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# EFFICIENCY EVALUATION OF INDIAN HIGHER EDUCATIONAL INSTITUTIONS USING GOVERNANCE AS ENVIRONMENTAL VARIABLE - A DEA APPROACH

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**Abstract**
Higher Education Institutions (HEIs) play a pivotal role in building human capital and fostering innovation. This is especially true within India's rapidly evolving academic ecosystem. This study evaluates 76 Indian HEIs ranked in the NIRF Top Hundred from 2020 to 2024. It introduces governance type - Centrally Funded Institutions (CFIs), State Funded Institutions (SFIs), and Privately Managed Institutions (PMIs) - as a non-discretionary variable in Data Envelopment Analysis (DEA). The Extended BCC (EBCC) model constructs governance-specific frontiers, and the resulting Extended Pure Technical Efficiency (EPTE) scores capture the influence of variations in autonomy, funding structures, and regulatory oversight. Comparative analysis with conventional PTE scores indicates an 18% increase in the number of efficient institutions under the EBCC framework, highlighting the significance of accounting for governance heterogeneity in efficiency assessment. PMIs show the largest gains, resulting in a twenty-seven percent improvement in efficiency classification. Paired t-tests confirm the statistical significance of these differences. Consistency analysis shows CFIs as stable, PMIs improving with greater consistency, and SFIs are highly efficient with minor variations. Ranking analysis shows that twelve institutions consistently achieved perfect efficiency across CCR, BCC, and EBCC models.
By correcting systemic bias and revealing hidden institutional capacities, the EBCC framework offers equitable benchmarks for policymakers, regulators, and accreditation bodies. Incorporating governance as a non-discretionary variable addresses a critical gap in DEA literature. This approach supports context-sensitive reforms and fosters balanced, resilient development of higher education in India.
**Keywords :** Technical Efficiency, Environmental Variables, Governance, EPTE, Performance.

## 1. INTRODUCTION

Higher education plays a pivotal role in fostering economic growth, human capital development, and societal advancement, making its efficient functioning a subject of global policy interest (Marques Soares & dos Santos, 2024; Psacharopoulos & Patrinos, 2018). Higher education is universally acknowledged as a cornerstone of national development, fostering economic growth through the cultivation of skilled professionals and the expansion of human capital (Charnes et al., 1978).
In the context of evolving knowledge-based economies, universities are increasingly expected to contribute beyond traditional teaching and research roles by fostering innovation, advancing societal engagement, and strengthening global competitiveness (Marginson & Yang, 2022). The growing demand for accountability, transparency, and optimal resource utilization has amplified the importance of evaluating the performance of higher education institutions (HEIs) from a multi-dimensional perspective (Guo & Ye, 2025).
Globally, the assessment of higher education institutions (HEIs) performance has progressed beyond simplistic output-based indicators, evolving toward comprehensive efficiency analyses that integrate both qualitative and quantitative dimensions (G. Johnes et al., 2022). International ranking frameworks such as the Times Higher Education (THE) and QS World University Rankings offer comparative visibility but often rely heavily on reputation-based metrics, which may not adequately reflect operational efficiency or contextual constraints (Nassa et al., 2021). Consequently, performance evaluation methods that integrate both outputs and inputs—while accounting for environmental factors—have gained traction in research and policymaking (Holý, 2024).
The Indian higher education landscape presents a complex environment. As of 2021–22, the system includes 1,168 universities and 45,473 colleges, serving approximately 43.3 million students and achieving a Gross

Enrolment Ratio (GER) of 28.4% (AISHE Final Report 2020-21, 2020). The system encompasses a diverse mix of public and private institutions varying in size and quality. The National Education Policy (NEP) 2020 outlines a comprehensive vision for inclusivity, quality improvement, and global competitiveness (Bandyopadhyay & Dresearcher, 2020). However, issues such as misallocation of resources, disparities in institutional capacity, and fragmented governance continue to pose challenges (Agarwal, 2007; Ahir, 2014; Loganathan & Subrahmanya, 2023). Recent summaries (Jalote et al., 2020; Nassa et al., 2021) emphasize the ongoing gap between policy goals and actual performance, resource allocation, and implementation.

In India, the National Institutional Ranking Framework (NIRF) has emerged as the leading national ranking mechanism, offering a multi-parameter assessment across teaching, research, graduation outcomes, outreach, and perception. While NIRF has improved transparency and data-driven evaluation, it has also faced criticism for its potential bias towards well-resourced institutions and its limited incorporation of efficiency-based measures (Singh & Rao, 2024). Given India's diverse higher education ecosystem—comprising centrally funded, state-funded, and private institutions—contextualized evaluations that consider governance type and structural constraints are essential for informed policy formulation (Aithal, 2017).

