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Evaluating digital competency among statistical educators: a comparative analysis of input-oriented DEA models

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ABSTRACT

As the educational landscape shifts towards online learning, assessing educators' digital competencies has become crucial. This study aims to evaluate the digital competencies of university educators using data envelopment analysis (DEA), specifically comparing the banker, charnes, and cooper (BCC) input-oriented models (super efficiency and Bi-O multi-criteria data envelopment analysis (MCDEA) super efficiency BCC models). The research was conducted in three phases. Initially, the BCC model assessed educators' digital competencies. Subsequently, the Bi-O MCDEA model evaluated these competencies within an online learning context. Finally, the effectiveness of the two models was compared. Data was collected through a survey administered to 30 educators from Universiti Teknologi MARA, with a response rate of 75%. Results showed that while the BCC model identified 23 out of 30 educators as efficient, the Bi-O MCDEA model recognized only two as efficient. This discrepancy highlights the different stringencies of the models and their impact on assessing digital competencies. The super efficiency (SE) model was then used to rank the efficient educators to determine the most proficient. The study underscores the need for precise assessment tools in online education to enhance digital competencies effectively. It suggests that integrating advanced DEA models can significantly improve the identification and training of educators, thereby enriching the educational outcomes in digital environments.

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1. INTRODUCTION

Malaysia's transition from traditional to online learning, as mandated by the Ministers of Education and Higher Education, is encountering challenges. Both educators and students must confront these hurdles, recognizing that online education heavily relies on technology, as supported by previous studies [1]-[6]. To ensure effective knowledge transfer, teachers must enhance their digital skills to facilitate smoother teaching and learning experiences. Evaluating teachers' digital competencies is essential for identifying training needs, improving the integration of technology into teaching practices, and ultimately enhancing student learning outcomes.

Myriad angle of studies regarding teachers' digital competencies been taken into interest by researchers such as studied by [7] focus on well-designed teacher training program to meet the demand of today's educator in adapting themselves in a new landscape of education. Moreover, Laar *et al.* [8] also do a study on measuring the actual levels of digital skills among professionals in the creative industries and found that most difficulties facing by them is digital information evaluation and problem-solving skills. While [9] emphasizes the importance of digital competence in technical and vocational education and training (TVET) programs, indicating that teaching staff are becoming increasingly aware of the evolving pedagogical approach in TVET.

Therefore, building on the findings of [5], [10], which highlighted a significant gap in digital integration among Malaysian educators, it becomes evident that educators with limited digital skills may impede the efficiency of the learning process, ultimately affecting the overall educational outcome. To address this gap, it is crucial to conduct studies aimed at bridging this digital proficiency divide among educators, ensuring the efficiency and effectiveness of online learning in Malaysia. One effective method to evaluate educators' efficiency in digital competency is by employing data envelopment analysis (DEA).

DEA is a mathematical programming technique that has found a number of practical applications for performance measurement of similar units, such as a set of hospitals, a set of schools, and a set of banks. It has been used to measure the performance efficiency of the organizational units, which are called decision making units (DMUs) [11]. Stated that DEA is used to measure the efficiency of a DMU from the set of resources to generate a set of outputs. Initially, the DEA techniques were only applied to profit organizations, however, it was much slower to apply their application to non-profit organizations such as the education area [12], [13]. The main reason is that DEA has opened possibilities for use in cases which have been resistant to other approaches because of the complex (often unknown) nature of the relations between the multiple inputs and multiple outputs.

The DEA application has found extensive implementation and utility in various sectors, including transportation [14], [15], industry [16], medical [17], [18], and banking [19], [20] to revolutionize the way organizations measure and optimize their efficiency and productivity. Education field is also no exception. Developments in the field of education have resulted in extensive research to ensure the effectiveness of the changes made.In fact, we are now experiencing a change in the educational landscape, especially in terms of teaching and learning that lead to facing as been discussed in previous studies.

Therefore, this study was conducted to measure the online learning efficiency of universities with DEA method by recognizing appropriate inputs and outputs that were effectively selected in evaluating the performance of DMUs. Thus, this study aims to answer the following three objectives: i) to identify the best digital competency score among educator in statistical subject using banker, charnes, and cooper (BCC) input-oriented super efficiency model; ii) to determine the best digital competency score among educator in statistical subject by using the Bi-O multi-criteria data envelopment analysis (MCDEA) super efficiency BCC model; and iii) to compare between the two models that can determine the best digital competency score among educator in statistical subject.

