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# The Efficiency of STEM Departments in a Zimbabwean University: A Data Envelopment Analysis-Malmquist Approach

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**ABSTRACT**

This study evaluates the efficiency of STEM departments at a Zimbabwean university using Data Envelopment Analysis and the Malmquist Productivity Index. Guided by Education 5.0 and persistent resource constraints, the analysis assesses performance using inputs (staff, budgets, programmes, teaching assistants) and outputs (graduates, publications, citations, grants). Overall efficiency improved from 24% in 2023 to 45% in 2024. Sensitivity tests show that programme offerings and graduate output are the strongest drivers of efficiency, while slack analysis highlights opportunities to optimise resource utilisation. Benchmarking identifies DMU14 and DMU33 as top performers that can serve as models for weaker departments. Unlike much of the global literature, this study emphasises resource reallocation rather than frontier shifts, reflecting the realities of low-funding environments. Recommendations include targeted budget adjustments, structured benchmarking, and policy measures to address STEM-specific costs. The findings support evidence-based decision-making and advance methodological debates on DEA in resource-constrained settings.

**Keywords:** STEM, efficiency, data envelopment analysis, Malmquist productivity index

# INTRODUCTION

In an era of knowledge economies, higher education institutions are increasingly expected to serve as engines of innovation, industrialisation, and economic growth, particularly through Science, Technology, Engineering, and Mathematics (STEM) disciplines (Bain & Cummings, 2021). These departments are vital not only for producing high-level skills but also for solving pressing national problems through applied research and technological advancement (Hebebci & Usta, 2022). In Zimbabwe, the government's Education 5.0 policy repositions universities as catalysts for industrial transformation, charging them with five mandates: teaching, research, community engagement, innovation, and industrialisation (Mutongoreni & Mbohwa, 2025). However,

**Table 1**. 2018 National Critical Skills Audit Report Summary

| Sector | Availability | Surplus/Deficit |
|---|---|---|
| Engineering and Technology | 6.43% | -93.57% |
| Natural and Applied Sciences | 3.09% | -96.91% |
| Business and Commerce | 121% | 21% |
| Agriculture | 12% | -88% |
| Medical and Health Sciences | 5% | -95% |
| Applied Arts and Humanities | 82% | -18% |
| Average | 38.25% | -61.75% |

this ambitious vision unfolds within a backdrop of severe resource constraints in scientific infrastructure, posing difficult questions about the efficiency of existing STEM departments in delivering on these goals (Hwami, 2024). Despite a national literacy rate exceeding 95%, Zimbabwe's last National Critical Skills Audit revealed a critical shortage in key STEM areas, with deficits of over 90% in engineering, natural sciences, and health sciences, as shown in **Table 1**.

This gap reflects not only a misalignment between graduate output and market needs but also systemic inefficiencies in how university resources are deployed and managed. Most public universities rely heavily on tuition fees, which are often pegged below operational cost levels due to regulatory controls (Ngcobo, Marimuthu & Stainbank, 2024). Consequently, departments are forced to stretch thin budgets across teaching, research, and infrastructure maintenance, with little room for innovation or experimentation. This raises fundamental concerns about whether STEM departments are operating efficiently, and whether marginal improvements in inputs could yield substantial gains in productivity and output (Chen & Chang, 2021).

Despite the policy turn toward Education 5.0, the funding envelope for Zimbabwean higher education has not expanded commensurately, creating a widening efficiency gap between mandated outputs and available inputs (Zishiri, Jekese & Muchabaiwa, 2024). In STEM departments, this gap is especially acute because laboratories, specialised equipment, consumables, and highly qualified academic staff are cost-intensive (Chirinda, Sunzuma & Muredzi, 2025). When resources are thin, departments may respond by increasing student–staff ratios, postponing equipment renewal, or curtailing research support, strategies that can depress both the level of technical efficiency and the rate of productivity change over time (Chasokela & Moyo, 2025). Yet, policy and managerial decisions continue to be made with scant empirical evidence on whether observed underperformance stems from pure technical inefficiency (doing things wrong), scale inefficiency (doing things at the wrong size), or technological regress (the production frontier itself shifting inward).

Globally, higher education systems have faced similar scrutiny, and the dominant empirical message is that efficiency is heterogeneous, path-dependent, and sensitive to how multi-output missions are modelled (Dipierro & De Witte, 2025). Studies using Data Envelopment Analysis (DEA) and the Malmquist Productivity Index consistently show that productivity change in universities is driven by both efficiency change (catching up to the frontier) and technological change (movement of the frontier) (Lou et al., 2024). Evidence shows sizeable dispersion in technical efficiency, particularly when funding contractions coincide with massification (Marshall, 2023). Moreover, STEM-heavy institutions or departments often appear less efficient in naïve models because their cost structures are higher and their outputs (for example, patents, prototypes, industry linkages) are poorly captured by traditional academic proxies such as publications or graduation counts, strengthening the case for a carefully specified DEA model tailored to STEM realities (Billing et al., 2023).

Thus, the need for efficiency measurement is particularly urgent in STEM fields. Without efficient resource utilisation, universities risk producing underprepared graduates, failing to meet national development goals, and squandering scarce financial inputs (Gabriel, 2023). Additionally, efficiency analysis can illuminate hidden capacity, departments that could produce more with existing resources, or reveal structural inefficiencies that require strategic investment (Luangpaiboon et al., 2024). At a time when Zimbabwean universities are being asked to do more with less, understanding efficiency is no longer optional; it is central to educational sustainability and national competitiveness.

This study applied the DEA-Malmquist approach to assess the efficiency and productivity change of STEM departments in a Zimbabwean university, offering a dynamic perspective on how departmental performance has evolved over time. The following section is the literature review.

# LITERATURE REVIEW

## Overview of Efficiency in Higher and Tertiary Education

Efficiency in higher and tertiary education refers to the extent to which institutions convert educational inputs, such as staff, funding, and infrastructure, into desirable outputs, including graduates, research, and innovation (Agasisti, 2023). In resource-constrained settings such as Zimbabwe, efficiency is not only a performance concern but a survival imperative. The literature distinguishes between technical efficiency (doing things right), allocative efficiency (using the right input mix), and scale efficiency (operating at an optimal size), each of which can constrain institutional performance in different ways (Andersson & Sund, 2022; Aparicio et al., 2023). While developed countries have long adopted performance-based funding and benchmarking to improve efficiency, developing countries face structural challenges, including underfunding, poor data systems, and weak accountability mechanisms (Lohmann et al., 2022; Plaček et al., 2024). Consequently, inefficiencies often go undiagnosed and unaddressed, particularly in capital-intensive departments such as STEM.

However, measuring efficiency in higher education is fraught with complexity due to the sector's multi-output, multi-input nature and the public-good character of many outputs (Naderi, 2022). Critics argue that the sector resists simple productivity metrics because not all outputs are quantifiable, and not all inputs are substitutable (Agasisti, 2023). Moreover, universities have diverse missions, some emphasize teaching, others research, and others community engagement, which complicates cross-institutional comparisons (Robbins & Adams, 2023). In Zimbabwe, the implementation of Education 5.0 has expanded this mandate even further, yet performance monitoring systems remain underdeveloped (Mutongoreni & Mbohwa, 2025). The gap between expected institutional outputs and available resources, what might be termed the efficiency gap, is widening, especially in STEM fields where teaching and research rely heavily on up-to-date technology and other resources inter alia (Chirinda et al., 2025). These contextual challenges made Zimbabwe an ideal case for exploring efficiency using non-parametric tools such as DEA.