Against this backdrop, Data Envelopment Analysis (DEA) has emerged as a robust non-parametric method for evaluating the relative efficiency of decision-making units (DMUs), including universities (Charnes et al., 1978). DEA allows for the simultaneous consideration of multiple inputs and outputs without requiring explicit functional forms, making it well-suited for the education sector's complex production processes (J. Johnes, 2006). Recent advancements, such as the incorporation of environmental and categorical variables, have further enhanced DEA's ability to account for structural and contextual differences among institutions (Banker & Morey, 1986). Studies applying DEA in higher education globally and in India have demonstrated its potential to complement ranking frameworks by providing deeper insights into operational efficiency and performance gaps (Marques Soares & dos Santos, 2024).

## 2. REVIEW OF LITERATURE

Data Envelopment Analysis (DEA) has become a popular non-parametric, efficiency-based assessment method. Introduced by Charnes et al. (1978) and expanded by Banker et al. (1984), DEA allows for the comparison of decision-making units (DMUs) with multiple inputs and outputs without assuming a particular functional form (Cook & Seiford, 2009; J. Johnes, 2006a; Worthington, 2001). Early use in higher education includes studies by Avkiran (2001) and Worthington & Lee (2008), which evaluated the technical and scale efficiencies of Australian universities. More recent international research has used DEA to analyze cost efficiency (G. Johnes et al., 2022), research and teaching performance (Kao & Hung, 2008), financing (Yu et al., 2024), and even sustainability efforts in HEIs (Zuluaga et al., 2023).

DEA's evolution has also involved methodological innovations. Three-stage DEA with SFA changes (Guo & Ye, 2025; Yu et al., 2024), meta-frontier and fuzzy models (Ahmad & Nana Khurizan, 2024; A. P. Singh et al., 2022), and network DEA in decomposed teaching-research subsystems (Dogan, 2023) illustrate how the method has been developed to address environmental heterogeneity, contextual equity, and complex input-output structures. Tran et al. (2023) demonstrate that international program provisions and institutional autonomy boost efficiency in Southeast Asia. Similarly, Agasisti & Pérez-Esparrells (2010) illustrate how national governance arrangements and funding shape the performance of institutions in Spain. In Turkey, Dogan, (2023), and Maral (2023) highlight scale inefficiencies and the gap between rankings and operational performance in research universities. (Holý, 2024) developed a ranking-based second-stage DEA framework using panel data to consider governance-related impacts at the national level. In Brazil, Marques Soares & dos Santos (2024) used DEA and the Malmquist index to identify "reference schools" among high schools, advocating knowledge transfer between institutions with similar contexts. Across the European Union, equity-oriented studies (Stumbrienė et al., 2022) reinforce the policy value of incorporating social inclusion within efficiency metrics. Collectively, these international studies demonstrate the versatility and methodological rigor of DEA in evaluating higher education systems.

Empirical DEA studies in India cover various institutional types and levels. Tyagi et al., (2009) used DEA to benchmark the departments of IIT Roorkee, while Debnath & Shankar (2009) evaluated B-schools. Bhattacharyya & Chakraborty (2014) combined DEA with TOPSIS to measure IIT performance. At the state level, Gourishankar & Sai Lokachari (2012) conducted benchmarking, Sunitha & Duraisamy (2013) found higher technical efficiency in Kerala's public diploma institutions compared to engineering colleges, and Sahoo et al. (2017) examined the efficiency of management institutions. Kaur (2021) assessed state-level efficiency and recommended rationalizing financial and human resources. Ranjan & Singh (2021) incorporated categorical variables—urban–rural and affiliation—to identify enrolment inefficiencies. Choudhury & Ghose (2023) discussed challenges faced by entrepreneurial universities in achieving third-mission goals. Studies on gender equity in enrolment revealed a positive link with technical efficiency. Mishra et al. (2023) used a two-stage DEA with truncated regression to analyze how environmental variables influence efficiency. Together, these studies demonstrate the versatility of DEA in addressing structural, policy, and social dimensions of Indian higher education.

In DEA, the accuracy and interpretability of results are highly sensitive to the choice of input–output variables and how decision-making units (DMUs) are defined. Recent methodological advances focus on including environmental and categorical variables into DEA models to better reflect institutional realities, such as the EBCC model's consideration of institutional heterogeneity across Indian higher education institutions (HEIs). This study adopts a structured approach to selecting variables and specifying DMUs to ensure relevance and comparability. Common inputs in higher education efficiency studies include faculty strength, operational expenditures, infrastructure, and intake capacity, while outputs usually include academic throughput, graduation rates, research achievements, and innovation metrics like citations, patents, MoUs, and externally funded projects (Ferro & D'Elia, 2020; Katharaki & Katharakis, 2010; Laureti et al., 2014). To improve empirical fit and reduce dimensionality, researchers have used techniques such as Principal Component Analysis (Ueda & Hoshiai, 1997), entropy indexing (Cantele et al., 2016), copula-based selection (Alpay & Aktürk Hayat, 2016), and stepwise selection methods (Subramanyam T, 2021). Additionally, hybrid machine learning–DEA models (Solanki & Virparia, 2022) have shown potential in enhancing model discrimination.
Recent methodological developments focus on incorporating environmental and categorical variables to better capture institutional realities (Reinhard et al., 2002; Witte & López-Torres, 2017; Subramanyam T et al., 2020). To control for contextual effects on managerial performance, more advanced techniques such as bootstrapped DEA (Dixit et al., 2024), conditional efficiency analysis (de Witte & Kortelainen, 2013), and truncated regression (Zarrin & Brunner, 2023) are increasingly used. This study builds on these methodological foundations to develop a robust DEA framework tailored to the Indian higher education context.
The present study aims to examine how DEA can be utilized to evaluate efficiency in Indian higher education, addressing the gap between performance measurement and resource optimization. By incorporating DEA into higher education analysis, policymakers and administrators can implement targeted reforms that promote sustainable and high-quality education for future generations. Synthesizing these elements, the study assesses the efficiency of 76 Indian HEIs consistently ranked among the top 100 in NIRF from 2020 to 2024. It employs both the standard BCC model and the EBCC model, which introduces governance type as a non-discretionary variable. This method improves contextual fairness while maintaining methodological rigor. Longitudinal trends are analyzed, and governance-related differences are statistically tested using paired sample t-tests to generate actionable insights.

