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Efficiency and Excellency: An SBM-DEA and ANN approach to analyse the efficiency of universities of Eastern India

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ABSTRACT

This study evaluates the efficiency of 30 universities in Eastern India using an integrated Slack-Based Measure Data Envelopment Analysis (SBM-DEA) and Artificial Neural Network (ANN) framework based on NAAC Self-Study Report data. Teaching Staff and Career Counselling were used as inputs, while Articles Published, Placement, and Student Satisfaction were considered outputs. The findings reveal significant efficiency variations among universities, with inefficiencies arising from poor resource utilization, scale mismatch, weak placement outcomes, and low student satisfaction. The SBM model identified hidden inefficiencies overlooked by traditional DEA models, while ANN demonstrated strong predictive accuracy. Student satisfaction emerged as a key determinant of institutional efficiency, aligning with the learner-centric objectives of NEP 2020.

Keywords: SBM-DEA, ANN, University Efficiency, Benchmarking.

1. Introduction

Education quality is a multifaceted concept crucial for societal development (Batra et al., 2023). Achieving educational equality is a key goal for education systems, with a focus on benefiting all students equally (Jiang et al., 2023). However, the understanding of quality in education is not culturally neutral and can be transformative or subjugating, highlighting the importance of considering diverse perspectives and values in educational settings (Großkopf, 2023). Total Quality Management (TQM) principles are increasingly recognized as essential in the education sector, promoting continuous improvement, leadership, customer orientation, and collaboration to enhance the overall quality of education and ensure success in a competitive environment (Mentesogullari, 2023). Further, Access to quality education is recognized as a fundamental right, with efforts to measure performance and improve education quality through efficient resource utilization (Ismail et al., 2022). Whereas, by optimizing resource use and identifying areas for improvement, efficiency analysis contributes to enhancing the quality of education (Kao and Hung, 2008). Additionally, Understanding the internal characteristics of universities, such as diversity in academic staff and student body, is essential for enhancing efficiency levels (Egorov and Serebrennikov, 2023). Moreover, evaluating higher education efficiency helps in setting strategic goals, improving managerial practices, and ensuring sustainable development of institutions (Kuzmina, 2021), and helps in setting specific targets for universities to enhance their effectiveness, contributing to educational management and forecasting future scenarios (Mihaljević and Jurčak, 2022).

Higher education institutions' efficiency has become a major research focus in efficiency analysis, especially over the past two decades (Karasaç, 2020). It can be facilitated "yardstick" competition in education sectors lacking market mechanisms, guide policy suggestions, and improve education monitoring (Kosor et al., 2019). In the context of higher education, data envelopment analysis (DEA) and other non-parametric techniques have been the most commonly used methods for measuring efficiency (Agasisti and Dal Bianco, 2009). DEA, as highlighted in multiple contexts (Zuluaga Ortiz et al., 2023; Lesik et al., 2022; Janikova, 2021), is utilized to assess the effectiveness of faculties and educational systems, providing insights into factors influencing efficiency. Studies (Koronakos and Sotiropoulos, 2020; Visbal-Cadavid et al., 2019) have shown the effectiveness of integrating Artificial Neural Networks (ANNs) with DEA to enhance evaluation processes, predicting efficiency and reduce computational burdens. Again, ANN model identifies non-linear relationships and provide increased accuracy in predictions (Tan, Ooi, Leong et al., 2014; Chong, 2013a; Sim et al., 2014). Moreover, by combining DEA with ANNs, educational institutions can gain deeper insights into their internal structures, identify inefficiencies, and make necessary adjustments to improve overall efficiency and quality of education (Singh et al., 2018; Kumar et al., 2023). Hence, our endeavour is to evaluate the efficiency of universities of eastern India with assessing the factors influencing it and develop a benchmark for the states' universities.

2. Review of Literature

2.1 Approaches to efficiency analysis in higher education

2.1.1 Data Envelopment Analysis

In higher education research, DEA is a valuable tool for simultaneously capturing multiple inputs and outputs, emphasizing the non-parametric analysis of the efficiency frontier (Wolszczak-Derlacz and Parteka, 2011). Again, DEA enables the identification of best practices in resource use among similar organizations, uncovering key areas for efficiency improvements and empowering institutions to achieve optimal performance (Abbott and Doucouliagos, 2003). Moreover, it allows for the assessment of efficiency in decision-making units (DMUs) within educational institutions, such as measuring the productivity of academic staff (Kumar et al., 2023), evaluating the relative efficiency of study programs (Dmitry et al., 2022), and measuring the efficiency of higher education institutions as a whole (Olariu and Brad, 2022). Overall, DEA serves as a valuable tool for enhancing efficiency, productivity, and quality in higher education settings. The mathematical assumption of DEA models are as follows:

For set of **n** DMUs, each DMU_j, where j=1, 2,……, n, uses **m** inputs, X_{ij}, where i=1,2,….., m, to produce **s** outputs, Y_{rj}, r=1, 2, ……., s, The CCR(1978) & BCC(1984) models are as follows:

Input-Oriented CCR

Min θ_k (θ_k= Efficiency Score of DMU k)

Subjected to

$\sum_{j=1}^{n} \lambda_j X_{ij} \leq \theta_k X_{ik}$, i=1, 2,….., m

$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq Y_{rk}$, r=1, 2, ……., s

$\lambda_j \geq 0$, j=1, 2,……, n

Output-Oriented CCR

Max θ_k (θ_k= Efficiency Score of DMU k)

Subjected to

$\sum_{j=1}^{n} \lambda_j X_{ij} \leq X_{ik}$, i=1, 2,….., m

$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq \theta_k Y_{rk}$, r=1, 2, ……., s

$\lambda_j \geq 0$, j=1, 2,……, n

Input-Oriented BCC

Min θ_k (θ_k= Efficiency Score of DMU k)

Subjected to

$\sum_{j=1}^{n} \lambda_j X_{ij} \leq \theta_k X_{ik}$, i=1, 2,.., m

$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq Y_{rk}$, r=1, 2, ……., s

$\lambda_j \geq 0$, j=1, 2,……, n

$\sum_{j=1}^{n} \lambda_j = 1$, which ensures VRS

Output-Oriented BCC

Max θ_k (θ_k= Efficiency Score of DMU k)