## Theoretical Perspectives

The Resource-Based View (RBV) is a strategic management theory that explains how organisations achieve and sustain competitive advantage by effectively acquiring, developing, and utilising internal resources (Ristyawan et al., 2023). Introduced by Wernerfelt (1984) and later refined by Barney (1991), RBV posits that firms are heterogeneous in terms of their resource endowments and that performance differences arise when organizations possess resources that are valuable, rare, inimitable, and non-substitutable (VRIN). In the university context, such resources include highly skilled academic staff, advanced research infrastructure, and robust institutional reputation. STEM departments are typically resource-intensive and rely on the coordinated deployment of human, technological, and financial resources. However, the presence of these resources alone does not guarantee efficiency; rather, it is their effective mobilisation and utilisation, what RBV refers to as capability development, that drives superior performance (Kero & Bogale, 2023). The Zimbabwean context, where resource scarcity and capability gaps are widespread, underscores the relevance of RBV in diagnosing why some departments outperform others under similar constraints (Zishiri et al, 2024).

However, RBV does not provide a quantitative mechanism for measuring how efficiently these resources are used; this is where the CCR model of Data Envelopment Analysis (DEA) becomes relevant. The CCR model, developed by Charnes et al. (1978), enables empirical evaluation of resource efficiency by comparing how different departments convert multiple inputs (resources) into outputs (graduates, research, innovations). In essence, DEA operationalises RBV by providing a methodological framework to assess how effectively internal resources are transformed into performance outcomes (Arbelo et al., 2021).

## Conceptualisation of the DEA and Malmquist Approaches

Data Envelopment Analysis (DEA) is a non-parametric method used to assess the relative efficiency of peer entities, such as departments or institutions, by comparing them to a best-practice frontier derived from observed data (Khalid et al., 2025). Unlike parametric models, DEA does not assume a specific functional form, allowing it to model complex production environments with multiple inputs and outputs (Salas-Velasco, 2024). This feature is especially relevant to universities, where departments differ in focus, size, and resource mix. DEA assigns an efficiency score of 1 (or 100%) to units on the frontier and less than 1 to inefficient units, offering a diagnostic tool to identify underperforming areas (Ajibesin & Vajjhala, 2024). However, DEA has limitations; it is sensitive to outliers, lacks a statistical error term, and its results are contingent on the choice of inputs and outputs (Fotova Čiković & Lozić, 2022). Despite these limitations, DEA remains widely adopted in higher education performance studies due to its flexibility and intuitive appeal (Liu et al., 2025).

To move beyond static efficiency measurement, the Malmquist Productivity Index complements DEA by capturing productivity change over time (Visic & Kordić, 2021). It decomposes total factor productivity (TFP) into two components: efficiency change (how much a department is catching up to the frontier) and technological change (how the frontier itself shifts over time) (Brzezicki, 2025). This dynamic view is crucial in the higher education sector, particularly in STEM fields where changes in pedagogy, technology, and policy rapidly alter the production environment (Chirinda et al., 2025). For Zimbabwean universities transitioning under Education 5.0, the Malmquist Index can reveal whether departments are improving due to better internal management or broader shifts in the academic and technological landscape (Fu & See, 2022). Critically, this approach avoids the static fallacy of assuming that today's best practice remains optimal tomorrow, allowing a more realistic appraisal of long-term departmental performance under changing institutional and national conditions (Andrejić et al., 2021).

## Empirical Studies: The Application of DEA and Malmquist Approaches in Higher and Tertiary Education Institution Studies

Recent empirical literature reveals growing interest in the application of DEA and the Malmquist Productivity Index in assessing efficiency within higher education systems, particularly in resource allocation, productivity, and institutional competitiveness. For instance, Liu et al. (2025) utilised both DEA and Malmquist Index to evaluate the internationalization efficiency of higher vocational education across China's provinces, revealing regional disparities driven by technological advancement and government support. Their use of a three-stage DEA further underscores the importance of environmental variables in shaping efficiency scores, a nuance often ignored in basic DEA applications. Similarly, Ren and Kongkaew (2024), in their analysis of educational resource efficiency in Sichuan, China, found that technological regress was the key factor in declining productivity, highlighting that even technically efficient institutions may suffer productivity losses due to external or system-wide technological stagnation. These findings are echoed in Kouamo and Tameko's (2023) study of Cameroonian universities, where DEA-Malmquist revealed systemic inefficiencies and declining productivity due to the underutilization of available inputs. Together, these studies signal the importance of adopting dynamic, context-sensitive efficiency tools to unpack not only static performance gaps but also the drivers of productivity over time.

At a broader level, Almeida et al. (2024) call for an evolution in the use of DEA, advocating for integration with qualitative and environmental analyses to enrich future research. This critique is supported by Brintseva (2024), who applied the CRS-oriented DEA-Malmquist framework to compare Polish and Ukrainian universities, finding that well-established institutions often exhibit less productivity growth potential, thus complicating simplistic notions of benchmarking. Temoso et al. (2023) extended the traditional DEA to a network model, capturing interdepartmental efficiency interactions in South African universities, and exposing the influence of funding structures and academic qualifications on both teaching and research. Similarly, the Nigerian study by Akinadewo and Odewole (2023) emphasizes efficiency not just in academic outputs but also in financial sustainability, using DEA to evaluate internally generated revenue among federal institutions. These diverse applications illustrate DEA's methodological flexibility but also caution against one-size-fits-all interpretations. The study's methods were examined next.

# METHODS

## DEA Model

Charnes et al. (1978) introduced the CCR model that evaluates the relative efficiency of Decision-Making Units. In this study, CCR was used. It is the first linear programming model of DEA that sought to maximise the relative efficiency score of the decision-making unit by selecting the set of weights for all the inputs and output variables. In this model, the score of each DMU must be less than or equal to 1. Where a score of one shows the most efficient, and 0 is the least efficient. This model calculates the overall efficiency for each decision-making unit, thus both pure technical efficiency and scale efficiency are aggregated into one value.

$DMU_j$ = The $j^{th}$ decision-making unit

$x_{ij}$ =The $i^{th}$ input of the $j^{th}$ decision making unit (where i=1,2,3..................9)

$y_{rj}$= The $r^{th}$ output of the $j^{th}$ decision making unit (where r=1, 2, 3 ................5)

$v_i$= The weight assigned to the $i^{th}$ input

$u_r$= The weight assigned to the $r^{th}$ output

$EF_j$=The efficiency of the $j^{th}$ decision making unit

Therefore, efficiency is defined as the ratio of the weighted sum of outputs to inputs.

$$\theta = EF_j = \frac{u_1y_{1j}+u_2y_{2j}+u_3y_{3j}+\cdots..+u_7y_{7j}}{v_1x_{1j}+v_2x_{2j}+v_3x_{3j}+v_{12}x_{12j}}$$

The CCR model equation (5) is as follows:

$$Max\ \theta$$

Subject to:

$$\frac{u_1y_{1j}+u_2y_{2j}+\dots\dots\dots\dots.+u_ry_{rj}}{v_1x_{1j}+v_2x_{2j}+\cdots\dots\dots\dots.+v_ix_{ij}} \leq 1$$

$$v_1\,, v_2, \dots\dots\dots\dots\dots\dots., v_i \geq 0$$

$$u_1, u_2\,, \dots\dots\dots\dots\dots, u_r \geq 0$$

The CCR model measures overall technical efficiency inclusive of scale effects. Decomposition into pure technical and scale efficiency is not attempted here, but is noted as a limitation. The choice of the CCR (constant returns to scale) model over the BCC (variable returns to scale) model is further justified by the nature of the Zimbabwean higher education context. In resource-constrained settings where departments are expected to operate under uniform policy mandates and standardised funding structures, the assumption of proportional scaling between inputs and outputs is theoretically defensible (Charnes et al., 1978). Specifically, the Education 5.0 framework applies the same five-mandate requirement across all STEM departments regardless of size, implying that scale is not a distinguishing factor in this setting. As Arbelo et al. (2021) note, the CCR model is particularly appropriate when the objective is to evaluate overall resource transformation efficiency without disaggregating scale effects, which aligns with the managerial and policy focus of this study. Moreover, given the small number of DMUs (n = 33) relative to the number of variables, the CCR model produces more discriminating and stable scores than the BCC model, which can inflate efficiency estimates in small samples (Chen & Chang, 2021). Thus, while the BCC model offers conceptual richness, its application would risk overstating departmental efficiency in a setting where scale differences are largely externally imposed rather than strategically determined.

