Ranking Efficient Decision-Making Units in Education: A Super-Efficiency Dea Model for Student Achievement

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ABSTRACT

Data Envelopment Analysis (DEA) is widely used to evaluate relative performance efficiency; however, conventional models may assign identical efficiency scores of 1.00 to multiple decision-making units (DMUs), limiting discrimination among efficient units. This study examines the application of output-oriented Super-Efficiency BCC DEA to distinguish efficient students at the individual level. An initial BCC assessment of 1,099 final-year diploma students at Universiti Teknologi MARA (UiTM), using CGPA and student satisfaction as reference input indicators and five competency dimensions as outputs, identified 134 efficient students. These students were selected for further super-efficiency assessment. The available pyDEA output demonstrates additional discrimination among a subset of the efficient students, although scores of 1.00 remain for other DMUs and a complete unique ranking cannot be claimed. The highest reported super-efficiency score was 1.7930 (DMU1133). The findings suggest that Super-Efficiency DEA can support the identification of potential student benchmarking cases, subject to the model specification and remaining ties.

Keywords: Data Envelopment Analysis; Super-Efficiency; Ranking; Academic Achievement; Decision-Making Units

INTRODUCTION

Although Data Envelopment Analysis (DEA) is a commonly employed method for performance assessment, conventional models such as CCR and BCC are constrained by a considerable deficiency in discriminatory capability. Due to the fact that these models assess efficiency within a limited range, numerous high-performing units achieve a flawless score of 1.0, hindering significant benchmarking or ranking of leading performers on the best-practice frontier. This constraint has resulted in a significant void in existing literature, as numerous studies conclude with a binary classification of efficient and inefficient units, lacking a comprehensive hierarchy or practical recommendations. Despite the introduction of Super-Efficiency DEA models to address ranking challenges, their application has predominantly been confined to macro-level institutional evaluations, such as ranking universities or departments, thereby creating a notable gap in micro-level assessments like the evaluation of individual students.

Moreover, current benchmarking frameworks predominantly depend on conventional metrics, like grades or graduation rates, and neglect to integrate multi-faceted, contemporary competencies into the evaluation of effective DMUs. Traditionally, scholarly success has been evaluated mostly through metrics such as the Cumulative Grade Point Average (CGPA). Nonetheless, grades by themselves cannot entirely encapsulate the varied competencies necessary for achievement in the 21st-century labor market or the complete spectrum of graduate qualities. The changing requirements of the contemporary labor market underscore a complex

connection between educational success and job preparedness; employers are progressively in search of graduates equipped with vital soft and technical competencies, including critical thinking, creativity, communication, adaptability, emotional intelligence, and digital literacy. Consequently, a more holistic method for assessing student competencies is crucial to connect traditional academic success with practical preparedness. The earlier educational phases emphasized either teacher-led teaching (Education 1.0) or solely experiential learning (Education 4.0), however the contemporary framework of Education 5.0 has arisen to reestablish a human-centered learning methodology. Education 5.0 prioritizes the comprehensive growth of students by merging technology adeptness with ethical principles, sustainability, and emotional intelligence to cultivate socially responsible and versatile graduates. In light of this worldwide transformation, Universiti Teknologi MARA (UiTM) has implemented a tailored educational framework known as the UiTM Academic Compass. At the core of this framework is Pillar 1: Coherent and Relevant Curriculum, which clearly states that academic success cannot be assessed exclusively through conventional grades. It should instead encompass an extensive array of student competencies, particularly emphasizing the importance of cultivating personal, adaptive, digital, 21st-century, and social skills.

This study seeks to rectify the methodological limitations of conventional DEA and meet the requirements of the Education 5.0 framework by employing a super-efficiency DEA model to improve discriminatory capability and precisely rank efficient DMUs at the individual student level. This research explicitly delineates and quantifies contemporary competencies by considering students' personal, adaptive, digital, 21st-century, and social skills as essential output metrics. These are assessed in conjunction with conventional academic metrics, particularly cumulative grade point average (CGPA) and student satisfaction, offering a thorough and pertinent framework for contemporary educational evaluation.

Ultimately, this methodology transitions performance assessment from a mere binary categorization to a detailed, nuanced standard. The super-efficiency approach can pinpoint genuinely exceptional outliers among students by permitting efficiency scores to surpass 1.0. Decisionmakers and institutional leaders can subsequently examine the methodologies of these elite performers and implement them in less effective units, facilitating data-informed strategic planning, enhanced resource distribution, and precisely focused interventions that correspond with the comprehensive objectives of contemporary higher education.

LITERATURE REVIEW

Conventional DEA and Its Limited Discriminatory Power

This concept includes research employing conventional DEA techniques to distinguish between efficient and inefficient units yet fundamentally lacks sophisticated methods to rank DMUs that attain the same score of 1.00. Nguyen Hoang and Nguyen Hong (2016) assessed graduation rates but emphasized the absence of a detailed ranking among effective institutions. In a similar vein, Zuluaga-Ortiz et al. (2022) assessed student performance and curricular effectiveness without considering the hierarchy among the efficient entities. Mammadov and Çimen (2019) evaluated educational facilities but did not incorporate sophisticated ranking systems. Ali et al. (2017) similarly belongs to this category, concentrating on resource distribution while neglecting the differentiation of rankings among efficient DMUs. This theme encompasses research that acknowledges the constraints of conventional DEA and utilizes Super-Efficiency models to prioritize efficient DMUs, albeit focusing solely on macro-level entities. Mogha (2023) employed super-efficiency to evaluate academic departments, whereas Liu et al. (2018) used it to assess the research output of liberal arts institutions. Moreover, Ulkhaq et al. (2024) utilized a dual-phase super-efficiency method to evaluate the ranking of educational institutions in Southeast Asia. Ramírez Valdivia et al. (2022) emphasized the use of sophisticated ranking techniques in assessing university research and curriculum results.