Subjected to

$\sum_{j=1}^{n} \lambda_j X_{ij} \leq X_{ik}$, i=1, 2,.., m

$\sum_{j=1}^{n} \lambda_j Y_{rj} \geq \theta_k Y_{rk}$, r=1, 2, ……., s

$\lambda_j \geq 0$, j=1, 2,……, n

$\sum_{j=1}^{n} \lambda_j = 1$, which ensures VRS

where,

X_{ij}: Amount of inputs i used by DMU_j

Y_{rj}: Amount of outputs r used by DMU_j

x_{ik}: Input i of the evaluated DMU_k

y_{rk}: Output r of the evaluated DMU_k

λ_j: Intensity weight assigned to DMU j

m: The Total number of inputs

s: The Total number of outputs

n: The Total number of DMUs

2.1.2 Slack- Based Measure (SBM) DEA

On the contrary, the traditional DEA faces challenges like sensitivity to data noise and inefficiency when new units are added, requiring re-evaluation of all original units (Zhong et al., 2021). Again, the classical DEA approach may yield inaccuracies in efficiency measurement due to its failure to account for the relaxation quantity, the potential influence of external environmental factors, and the presence of random errors associated with each subject (Zhang et al., 2020). Crucially, the efficiency score may deviate from the actual efficiency level (Zhao & Wu, 2010) and most significantly, the conventional DEA can't differentiate and compare when multiple decision-making units are simultaneously effective (Cao et al., 2023). In contrast, the Slacks-Based Measure (SBM) model in DEA, proposed by Tone (2001) and Fukuyama and Weber (2009), a non-radial, non-angle-based efficiency evaluation model (Zhang et al., 2020), which directly uses input and output slacks to determine relative efficiency, offering a more robust evaluation method (Mahla & Agarwal, 2021).

The Non-Oriented SBM (Slack- Based-Measure) under VRS assumption is as follows:

$$Min\rho = \frac{1-\left(\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{ik}}\right)}{1+\left(\frac{1}{s}\sum_{r=1}^{s}\frac{S_r^+}{y_{rk}}\right)}$$

Subjected to

$$\sum_{j=1}^{n}\lambda_j x_{ij} = x_{ik} - S_i^-, \quad i = 1,2,\ldots,m$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} = y_{rk} + S_r^+, \quad r = 1,2,\ldots,s$$

$$\sum_{j=1}^{n}\lambda_j = 1$$

$$\lambda_j \geq 0, \quad j = 1,2,\ldots,n$$

Where:

ρ: The SBM efficiency

x_{ik} : The observed i^{th} input value for DMU_k

y_{rk} : The observed r^{th} output value for DMU_k

S_i^- : The input excess (slack) vector

S_r^+: The Output shortfall (slack) vector

λ_j: The intensity vector

m: The Total number of inputs

s: The Total number of outputs

n: The Total number of DMUs

2.1.3 Artificial Neural Network (ANN)

Machine learning offers powerful data prediction and feature recognition, widely used in research to solve problems beyond traditional linear equations (Zhang et al., 2018; Zhong & Chen, 2020; Zhong et al., 2021). As DEA lacks inherent prediction capabilities, a significant limitation that is effectively addressed by the predictive strengths of ANNs (Kwon, 2017; Rezaee et al., 2018). The ANN functions by interconnecting input and output neurons through a hidden layer of neurons (Samarasinghe, 2016). The Evaluation of predictive accuracy, through training and testing data with Root Mean Square Error (RMSE) computation, consistently showed high precision (Liébana-Cabanillas et al., 2018). Literature reveals that, despite being rare, the combined approach of DEA and ANN shows promising outcomes, with most studies concentrating on predicting DEA efficiency as an indirect performance measure (Singh et al., 2018). Again, there is a paucity of research exploring the application of BPNN, a standardized ANN model, for efficiency analysis and benchmarking in conjunction with DEA (Kwon & Lee, 2015). Whereas, the combined model enhances the accuracy and effectiveness of performance modeling and benchmarking processes (Singh et al., 2018).

3. Data and Variables

We adopted data from NAAC Self-Study Reports (SSRs) of accredited state public universities in eastern India for efficiency analysis. The SSRs are in-depth, institution-specific reports on an institution's quality (curriculum, faculty, funds, research inputs, student outcomes, etc) prepared during the accreditation process. NAAC (established by UGC in 1994) provides accreditation to institutions based on seven criteria-Curriculum; Teaching & Learning; Research/Extension; Infrastructure; Student Support; Governance; values-each of which includes traditional DEA inputs and outputs. Critically, NAAC accredits using a DVV (Data Validation and Verification) procedure that rigorously assesses each institution's claims, including verification of each numerical output or input against actual evidence. During a DVV audit (checking that publications are listed by reputable journal aggregators, financial records add up, enrollment numbers match official lists, etc.), data can be challenged and revised; only confirmed figures are used. We downloaded publically accessible SSRs from NAAC's websites for all public universities in Odisha. Using confirmed, publicly available reports helped establish robust, consistent inputs (e.g. Total expenditures, number of teaching staff, facilities available) and outputs (e.g. Number of graduates, publications, placement rates, student satisfaction levels) for DEA.

3.1 Input and Output determination

In Data Envelopment Analysis (DEA), choosing the right inputs and outputs is essential and crucial for assessing the efficiency of Decision-Making Units (Dong et al., 2023; Dobos &Vörösmarty, 2024; Abdelfattah, 2022; Kazemi & Galagedera, 2023; Monzeli et al., 2020). Studies on higher education efficiency, key inputs include lecturer and staff numbers, budget, student and graduate counts, academic, RD contract research, and research output (Wildani et al., 2023; Mikušová, 2020; Stankevičienė & Kraujalienė, 2019). Again, number of teaching staff serve as a significant input for evaluating and enhancing teaching effectiveness (Qiao & Xiujun, 2020). Further, research indicates that universities with higher public education funding tend to have better efficiency scores due to more effective resource allocation for teaching and research activities.

Student satisfaction is paramount for university efficiency, serving as a comprehensive indicator of the overall academic experience (Khairusy & Febriani, 2023). But no studies have assessed university efficiency based on student satisfaction (Mainardes et al., 2014), though this method has been applied to banks and supermarkets (Cooper et al., 2006). Again, DEA studies have consistently utilized student enrollment as an output variable to evaluate university efficiency, demonstrating that student enrollment is crucial in determining the efficiency of higher education institutions (Wijesundara & Prabodanie, 2022; Acodile-Viado & Namoco, 2020; Ramzi & Ayadi, 2016; Zhang & Chen, 2015).

We utilized both literature mapping and empirical selection to select our variables. Literature mapping of prior DEA research resulted in a Sankey diagram (Figure 1) which illustrated commonly used indicators, and clusters emerged relating to staff numbers, student numbers, financial resources/infrastructure, graduates, publications, and academic quality. The correlation of potential input and output variables was analysed with a correlation heat map (Figure 2 and 3). Variables that did not show strong (or any positive) correlation with primary output variables were excluded to prevent using spuriously correlated inputs. The output and input variables selected are appropriate for an SBM-DEA model and are supported by prior research.

