.

Faculty	Reported efficiency	Rank	Gap to 1.000
1	0.971250	3	0.028750
2	0.896751	4	0.103249
3	0.865980	6	0.134020
4	0.726510	10	0.273490
5	0.991365	2	0.008635
6	0.890210	5	0.109790
7	0.769087	9	0.230913
8	0.579812	12	0.420188
9	0.698631	11	0.301369
10	1.000000	1	0.000000
11	0.769874	8	0.230126
12	0.843322	7	0.156678

3.2. Descriptive Comparison

The mean efficiency was 0.8336, the median was 0.8547, and the reported range was 0.5798–1.0000. The spread of 0.4202 indicates meaningful heterogeneity in relative performance within this specific comparison group. Only Faculty 10 attained a reported efficiency of exactly 1.000. The average gap to 1.000 was 0.1664. These calculations describe the supplied scores and do not establish resource savings or attainable output gains without individual input and output targets.

4. Discussion

The observed difference between Faculty 10 and the lower-ranking faculties underscores the capacity of DEA to differentiate relative input–output combinations across academic units. This is consistent with previous university efficiency research in which multiple academic inputs and outputs are combined to support internal benchmarking [1], [2], [3], [9]. Faculty 10 is a potential reference for closer inspection, but a higher DEA score does not by itself prove stronger teaching quality, research impact, or stakeholder satisfaction. DEA efficiency is relative to the selected peer group, indicators, and model specification [7], [10], [11].

The weak relative position of Faculty 8, and to a lesser degree Faculties 9 and 4, suggests that targeted diagnostic review could be worthwhile. Management should investigate the alignment of teaching and research staff, student capacity, publication activity, graduation outcomes, and award

recognition before prescribing changes. Since the source data do not include peer coefficients, input slacks, or output shortfalls, the study cannot quantify how many staff positions should change or how many additional graduates or publications are required. A benchmark-based follow-up using the original data is necessary before operational targets are assigned [10], [12].

An additional concern is comparability. Faculties may differ substantially in discipline, research intensity, laboratory requirements, program duration, and class size. Literature on academic efficiency shows that comparing heterogeneous institutions may distort apparent relative efficiency [3], [4], [5], [6]. Moreover, equal treatment of publications, graduates, and awards is not automatically justified. Indicator definitions, publication quality, and potential overlap between workforce and enrollment measures should be documented. Robustness checks may employ CCR and BCC models, alternative variable sets, cross-efficiency, or weight restrictions [8], [13], [14].

The analysis is limited by unavailable primary observations and incomplete reporting of the original DEA model. The ranking column refers to a parameter setting reported as $\chi = 1.5$ and $\sigma = 0.1$, but its role in optimization is not sufficiently explained in the submitted text. This study therefore preserves those scores without claiming independent validation. Future work should release the anonymized 12-by-6 data matrix, clarify model orientation and returns to scale, report software and parameter settings, and compare results with sensitivity or multi-period productivity analysis [12], [15].

4. Conclusion

This study interpreted the reported DEA evaluation of 12 faculties at Sharif University of Technology using three staffing/enrollment inputs and three teaching/research outputs. Faculty 10 achieved the highest reported efficiency of 1.000000, followed by Faculties 5 and 1; Faculty 8 ranked last with 0.579812. Faculty 4 ranked tenth rather than last, correcting an inconsistency in the original narrative. The mean efficiency of 0.8336 suggests that performance varies across faculties and that benchmarking may guide further diagnostic evaluation. These figures should not be interpreted as causal effects or operational resource-adjustment targets without the underlying data. Future studies should document the model specification, re-estimate efficiency from the original observations, assess differences in faculty missions, and test robustness using alternative DEA specifications.

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