Methodological comparison

Measuring discriminatory power

In Data Envelopment Analysis (DEA), discriminatory power refers to a model's ability to distinguish efficient from inefficient decision-making units (DMUs) and differentiate among those classified as efficient.

Conventional DEA models often assign identical efficiency scores of 1.00 to multiple DMUs, limiting their ability to establish meaningful rankings. In this study, discriminatory power is assessed by examining the extent to which the Super-Efficiency BCC model differentiates among DMUs initially classified as efficient under the conventional BCC model.

Advantages and drawbacks of super-efficiency models

Super-Efficiency DEA extends conventional efficiency assessment by excluding the evaluated efficient DMU from its reference set, allowing further differentiation among efficient units. This approach facilitates relative ranking and the identification of potential benchmarking cases beyond conventional efficiency classification. However, super-efficiency models may encounter infeasibility under Variable Returns to Scale (VRS), and tied efficiency scores may remain, preventing a completely unique ranking. Therefore, super-efficiency results should be interpreted as model-dependent measures of relative performance rather than absolute indicators of student achievement.

Educational Competencies as Output Variables

Historically, scholarly success has predominantly been assessed via conventional metrics like the Cumulative Grade Point Average (CGPA). Nevertheless, contemporary educational systems and employers are progressively contending that grades alone fail to encompass the comprehensive array of graduate competencies necessary for today's job market, as professional preparedness necessitates a multifaceted skill set (Araújo, 2017; Molina-Espinosa et al., 2024; Kumar & Anburaj, 2024). As a result, tertiary education has transitioned to competency-oriented evaluations that prioritize extensive, practical abilities including critical thinking, creativity, emotional intelligence, and digital literacy (Opertti, 2022). Modern paradigms, exemplified by the Education 5.0 initiative at Universiti Teknologi MARA (UiTM), stipulate that scholarly success should encompass a holistic array of student skills, particularly emphasizing personal, adaptive, digital, 21st-century, and social competencies. Assessing these particular contemporary skills as outcomes in performance frameworks guarantees that students are not merely acquiring academic knowledge but are also cultivating the flexibility required for career preparedness (Almazroa & Alotaibi, 2023; Behle, 2020; Datnow et al., 2022). Consequently, by regarding these multifaceted competencies as essential output variables in conjunction with conventional academic inputs, the evaluation of performance transitions from a limited focus on grades to a comprehensive, efficiency-centered appraisal of student success.

Debates and conflicting findings

A significant methodological discourse in efficiency assessment centers on the presumption of returns to scale, particularly the selection between the Constant Returns to Scale (CCR) and Variable Returns to Scale (BCC) frameworks. The CCR model enforces a rigorous efficiency frontier, consequently limiting the quantity of fully efficient DMUs and inherently providing enhanced initial discriminatory capability. Nonetheless, this conservative methodology is frequently regarded as excessively inflexible and less appropriate for diverse educational settings where student abilities differ markedly. Conversely, the BCC model offers a more accurate assessment by distinguishing pure technical efficiency and including variable scale impacts. The primary limitation of the BCC model is in its propensity to yield elevated overall efficiency ratings, leading to an increased number of connected DMUs and so diminishing its ability to discriminate effectively. As seen in Table 1, this deficiency in discriminatory capability is a common concern in modern educational research. Numerous empirical investigations have effectively employed conventional DEA models to assess factors like graduation rates, school infrastructure, and overall student performance; yet they invariably fall short of including the sophisticated mechanisms necessary to distinguish and rank the highest-performing educational institutions. This empirical deficiency underscores the essential need for utilizing sophisticated approaches, like super-efficiency models, to regain detailed discriminatory capability while preserving the practical scale assumptions of the BCC framework. Thus, as shown in the last row of Table 1, this research directly tackles these outstanding concerns by implementing a Super-Efficiency DEA model to enhance the evaluation and comparison of individual student performance efficiency.

Table 1: Review of Previous Studies on Educational Efficiency and Ranking

Reference	Focus Area	Key Contribution to Education
(Ramírez Valdivia et al., 2022)	Research productivity in university	Explore curriculum and research outcomes as input and outputs in DEA emphasizing the need for advanced ranking methods
(Nguyen Hoang & Nguyen Hong, 2016)	Graduate rates in higher education	Focused on graduate rates as an output, highlighting the lack of nuanced ranking among efficient educational institutions
(Zuluaga-Ortiz et al., 2022)	Student achievement	Used student academic performance and curriculum as inputs to evaluate efficiency but did not address ranking among efficient units.
(Mammadov & Çimen, 2019)	Efficiency in School Facilities	Assessed the role of facilities in educational efficiency but lacked advanced ranking mechanisms for efficient schools.
(De La Hoz et al., 2021)	Academic efficiency of engineering programmes	Combined clustering, DEA, and machine learning to assess and predict programme-level academic efficiency, without focusing on super-efficiency ranking of individual students
(Kumar & Thakur, 2019)	Efficiency and ranking of higher education institutions	Applied dynamic DEA to evaluate and rank higher education institutions using institutional inputs and outputs, rather than ranking individual students.
(Ali et al., 2017)	Efficiency in Resource Allocation	Focused on human and financial resources in schools but did not address ranking differentiation among efficient DMUs.
This study	**Student Achievement Efficiency**	**Introduce Super Efficiency BCC model to improve ranking and benchmarking of student achievement efficiency**