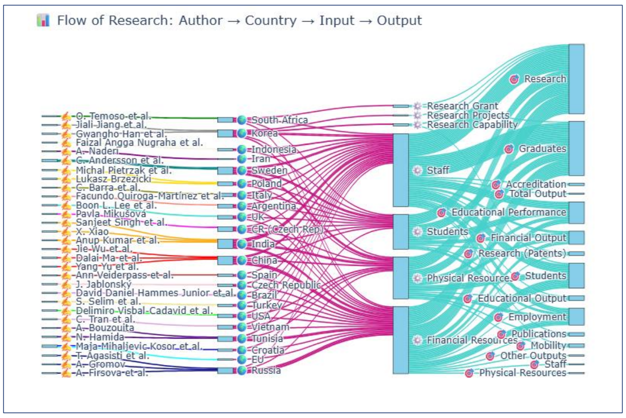


Figure- 1. Sankey Diagram on Authors Selection of Inputs and Outputs

Among inputs, Teaching Staff (TS) strongly correlated with Expenditure (r=0.85*), Seed Money for Research (r=0.91*), and Workshop/Seminar Participation (r=0.82*). Given these inter-correlations, TS was retained as the representative input (I1) to reduce redundancy, following Nazarko and Šaparauskas (2014). Career Counselling (CC) showed moderate but significant correlations with SMR (r=0.42) and WSP (r=0.48***), exceeding the r>0.20 threshold advised by Wang and Chen (2020). Thus, CC was selected as Input 2 (I2), representing the institutional support ecosystem beyond academic instruction.

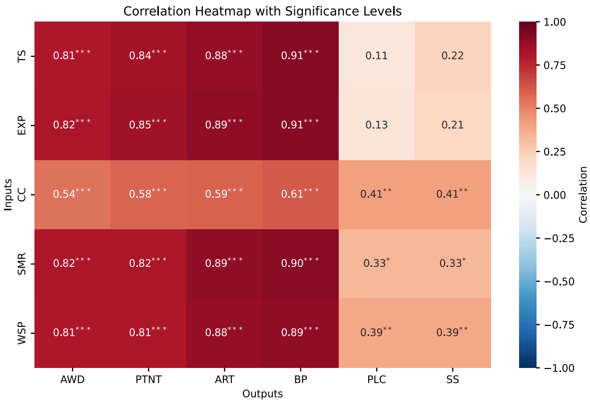


Figure- 2. Correlation Heat map of Potential inputs and Outputs

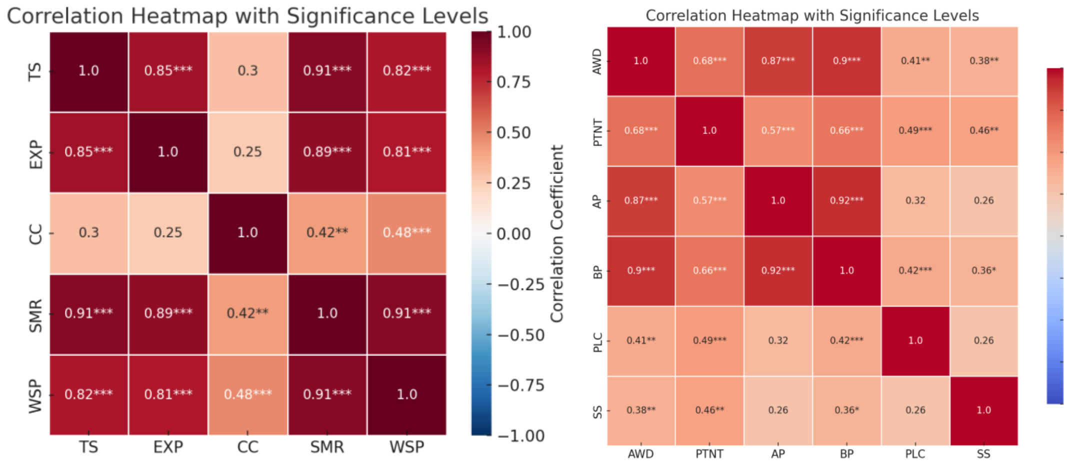


Figure-3. Intra- Correlation heat map among inputs and outputs

Similar considerations guided the selection of the output variables. Articles Published (AP) showed high correlations with Patents (PTNT) (r = 0.57***), Books Published (BP) (r = 0.92***), and Research Awards (AWD) (r = 0.87***). It is evident that AP can be regarded as an aggregated measure of research performance, encompassing different types of scholarly output. Witte and López-Torres (2017) suggest that in cases where output variables show a high degree of correlation, using one representative variable simplifies the model and improves its interpretation without compromising its validity. Thus, AP was classified as Output 1 (O1).

Additionally, two other indicators of institutional performance – Placement (PLC) and Student Satisfaction (SS) – were included as Output 2 (O2) and Output 3 (O3). Although PLC and SS had moderate correlations with research-oriented measures (r > 0.25), they were indispensable for measuring the quality of services provided by higher education institutions to students.