## 3. RESEARCH QUESTIONS

1. To what extent does including governance in DEA change the number and classification of efficient Indian HEIs compared to standard TE and PTE models?
2. Does incorporating governance-based environmental adjustments through the EBCC (EPTE score) model lead to a higher average technical efficiency score across institutions?
3. Is the difference between efficiency scores derived from the BCC and EBCC models statistically significant over the five years (2020–2024)?
4. Do efficiency patterns differ significantly across governance types over the five years?

## 4. METHOD

This study employs a quantitative, longitudinal research design using panel data spanning from 2020 to 2024 to assess the efficiency of seventy-six Indian Higher Education Institutions (HEIs) that have consistently ranked among the NIRF Overall Top 100. To evaluate institutional performance across time, the study employs Data Envelopment Analysis (DEA)—a robust, non-parametric method that accommodates multiple inputs and outputs without requiring any specific functional form. This makes DEA particularly suitable for assessing the relative efficiency of heterogeneous institutions operating under varied constraints.
The analytical approach is structured around three DEA models, each offering a distinct perspective on technical efficiency. The first model, the CCR model, assumes Constant Returns to Scale (CRS) and estimates Overall Technical Efficiency (TE). The second, the BCC model, relaxes the CRS assumption to allow Variable Returns to Scale (VRS), thereby estimating Pure Technical Efficiency (PTE). While both these models evaluate all 76 HEIs as a single group of Decision-Making Units (DMUs), the third model—the Extended BCC (EBCC)—enhances the analysis by incorporating governance structure as an environmental factor. This model addresses contextual heterogeneity by comparing institutions only within governance-based groups, thereby calculating EPTE.
In this study, institutions were grouped by their main funding source—central, private, or state. This created three distinct and internally similar groups: CFIs (D1–D35), which consist of 35 Centrally Funded Institutions; PMIs (D36–D57), consisting of 22 Privately Managed Institutions; and SFIs (D58–D76), consisting of 19 State Funded Institutions. Since these institutions operate under different policies and levels of autonomy, this grouping reflects their unique contexts. Each institution was then assessed only against others within its own homogeneous group ($G \in \{C, P, S\}$). This way, comparisons are fairer and more meaningful, since every institution faces similar conditions within its category.

All three models adopt an input-oriented approach, reflecting the realistic objective of educational institutions to minimize resource inputs while maintaining or improving output performance. The study uses three input variables that capture the resource base of each institution: Student Strength (SS), Faculty Quality and Experience (FQU), and Financial Resources and Utilization (FRU). Correspondingly, three output variables were selected to reflect institutional outcomes. In line with the NIRF framework, three standardized components—Quality of Publications (QP), Intellectual Property Rights (IPR), and Footprint of Projects and Professional Practice (FPPP)—were extracted and combined into a single composite output labelled Research Output (RO), considered alongside Graduation Outcome (GO) and Perception Score (PS). These input–output combinations align with national benchmarking criteria and capture the critical dimensions of higher education performance.
The DEA models were executed using EMS 3.1, and all statistical analyses and visualizations were performed using R (version 4.5.1) and IBM SPSS. To track efficiency over time, line graphs and bar charts depicted average efficiency trends and the number of efficient institutions per year. Standard deviation (SD) and coefficient of variation (CV) were used to assess the stability of efficiency scores across the five years. Additionally, paired t-tests were conducted to determine the statistical significance of efficiency differences across years and governance types. Heatmaps were used to provide intuitive visualizations of institutional performance distributions. Methodologically, DEA evaluates the efficiency of each DMU by minimizing the input contraction ratio θ, subject to the condition that a weighted combination of peer institutions does not exceed the DMU's inputs and meets or exceeds its outputs. In the BCC model, the reference set includes all DMUs and is solved using the following constraints:
Min θ
Subjected to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{ih} \ \forall \text{ i}$$

$$\sum_{j=1}^{n} \lambda_j y_{oj} \geq y_{oh} \ \forall \text{o}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0$$