The evolution of efficiency ranking and discriminatory power

Data Envelopment Analysis (DEA) is recognized as a powerful, non-parametric technique for assessing the comparative efficiency of Decision-Making Units (DMUs). Notwithstanding their extensive utilization, a fundamental constraint of conventional DEA models like the Charnes, Cooper, and Rhodes (CCR) and Banker, Charnes, and Cooper (BCC) frameworks is their intrinsically limited ability to discriminate. In these models, numerous DMUs are often categorized as entirely efficient, obtaining the same efficiency ratings of precisely 1.00. As a result, although conventional DEA successfully distinguishes between efficient and inefficient units, it does not differentiate among the highest achievers. This constraint is apparent in the research conducted by Nguyen Hoang and Nguyen Hong (2016) and Zuluaga-Ortiz et al. (2022), which employed conventional DEA to assess academic performance and graduation statistics but notably lacked the sophisticated techniques necessary for ranking the efficient entities. The inability to distinguish between linked DMUs renders the creation of a comprehensive hierarchy or practical benchmarking framework unfeasible. To address the rigid limitation of efficiency scores at one, methodological progress has progressively shifted towards super-efficiency DEA models. The super-efficiency method methodically omits the assessed efficient DMU from its reference set, permitting its efficiency score to surpass 1.00. This theoretical expansion offers a more nuanced differentiation among high-performing units, allowing researchers to categorize the exceptionally efficient outliers and set authentic best-practice standards. Nonetheless, an examination of current literature indicates that the utilization of super-efficiency models has been significantly confined to macro-level, organizational assessments. For example, Mogha (2023) and Liu et al. (2018) adeptly utilized super-efficiency techniques to evaluate academic departments and measure the research output of liberal arts institutions, respectively. In a comparable manner, Ulkhaq et al. (2024) effectively employed a two-stage super-efficiency model exclusively for the purpose of ranking regional schools in Southeast Asia.

This comprehensive focus highlights a considerable gap in research: there is a marked lack of super-efficiency ranking and benchmarking applied at the micro-level for individual students. Furthermore, current ranking systems mostly rely on traditional academic indicators such as graduation rates and test scores, failing to consider or appraise modern, complex competencies. To address these persistent limitations, this research utilizes a Super-Efficiency BCC model to improve the restricted discriminatory power of traditional DEA at the individual student level. This study provides an in-depth and pragmatic evaluation of student performance effectiveness by analyzing extensive 21st-century outcomes with traditional academic metrics, thus addressing the current shortcomings in contemporary educational evaluation.

METHODOLOGY

Decision Making Units (DMUs) and Variable Selection

This study conceptualizes academic achievement efficiency as the relative attainment of multidimensional student competencies in relation to accumulated academic achievement and perceived satisfaction with the university learning experience. The selection of input and output variables was guided by Pillar 1, Coherent and Relevant Curriculum, of the Education 5.0@UiTM framework, which emphasizes relevant student competencies alongside academic achievement. Individual final-year diploma students were treated as decision-making units (DMUs). Two indicators, Cumulative Grade Point Average (CGPA) and student satisfaction, were specified as inputs. CGPA represents accumulated academic achievement during diploma studies, while satisfaction reflects students' perceptions of their university learning experience. These indicators establish observed academic and experiential reference conditions against which competency attainment is evaluated. Specifically, the study examines whether students with given levels of CGPA and satisfaction demonstrate relatively efficient competency outcomes compared with peers. Five competency dimensions, namely personal, adaptive, digital, social, and 21st-century competencies were specified as outputs, representing multidimensional capabilities aligned with Education 5.0@ UiTM. This structure supports an output-oriented DEA assessment of the relative potential for increasing competencies at the observed input levels. CGPA and satisfaction are reference indicators, not conventional consumable resources. The resulting efficiency scores are conditional on this model specification and do not demonstrate causal relationships between the selected inputs and outputs.

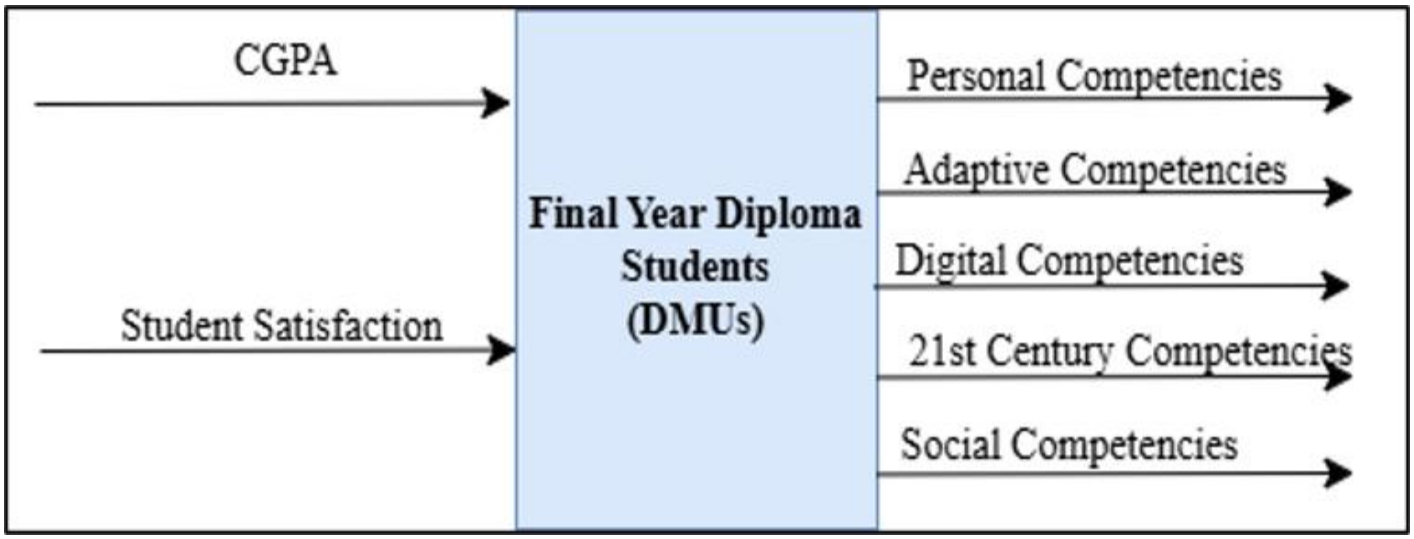


Figure 1: Input and Output Selection (source: own calculation)