## Malmquist Index

Malmquist Index is a measure of productivity change over time (Visic & Kordić, 2021). It focuses on both technical efficiency and technological progress. It is a way to evaluate the efficiency and productivity of decision-making units (DMUs) in different time periods. The Malmquist index is calculated using the following formula:

$$Malmquist\ Index(MI) = \frac{Efficiency\ at\ time(t+1)}{Efficiency\ at\ time(t)} \times \frac{Technology\ at\ time\ (t+1)}{Technology\ at\ time\ (t)}$$

The Malmquist Index is composed of two main components:

1. Efficiency change (EC)- Measures the change in efficiency of a DMU over time
2. Technology change (TC)- Measures the shift in the production frontier over time, indicating technological progress or regress

Technology change (TC) is calculated as:

$$TC = \frac{D^{t+1}}{D^t}$$

Where:

$D^{t+1}$ is the distance function at time t+1

$D^t$ is the distance function at time t

$$D^t = \frac{1}{\theta(t)}$$

## Research Variables

**Table 2** shows the list of input and output variables and their sources. For the sake of simplicity, the input variables were denoted as X, and the output variables were denoted as Y. There were nine input variables and five output variables. The variables were categorised into two groups: the most cited and the least cited. Publications (Y2) were counted for the period 2023–2024, limited to journal articles with departmental affiliation. Citations (Y5) were retrieved from Google Scholar using the same affiliation filter. Duplicates were manually removed. **Table 3** shows the most cited variables; the results found in these variables were used in drawing conclusions. From an RBV perspective, academic staff (X2), budget (X3), programmes (X6), and teaching assistants (X9) represent valuable, non-substitutable resources. Graduates (Y1) and publications (Y2) are key outputs that reflect resource deployment. DEA operationalises RBV by measuring how efficiently these resources convert into outputs. Most cited variables reflect established practice in higher education DEA studies and were cross-checked for relevance to Zimbabwe's Education 5.0 context (for example, programmes

**Table 2.** Input and output variables with their sources

| Inputs variables | $X_i$ | Sources of Data |
|---|---|---|
| Number of undergraduate students | $x_1$ | Admissions department |
| Number of academic staff | $x_2$ | Human resources Department |
| Allocated -operational department budget | $x_3$ | Accounts department |
| Number of taught modules | $x_4$ | Admissions department |
| Number of postgraduate students | $x_5$ | Admissions department |
| Number of departmental programs | $x_6$ | Admissions department |
| Number of academic staff laptops | $x_7$ | ICTS department |
| Number of technical personnel | $x_8$ | ICTS department |
| Number of teaching assistants | $x_9$ | Human resources department |
| Outputs variables | $Y_k$ | Sources of Data |
| Number of graduates | $y_1$ | Admissions department |
| Number of publications | $y_2$ | The author |
| Number of PhD graduates | $y_3$ | Admission department |
| Research grants | $y_4$ | Research department |
| Number of citations | $y_5$ | Google Scholar |

**Table 3.** Most cited variables

| Most cited variables | Denotation |
|---|---|
| Number of academic staff | $x_2$ |
| Allocated -operational department budget | $x_3$ |
| Number of departmental programs | $x_6$ |
| Number of teaching assistants | $x_9$ |
| Number of graduates | $y_1$ |
| Number of publications | $y_2$ |
| Research grants | $y_4$ |
| Number of citations | $y_5$ |

and graduates align with national skills goals. With 33 DMUs and 6 variables (4 inputs, 2 outputs), the sample meets the common rule-of-thumb (DMUs ≥ 3 × (inputs + outputs)).

# RESULTS

Descriptive statistics gave a first-hand understanding of the data. Measures of central tendency and of dispensation for the data were examined in terms of the mean, upper-quartile, lower-quartile, variance, and standard deviation for each variable. **Table 4** shows the descriptive statistics of each variable. The count column showed the number of departments in the study.

**Table 4.** Descriptive statistics

| Description | Count | Mean | St-dev | Minimum | Maximum |
|---|---|---|---|---|---|
| X1 | 33 | 247.42 | 144.25 | 13 | 617 |
| X2 | 33 | 9.21 | 3.85 | 2 | 17 |
| X3 | 33 | 38105.50 | 33252.54 | 12475.01 | 124750.14 |
| X4 | 33 | 46.15 | 26.32 | 7 | 105 |
| X5 | 33 | 20.27 | 29.38 | 0 | 123 |
| X6 | 33 | 3.18 | 2.44 | 1 | 15 |
| X7 | 33 | 5.94 | 3.46 | 0 | 15 |
| X8 | 33 | 1.06 | 1.30 | 0 | 5 |
| X9 | 33 | 1.15 | 1.39 | 0 | 6 |
| Y1 | 33 | 56.85 | 46.09 | 0 | 183 |
| Y2 | 33 | 5.27 | 6.38 | 0 | 25 |
| Y3 | 33 | 0.21 | 0.65 | 0 | 3 |
| Y4 | 33 | 1262.18 | 3546.70 | 0 | 16771.77 |
| Y5 | 33 | 58.88 | 64.15 | 0 | 230 |

The second column calculated the mean of each variable for 33 departments. Correlation analysis was used to measure and analyse the degree of relationship between variables.

**Figure 1** shows the correlation matrix for the input variables. All the correlation coefficients > 0.5 were highly correlated, thus they give the same information. The most cited input variables were not correlated, thus they gave significant information. A correlation threshold of 0.5 was applied pragmatically to avoid multicollinearity, which can distort DEA weights. This follows common practice (for example, Gökşen et al., 2015), while recognising that correlated variables may still be conceptually distinct. It is important to acknowledge, however, that correlation-based exclusion is a statistical heuristic rather than a definitive guide to variable relevance. A variable may be statistically correlated with another yet remain conceptually distinct and theoretically important. For example, the number of undergraduate students (X1) and the number of graduates (Y1) are likely correlated but represent fundamentally different stages of the educational production process. Similarly, the number of taught modules (X4) may correlate with academic staff (X2) yet reflects a distinct dimension of departmental workload and curriculum breadth. By excluding such variables on correlation grounds alone, there is a risk of omitting inputs or outputs that are conceptually meaningful within Zimbabwe's Education 5.0 framework, particularly those related to teaching load and innovation outputs.

Future studies should consider complementing correlation screening with expert judgment or principal component analysis to ensure that the final variable set balances statistical parsimony with conceptual completeness (Almeida et al., 2024). In this study, the final variable set was validated against the most-cited variables in the DEA higher education literature and cross-checked for alignment with national STEM performance priorities, providing a reasonable basis for confidence in the selected specification. **Figure 2** shows the correlation matrix for the output variables. All the correlation coefficients > 0.5 were highly correlated, therefore, to remove repetition, one of the variables had to be dropped. Initial correlation analysis (Figs. 1–2) showed redundancy among several variables (r ≥ 0.5). Following the flow chart (Fig. 3), we retained non-redundant variables most cited in the literature. The final DEA model uses 4 inputs (X2, X3, X6, X9) and 2 outputs (Y1, Y2). All reported results refer to this final specification. **Figure 3** shows the flow chart diagram in terms of the steps taken to identify the input and output variables. From the diagram, the variables that were used in this analysis were; 4 input variables and 2 output variables. These were: the number of graduates and the number of publications as outputs; and then for inputs, there was the number of academic staff, allocated departmental operational- budget, number of teaching assistants and number of programmes. Data visualisation gave a good understanding of data in pictorial form.