For the EBCC model, the constraints are applied only to DMUs belonging to the same governance group G ∈ {C, P, S}, modifying the formulation as:

Min $\theta^G$

Subjected to

$$\sum_{J\epsilon G} \lambda_j x_{ij} \ \leq \theta^G x_{ih} \forall \ i$$

$$\sum_{J\epsilon G} \lambda_j y_{oj} \ \leq y_{oh} \forall \ o$$

$$\sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0$$

This governance-sensitive DEA formulation produces EPTE scores that are adjusted for structural differences among institutions, improving the interpretive relevance of efficiency outcomes in the Indian higher education landscape. All the data were obtained from the publicly available NIRF portal (Ministry of Education, 2024). Institutional identities were kept anonymous with the help of codes (D1–D76) for maintaining confidentiality. Ethical clearance was not required, as the study used only publicly available secondary data."

## 5. RESULTS AND DISCUSSION

This study applies DEA to evaluate the efficiency of Indian HEIs consistently ranked in NIRF's Top 100 from 2020 to 2024, with governance type as a key non-discretionary variable. By comparing conventional and extended DEA models, the research aims to capture the average effect of governance on institutional efficiency and highlight potential structural inequities. This approach not only advances methodological applications in efficiency measurement but also provides policy-relevant insights for improving equity and competitiveness in India's higher education sector.

***RQ1***- To what extent does the inclusion of governance in DEA alter the number and classification of efficient Indian HEIs compared to standard TE and PTE models?

To explore RQ1, Figures 1 and 2 highlight the evolving impact of governance on efficiency classifications across DEA models.

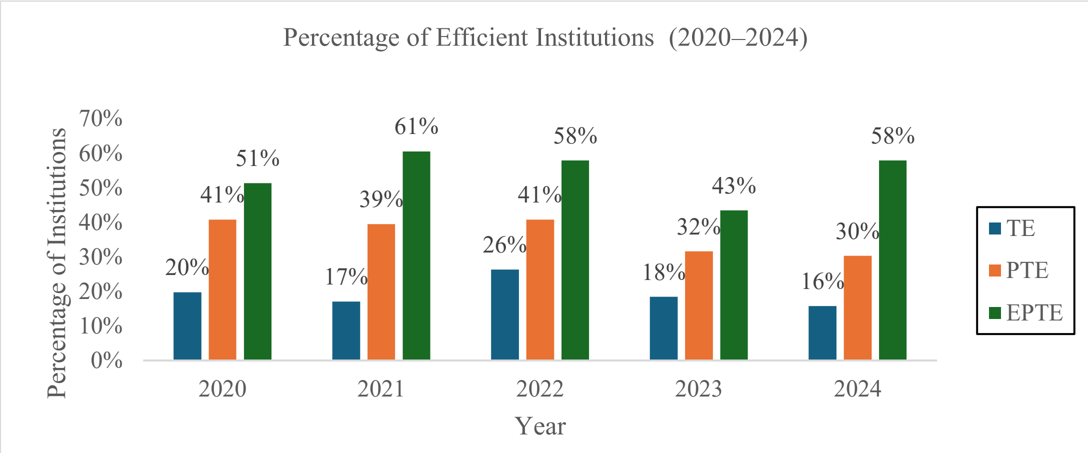


*Figure 1:Percentage of Institutions Classified as Efficient under TE, PTE, and EPTE Models (2020–2024)*

Figure 1 depicts a progressive rise in the share of institutions categorized as efficient over the five-year span, with the EBCC model consistently recognizing a larger subset. As shown in Figure 1, there is a discernible, year-on-year increase in the percentage of efficient institutions, with the EBCC model consistently identifying a higher proportion over the five-year period. This upward trend signals the subtle yet meaningful influence of governance in reframing institutional efficiency.

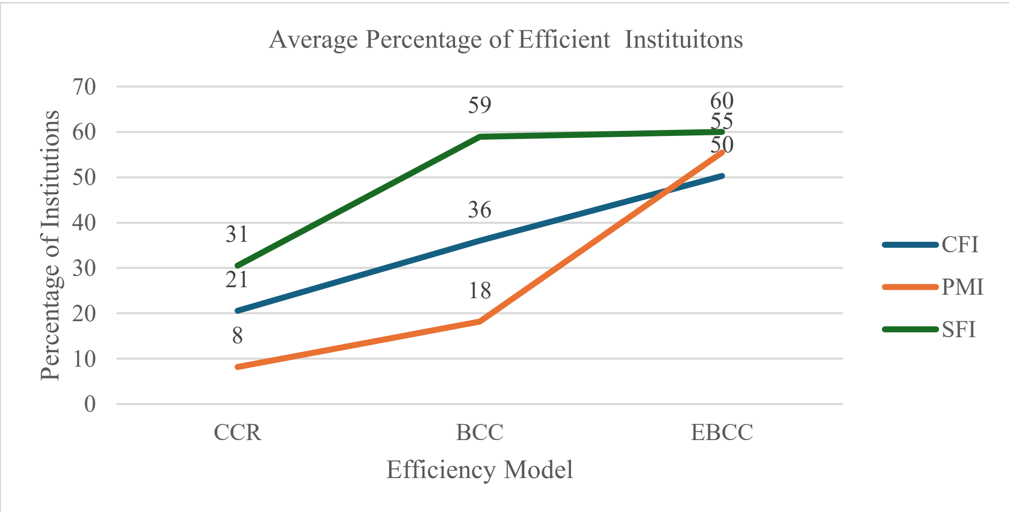


*Figure 2: Average Percentage of Efficient Institutions across Governance Types under CCR, BCC, and EBCC Models*