This paper makes two significant contributions. Firstly, it showcases a performance evaluation technique for assessing the digital competency of statistical educators. This research can serve as a reference point for future studies on digital competency across various educational levels. Secondly, by developing the BCC input-oriented super efficiency model, this study enables the ranking of educators based on their digital competency, ranging from the most efficient to the least efficient, within selected campuses.

2. RELATED WORKS

The application of DEA in the field of education is illustrated in Figure 1, which displays data from throughout the world. The use of DEA has grown rapidly over the past six years, across a wide range of industries and markets around the world. DEA has been applied to the field of education to assess the effectiveness of institutions like colleges and universities and to find ways to boost student achievement. Through using DEA to evaluate the effectiveness of educational institutions, it is feasible to determine which are performing well and which are underperforming. This information can be utilized to assist education field management in enhancing their efficiency and productivity.

Over the past six years, DEA has become a widely used method for gauging the effectiveness of a wide range of institutions and infrastructures. However, it is clear that DEA application particularly in education is still not widely used in Malaysia (Figure 1). Therefore, this opens the door for scholars to go headfirst into this area of inquiry. As the approach develops and finds new uses across industries and fields, it becomes an increasingly useful resource for organizations that want to boost their effectiveness and competitiveness.

The application of DEA is evolving and expanding. Findings from this selected article show that several methods have been integrated with the DEA model. Findings from this selected articles showed that several of method been integrated with DEA model. DEA integrated model with statistical techniques been used by [21] integrated DEA model with PLS method to propose function objectively analyses the relationships between the academic competencies obtained in secondary education and the university. While study by [22] integrate DEA model with multivariate analysis to identify the strengths and weaknesses of each type of school and the connections with the way in which the efficiency is obtained. While [23] investigated the causal nexus between the inputs and performances in the different types of secondary schools and tries to further establish an efficiency score using integration between DEA model with Tobit method. Iphigénie [24] also used the same method to find the determining factors of the efficiency of Congolese higher education establishments.

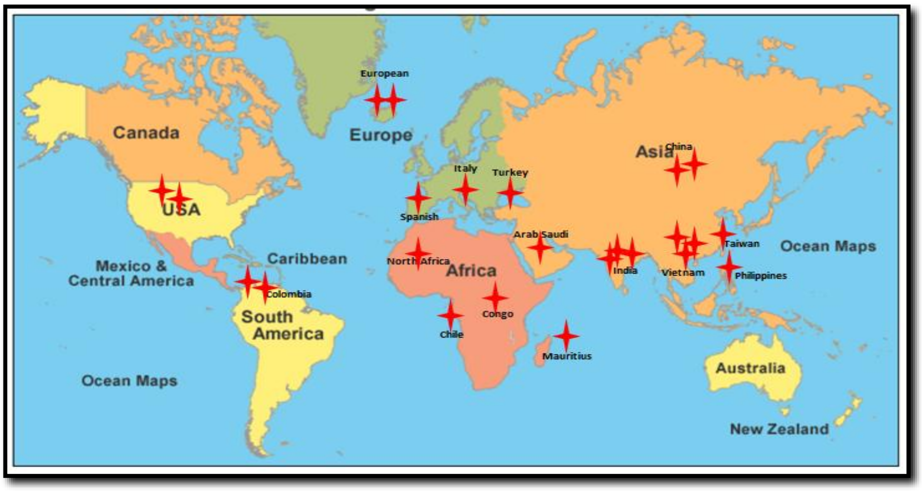

Figure 1. Geographic distribution of contribution countries to apply DEA method

3. METHOD

3.1. Sample of data

The dataset in this study was collected through a survey questionnaire personally distributed to educators who teach statistical subjects for Semester October 2021–March 2022 in Universiti Teknologi MARA. Out of 40 educators that teach that particular statistical course, a total of 30 educators responded to this study. This study been conducted by using voluntary participant sampling design. This gives a respond rate of 75%. The dataset from the questionnaire consists of two main sections, which are section A that includes a demographic profile (4 questions), and section B that consists of digital efficiency in e-learning questions (8 questions). The description for the questionnaire has been detailed in Table 1.