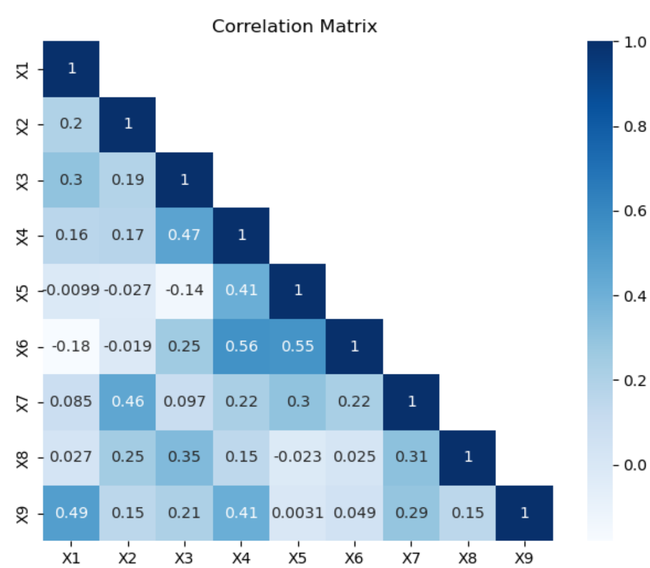


**Figure 1.** Correlation matrix for input variables

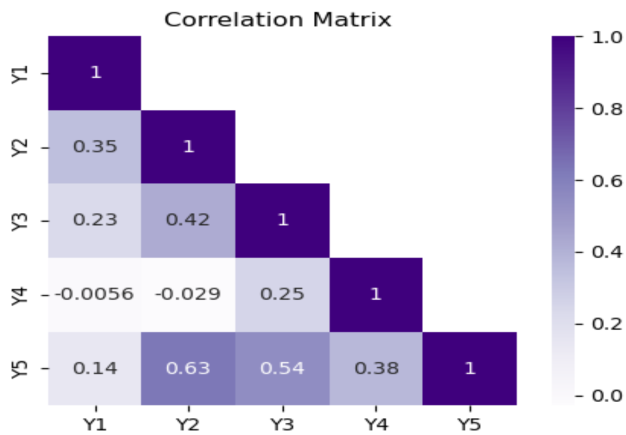


**Figure 2.** Correlation matrix for the output variable

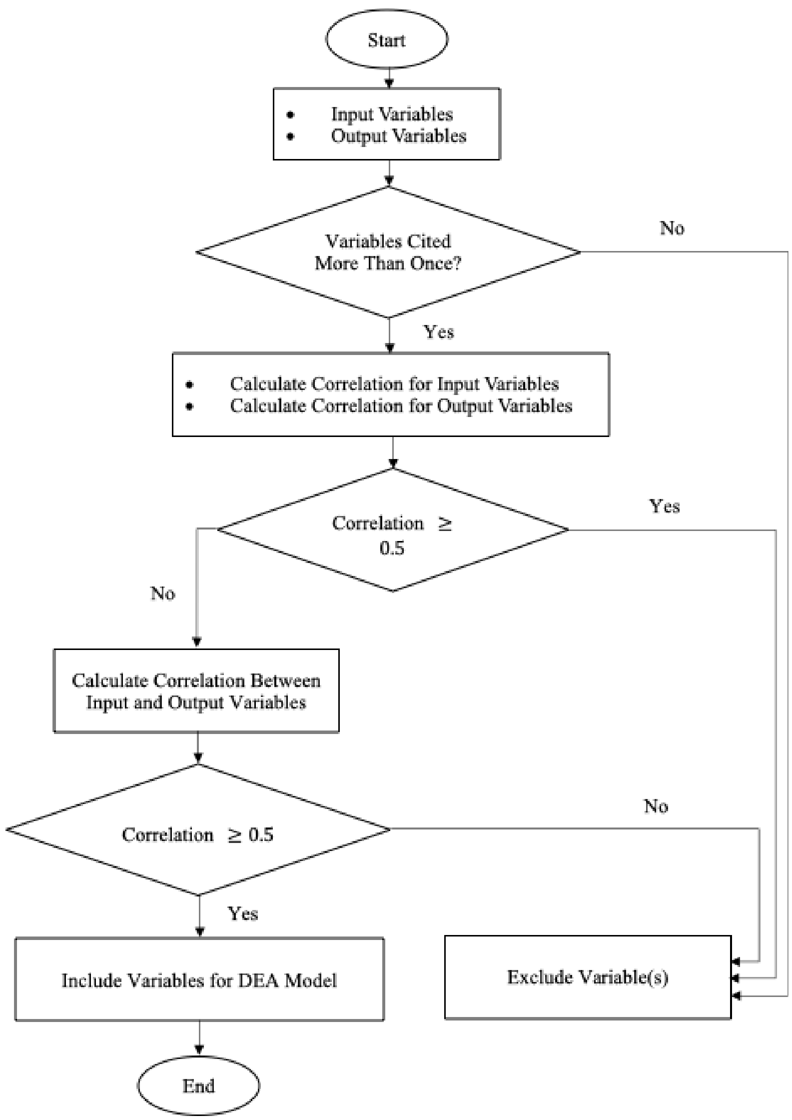


**Figure 3.** Flow chart diagram for variable selection

The number of undergraduate students for both 2023 and 2024 is shown in the **Supplementary**. The x-axis showed that the departments numbered from 1 to 33. Department number 1 in 2023 had over 250 undergraduate students, and in 2024 it had exactly 300 students. Different colours were used to show the number of undergraduates for 2024. Scatter plots were used in paired comparisons to check the linear relationship. In terms of the number of undergraduates compared to the number of graduates is given in the **Supplementary**. In this case, the size of dots in the scatter plot showed the year for the variable, and the colour of the dot showed the variable name. In the pie chart, the variables with monetary values were removed so as to avoid bias in the distribution of percentages (see **Supplementary**).

**Table 5** shows the efficiency scores for both 2023 and 2024. Departments with an efficiency score of less than one were deemed inefficient. **Table 6** shows the input slack variables for 2024; the slack variables show how much an input value could be reduced without affecting the output. For instance, in DMU29, the input variable had a slack of 3.624. Thus, the efficient level could be the current level minus 3.624 units. The output slack variables showed how much an output value could be reduced without utilising additional input. For instance, in DMU32, the output variable had a slack of 3.460. Thus, the efficient level could be the current level plus 3.460 units. More precisely, an input slack for a given DMU indicates the quantity by which that input can be proportionally reduced, after radial contraction to the efficiency frontier, without reducing any output below its observed level.

**Table 5.** Efficiency scores for the most cited variables

| | Efficiency scores-most cited variables | |
|---|---|---|
| | 2023 | 2024 |
| DMU1 | 0.525 | 0.511 |
| DMU2 | 0.202 | 0.487 |
| DMU3 | 0.794 | 0.154 |
| DMU4 | 0.747 | 0.316 |
| DMU5 | 0.882 | 0.750 |
| DMU6 | 0.704 | 1.000 |
| DMU7 | 1.000 | 0.616 |
| DMU8 | 0.557 | 0.423 |
| DMU9 | 1.000 | 0.418 |
| DMU10 | 1.000 | 1.000 |
| DMU11 | 0.758 | 1.000 |
| DMU12 | 0.636 | 0.600 |
| DMU13 | 0.710 | 1.000 |
| DMU14 | 1.000 | 1.000 |
| DMU15 | 0.426 | 0.931 |
| DMU16 | 0.615 | 1.000 |
| DMU17 | 1.000 | 0.966 |
| DMU18 | 0.614 | 0.122 |
| DMU19 | 0.531 | 1.000 |
| DMU20 | 0.834 | 0.904 |
| DMU21 | 1.000 | 0.990 |
| DMU22 | 0.684 | 0.820 |
| DMU23 | 0.642 | 1.000 |
| DMU24 | 0.402 | 0.936 |
| DMU25 | 0.277 | 1.000 |
| DMU26 | 0.358 | 1.000 |
| DMU27 | 0.924 | 1.000 |
| DMU28 | 0.553 | 1.000 |
| DMU29 | 0.195 | 0.362 |
| DMU30 | 0.871 | 1.000 |
| DMU31 | 1.000 | 1.000 |
| DMU32 | 1.000 | 0.200 |
| DMU33 | 0.731 | 1.000 |

It therefore represents non-radial waste that remains after the initial projection onto the frontier. An output slack, by contrast, indicates the quantity by which an output must be augmented — without consuming additional inputs, for the DMU to reach its target on the efficient frontier. For DMU29, for example, an input slack of 3.624 on academic staff (X2) means that, having already contracted all inputs proportionally to achieve the frontier, the department carries an additional surplus of 3.624 staff units that confer no incremental output benefit. Correspondingly, an output slack of 3.460 for DMU32 on publications (Y2) means that this department must increase its publication output by 3.460 units, without increasing any input, to achieve full technical efficiency. These values, therefore, provide actionable targets: departments should reduce input slacks through redeployment or reassignment and address output slacks through targeted research and graduation support (Luangpaiboon et al., 2024).