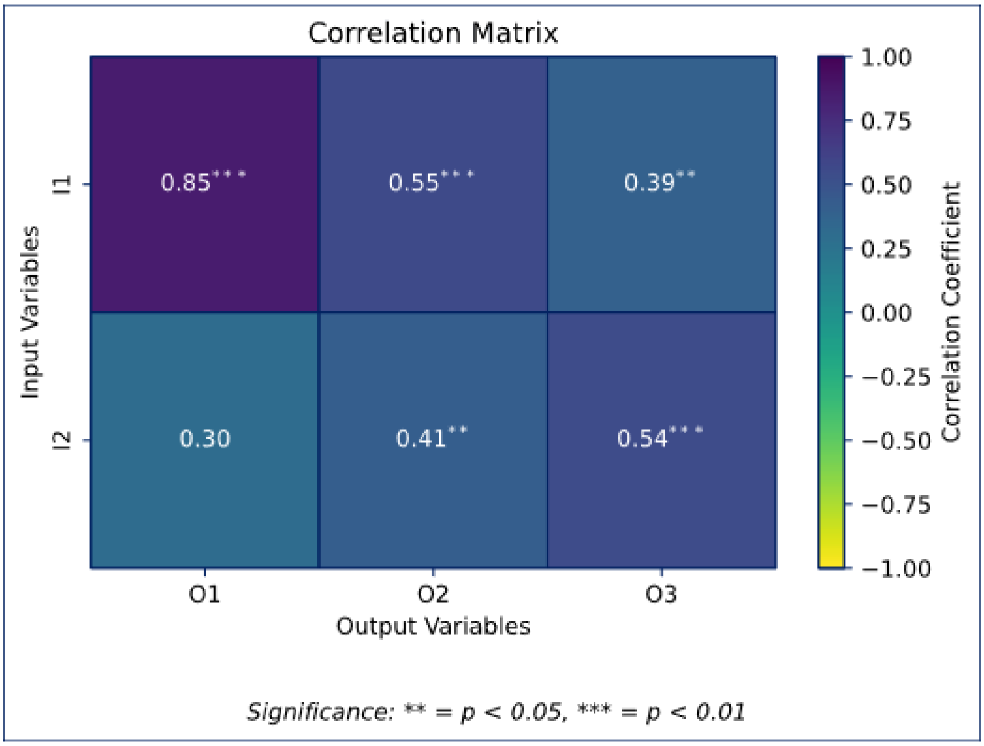


Figure-4. Correlation heat map for selected Inputs and Outputs

4. Data analysis and findings

The analysis was conducted in two sequential phases: first, involved using a Slack-Based Measure (SBM) DEA model for estimating the efficiency of universities based on VRS, while the second involved the ANN model used to predict the efficiency score and classification of DMUs (Singh et al., 2018; Tone, 2004)(Tone, 2003; Singh et al., 2018).

4.1 Efficiency Analysis using SBM-DEA

SBM-DEA is a non-radial and non-oriented approach that considers the input/output slacks in the analysis, making its efficiency measurement more reliable than traditional DEA approaches (Mahla & Agarwal, 2021; Zhang et al., 2020). The SBM analysis reveals that only a few universities achieve full efficiency (1.0). The majority of the DMUs are found to have scores within the 0.6-0.9 range (Table-1), indicating considerable inefficiency. For example, while DMU1 and DMU3 scored 1.00 under the variable-returns BCC model, their SBM scores dropped to 0.88 and 0.85 respectively once slacks were considered. Further, Table 1 compares sample CCR/BCC (radial) scores versus SBM (Non-radia) scores for Specified DMUs.

Table-1. Efficiency Scores from Varios DEA Models

DMU	CRS_IO	VRS_IO	SE_IO	SBM_IO	CRS_OO	VRS_OO	SE_OO	SBM_OO
DMU1	0.412	0.516	0.797	0.516	2.429	1.112	2.184	1.112
DMU2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU3	0.470	1.000	0.470	1.000	2.129	1.000	2.129	1.000
DMU4	0.667	0.841	0.793	0.841	1.500	1.046	1.433	1.046
DMU5	0.473	0.524	0.902	0.524	2.116	1.240	1.707	1.240
DMU6	0.644	1.000	0.644	1.000	1.553	1.000	1.553	1.000
DMU7	0.152	0.284	0.534	0.284	6.600	1.174	5.624	1.174
DMU8	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU9	0.449	0.477	0.942	0.477	2.227	1.220	1.826	1.220
DMU10	0.608	0.892	0.682	0.892	1.644	1.054	1.559	1.054
DMU11	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU12	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU13	0.525	0.666	0.788	0.666	1.905	1.047	1.820	1.047
DMU14	0.413	0.925	0.447	0.925	2.421	1.031	2.348	1.031
DMU15	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU16	0.515	0.646	0.798	0.646	1.941	1.201	1.616	1.201
DMU17	0.257	0.406	0.633	0.406	3.895	1.070	3.641	1.070
DMU18	0.255	0.275	0.927	0.275	3.916	1.322	2.721	1.322
DMU19	0.803	0.946	0.848	0.946	1.246	1.026	1.214	1.026
DMU20	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU21	0.604	1.000	0.604	1.000	1.656	1.000	1.656	1.000
DMU22	0.386	0.450	0.857	0.450	2.590	1.184	2.188	1.184
DMU23	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU24	0.541	0.903	0.599	0.903	1.849	1.047	1.765	1.047
DMU25	0.393	0.397	0.990	0.397	2.544	1.109	2.294	1.109
DMU26	0.605	0.634	0.954	0.634	1.654	1.112	1.488	1.112
DMU27	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU28	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU29	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
DMU30	0.968	1.000	0.968	1.000	1.033	1.000	1.033	1.000

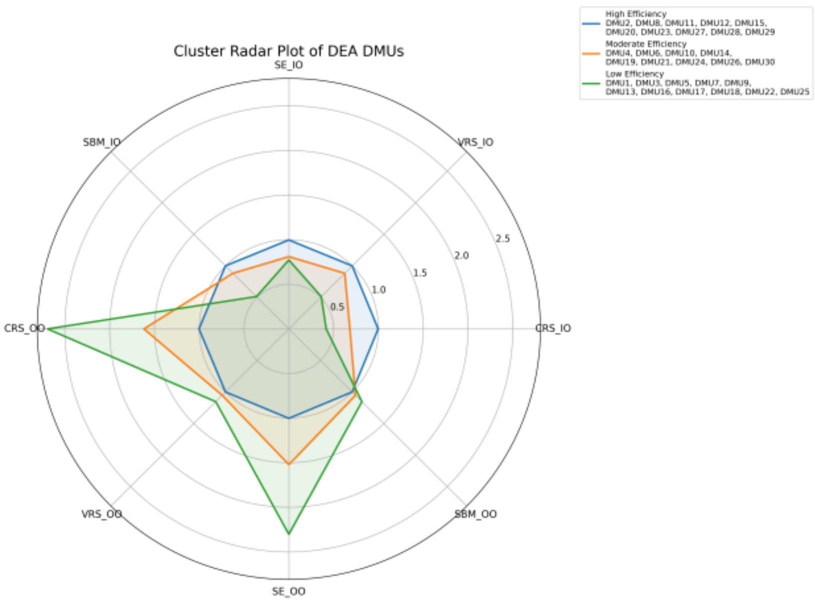


Figure-5. Cluster Radar plot of DEA DMUs

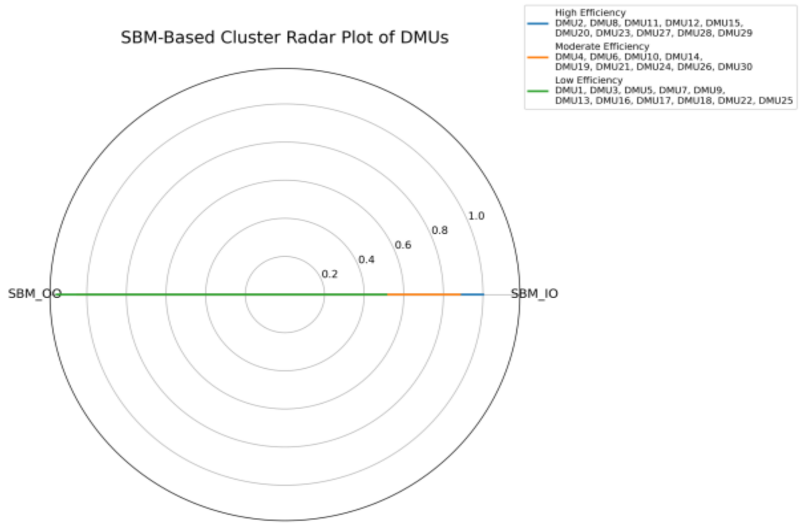


Figure- 6. SBM Based Cluster Radar Plot

The comprehensive DEA radar plot (Figure-5) reveals clear efficiency differentiation among the clusters. The High Efficiency cluster forms a compact and symmetrical structure near the efficiency frontier, indicating strong technical and scale efficiency with minimal slack inefficiencies. The Moderate Efficiency cluster shows moderate dispersion, suggesting acceptable managerial performance but some scale inefficiencies. In contrast, the Low Efficiency cluster exhibits substantial distortion, particularly in CRS_OO and SE_OO dimensions, reflecting severe inefficiency, scale mismatch, and significant output improvement requirements.