Sampling Design and Data Collection

This research used a descriptive, cross-sectional methodology to evaluate the academic performance efficacy of students in a higher education setting. The intended demographic comprises 24,074 final-year diploma candidates registered at 15 Universiti Teknologi MARA (UiTM) campuses around the country. To guarantee optimal representativeness and mitigate sampling bias that could significantly skew the efficiency frontier in Data Envelopment Analysis (DEA), this research utilized a probability-based multistage cluster sampling

methodology. To ascertain an exact sample size, a margin of error of 3% and an alpha level of 0.05 were utilized, yielding a necessary minimum sample size of 1,064 students. The sampling process was carried out in three phases:

Stage 1 (Primary Cluster): The nationwide campuses were categorized into five geographic regions (Northern, Central, East Coast, Southern, and East Malaysia), and one primary campus was randomly selected per region. Stage 2 (Secondary Cluster): A random sample of one specific branch was chosen per campus, resulting in the selection of the Tapah, Puncak Perdana, Machang, Segamat, and Samarahan branches. Stage 3 (Tertiary Cluster): To ensure a diverse representation of academic disciplines, 50% of the diploma programs offered at each selected branch were randomly chosen for inclusion. Through this rigorous execution, a robust final sample of 1,099 valid final-year diploma students was successfully collected.

Instrument Development and Validation

Data were collected using the Student's Competency Questionnaire (SCQ), developed in alignment with Pillar 1 of the Education 5.0@UiTM framework. The instrument employed a 10-point Likert scale, ranging from 1 (Not Competent at All) to 10 (Very Competent), to assess students' personal, adaptive, digital, social, and twenty-first-century competencies. Content validity was evaluated by three experts specialising in Educational Technology, Statistical Modelling, and Decision Making, with Content Validity Index (CVI) values ranging from 0.96 to 1.00. A pilot study involving 59 final-year diploma students was conducted to assess the instrument's reliability. The results showed Cronbach's alpha coefficients exceeding 0.90 across all constructs, with corrected item-total correlations ranging from 0.540 to 0.884, indicating satisfactory internal consistency. For the DEA analysis, the scores of items within each competency construct were averaged to obtain a single construct-level score. These five competency scores were subsequently used as output variables in the DEA model.

Data-Preprocessing

Prior to the DEA analysis, data screening and cleaning procedures were conducted to assess the completeness and suitability of the dataset for efficiency evaluation. The initial dataset comprised 1,186 final-year diploma students. The screening process involved identifying missing values, data entry errors, and potential multivariate outliers. Observations with missing values in the selected DEA variables or unresolved data entry errors were excluded from the analysis.

Multivariate outliers were assessed using squared Mahalanobis Distance, which measures the multivariate distance of each observation from the sample centre while accounting for the covariance structure among the variables. The screening procedure considered seven DEA variables, comprising two inputs (CGPA and student satisfaction) and five competency outputs (personal, adaptive, digital, social, and twenty-first-century competencies). A threshold of 18 was applied to identify potentially extreme observations. This threshold is close to the chi-square critical value of 18.475 at the 0.01 significance level with seven degrees of freedom. Observations exceeding the specified threshold were excluded from the subsequent DEA analysis to reduce the influence of extreme observations on the estimated efficiency frontier.

Overall, 87 observations were excluded during data screening due to missing values, data entry errors, and multivariate outliers, resulting in a final analytical sample of 1,099 students. The final dataset was subsequently used for the CCR and BCC efficiency assessments and comparisons of BCC efficiency scores across campuses and diploma programmes.

Research Framework for Enhancing Ranking and Benchmarking

This methodology outlines the steps to assess the most efficient DMUs using the Super-efficiency DEA model (best model). Thus, the full research process as illustrated in Figure 2.