A list of highly efficient DMUs that were benchmarking targets is shown in the **Supplementary**. This meant inefficient departments should improve their efficiency. For instance, DMU18 benchmarked DMU9 and DMU17 in 2023. A frequency reference set shows the number of DMUs that each of the other listed DMUs benchmarks. For instance, DMU 28 benchmarks 8 DMUs (see **Supplementary**). According to **Figure 4**, for instance, DMU 14 benchmarks 12 DMUs.

**Table 6.** Input Slack variables for 2024

| | 1 | 2 | 3 | 4 | 1 | 2 |
|---|---|---|---|---|---|---|
| DMU1 | 0.000 | 1406.585 | 0.000 | 0.000 | 0.000 | 3.751 |
| DMU2 | 0.000 | 5108.434 | 0.000 | 0.000 | 0.000 | 0.000 |
| DMU3 | 0.000 | 53.040 | 0.000 | 0.356 | 0.000 | 4.180 |
| DMU4 | 0.000 | 457.212 | 0.000 | 0.0 | 0.000 | 1.050 |
| DMU5 | 1.897 | 0.000 | 0.000 | 3.308 | 0.000 | 4.301 |
| DMU6 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DMU7 | 0.000 | 0.000 | 0.000 | 0.007 | 0.000 | 0.000 |
| DMU8 | 0.000 | 524.192 | 0.000 | 0.00 | 0.000 | 6.239 |
| DMU9 | 0.000 | 6393.056 | 0.000 | 0 | 0 | 10.983 |
| DMU10 | 0.000 | 0.000 | 0.000 | 0 | 0 | 0 |
| DMU11 | 0.000 | 0.000 | 0.00 | 0.00 | 0.000 | 0 |
| DMU12 | 0.000 | 5231.541 | 0.000 | 0.000 | 0.000 | 0.000 |
| DMU13 | 0.000 | 0.000 | 0.00 | 0 | 0 | 0 |
| DMU14 | 0.000 | 0.000 | 0.00 | 0 | 0 | 0 |
| DMU15 | 0.000 | 1064.673 | 0.000 | 0.000 | 0.000 | 9.258 |
| DMU16 | 6.000 | 0.000 | 0.000 | 0.0 | 0.000 | 2.000 |
| DMU17 | 12.941 | 0.000 | 0.000 | 0.000 | 0.000 | 6.997 |
| DMU18 | 0.449 | 0.000 | 0.000 | 0 | 0 | 0.443 |
| DMU19 | 0.000 | 0.000 | 0.000 | 0 | 0 | 0 |
| DMU20 | 0.000 | 904.241 | 0 | 0 | 0 | 10.027 |
| DMU21 | 8.152 | 0.000 | 0.000 | 0 | 0.000 | 4.373 |
| DMU22 | 0.000 | 1922.668 | 0.000 | 0.000 | 0.000 | 13.478 |
| DMU23 | 0.000 | 0.000 | 0.000 | 0.0 | 0.000 | 3.000 |
| DMU24 | 10.589 | 0.000 | 0.000 | 0.000 | 0.000 | 8.970 |
| DMU25 | 0.000 | 0.000 | 0.000 | 0.00 | 0.000 | 0.000 |
| DMU26 | 0.000 | 0.000 | 0.000 | 0.00 | 0.000 | 0.000 |
| DMU27 | 0.000 | 0.000 | 0.000 | 0.00 | 0.000 | 0.000 |
| DMU28 | 0.000 | 0.000 | 0.000 | 0.00 | 0.000 | 0.000 |
| DMU29 | 3.624 | 4011.954 | 0.000 | 0.00 | 0.000 | 2.356 |
| DMU30 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DMU31 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| DMU32 | 0.000 | 0.000 | 0.000 | 0.000 | 3.460 | 0.000 |
| DMU 33 | 0 | 0 | 0 | 0 | 0 | 0 |

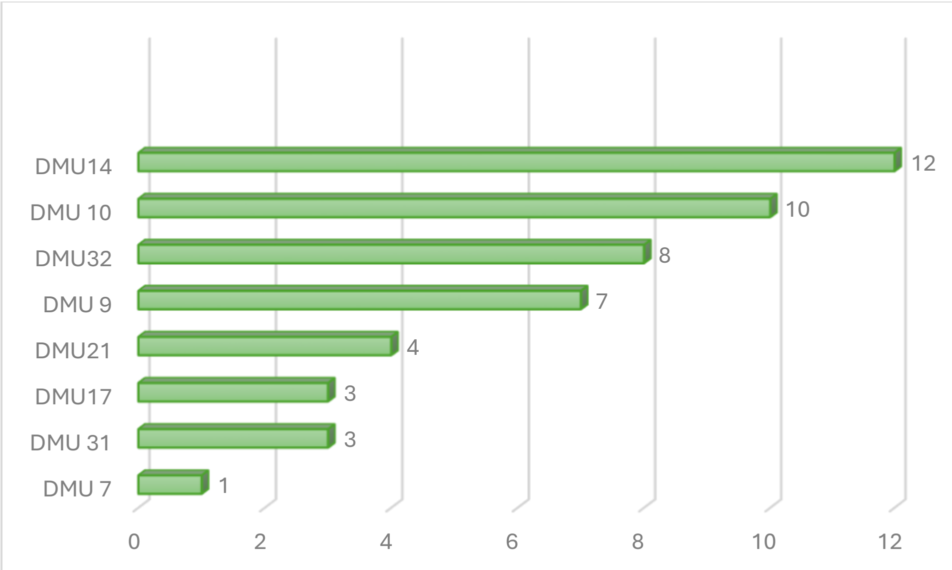


**Figure 4.** Frequency reference set for 2023

The output target variable showed that the prevailing output level was inadequate (**Supplementary**). For instance, DMU 33 with the output variable 2 had a value of 47. This meant that DMU 33 should be increased by 47 units to achieve efficiency, as shown in the **Supplementary**. The input target variable showed that the current output level was excessive. For instance, DMU 27 with the input variable 1 had a value of 8. This meant that DMU 27 should be decreased by 8 units to achieve efficiency. To clarify the interpretation, the output target variable represents the minimum output level a DMU must achieve to be considered technically efficient, given its observed inputs. A value above the DMU's current output, therefore, signals an output shortfall.

For DMU33, the target value of 47 for output variable 2 (Y2, publications) means that the department needs to produce 47 additional publications above its current level, without any increase in inputs, to reach the efficient frontier. Conversely, the input target variable represents the maximum input level a DMU may use while remaining efficient, given its observed outputs. A value below the DMU's current input signals an input excess. For DMU27, the target value of 8 for input variable 1 (X2, academic staff) means the department should operate with no more than 8 academic staff members to be efficient, implying a reduction from its current level. Together, input and output targets constitute the efficiency projection: the point on the DEA frontier that is closest to the DMU in input-output space, and toward which the department should move to eliminate inefficiency (Charnes et al., 1978).