The SBM-based radar plot (Figure- 6) provides a more focused assessment of slack inefficiencies. The High Efficiency cluster remains highly stable with SBM scores close to unity, confirming efficient resource utilization and balanced output generation. The Moderate Efficiency cluster demonstrates manageable slack inefficiencies, whereas the Low Efficiency cluster shows considerable divergence from the frontier, especially in SBM_OO scores, indicating underutilized resources and operational inefficiencies. Overall, the SBM radar plot offers a more rigorous evaluation of hidden inefficiencies compared to conventional radial DEA measures.

Table-2 Ranking and Benchmarking Across the DEA Models

DMU	CRS_IO	VRS_IO	SE_IO	SBM_IO	CRS_IO_Rank	VRS_IO_Rank	SE_IO_Rank	SBM_IO_Rank
DMU1	0.412	0.516	0.797	0.516	25	24	20	24
DMU2	1	1	1	1	1	1	1	1
DMU3	0.47	1	0.47	1	22	1	29	1
DMU4	0.667	0.841	0.793	0.841	13	19	21	19
DMU5	0.473	0.524	0.902	0.524	21	23	16	23
DMU6	0.644	1	0.644	1	14	1	24	1
DMU7	0.152	0.284	0.534	0.284	30	29	28	29
DMU8	1	1	1	1	1	1	1	1
DMU9	0.449	0.477	0.942	0.477	23	25	14	25
DMU10	0.608	0.892	0.682	0.892	15	18	23	18
DMU1	1	1	1	1	1	1	1	1

1								
DMU12	1	1	1	1	1	1	1	1
DMU13	0.525	0.666	0.788	0.666	19	20	22	20
DMU14	0.413	0.925	0.447	0.925	24	16	30	16
DMU15	1	1	1	1	1	1	1	1
DMU16	0.515	0.646	0.798	0.646	20	21	19	21
DMU17	0.257	0.406	0.633	0.406	28	27	25	27
DMU18	0.255	0.275	0.927	0.275	29	30	15	30
DMU19	0.803	0.946	0.848	0.946	12	15	18	15
DMU20	1	1	1	1	1	1	1	1
DMU21	0.604	1	0.604	1	17	1	26	1
DMU22	0.386	0.45	0.857	0.45	27	26	17	26
DMU23	1	1	1	1	1	1	1	1
DMU24	0.541	0.903	0.599	0.903	18	17	27	17
DMU25	0.393	0.397	0.99	0.397	26	28	11	28
DMU26	0.605	0.634	0.954	0.634	16	22	13	22
DMU27	1	1	1	1	1	1	1	1
DMU28	1	1	1	1	1	1	1	1
DMU29	1	1	1	1	1	1	1	1
DMU30	0.968	1	0.968	1	11	1	12	1

The DEA-based ranking analysis in terms of CRS_IO, VRS_IO, SE_IO, SBM_IO, CRS_OO, VRS_OO, SE_OO, and SBM_OO models show significant differences in the efficiency and scales of operations for all 30

DMUs. DMU2, DMU8, DMU11, DMU12, DMU15, DMU20, DMU23, DMU27, DMU28, and DMU29 were able to occupy the frontiers in most cases, implying high technical efficiency, optimal scale of operations, and minimal slack inefficiency, making them benchmark DMUs. On the other hand, DMU7, DMU17, DMU18, DMU22, and DMU25 had relatively poor rankings, indicating considerable inefficiency in the usage of resources, scale mismatch, and production. The major reasons for poor performance include underutilization of teaching staff and institutional resources, low student satisfaction, weak placement and career counselling systems, inadequate research productivity, limited industry-academia collaboration, and ineffective administrative and governance practices. In several cases, the universities possessed considerable academic and infrastructural resources but failed to convert them efficiently into desired outputs such as publications, placements, and improved student experience. The findings further indicate that improving student support services, research ecosystem, digital infrastructure, and employability-oriented initiatives can significantly enhance institutional efficiency.

4.2 ANN Model for Prediction and Classification of DMUs Efficiency

4.2.1 Efficiency prediction Model

Given DEA's inherent lack of predictive capability, an ANN feedforward model was developed to predict efficiency scores and classify DMUs (Kwon & Lee, 2015; Zhong et al., 2021). The sample architecture (Figure-7) consisted of an input layer, a hidden layer with neurons (ReLU activation), and output layer with linear activation.

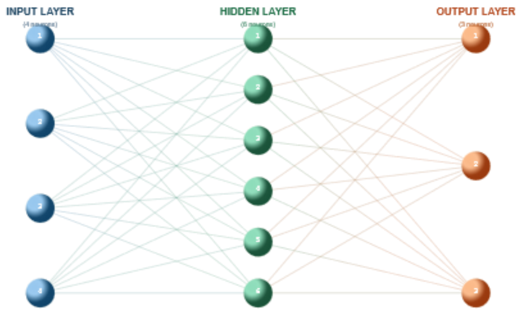


Figure 7. Sample ANN Architecture

Table-3. Model Summary

Category	Details
Objective	Map predictors to continuous responses
Predictors	DEA_TEST (20 samples, 6 features)
Responses	TARGET (20 samples, 1 feature)
Algorithm	Levenberg-Marquardt
Data Division	Random (Train: 20, Val: 5, Test: 5)
Layer Size	10 neurons

The Artificial Neural Network (ANN) model (Table-3) developed for efficiency prediction in higher education institutions is a feedforward model designed to capture complex, non-linear relationships among institutional performance variables. The network architecture comprises an input layer sized according to selected efficiency-related features (e.g., Teaching Staff, Career counselling), a hidden layer consisting of six neurons with non-linear activation functions such as ReLU or hyperbolic tangent, and an output layer with a single neuron that uses a linear activation function to provide continuous efficiency scores (Nielsen, 2015).