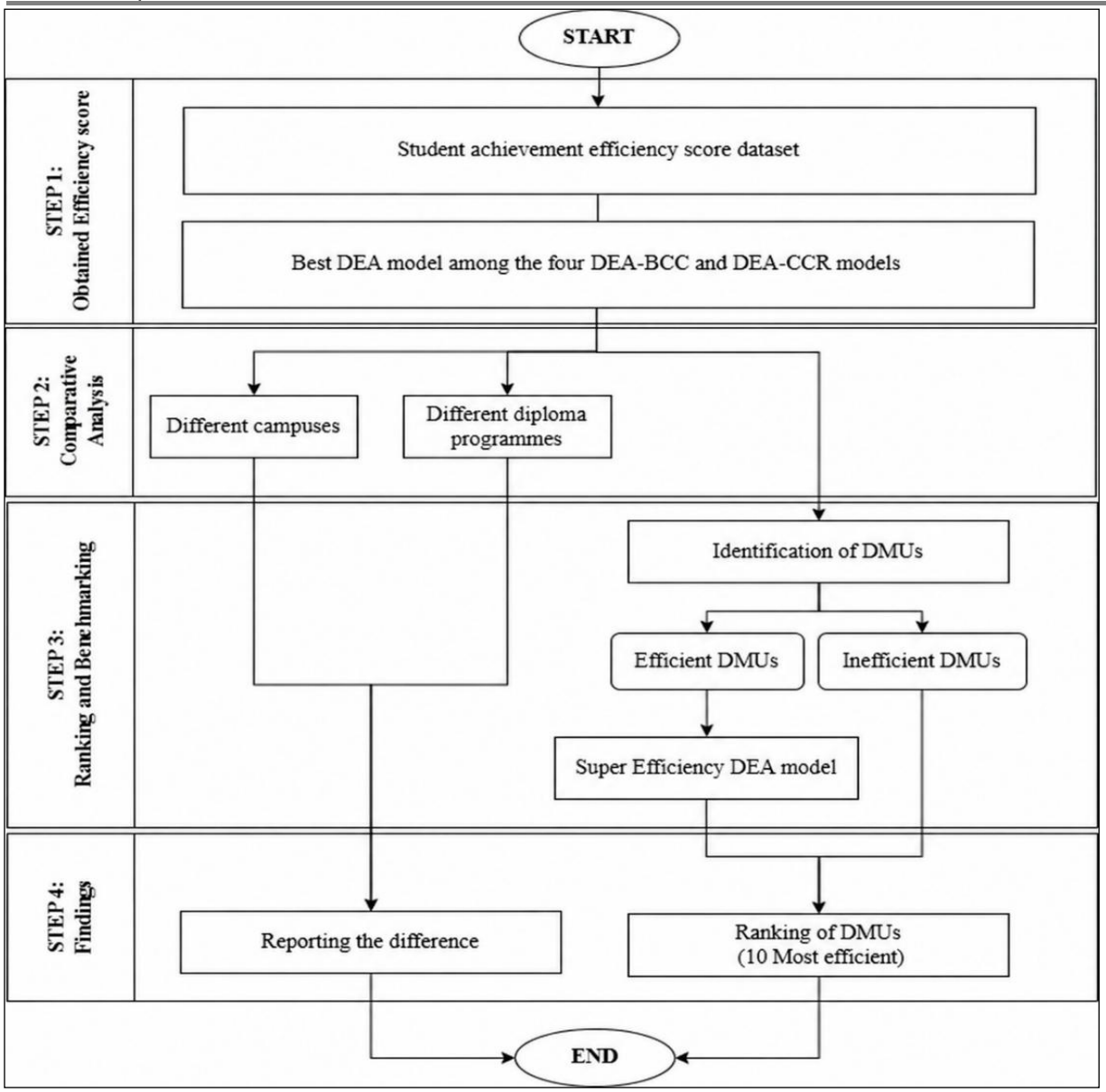


Figure 2: Benchmarking process for Efficient DMU using SE-DEA model

Phase 1: Attained Efficiency Assessment

The initial assessment used the output-oriented Banker, Charnes, and Cooper (BCC) model under Variable Returns to Scale (VRS). The VRS assumption accommodates potential differences in the relative efficiency frontier across students observed academic and learning-experience profiles. The output-oriented approach evaluates proportional potential for improvement in competencies at the observed CGPA and satisfaction levels. Among the 1,099 students initially assessed, 134 were classified as fully efficient, each with a BCC score of 1.00. Because these identical scores do not distinguish their relative performance, the efficient students were selected for the subsequent Super-Efficiency BCC assessment.

Phase 2: Comparative Analysis

Following the efficiency assessment and ranking DMUs.,the technique utilizes statistical and descriptive instruments to produce actionable insights.

(1) Comparative Statistical Analysis: The Kruskal–Wallis H test was employed to examine differences in conventional BCC efficiency scores across university campuses and diploma programmes. This non-parametric approach was selected because DEA efficiency scores may not satisfy the normality assumption.

(2) Profiling and Benchmarking: The ten highest-ranked efficient DMUs were identified based on their super-efficiency scores. These DMUs were subsequently profiled according to demographic and academic characteristics, including gender, diploma programme, family income group, and parental educational attainment. This descriptive profiling provides additional information on the characteristics of highly ranked efficient students and identifies potential benchmarking cases for further institutional investigation.

Phase 3: Evaluation and Comparison utilizing the Super-Efficiency DEA Framework

The conventional BCC model cannot distinguish between efficient decision-making units (DMUs) that share scores of 1.00. After identifying 134 efficient DMUs among 1,099 final-year diploma students, the study extracted these efficient DMUs into a separate reference dataset for Super-Efficiency BCC analysis using pyDEA. The model used Variable Returns to Scale (VRS) and an output orientation. Each evaluated DMU was excluded from its reference set so that its relative performance could be assessed against the remaining efficient DMUs. The resulting scores were used to identify higher-ranked efficient students and potential benchmarking cases. Because tied scores may persist, this procedure is interpreted as enhancing discriminatory power rather than guaranteeing a complete unique ranking. The general output-oriented Super-Efficiency BCC formulation is given in Equation (1).

Maximize θ_o

subject to;

$$\sum_{j\neq 0}^{n} \lambda_j x_{ij} \leq x_{io,(\forall_i)} \qquad (1)$$

$$\sum_{j\neq 0}^{n} x_j y_{rj} \geq \theta_o y_{ro,(\forall_{ri})}$$
$$\sum_{j\neq 0}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0, \forall_i$$

where x_{ij} is input i for reference DMU_j, and x_{io} is the corresponding input for evaluated DMU o; y_{rj} and y_{ro} are output r for DMU_j and evaluated DMUo, respectively; and λ_j is the non-negative intensity weight of reference DMU_j. The notation $j \neq o$ indicates that the evaluated DMU is excluded from its reference set. The output-oriented radial factor is denoted by φ_o. When efficiency is reported using the reciprocal convention, the super-efficiency score is $SE_o = 1/\varphi_o^*$, where φ_o^* is the optimal radial factor. The convexity constraint $\Sigma_{(j\neq o)} \lambda_j = 1$ imposes Variable Returns to Scale (VRS), and $\lambda_j \geq 0$ ensures non-negative intensity weights.