The output slack variables for 2023 are shown in the **Supplementary**. The slack variables showed how much an output value could be reduced without utilising additional input. For instance, in DMU28, the output variable had a slack of 5.368. Thus, the efficient level could be the current level plus 5.368 units. The slack variables showed how much an input value could be reduced to without affecting the output. For instance, in DMU25, the input variable 3 had a slack of 0.031. Thus, the efficient level could be the current level minus 0.031 units. An output slack indicates the additional output that a DMU must generate, without consuming any further inputs, to reach its efficient frontier projection. It therefore signals an underutilisation of productive capacity. For DMU28 in 2023, an output slack of 5.368 on variable 1 (Y1, graduates) means the department could have produced 5.368 additional graduates with no increase in its inputs. An input slack for 2023, by contrast, indicates the residual excess of a given input that remains after the radial reduction to the frontier. For DMU25, an input slack of 0.031 on variable 3 (X6, departmental programmes) means the department carries 0.031 surplus programme units beyond what its efficient peers require to produce the same outputs. These values together enable managers to identify both where capacity is being left unused (output slacks) and where resources are being over-deployed (input slacks), providing a dual lens for operational improvement (Ajibesin & Vajjhala, 2024).

The output target variable showed that the current output level was inadequate. For instance, DMU 33 with the output variable had a value of 165. This meant that DMU 33 should be increased by 165 units to achieve efficiency as shown in the **Supplementary**. The input target variable showed that the current output level was excessive. For instance, DMU 30 with the input variable 1 had a value of 6.095. This meant that DMU 30 should be decreased by 6.095 units to achieve efficiency. More precisely, for 2023, the output target variable for DMU33 of 165 on output variable 1 (Y1, graduates) indicates that the department needed to produce 165 graduates to be efficient in 2023; that is, this is the frontier projection of its graduate output, not the additional amount needed. The gap between the target (165) and its actual output, therefore, represents the combined radial and slack shortfall. Correspondingly, the input target variable for DMU30 of 6.095 on input variable 1 (X2, academic staff) indicates that, to operate efficiently in 2023, DMU30 should have deployed no more than 6.095 staff members; any deployment above this level constitutes an input excess relative to the frontier. This distinction between the target value (the efficient frontier projection) and the slack value (the non-radial residual excess or shortfall) is important: targets include both radial scaling and slacks, whereas slacks capture only the non-radial component (Charnes et al., 1978).

**Table 7** and **Figure 5** showed the sensitivity analysis. This highlighted what would be the efficiency score per department if one of the identified variables had been left out. It was clearly seen that dropping the number of graduates had a big effect, as it led to some departments having an efficiency score of zero, and the mean efficiency score was the lowest.

**Table 7.** Sensitivity analysis for the 2024 data

| | Efficiency Score after dropping one variable at a time | | | | | |
|---|---|---|---|---|---|---|
| DMUs | None | X3 | X2 | X6 | X9 | Y1 |
| DMU 1 | 0.511 | 0.511 | 0.503 | 0.275 | 0.366 | 0.511 |
| DMU 2 | 0.487 | 0.487 | 0.296 | 0.164 | 0.477 | 0.263 |
| DMU 3 | 0.154 | 0.154 | 0.081 | 0.148 | 0.154 | 0.154 |
| DMU 4 | 0.316 | 0.316 | 0.311 | 0.177 | 0.231 | 0.316 |
| DMU 5 | 0.75 | 0.35 | 0.75 | 0.465 | 0.75 | 0.75 |
| DMU 6 | 1 | 0.943 | 0.889 | 0.827 | 1 | 1 |
| DMU 7 | 0.616 | 0.571 | 0.555 | 0.483 | 0.616 | 0.609 |
| DMU 8 | 0.423 | 0.423 | 0.418 | 0.169 | 0.225 | 0.423 |
| DMU 9 | 0.418 | 0.418 | 0.351 | 0.272 | 0.279 | 0.418 |
| DMU10 | 1 | 1 | 0.948 | 0.872 | 0.924 | 1 |
| DMU 11 | 1 | 0.858 | 1 | 0.557 | 1 | 0.898 |
| DMU 12 | 0.6 | 0.6 | 0.523 | 0.332 | 0.505 | 0.533 |
| DMU 13 | 1 | 1 | 1 | 0.317 | 1 | 1 |
| DMU 14 | 1 | 1 | 1 | 0.877 | 1 | 1 |
| DMU 15 | 0.931 | 0.931 | 0.877 | 0.278 | 0.297 | 0.931 |
| DMU 16 | 1 | 0.82 | 1 | 0.427 | 0.423 | 1 |
| DMU 17 | 0.966 | 0.799 | 0.966 | 0.296 | 0.347 | 0.966 |
| DMU 18 | 0.122 | 0.117 | 0.122 | 0.062 | 0.066 | 0.122 |
| DMU 19 | 1 | 0.891 | 1 | 0.707 | 0.436 | 1 |
| DMU 20 | 0.904 | 0.904 | 0.859 | 0.185 | 0.229 | 0.904 |
| DMU 21 | 0.99 | 0.82 | 0.99 | 0.394 | 0.399 | 0.99 |

**Table 7.** ***Contiuned***

| | Efficiency Score after dropping one variable at a time | | | | | |
|---|---|---|---|---|---|---|
| DMU 22 | 0.82 | 0.82 | 0.75 | 0.086 | 0.222 | 0.82 |
| DMU 23 | 1 | 0.891 | 1 | 0.707 | 0.423 | 1 |
| DMU 24 | 0.936 | 0.799 | 0.936 | 0.232 | 0.282 | 0.936 |
| DMU 25 | 1 | 0.723 | 1 | 1 | 1 | 1 |
| DMU 26 | 1 | 1 | 1 | 1 | 1 | 1 |
| DMU 27 | 1 | 0.577 | 1 | 1 | 0.541 | 1 |
| DMU 28 | 1 | 0.984 | 1 | 1 | 1 | 0.692 |
| DMU 29 | 0.362 | 0.362 | 0.362 | 0.079 | 0.127 | 0.362 |
| DMU 30 | 1 | 1 | 1 | 0.936 | 1 | 1 |
| DMU 31 | 1 | 1 | 1 | 0.592 | 0.943 | 1 |
| DMU 32 | 0.2 | 0.198 | 0.168 | 0.183 | 0.168 | 0.12 |
| DMU 33 | 1 | 1 | 1 | 1 | 1 | 1 |