Table 1. The description of digital competency survey questionnaire

Section	No of item	Description
Section A	4	Campus (The campus that educator teach)
		Experience in teaching
		Teaching CODE FOR THIS semester
		Academic qualification
Section B	8	Learning management system (LMS) platform used for this semester
		Online class meeting platform for this current semester
		Number of gadgets used for this current semester
		Number of hours spent in e-Learning training
		Number of registered courses enroll to improve teaching and learning
		Amount spent on digital equipment (E.g.: RM2,499)
		Total costs of equipment invested during e-Learning (Facilities, Material, and Courses) (E.g.: RM1,000)
		Number of students enrolled for statistic course code for this current semester

This study also including four variable as inputs namely academic qualification, hours spend in e-learning course, total cost spending on digital equipment and total number of registered course improve in teaching and learning while two variable for output namely total students enrolled for statistics course code and total cost invested during e-learning period. Table 2 provides a breakdown of educators' involvement across 11 UiTM campuses in Malaysia. This study will recognize educators as DMU. Thus, the findings of DMUs in this study illustrated.

3.2. Software used

This study used the Lingo 20.0 software to formulate and calculate the efficiency of the DMUs. The Lingo 20.0 software was selected for use in this study's calculation because it allows the users to solve the linear programming problem that coincides with the DEA models. This software is also quicker, simpler, and more productive compared to other software.

Table 2. The description of educators according to UiTM campus

Campus	Number of DMU	DMU
Melaka	4	DMU1, DMU6, DMU9, DMU10
Samarahan 2	4	DMU2, DMU23, DMU24, DMU25
Merbok	2	DMU3.DMU4
Arau	3	DMU5, DMU19, DMU20
Tapah	7	DMU11, DMU13, DMU14, DMU22, DMU26, DMU27, DMU18
Seremban	3	DMU12, DMU17, DMU29
Shah Alam	2	DMU8, DMU30
Terengganu	1	DMU8
Machang	2	DMU15, DMU28
Johor	1	DMU16
Raub	1	DMU21

3.3. Implementation of input-oriented data envelopment analysis models

To achieve these three objectives, this study involved three phases. The first phase is to identify the best digital competency score by using BCC input-oriented super efficiency model. The second phase is to determine the best digital competency score among educator in statistical subject by using Bi-O MCDEA super efficiency BCC model and the last phase is to compare between two models that can be determine best digital competency score among educator in statistical subject.

Phase 1: to identify the best digital competency score among educator in statistical subject by using the BCC input-oriented super efficiency model.

Coinciding with the first objective, Phase 1 of this study will utilize the BCC input-oriented super efficiency model to identify the best digital competency score among educators in statistical subject. This study also will use the BCC input-oriented approach in order to minimize the input and provide the same amount of output for educator's digital competency. This phase will begin by calculating the efficiency of the DMUs educator's digital competency using the BCC input-oriented model. The calculation of the DMUs efficiency can be utilized by using the BCC input-oriented model as shown in (1).

$$Max, \theta_0 = \sum_{j=1}^{m} u_j\, y_{j0} + u_0$$

Subject to:

$$\sum_{i=1}^{s} v_i x_{i0} = 1 \tag{1}$$

$$\sum_{j=1}^{m} u_j y_{jk} - \sum_{i=1}^{s} v_i x_{ik} + u_0 \leq 0, k = 1, \dots \dots .., n.$$

$$u_i, v_j \geq 0$$

Where, θ_0 means the efficiency score for DMU_0, x_{i0} is the vector of input DMU_0, y_{j0} is the vector of output DMU_0,x_{ik} and j_{ik} are the actual amount of input i for DMU_k and the actual amount of output j for DMU_k respectively, v is the weight attached to the input, and lastly u is the weight attached to the output.