RESULTS AND FINDINGS

Descriptive Statistics

After meticulous data pre-processing and the elimination of multivariate outliers utilizing a Mahalanobis Distance threshold of 18, a dependable final dataset comprising 1,099 DMUs was created. The descriptive statistics indicate that the students' CGPA spans from 2.06 to 4.00 (Mean = 3.39, SD = 0.34), suggesting a moderate degree of variability. Satisfaction ratings indicate a significant degree of fulfillment (Mean = 7.99, SD = 0.22) on the 10-point scale. The average scores for the competency outputs are uniformly elevated: Personal (Mean = 8.16, SD = 0.16), Adaptive (Mean = 8.21, SD = 0.20), Digital (Mean = 8.30, SD = 0.22), 21st-Century (Mean = 8.01, SD = 0.33), and Social competencies (Mean = 8.23, SD = 0.24). Prior to calculating the DEA efficiency scores, the correlations among the variables were analyzed by Spearman's Rank-Order Correlation to confirm that the dataset adhered to the monotonicity premise of DEA, which asserts that an increase in inputs must not lead to a decrease in outputs. The examination indicated that CGPA demonstrates a weak yet positive, statistically significant correlation with all competency-based outcomes (range from $r = 0.26$ to $r = 0.29$, $p < 0.05$). This suggests that scholarly success and student abilities are complementary but separate aspects of performance, not overlapping evaluations. Conversely, student satisfaction exhibits a consistently moderate to robust positive correlation with all output variables (e.g., Social Competencies, $r = 0.67$, $p < 0.01$). Additionally, robust positive inter-correlations were noted among the competency outputs (e.g., Personal and Adaptive

Competencies, r = 0.90, p < 0.001), indicating the intrinsically linked essence of comprehensive student development. Given that DEA does not necessitate independence among outputs, these associations do not contravene model assumptions, therefore experimentally substantiating the input-output framework for efficiency assessment.

Comparative Analysis of CCR and BCC Models

The initial efficiency assessment was conducted using both the Charnes, Cooper, and Rhodes (CCR) model under Constant Returns to Scale (CRS) and the Banker, Charnes, and Cooper (BCC) model under Variable Returns to Scale (VRS). The CCR model identified 17 of the 1,099 DMUs as fully efficient, with a mean efficiency score of 0.783 (SD = 0.083). In comparison, the BCC model identified 134 fully efficient DMUs, with a higher mean efficiency score of 0.882 (SD = 0.095). These descriptive differences reflect the distinct returns-to-scale assumptions underlying the two models. The BCC model was selected as the primary evaluation framework because its VRS assumption accommodates variations in the relationship between academic input indicators and competency outputs without imposing constant proportionality. Furthermore, the BCC model evaluates pure technical efficiency by accounting for the effects of scale, making it conceptually appropriate for assessing students with heterogeneous academic and learning experience profiles. However, the identification of 134 fully efficient DMUs with identical efficiency scores of 1.00 highlights the limited discriminatory power of the conventional BCC model. Therefore, the Super-Efficiency BCC model was subsequently applied to these efficient DMUs to enhance discriminatory power and facilitate their relative ranking and benchmarking.

Testing the difference in Efficiency Scores across Five Campuses

A Kruskal–Wallis H test was conducted to examine differences in BCC efficiency scores among 1,099 final-year diploma students across five UiTM campuses: Machang, Puncak Perdana, Samarahan, Segamat, and Tapah. The results revealed statistically significant differences in efficiency-score distributions across campuses, H(4) = 96.78, p < .001. Subsequent Dunn's post-hoc pairwise comparisons with Bonferroni correction indicated statistically significant differences between Samarahan and Segamat, Samarahan and Tapah, and Samarahan and Machang. The remaining pairwise comparisons were not statistically significant after Bonferroni correction, as illustrated in Figure 3.

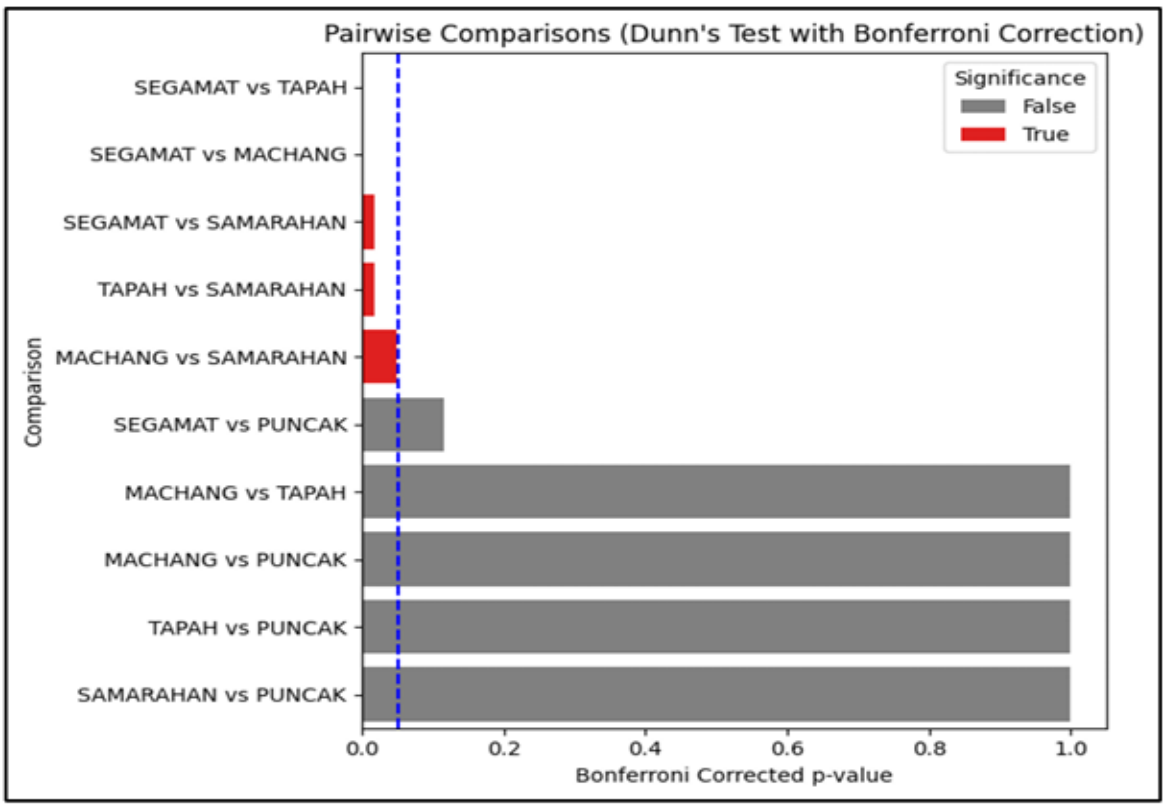


Figure 3: Dunn's Post hoc Pairwise Comparisons of Academic Achievement Efficiency across Campuses