The above Figure 2 clearly depicts that PMIs register the most visible change when governance is accounted for, suggesting that contextual factors may recalibrate performance assessments in their favour. CFIs reflect moderate shifts, while SFIs remain largely unaffected—maintaining high and stable efficiency, regardless of the model applied.

***RQ2***- Does the incorporation of governance-based environmental adjustments via the Extended BCC (EBCC) model result in a higher average technical efficiency score across institutions?
To address RQ2, the study investigated the average efficiency scores across governance sectors over a five-year period. These trends are visually presented in Figure 3, while Figure 4 illustrates the underlying distribution of the data using a frequency-based overlapping histogram. Together, these provide both a temporal and statistical perspective on governance efficiency patterns. To further assess the consistency of performance across governance types, an analysis of efficiency variability was undertaken. Table 1 reports the variability scores enabling a comprehensive comparison of absolute and relative stability across Central, State, and Private institutions. This consolidated view highlights governance-adjusted efficiency differences while also capturing the consistency of institutional performance over time.

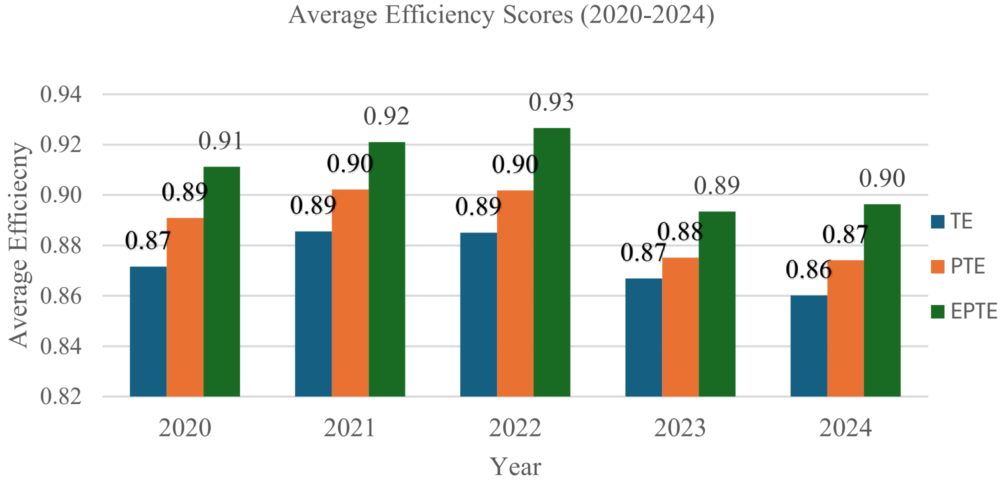


*Figure 3: Average Efficiency Scores across DEA Models (2020–2024)*

Figure 3 shows that, across the five-year period, the EBCC model consistently yielded higher average efficiency scores compared to both the CCR and BCC models.

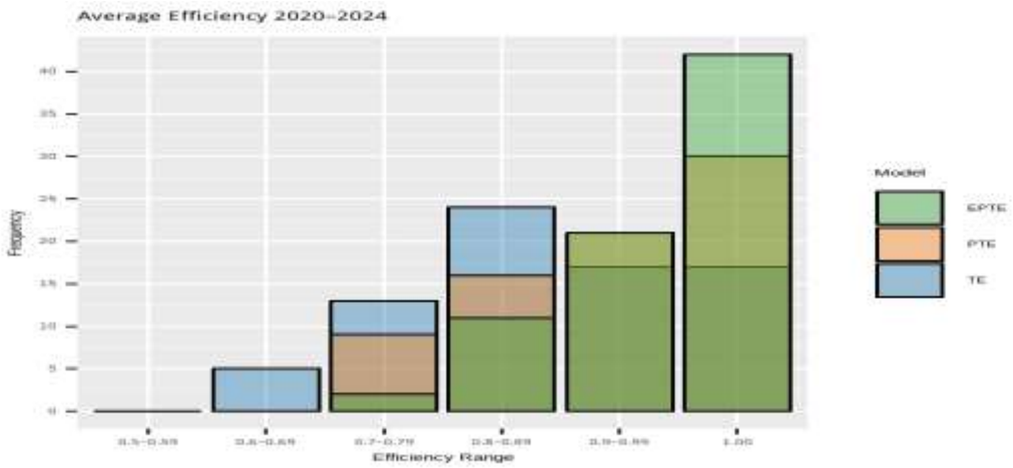


*Figure 4: Comparison of Average Efficiency Scores Across DEA Models (2020–2024)*

Figure 4 reveals a distinct shift of institutions toward higher efficiency intervals under the EBCC model, with noticeably fewer cases appearing in lower efficiency ranges. This indicates a reclassification trend, highlighting the EBCC model's capacity to generate more favourable efficiency scores.