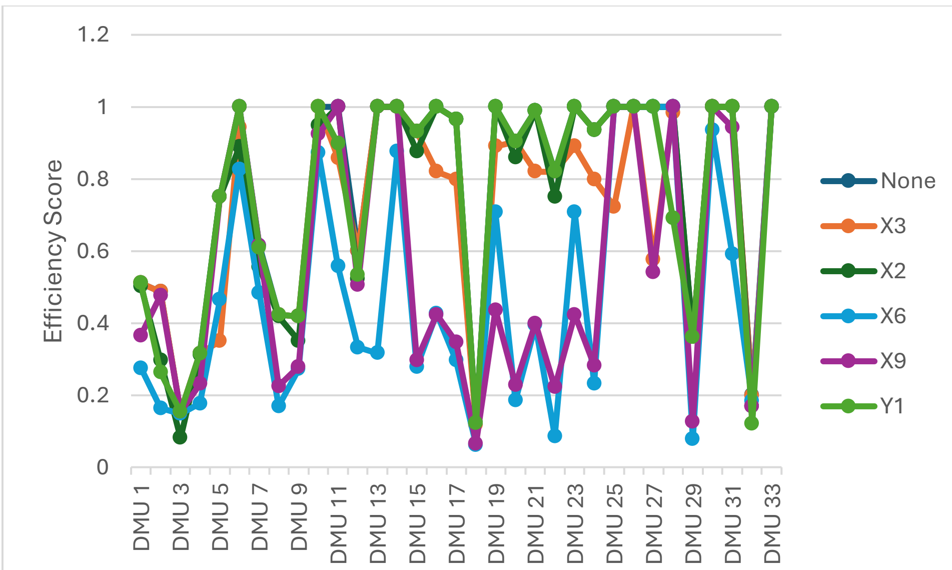


**Figure 5.** Efficiency score sensitivity graph

From **Table 8**, DMU 33 had a Malmquist index (MI) of 1.367989, showing an increase in technological change. A Malmquist score >1 shows an increase in productivity change. Among improving DMUs, most gains came from efficiency change rather than technological progress, indicating catch-up rather than frontier shift. This distinction between efficiency change and technological change carries important interpretive implications for Zimbabwe's higher education environment. Efficiency change (EC) reflects the degree to which a department is converging toward the best-practice frontier defined by the most productive peers in the same time period. A value of EC > 1 indicates that a department is catching up to its efficient peers, meaning it is making better use of its existing resources over time. By contrast, technological change (TC) captures shifts in the frontier itself, reflecting whether the overall best-practice level of performance has improved or deteriorated across all departments. A TC > 1 indicates that the frontier has expanded, driven by innovation, infrastructure improvements, or paradigm shifts in academic delivery. In this study, the predominance of EC over TC among improving DMUs suggests that departmental gains were largely managerial in nature, rooted in improved administration, better deployment of existing staff, and more effective programme management, rather than in system-wide technological advancement. This pattern is consistent with Dipierro and De Witte (2025), who found that managerial efficiency was the primary driver of performance in underfunded European universities. The near-absence of positive TC signals suggests that Zimbabwe's STEM departments have not yet benefited from a genuine technological frontier shift, likely because infrastructure deficits, limited research funding, and constrained access to advanced laboratory equipment continue to suppress the academic production frontier (Chirinda et al., 2025). Departments such as DMU3 (MI = 0.194) and DMU18 (MI = 0.199) experienced productivity decline in both components, suggesting compounding inefficiencies that require targeted managerial and infrastructural interventions. Conversely, high-performing departments such as DMU25 (MI = 3.610) and DMU26 (MI = 2.793) achieved strong catch-up gains, indicating that significant productivity improvements are achievable within existing resource constraints when departments manage their inputs effectively. These findings reinforce the argument that, under Education 5.0, the most actionable lever available to Zimbabwean STEM departments in the short-to-medium term is efficiency improvement rather than frontier advancement, underscoring the continued relevance of resource reallocation and benchmarking strategies recommended in this study (Zishiri et al., 2024).

**Table 8.** Malmquist index score

| DMU | MI |
|---|---|
| DMU1 | 0.973333 |
| DMU2 | 2.410891 |
| DMU3 | 0.193955 |
| DMU4 | 0.423025 |
| DMU5 | 0.85034 |
| DMU6 | 1.420455 |
| DMU7 | 0.616 |
| DMU8 | 0.759425 |
| DMU9 | 0.418 |
| DMU10 | 1 |
| DMU11 | 1.319261 |
| DMU12 | 0.943396 |
| DMU13 | 1.408451 |
| DMU14 | 1 |
| DMU15 | 2.185446 |
| DMU16 | 1.626016 |
| DMU17 | 0.966 |
| DMU18 | 0.198697 |
| DMU19 | 1.883239 |
| DMU20 | 1.083933 |
| DMU21 | 0.99 |
| DMU22 | 1.19883 |
| DMU23 | 1.557632 |
| DMU24 | 2.328358 |
| DMU25 | 3.610108 |
| DMU26 | 2.793296 |
| DMU27 | 1.082251 |
| DMU28 | 1.808318 |
| DMU29 | 1.85641 |
| DMU30 | 1.148106 |
| DMU31 | 1 |
| DMU32 | 0.2 |
| DMU33 | 1.367989 |

# DISCUSSION

The findings of this study reveal that the proportion of efficient departments rose from 24% (2023) to 45% (2024). These results align with recent DEA-based studies in higher education, though there are notable differences in context and methodology. For example, Liu et al. (2025) found similar efficiency improvements in Chinese vocational institutions, attributing gains to technological advancements and government support. However, such factors are less prominent in Zimbabwe's resource-constrained setting. By contrast, our results differ from Ren and Kongkaew's (2024) study in Sichuan, where technological decline was the main cause of reduced productivity, whereas Zimbabwean departments showed progress despite infrastructural limitations.

The Malmquist Index analysis indicated that 55% of departments experienced productivity growth, primarily due to improved efficiency rather than technological advancements. This finding supports Dipierro and De Witte's (2025) European study, which identified managerial efficiency as a key factor in underfunded institutions. However, our results contrast with Almeida et al. (2024), who found that frontier shifts (technological change) were the main driver of productivity in well-resourced universities. This difference highlights how resource availability shapes efficiency outcomes.

The sensitivity analysis showed that departmental programmes and graduate output were the most influential variables, a pattern also observed by Temoso et al. (2023) in South African universities. However, unlike their study, which identified funding structures as the primary efficiency factor, our research emphasised staffing and budget allocation as critical. This divergence likely reflects Zimbabwe's unique financial constraints (Zishiri et al., 2024). The benchmarking framework further revealed inefficiencies in resource use (Brzezicki, 2025). Slack analysis suggests that reallocating excess inputs (for example, staff or budget) could potentially improve efficiency, though direct evidence of reallocation outcomes requires further study.

Finally, the study's focus on slack variables aligns with Salas-Velasco's (2024) nonparametric efficiency analysis, which recommended reducing unnecessary inputs in underperforming units. However, while their research proposed institutional mergers for scale efficiency, our findings suggest that internal restructuring is more feasible for Zimbabwean STEM faculties, given their smaller scale. These findings contribute to global debates on higher education efficiency while offering solutions for resource-limited environments. To strengthen the practical relevance of these findings, it is important to draw explicit linkages between the empirical results and the specific managerial actions they suggest. First, the slack analysis (**Tables 9** and **6**) identifies that DMU29 carries excess academic staff (slack = 3.624) and budget (slack = 4,011.95), while simultaneously underperforming in graduate output. This finding directly supports the recommendation that university management should initiate a formal resource redeployment review for DMU29, redirecting surplus staffing capacity toward postgraduate supervision and grant-writing support, activities that would directly increase the output variables most influential in efficiency scoring (Luangpaiboon et al., 2024). Second, the sensitivity analysis (**Table 7**) shows that dropping programme offerings (X6) produced the largest decline in efficiency scores across nearly all departments, with DMU2 falling from 0.487 to 0.164.

This finding provides a direct empirical basis for the recommendation that academic planning committees should prioritise programme portfolio reviews, ensuring that departments maintain a minimum number of accredited, enrolment-viable programmes as a condition for budget allocation. Third, the persistence of only three departments (DMU10, DMU14, DMU31) at full efficiency across both years provides a robust, evidence-based case for establishing a formal peer-learning structure. University management should facilitate structured visits, practice-sharing seminars, or joint curriculum reviews between these consistently efficient departments and the lowest performers (for example, DMU18 with a score of 0.122 in 2024 and DMU3 with 0.154), thereby operationalising the benchmarking framework identified through the frequency reference sets (Figures 7 and 8). These targeted managerial actions, grounded directly in the study's quantitative findings, provide a practical pathway for institutional improvement that is both evidence-based and feasible within Zimbabwe's resource-constrained environment (Zishiri et al., 2024).

While the efficiency scores of top-performing departments such as DMU10, DMU14, and DMU33 are encouraging from a resource utilisation perspective, it is important to interpret these results through a critical lens. From a critical digital pedagogy perspective, high DEA efficiency scores may, in part, reflect an intensification of digital labour rather than genuine improvements in learning quality or institutional equity. As Ncube and Tawanda (2025) argue, the adoption of digital tools in resource-constrained higher education settings can inadvertently reproduce existing power asymmetries: departments that appear efficient under standard DEA metrics (maximising graduates and publications relative to inputs) may be achieving these outputs by increasing reliance on online platforms that shift the burden of learning onto students who lack reliable internet access or devices. This is particularly relevant in Zimbabwe's STEM context, where digital infrastructure deficits are pronounced (Chasokela & Moyo, 2025). Efficiency measurement frameworks should therefore be complemented by qualitative assessments of whether observed output gains translate into equitable, meaningful, and critically engaged learning experiences, not merely throughput metrics (Ncube & Tawanda, 2025). University management should ensure that benchmarking efforts guided by DEA results do not inadvertently incentivise a superficial digitalisation that privileges measurable outputs over transformative pedagogy.