Testing the difference in Efficiency Scores across Diploma Programs

A Kruskal-Wallis H test was conducted to examine differences in BCC efficiency scores among 1,099 final-year diploma students across 20 diploma programmes. The results indicated statistically significant differences in efficiency-score distributions across programmes, $H(19) = 38.153$, $p = .006$, with a small effect size ($\varepsilon^2 = .018$). Subsequent Dunn's post-hoc pairwise comparisons with Bonferroni adjustment identified a statistically significant difference between AC110 and BA111 (adjusted $p = .013$). No other pairwise comparisons reached statistical significance after adjustment for multiple comparisons.

Identification of the Most Efficient DMUs using the Super-efficiency BCC Model

The conventional BCC model identified 134 efficient students with identical efficiency scores of 1.00, highlighting its limited ability to differentiate among efficient DMUs. To address this limitation, the Super-Efficiency BCC model was applied exclusively to the initially efficient students to enhance discriminatory power and identify relatively higher-performing DMUs. The results demonstrated improved discrimination among a subset of efficient students, with DMU1133 achieving the highest reported super-efficiency score of 1.7930, followed by DMU556 (1.7186) and DMU1185 (1.3501). However, several DMUs retained identical super-efficiency scores of 1.00, indicating that the model did not eliminate ties.

These findings suggest that the Super-Efficiency BCC model enhanced the differentiation of efficient students rather than producing a complete ranking of all 134 DMUs. The super-efficiency scores represent relative efficiency measures within the specified DEA framework and should not be interpreted as absolute competency levels or percentage differences in student performance. Table 2 presents the super-efficiency scores of the initially efficient DMUs.

Table 2: Result on Efficiency Scores and Super-efficiency BCC Model

DMU1133(1.79)	DMU556(1.72)	DMU1185(1.35)	DMU11(1.16)	DMU1177(1.13)
DMU103(1.11)	DMU110 (1.07)	DMU1079(1.04)	DMU1104(1.04)	DMU495(1.02)
DMU983(1.02)	DMU406(1.01)	DMU552(1.01)	DMU438(1.01)	DMU1068(1.00)
DMU975(1.00)	DMU54(1.00)	DMU523(1.00)	DMU128(1.00)	DMU14(1)
DMU17 (1)	DMU18 (1)	DMU19(1)	DMU20(1)	DMU21(1)
DMU27(1)	DMU34(1)	DMU42(1)	DMU50(1)	DMU55(1)
DMU56(1)	DMU77(1)	DMU80(1)	DMU83(1)	DMU116 (1)
DMU125(1)	DMU207(1)	DMU210(1)	DMU221(1)	DMU222(1)
DMU226(1)	DMU363(1)	DMU366(1)	DMU371(1)	DMU400(1)
DMU411(1)	DMU432(1)	DMU445(1)	DMU451(1)	DMU457(1)
DMU458(1)	DMU464(1)	DMU466(1)	DMU468(1)	DMU470(1)
DMU497(1)	DMU519(1)	DMU520(1)	DMU522(1)	DMU526(1)
DMU578(1)	DMU583(1)	DMU588(1)	DMU589(1)	DMU599(1)
DMU602(1)	DMU605(1)	DMU611(1)	DMU617(1)	DMU618(1)
DMU624(1)	DMU626(1)	DMU628(1)	DMU630(1)	DMU680(1)

DMU681(1)	DMU685(1)	DMU688(1)	DMU691(1)	DMU735(1)
DMU745(1)	DMU776(1)	DMU777(1)	DMU784(1)	DMU794(1)
DMU810(1)	DMU811(1)	DMU815(1)	DMU823(1)	DMU827(1)
DMU830(1)	DMU834(1)	DMU835(1)	DMU836(1)	DMU845(1)
DMU848(1)	DMU852(1)	DMU853(1)	DMU854(1)	DMU868(1)
DMU879(1)	DMU883(1)	DMU894(1)	DMU895(1)	DMU912(1)
DMU922(1)	DMU933(1)	DMU937(1)	DMU949(1)	DMU950(1)
DMU987(1)	DMU991(1)	DMU995(1)	DMU1006(1)	DMU1007(1)
DMU1023(1)	DMU1030(1)	DMU1031(1)	DMU1035(1)	DMU1036(1)
DMU1047(1)	DMU1048(1)	DMU1069(1)	DMU1075(1)	DMU1085(1)
DMU1100(1)	DMU1112(1)	DMU1126(1)	DMU1129(1)	DMU1143(1)
DMU1156(1)	DMU1159(1)	DMU1173(1)	DMU 1103(1)	

Table 3 presents the profiles of the ten highest-ranked efficient DMUs based on their super-efficiency scores, including diploma programme, campus, gender, family income, and parental educational attainment. DMU1133 from the EC110 programme at Samarahan campus achieved the highest super-efficiency score (1.7930), followed by DMU556 from BA111 at Machang campus (1.7186) and DMU1185 from CAFF114 at Puncak Perdana campus (1.3501). The top-ranked students represented different academic programmes and socioeconomic backgrounds, with family income categories ranging from B40 to T20 and parental educational qualifications ranging from SPM to postgraduate degrees. These findings provide a descriptive profile of highly ranked efficient students; however, no conclusions regarding the influence of demographic or socioeconomic characteristics on efficiency can be drawn without further inferential analysis.