Table 1:Governance-wise mean efficiency scores under BCC and EBCC models with variability indicators (SD and CV) for 2020–2024.

| Governance Type | Mean Efficiency (PTE) | SD (PTE) | CV (PTE) | Mean Efficiency (EPTE) | SD (EPTE) | CV (EPTE) |
|---|---|---|---|---|---|---|
| CFIs | 0.94 | 0.06 | 0.06 | 0.95 | 0.04 | 0.04 |
| PMIs | 0.86 | 0.1 | 0.12 | 0.91 | 0.05 | 0.05 |
| SFIs | 0.96 | 0.05 | 0.05 | 0.97 | 0.06 | 0.06 |

Table 1 shows that CFIs maintained stable performance, with mean efficiency slightly increasing from 0.94 (PTE) to 0.95 (EPTE) and variability decreasing (CV: 0.06 → 0.04). PMIs recorded the most notable improvement, with mean efficiency rising from 0.86 to 0.91 and variability declining (CV: 0.12 → 0.05). SFIs showed marginal efficiency gains from 0.96 to 0.97, with a small increase in variability (CV: 0.05 → 0.06).

***RQ3-*** Is the difference between efficiency scores derived from the BCC and EBCC models statistically significant over the five years (2020–2024)?
To address Research Question 3 (RQ3), paired sample t-tests were used to compare efficiency scores between the PTE and EPTE across the years 2020 to 2024, and the results are displayed in Table 2.

Table 2: Paired Sample t-Test Results Comparing PTE and EPTE (2020-2024)

| Hypothesis | t-value | p-value | Mean Difference |
|---|---|---|---|
| 2020 | -4.55 | .00** | -.04 |
| 2021 | -2.28 | .03* | -.03 |
| 2022 | -2.20 | .03* | -.02 |
| 2023 | -5.09 | .00** | -.05 |
| 2024 | -6.28 | .00** | -.06 |

Note * $p < .05$; ** $p < .01$

Table 2 presents the five-year trend, revealing statistically significant differences between PTE and EPTE scores. The paired-samples t-test confirms EPTE scores were consistently higher than PTE scores, although the negative t-values reflect the subtraction order (PTE – EPTE) rather than a true negative effect. The increasing gap, reaching its peak in 2024, highlights a gradual divergence in efficiency outcomes when governance-related factors are incorporated.
***RQ4-*** Do efficiency patterns differ significantly across governance types (Central, State, and Private) when comparing BCC and EBCC model outputs over the five years?

To address RQ4, efficiency patterns were analysed across both structural (governance) and temporal (year-wise) dimensions. Two complementary statistical approaches were employed: (i) a one-way ANOVA in SPSS to test governance-wise differences, (ii) pairwise year-wise comparisons using multiple t-tests in R to assess temporal variations. The results of ANOVA are displayed in Table 3, and the magnitude of t t-test is illustrated in Figure 5, while Figure 6 uses a heat map to depict the statistical significance, offering a detailed view of governance-sensitive efficiency dynamics.

Table 3: One-way ANOVA results for governance-wise efficiency comparisons (BCC vs EBCC, (2020– 2024).

| Year | Model | Between-Groups SS | Mean Square (Between / Within) | Sig. (p) |
|---|---|---|---|---|
| 2020 | EBCC | 0.01 | 0.005 / 0.003 | 0.198 |
| | BCC | 0.146 | 0.073 / 0.007 | 0** |
| 2021 | EBCC | 0.008 | 0.004 / 0.004 | 0.425 |
| | BCC | 0.11 | 0.055 / 0.005 | 0** |
| 2022 | EBCC | 0.003 | 0.002 / 0.004 | 0.651 |
| | BCC | 0.111 | 0.055 / 0.004 | 0** |
| 2023 | EBCC | 0.016 | 0.008 / 0.003 | 0.082 |
| | BCC | 0.151 | 0.075 / 0.006 | 0** |
| 2024 | EBCC | 0.006 | 0.003 / 0.002 | 0.198 |
| | BCC | 0.179 | 0.090 / 0.005 | 0** |

Note ** $p < .01$, d.f 2/73

The one-way ANOVA results presented in Table 3 reveal significant governance-based differences in mean efficiency scores under the standard BCC model, with CFIs and SFIs consistently outperforming PMIs across all five years ($p < .01$). In contrast , EPTE scores derived from the EBCC model showed statistically non-significant variation across governance types ($p > .05$), with only 2023 approaching significance ($p = 0.082$).