Mathematically, for an input vector x, the hidden layer output h, and the predicted efficiency $\hat{Y}$, the transformations are represented as:

$$h = \delta(w_1 x + b_1),\ \hat{y} = w_2 h + b_2$$

where w_1, w_2 are weight matrices, b_1, b_2 are bias vectors, an δ denotes the activation function (Bishop, 2006).

The network was trained using the Levenberg-Marquardt (LM) optimization algorithm, a robust method that combines the stability of gradient descent with the speed of the Gauss-Newton method (Hagan & Menhaj, 1994). The weight update rule is given by:

$$w_{k+1} = w_k - (J^T J + \mu I)^{-1} J^T e$$

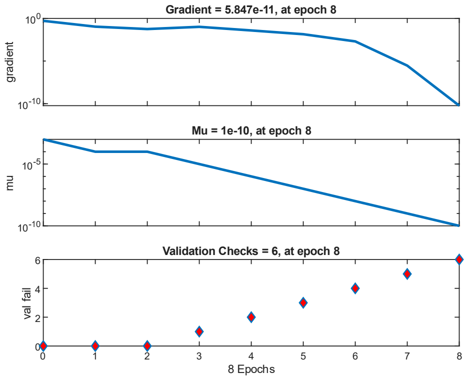
Where w_k is the weight vector at iteration k, J is the Jacobian matrix of network errors, $\mu = 10^{-10}$ is the damping factor, e is the error vector, and I is the identity matrix (Marquardt, 1963).

Table-4. Radial Model Training performance

Parameter	Initial Value	Stopped value	Targate Value
Epoch	0	8	1000
Performance(MSE)	0.0677	1.54e-19	0
Gradient	0.216	5.847e-11	1.00e-7
Mu	0.001	1.00e-8	1.00e+10
Validation Checks	0	6	6

Table-5. Non-Radial Model Training Performance

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	12	1000
Elapsed Time	-	00:00:00	-
Performance	0.352	1.56e-18	0
Gradient	0.005	3.37e-10	1e-07
Nu	0.001	1e-08	1e+10
Validation Checks	0	5	6



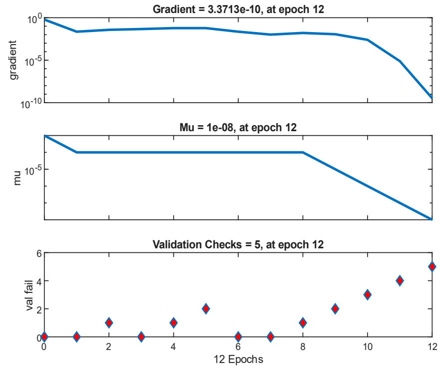


Figure -8. Radial Model Training **Figure -9.** Non-Radial Model Training

Training utilized early stopping, triggered by six validation checks to prevent overfitting (Prechelt, 1998). The network achieved convergence by epoch 8 for Radial (Table 4 and Figure 8) and at epoch 12 for Non- radial (Table 5 and Figure 9) with a final gradient magnitude of 5.847 10^{-11} (Radial) and 3.3713 10^{-10} (non-radial), indicating proximity to a local minimum and optimization stability (Nocedal & Wright, 2006).

Table-6. Result of Training, Validation and Testing (Radial)

Type	Observations	MSE	R
Training	20	0.0130	0.9064
Validation	5	0.0129	0.8278
Test	5	0.0268	0.8594
Additional Test	30	0.0153	0.8746

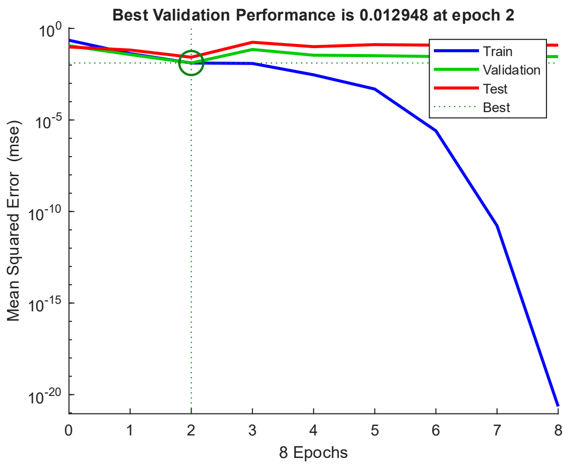


Figure-10. Radial Model performance Plot

The Radial model performance (Table 6 and Figure 10) was evaluated using the coefficient of determination (R) and Mean Squared Error (MSE). The training data set yielded R = 0.90644, the validation set R = 0.82784 with a minimum loss of 0.012548 at epoch 2, and the test set R = 0.85939. The overall model accuracy stood at R = 0.87458, reflecting a high generalization capacity (Figure 11).

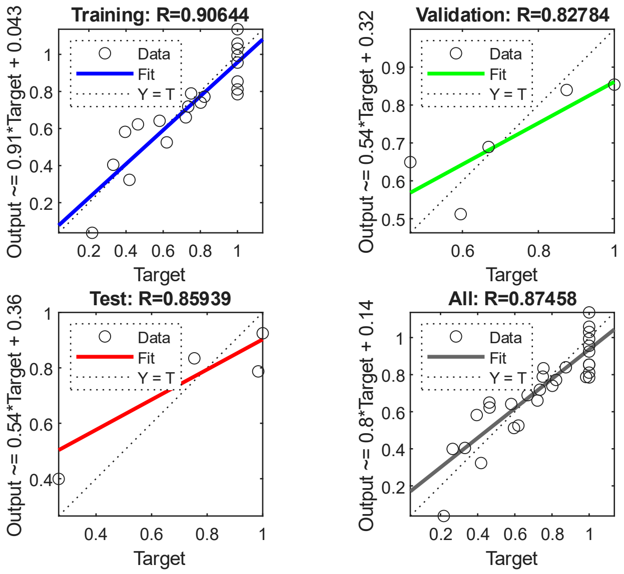


Figure-11. Radial Model Accuracy plot

Table-7. Result of Training, Validation and Testing (Non-Radial)

Type	Observations	MSE	R
Training	20	0.0100	0.9827
Validation	5	0.0085	0.8887
Test	5	0.0098	0.9511
Additional Test	30	0.0029	0.9449