Table 3: Ranking of the Top 10 Most Efficient DMUs Using the Super-Efficiency BCC Model

No	**DMU**	**Diploma Program**	**Gender**	**Campus**	**Family Income Group**	**Parent's Education**	**Super-efficiency Score**
1	DMU 1133	EC110	Male	Samarahan	B40(B4:RM3,970-RM 4,849)	SPM	1.7930
2	DMU 556	BA111	Female	Machang	B40(B2:RM2,500-RM 3,169)	SPM	1.7186
3	DMU 1185	CAFF114	Female	Puncak Perdana	B40(B3:RM3,170-RM 3,969)	Master Degree (Father) SPM (Mother)	1.3501
4	DMU 11	AC110	Female	Segamat	M40(M3:RM7,110-RM8,699)	Master Degree (Father) SPM(Mother)	1.1640

5	DMU 1177	EC110	Female	Samarahan	T20(T2:More than RM15,039)	Master Degree(Father) PhD(Mother)	1.1326
6	DMU 103	BA111	Male	Segamat	B40(B4:RM3,970-RM 4,849)	SPM(Father) SPM(Mother)	1.1099
7	DMU 110	BA111	Female	Segamat	M40(M4:RM8,700-RM10,959)	SPM(Father) SPM(Mother)	1.0685
8	DMU 1079	AS120	Female	Samarahan	B40(B3:RM3,170-RM 3,969)	SPM(Father) SPM(Mother)	1.0392
9	DMU 1104	BA118	Female	Samarahan	M40(M1:RM4,850-RM5,879)	SPM(Father) SPM(Mother)	1.0387
10	DMU495	AM110	Female	Machang	B40(B1:Less than RM2,500)	SPM(Father) SPM(Mother)	1.0204

Discussion and Managerial Implications

The findings demonstrate that the Super-Efficiency BCC model enhances the discriminatory power of conventional DEA by providing further differentiation among the 134 initially efficient DMUs. While the conventional BCC model assigned identical efficiency scores of 1.00 to these students, the super-efficiency approach identified relatively higher-performing DMUs, thereby supporting more informative ranking and benchmarking. Although some tied scores remained, the approach offers an additional perspective for evaluating multidimensional academic achievement efficiency beyond conventional efficiency classification.

From a managerial perspective, identifying highly ranked efficient students provides potential benchmarking cases for higher education institutions. University administrators and educators may further investigate these students' learning strategies, academic practices, and competency development to inform targeted academic support and quality-improvement initiatives aligned with the Education 5.0@UiTM framework. The presence of highly ranked students from different academic programmes, campuses, and socioeconomic backgrounds also highlights the diversity of student profiles. However, these descriptive findings should not be interpreted as evidence that demographic characteristics or institutional factors directly influence efficiency without further investigation.

CONCLUSION

The primary objective of this study was to enhance the discriminatory power of conventional Data Envelopment Analysis (DEA) by applying Super-Efficiency BCC DEA to distinguish and rank efficient decision-making units (DMUs) at the individual student level. Conventional DEA models may assign identical scores of 1.00 to multiple efficient DMUs, preventing further differentiation (Nguyen Hoang & Nguyen Hong, 2016; Zuluaga-Ortiz et al., 2022). The initial output-oriented BCC assessment of 1,099 final-year diploma students identified 134 fully efficient DMUs. Subsequent Super-Efficiency BCC assessment focused on these efficient students. The available findings indicate improved discrimination for a subset, with DMU1133 attaining the highest reported score of 1.7930, although remaining ties preclude a completely unique ranking. This extends the use of super-efficiency approaches to student-level evaluation (Liu et al., 2018; Mogha, 2023; Ulkhaq et al., 2024).

The study further contributes to competency-based academic achievement evaluation by specifying CGPA and student satisfaction as input indicators and personal, adaptive, digital, social, and twenty-first-century competencies as outputs. Guided by Pillar 1, Coherent and Relevant Curriculum, of Education 5.0@UiTM, the output-oriented model assesses relative competency attainment at observed levels of academic achievement and perceived learning satisfaction. This extends grade-based evaluation to broader competencies relevant to contemporary education and workforce demands (Araújo, 2017; Molina-Espinosa et al., 2024; Opertti, 2022). Efficiency scores are conditional on the selected indicators and do not establish causal relationships.

The benchmarking analysis described highly ranked efficient students with varied academic and socioeconomic backgrounds. For example, the highest-ranked student was enrolled in an engineering diploma programme and belonged to the B40 income group. Such profiles are descriptive and do not establish relationships between efficiency, household income, or parental educational attainment. Although demographic and family factors have been discussed elsewhere (Wang & Chen, 2025), inferential evidence would be needed to evaluate such associations in the present study.

From a practical perspective, Super-Efficiency BCC DEA offers supplementary benchmarking information by distinguishing some efficient students from their efficient peers. These students may be selected for further investigation of learning practices and competency development to inform academic advising and quality-improvement planning. The broader competency-based perspective is consistent with contemporary educational priorities (Araújo, 2017; Molina-Espinosa et al., 2024; Opertti, 2022). Campus-level differences should not be attributed directly to teaching methods, resources, or institutional environments without further evidence (Dechavez, 2024; Mammadov & Çimen, 2019).

Several limitations should be acknowledged. The cross-sectional design captures relative efficiency at a single point in time, while the self-reported competency measures may be subject to response bias. Efficiency estimates depend on the selected input-output specification, and remaining tied super-efficiency scores limit complete differentiation among efficient DMUs. Furthermore, the findings are specific to final-year diploma students at Universiti Teknologi MARA and may not be generalisable to other educational settings. Future studies could examine alternative model specifications and longitudinal changes in efficiency.

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