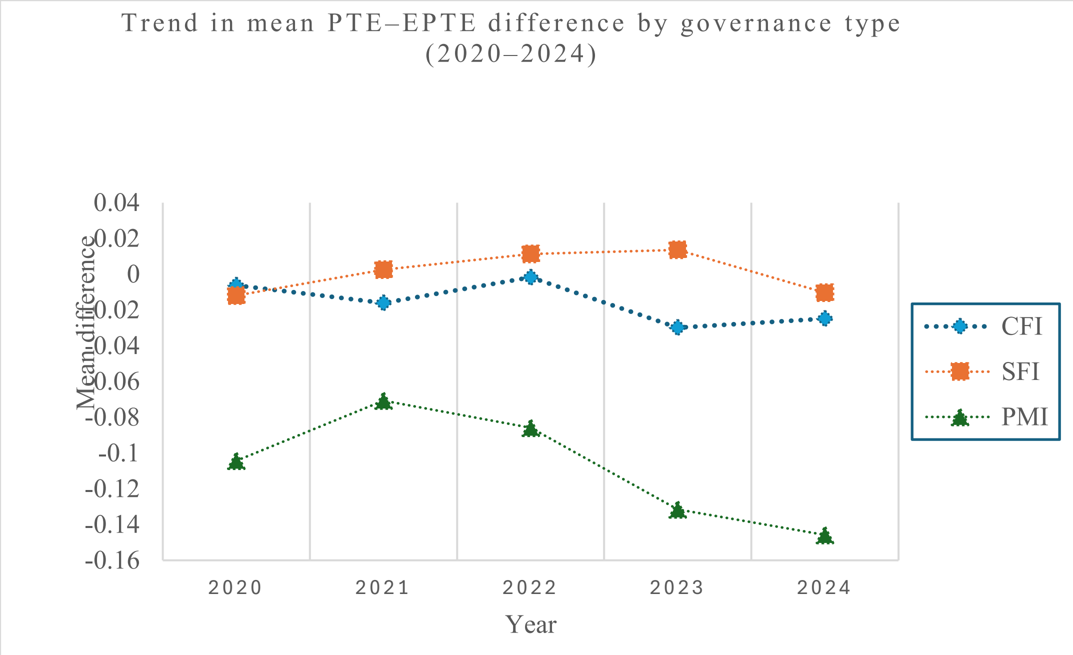


*Figure 5: Longitudinal trends in the average difference between PTE and EPTE scores for Central, State, and Private institutions (2020–2024).*

Figure 5 shows the average differences in efficiency scores, with Private institutions exhibiting consistently negative gaps, where CFIs remained stable, while SFIs showed slight fluctuations.

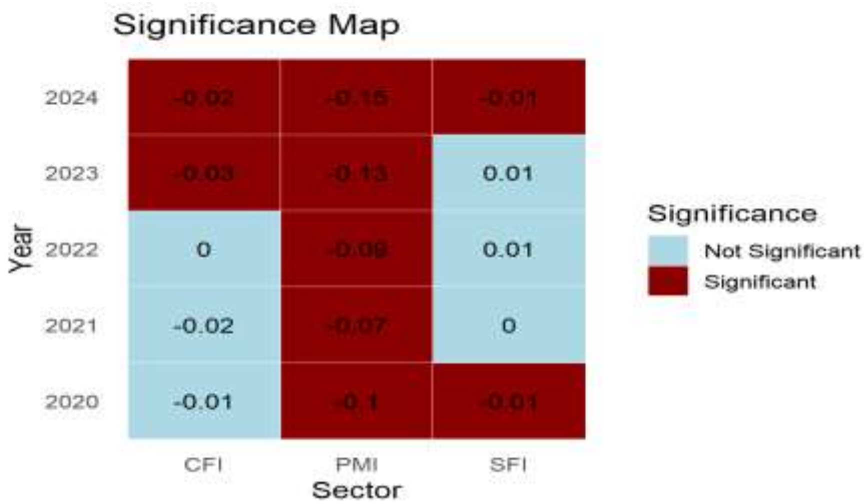


*Figure 6: Heat map depicting significance levels (ranging from 0.00 to 1.00) across CFI, PMI, and SFI from 2020 to 2024.*

Figure 6 presents the corresponding significance levels. Private institutions showed statistically significant differences in all years ($p < .05$), while Central and State institutions showed significance only in select years.
To further substantiate the above, a comprehensive ranking analysis was conducted by evaluating institutional performance across three DEA models—CCR (Constant Returns to Scale), BCC (Variable Returns to Scale), and EBCC (Extended BCC). Rankings from each model were aggregated, and the average rank was computed to derive a composite performance indicator for each Decision-Making Unit (DMU). It was found that there were 12 institutions which are consistency ranked one based on the efficiency scores. This integrative approach enabled the identification of institutions with consistent efficiency across models, as well as those exhibiting model-specific sensitivities. These results support RQ-4, indicating that governance type influences efficiency patterns both across institutional categories and over time.