The efficiency findings of this study also intersect with broader questions about the relationship between departmental performance and student academic achievement. Dangaiso and Tsvere (2025) demonstrate that service quality dimensions, including teaching responsiveness, resource adequacy, and institutional support, are significantly and positively associated with student academic achievement. Their findings have direct implications for the present study: STEM departments identified as technically efficient through DEA may nonetheless fall short of service quality benchmarks if their efficiency is achieved by reducing staff-student interaction, deferring equipment maintenance, or curtailing student support services. In other words, DEA efficiency as measured in this study captures input-output transformation ratios, but does not directly capture the quality of the educational experience delivered. Future assessments of STEM departmental performance in Zimbabwe should therefore integrate DEA efficiency metrics with service quality instruments to provide a more holistic picture of institutional effectiveness, one that accounts not only for the volume of outputs produced, but also for the quality of the processes through which those outputs are generated (Dangaiso & Tsvere, 2025).

# CONCLUSION

The first objective of the research was to identify the input and output variables. Variables were categorised into two groups, that is, most cited and the least cited. Most cited means these variables were found in more than one article, as compared to some that were only cited once. This means that the variables that were cited more than once carry some information that was to be further analysed. Correlation analysis was made to assess the correlation between the input and output variables. It is also a fact that for any given input, there should be corresponding to a corresponding output; therefore, the relationship between inputs and outputs was analysed. For this research, only four input variables were identified with two output variables. These were the number of academic staff, the departmental budget, the departmental programs, and the number of teaching assistants, as for the outputs, it was the number of graduates and the number of publications.

The second objective was to identify the efficiency score for each department. 24% of all the departments were efficient in 2023, and 45% were efficient in 2024. 12 DMUs improved in terms of efficiency in 2024. 5 DMUs declined in efficiency in 2024. Only 3DMUs remained efficient in both years; these were DMU10, DMU14, and DMU31.

21% of the DMUs had a slack variable greater than zero for the first input variable in 2024, meaning that it was better than 2023, as it was 39%. This inferred that the input variable could be reduced without affecting the output. For example, in 2024, 1.897 could be reduced in input variable 1 whilst maintaining the same output. This was also true with the slack output variable, as it showed that the DMU could improve the output without utilising any additional inputs. The target variable emphasizes the slack variables such that the input target variable shows how many input variables could be removed whilst maintaining the same output level. The output target variable showed how many output variables could be added without increasing the input for a DMU to operate optimally. Additionally, the number of departmental programmes and the number of graduates had the greatest impact on the efficiency scores, as demonstrated by the sensitivity analysis. In summary, 55% of the departments showed a productivity increase through the Malmquist score, 10% showed that there was no change in productivity within the two years, and 35% showed a decline in productivity.

The third objective was to create a benchmarking framework for the inefficient departments, which was achieved by the frequency reference set. DMU 33 was the best department as it benchmarked 15 DMUs in 2024, whereas DMU 14 was the best for 2023 because it benchmarked 12 DMUs. All inefficient DMUs are benchmarked by efficient DMUs. This is done by considering the input and output variables of an inefficient department and the input and output variables of an efficient department. In other words, a DMU is benchmarked by a similar DMU in terms of resources.

# RECOMMENDATIONS

## Resource Reallocation Guided by Slack Analysis

**Table 6** showed that DMU29 has an input slack of 3.624 (staff) and 4011.95 (budget); DMU5 has a staff slack of 1.897; DMU24 has a staff slack of 10.589. Departments with positive input slacks (for example, DMU29, DMU5, DMU24) should redeploy surplus staff and budget to research support, mirroring efficient DMU33, which operates with zero slacks.

## Benchmarking using Top Performers

DMU33 benchmarks 15 DMUs in 2024 (**see Supplementary**); DMU14 benchmarked 12 in 2023 (**Figure 4**). DMU10, DMU14, and DMU31 remained efficient in both years (**Table 5**). Thus, inefficient departments (e.g., DMU3 efficiency 0.154, DMU18 0.122) should directly observe and adopt resource practices from DMU33, DMU14, or DMU31.

## Prioritise Graduate Output and Programmes in Funding

Sensitivity analysis (**Table 7**) showed dropping graduates (Y1), or programmes (X6), causes the largest efficiency declines (e.g., DMU2 falls from 0.487 to 0.164). It was recommended that universities should link performance funding to graduate output and programme relevance. Departments with low efficiency but high slack (for example, DMU22) must justify programmes before receiving additional resources.

## Differentiated STEM Funding Models

Finding: Malmquist index (**Table 8**) shows 55% of departments improved via efficiency change, not technological progress. DMU3 (MI=0.194), DMU18 (0.199), and DMU4 (0.423) declined. It was recommended that universities should introduce STEM cost-weighted funding for laboratories and technical staff. Departments with MI <0.8 receive temporary investment conditional on slack reduction.

## Biennial DEA-Malmquist Assessments

Only three DMUs remained efficient in both years; five declined (for example, DMU3 from 0.794 to 0.154; DMU9 from 1.000 to 0.418). Thus, it was recommended that universities should conduct DEA-Malmquist biannually. Departments with efficiency drop >0.2 or MI <0.8 trigger an operational review using benchmarking targets (for example, DMU3 benchmarked DMU30 and DMU33 in 2024).

## Address Output Shortfalls from Target Variables

DMU9 needs +41 graduates and +13.98 publications; DMU22 needs +16.48 publications (see **Supplementary**). Also, DMU3 needed +52.47 graduates in 2023 is shown in **Supplementary**. Thus, for departments with output slacks >20% of current output, universities must negotiate specific improvement targets without additional inputs (for example, DMU9 reallocate budget slack of 6,393 to thesis supervision).

# IMPLICATIONS

This study brings out some important takeaways for STEM departments, university management, and students:

## Implications for STEM Departments

The results show an encouraging trend. More departments became efficient in 2024 compared to 2023, which is a positive sign of progress. Departments that managed to stay efficient in both years, such as DMU10, DMU14, and DMU31, should be acknowledged for their consistency. Their practices can serve as useful examples for those still struggling. For the departments that are currently inefficient, this is a chance to learn from their peers. By looking at how similar departments are making the most of their staff, budget, and programs, they can identify ways to improve. The findings also show that some departments are using more resources than necessary. This means there is an opportunity to reduce certain inputs without affecting their outputs.

## Implications for University Management

University leaders should pay close attention to these efficiency scores. They offer a clear picture of which departments are doing well and which ones need support. The slack variables, in particular, help identify areas where resources might be wasted. By understanding this, management can make better decisions about where and how to allocate staff, funding, and other resources. Focusing on improving the performance of underperforming departments can lead to better outcomes across the institution.

## Implications for Students

Students benefit directly from being in efficient departments. These departments tend to have stronger academic performance, more research output, and better graduation rates. All of this contributes to a better reputation, which can improve job placement and opportunities after graduation. For students, this means a better learning environment and a more valuable university experience.

## Limitations and Future Research Direction

Looking ahead, in light of the limitations of the study, future studies could apply methods such as Stochastic Frontier Analysis (SFA) to measure efficiency from a different angle. It would also be useful to expand the research beyond one university to compare efficiency trends across multiple institutions. This broader perspective could offer a deeper understanding of what drives performance in STEM departments. Lastly, bootstrap DEA and outlier tests were not performed; results should be interpreted conservatively.

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All authors meet the ICMJE and COPE criteria for authorship. All authors have approved the final manuscript.

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**Ethical statement:** This study utilised secondary institutional data on the performance of STEM departments within a Zimbabwean university. No human participants were directly involved, and no personal or identifiable information was collected or analysed. The study was conducted in accordance with accepted ethical standards for academic research, and all data were handled confidentially and used solely for research purposes.

**AI statement:** The authors used the AI tool Grammarly for grammar checking and language editing to improve the clarity and fluency of the manuscript. After using this AI tool, the authors reviewed, revised, and verified the final version of the work. The authors take full responsibility for the content, accuracy, and integrity of the published work.

**Data sharing statement:** The datasets generated during and/or analyzed during the current study are available from the corresponding author upon request.

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