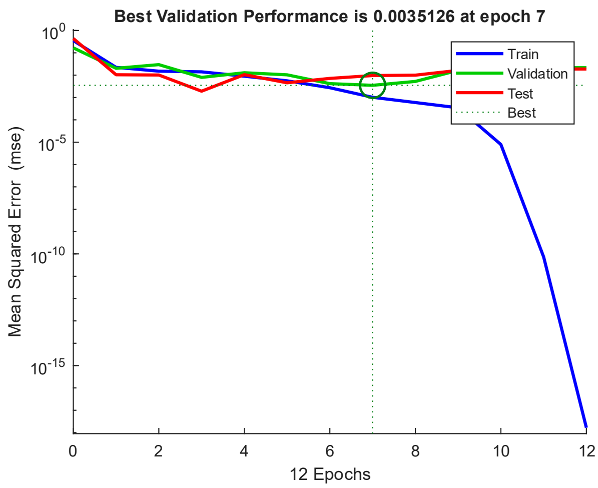


Figure- 12. Non-Radial Model Performance Plot

Whereas, The Artificial Neural Network (ANN) model designed to predict non-radial efficiency scores demonstrates strong predictive performance and robust generalization, as evidenced by its metrics (Table 7 and

Figure 12) across training, validation, and test datasets. The model achieved a training correlation coefficient (R) of 0.9827 (MSE = 0.0100) with 20 observations, indicating near-perfect fit to the training data (Bishop, 2006). While the validation (R =0.8887, MSE = 0.0085) suggests mild over-fitting, the model generalizes exceptionally well to unseen data, with a test Coefficient (R) of 0.9511 (MSE = 0.0098) and an additional test (R = 0.9449, MSE = 0.0029) across 30 observations (Goodfellow et al., 2016). Notably, the best validation performance (MSE = 0.0055126) at epoch 7 highlights the efficacy of early stopping to prevent over-fitting, as training continued for 12 epochs without significant degradation in validation loss (Prechelt, 1998).

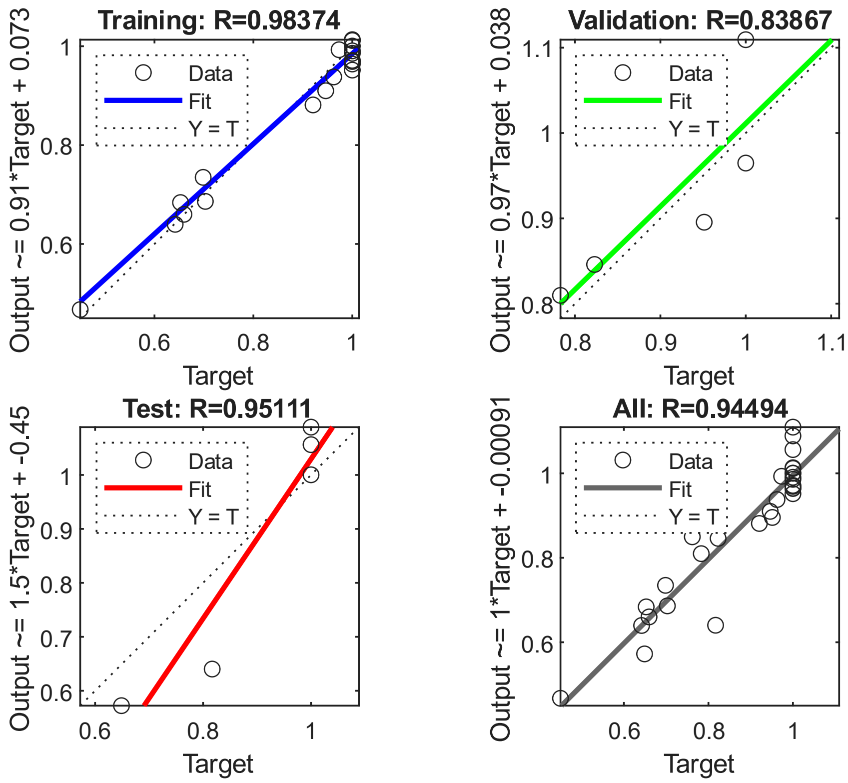


Figure -13. Non-Radial Model Accuracy plot

The low MSE values across all datasets (< 0.01) confirm the model's precision in minimizing prediction errors. The high R scores (> 0.94) for the test and additional test sets (Figure 13) underscore its reliability in capturing non-linear relationships inherent in non-radial efficiency metrics, such as resource allocation and operational effectiveness (Zhou et al., 2018). The compact architecture, combined with rigorous optimization techniques like the Levenberg-Marquardt algorithm, ensures computational efficiency and scalability for larger datasets (Nocedal & Wright, 2006).

The MSE is defined as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where y_i and $\hat{y}_i$ represent the actual and predicted efficiency values, respectively.

From a practical standpoint, this ANN model provides critical support for policymakers and educational administrators. It enables real-time efficiency monitoring and informed resource allocation decisions, offering an edge over traditional methods like Data Envelopment Analysis (DEA), which assumes deterministic frontiers. Furthermore, institutions identified with lower predicted efficiency values can be targeted for strategic interventions (Zhou et al., 2018).

5. Discussion

The initial stage, through the DEA approach, builds up what is called the "efficiency frontier" in order to recognize that universities are using inputs like teaching staff, funds and research seed money in a productive way with regards to the outputs like the number of published articles, number of student placement and students' satisfaction. The reasons why the DEA approach was utilized, is because of its ability to take into consideration multiple inputs and outputs simultaneously with no needs for any parametric functional form. Although, one of the major weaknesses of standard DEA model has been noticed to be that of "data noise" together with the inability to distinguish between different units located at the same frontier. Thus, it was utilized the Slack Based Measure (SBM) which provides a more efficient solution through an explicit incorporation of the slacks for both input and output in the score.

The ANN outputs add a layer of prediction which the DEA is missing. For instance, the Non- Radial ANN Model, had the capacity to predict efficiency scores with a remarkably correlation coefficients of 0.9827 in the training phase and 0.9511 in the test phase. Moreover, the very low Mean Squared Error (MSE < 0.01) in all the databases confirmed that it is able to map and model these non-linear relationship between variables at institution level, thus, if DEA helps in identifying who is currently efficient, ANN proves that the underlying structure of efficiency is generalized on previously unseen data.

From the outcomes of ANN model and SBM technique, we can make a series of recommendations in which to focus to improve the performance and resource allocation for the underperforming universities. Thus, our recommendations were focused on the high impact input and this can be explained and analyzed in more details below:

We assign high priority to Human Capital and Staff Productivity. The Number of Teaching Staff (I1) has shown to be a key factor for increasing institutional performance and should be therefore a priority, however it must be stressed that the effectiveness, not the numbers of staff engaged matters. Moreover, universities must focus on effective and efficient strategies in order to have a motivation factor such as increment for stagnation to continue working productively.

Through the ANN model we can identify the area where the universities must strategize and this is on Student Support Services; here, we emphasize on Career Counseling (I2) and Organizing Workshop; both the input and the outcome are extremely correlated to each other and by enhancing the Career Counseling service we increase the student placement percentage (O2) and by providing more training through workshops, we enhance the probability of finding a job that better suits student's skills.