## 5. SUMMARY

This study explores the technical efficiency of Indian Higher Education Institutions (HEIs) through the Extended BCC model, innovatively integrating governance type—Central, State, or Private—as a non-discretionary environmental variable. Departing from conventional DEA models that rely on a common production frontier, EBCC constructs governance-specific frontiers, enabling more nuanced and context-sensitive evaluations that reflect disparities in autonomy, funding, and regulatory oversight.

The empirical findings reveal that governance-sensitive modeling significantly enhances the accuracy and fairness of efficiency assessments. Over five years, the number of institutions classified as efficient increased by 18% under the EBCC framework, compared to the traditional BCC model. Notably, PMIs showed the most substantial gains, with a 27% improvement in efficiency classification, thereby challenging the prevailing narrative of their underperformance. These results highlight how institutional ability can remain hidden when structural constraints are not considered. Over the five years, average efficiency scores increased by approximately 2% annually across all governance types, demonstrating the EBCC model's robustness in capturing consistent performance improvements over the standard BCC model. This trend underscores the material influence of governance considerations on how institutional performance is captured and interpreted within DEA frameworks.

From a methodological perspective, EBCC addresses a long-standing gap in the DEA literature by treating governance as a structural determinant of performance—a perspective supported by Gori et al. (2025) and Tran et al. (2023). PMIs, though often constrained by limited resources and minimal policy support, demonstrated clear improvement once governance adjustments were introduced, with greater performance stability. SFIs, though maintaining relatively high efficiency, showed moderate fluctuations across the years, a pattern likely shaped by the uneven nature of state-level governance and policy shifts. Meanwhile, CFIs consistently showed stable outcomes, highlighting the steadying effect of centralized governance structures (Goyal & Dutta, 2021). Such governance-based differentiation offers more than statistical refinement—it reflects the complex realities of India's highly fragmented higher education system. Institutions vary not only in scale and mission, but also in their ability to respond to external pressures and adapt to evolving policy environments. The differentiated trajectories revealed by the EBCC model provide a richer understanding of institutional resilience, adaptability, and underlying capacity.

These findings resonate with scholarly calls for performance assessment models that embrace institutional heterogeneity. Advocates such as Johnes & Yu (2008), Witte & López-Torres (2017) argue for the inclusion of non-discretionary variables to improve fairness. Complementing this perspective, Maral (2023), Ranjan & Singh (2021), Xue et al. (2021), and Zhou et al. (2024) underscore the importance of context-sensitive approaches, particularly within education systems characterized by policy fragmentation. The present study highlights that efficiency patterns in Indian HEIs differ both structurally and temporally when governance is explicitly considered. Structural comparisons reveal that CFIs consistently maintained higher and more stable efficiency, SFIs experienced moderate fluctuations shaped by state-level policy variability, and PMIs recorded the most substantial gains once governance-specific frontiers were applied. This finding demonstrates that governance-adjusted frontiers mitigate systemic disadvantages faced by PMIs, offering a more equitable efficiency assessment. From a temporal perspective, efficiency trajectories show CFIs as steady performers, SFIs gradually improving, and PMIs demonstrating marked year-on-year improvements, thereby challenging conventional perceptions of underperformance. Ranking analysis reinforced these findings, with CFIs dominating top positions while several PMIs and SFIs lagged. Collectively, these outcomes align with Holý (2024) and others in underscoring how governance structures and evolving contexts jointly determine institutional efficiency, reinforcing the necessity of governance-adjusted DEA models for fairer and more accurate evaluations.

This study concludes that governance-adjusted DEA models, exemplified by EBCC, are essential for producing equitable, robust, and context-sensitive evaluations within structurally diverse education systems. By explicitly acknowledging governance as an environmental variable, the model corrects systemic bias, unveils latent institutional strengths, and aligns efficiency classifications with operational realities. In governance-fragmented systems like India's, such methodological innovation is not merely desirable—it is critical for fostering a responsive, resilient, and reform-ready higher education ecosystem (Jha & Kumar Jha, 2025; Olariu & Brad, 2022; Ranjan & Singh, 2021; Xue et al., 2021).

## 6. CONCLUSION

Efficiency in higher education cannot be evaluated comprehensively without considering governance. This study finds that including governance in the EBCC model led to a reassignment of institutions into new performance categories. Specifically, PMIs—often considered underperforming—showed greater resilience and potential when governance was considered. The study also found that governance-aware assessment improved accuracy in measuring institutional consistency and equity among Indian HEIs. These findings suggest that governance-adjusted DEA models can provide more accurate benchmarking and informed policy or funding decisions, especially for addressing structural reforms among PMIs and SFIs. Future research could incorporate variables such as institutional autonomy, regional disparities, or internationalization strategies to further examine factors influencing efficiency in higher education.

This study has some limitations. It relies only on secondary data from public rankings and institutional reports, which may limit the breadth and accuracy of some contextual or qualitative aspects. The analysis includes only the governance type as an environmental variable. This is important, but it ignores other key factors, such as the institution's age or geographic location. Future research should include these elements to provide a fuller view of what shapes higher education performance, as these factors may significantly impact efficiency.

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