One of the major revelations from the models has been how student satisfaction (O3) is one of the main drivers of performance in a University; High student satisfaction levels can serve as a proxy for both a well-functioning institution and as an experience indicator of the learning process. All institutions that are doing poorly need to invest in the improvement of both their physical and academic resources such as library resources, fix assets and lecture room technology in order to boost student experience.

Public funding, although not specified in inputs, appears as the main driver in many cases for performance enhancement. Especially for Universities located in Eastern India, allocation of the seed money for research should be considered a priority if the main objective is to maximize the number of published articles (O1). Whereas, for the center of India the efficiency depends on the utilization and maximization of the inputs rather than solely on volume.

ANN results imply that, for the bottom performing universities, the goal should be non-radial optimization, meaning simply increasing one input (such as funding) can't raise quality in a linear fashion; the poor universities should try to tackle "slacks"- where an input is there but is not performing well such as a large but unemployed pool of lecturers, or badly directed career services etc, in order to get to the efficiency frontier.

Policy and management implications are significant. The DEA results can be used to diagnose the problems. This is clear when the student satisfaction is included as an output which has previously seldom been in studies about university efficiency and demonstrates that universities are becoming increasingly customer focused. The identification of slacks for outputs such as career guidance or workshop facilitation demonstrates how to address inefficiency where input must be reallocated to create desired outputs.

The implication from ANN results seems even more important and implies continuous, rather than snapshot monitoring, which is enabled by the ANN having a good generalization capacity R=0.87458 for the total model, hence allowing for yardstick competition, and "strategic interventions" are feasible before an institution is miles away from its peers.

The overall result from comparing the analysis is that the DEA provides the current efficiency status and best practices; whereas the ANN can provide the stability for long-term planning through high generalization power. The combination of SBM-DEA and ANN move the study from a "black box" of university operation to providing a clearer road-map to improvement and, as such, educational leaders across India can ensure more stable institutional growth and access to higher quality education.

6. Implications

6.1 Theoretical Implications

Best of our knowledge, this is the first study applying the non-radial SBM-DEA and ANN to analyse the efficiency in higher education. On one hand, the study contributes to the DEA theory by empirically verifying the effect of student-oriented outputs on the efficiency and further develop the production theory of the university. Also, it empirically provides evidence that SBM efficiency is more statistically learnable than radial efficiency, which is consistent with other DEA-ML studies in recent years (Zhong et al., 2021; Visbal-Cadavid et al., 2019). Based on the identification of O3, our study negates the traditional research-cantered view and advocates the service-dominant logic in higher education.

6.2 Managerial Implications

University administrators should Really consider employing SBM-DEA to highlight inefficiently utilized resources and exposure of potential shortfalls. Then, the ANN setup works as a decision- aid instrument: for instance, it can forecast the efficiency impact of augmenting the number of counsellors or decreasing the staff strength. Besides, furnishing the students with proper satisfaction amenities (like counselling, feedback systems, campus facilities) is probably a more productive approach to the concern than solely increasing the number of publications or admissions. Those universities that consistently deliver quality at cost should be our role models; In fact, administrators may visit their peer institutions with a score of SBM=1 to borrow their best practices in teaching and student participation. Moreover, these efficiency models should be regularly updated with the data coming from the student satisfaction surveys, which is one of the routine practices of NAAC.

6.3 Policy Implications

The role of state and central authorities in education can be strengthened by a greater linking of grant and accreditation to efficiency outputs that are not publications. Current grant allocations appear to be more a function of enrolment or research output than efficiency. Our research supports funding based on differential performance; reward institutions that achieve high SBM-efficiency (and that too, especially in terms of student outcomes). Policy makers could constitute a commission to examine faculty staffing norms when the slacks are prevalent for teaching staffs and work towards optimizing hiring and retirement patterns. Accrediting agencies (UGC/NAAC) must develop indices that include satisfaction and the quality of placements into their performance parameters since NEP 2020 looks beyond narrow research and other quantitative factors. The inclusion of Student Satisfaction (O3) as an output variable aligns strongly with the learner-centric and outcome-based philosophy of NEP 2020, which emphasizes holistic development, employability, quality enhancement, digital learning, and student well-being. By incorporating student satisfaction into efficiency assessment, the study extends traditional research-oriented efficiency frameworks toward a more service-oriented and student-centered evaluation of higher education institutions. Thus, there can be linkages of grants/autonomy to improvements in efficiency of student outcome indicators.

7. Limitations and Future Research Scopes

This work has certain limitations. The data are cross-sectional and as such do not show how efficiency changes over time; a dynamic (Malmquist) DEA using recurrent neural networks (RNN/LSTM) would show how universities can evolve (Koronakos & Sotiropoulos, 2020). We also omitted undesirable outputs such as dropout and employment which can be incorporated into SBM-DEA (Tone, 2003) and these should be included in future work as negative factors which incur penalties. Environmental factors which might influence universities such as state-level socioeconomic conditions and governance were only partly accounted for; they could be modeled using a three-stage DEA or regression Tobit to distinguish between their influences (Zhang et al., 2020; Wu et al., 2019). Our analysis also uses a simple ANN and the results should be compared to other ML techniques such as Random Forest, XGBoost and SVM in order to ensure robustness (Visbal-Cadavid et al., 2019). Case studies of individual universities could complement the quantitative analysis, using qualitative research to determine the management practices which drive their particular levels of efficiency (Kumar et al., 2023).

8. Conclusion

Based on this research, the integrated SBM-DEA and ANN technique was able to analyse the efficiency of universities located in the eastern part of India quite well. Efficiency is not only low but also there is a great deal of variability: Per the SBM-DEA approach, only very few of the decision-making units (DMUs) can be considered fully efficient. Besides, almost all universities have been found to work with quite a lot of input slacks (In particular teaching staff/expenditure) while at the same time they have output shortfalls (mostly student satisfaction). The non-radial SBM model at the same time revealed inefficiencies which were not noticed by the traditional radial DEA models.

Machine Learning is a Great Complement: What is more, the ANN model, In particular for non-radial efficiency scores, even outperformed with predictive power the DEA results (overall R = 0.9449). It shows that one can establish machine learning as an effective leading intelligence tool that not only brings real-time efficiency prediction but also new university classification without computational re-runs. Besides research output, student satisfaction (O3) matters most for highest positive correlation with efficiency. So, universities that pay no attention to student experience and only focus on publishing lots of scientific articles should expect to be most of the inefficient ones. From our perspective, the main focus areas of poorly performing universities should be first and foremost reduction of excess inputs (e.g. finding the optimum faculty size) as well as devoting extra funds to the initiatives which can directly increase student satisfaction.

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