Throughout this model, DMU is considered efficient if θ equals to 1, while inefficient DMU occurs if θ is less than 1 [25]. It may be difficult to determine which DMU is the best educator digital performance since the BCC model only gives the value 1 as an efficient score. Hence, the super efficiency (SE) model is used to rank these DMUs because of its ability to remove DMU_0 from the second constraint. Next, the efficient DMUs will be ranked using the SE model as (2).

$$Max, \theta_0 = \sum_{j=1}^{m} u_j\, y_{j0} + u_0$$

Subject to:

$$\sum_{i=1}^{s} v_i x_{i0} = 1, \tag{2}$$

$$\sum_{j=1}^{m} u_j y_{jk} - \sum_{i=1}^{s} v_i x_{ik} + u_0 \leq 0, k = 1, \dots \dots .., n, k \neq 0,$$

$$u_i, v_j \geq 0$$

Where it defined θ_0 is the efficiency score for DMU_0 with x_{i0} and y_{j0} the vector of input DMU_0 and the vector of output DMU_0 respectively. While x_{ik} is the actual amount of input i for DMU_k and j_{ik} is the actual amount of output j for DMU_k. v and u are the weight attached to the input and output respectively.

The DMU with the highest efficiency value is deemed the most efficient, whereas the DMU with the lowest efficiency value is deemed the least efficient. After calculating and ranking the efficiency of educator digital performance by using the BCC input-oriented super efficiency model, Phase 1 is completed. The result of Phase 1 will be compared with the next model of Phase 2 in Phase 3.

Phase 2: to determine the best digital competency score among educator in statistical subject by using the Bi-O MCDEA super efficiency BCC model.

The second phase coincides with the second objective of this study which is to determine the best the best digital competency score among educator in statistical subject by using the Bi-O MCDEA super efficiency BCC model. This study will use this model because there is lack of the research been conducts and utilizes this model to analyze the best digital competency score among educator in statistical subject especially during online learning. The first step of the second phase is calculating the DMUs by using the Bi-O MCDEA BCC model. The calculation of Bi-O MCDEA BCC model can be calculated as (3).

$$\min h = \left(w_2 M + w_3 \textstyle\sum_j d_j\right)$$

Subject to:

$$\sum_{i=1}^{s} v_i x_{i0} = 1, \tag{3}$$

$$\sum_{j=1}^{m} u_r y_{rk} - \sum_{i=1}^{s} v_i x_{ij} + d_j + c_0 \leq 0, j = 1, \ldots \ldots .., n,$$

$$M - d_j \geq 0, j = 1, \ldots \ldots .., n,$$

$$u_r \geq \varepsilon, r = 1, .., s,$$

$$v_i \geq \varepsilon, i = 1, .., m,$$

$$v_i \geq \varepsilon, i = 1, .., m,$$

$$d_j \geq j = 1, .., n,$$

Where define d_0 is DMU_0 represented variable deviation for, d_j is the variable deviation for DMU_j, h is the efficiency score for inefficient DMU, M is the maximum quantity for all variable $d_j(j = 1, \ldots, n)$, and w_0 is the weights ($where\ \theta > 0$). While the weightage for output and input defined as u_r and v_i respectively. Number of DMU_s represented by n, number of outputs as s, number of inputs as $m.x_{ij}$ is the value of input i from DMU_j, y_{rj} is the value of output r from DMU_j, and c_0 is the free sign.

According to the Bi-O MCDEA BCC model, d_0 and d_j (j=1,...,n) represent the variable deviations for DMU_0 and each DMU_j, respectively. After that, DMU is deemed efficient when its efficiency score equals 1.00, whereas a score less than 1.00 indicate inefficiency. Unlike other models, Bi-O MCDEA BCC must calculate $h=1-d_j$ to determine the value 1.00. Since the Bi-O MCDEA BCC model cannot rank the efficient DMUs by itself, the SE model will be utilized to rank the efficient DMUs that have an efficiency of more than 1. The SE model can be calculated as (4).

$$\text{Max}, \theta_0 = \sum_{j=1}^{m} u_j y_{j0} + u_0$$

Subject to:

$$\sum_{i=1}^{s} v_i x_{i0} = 1, \tag{4}$$

$$\sum_{j=1}^{m} u_j y_{jk} - \sum_{i=1}^{s} v_i x_{ik} + u_0 \leq 0, k = 1, \ldots, n, k \neq 0$$

$$u_i, v_j \geq 0$$

Notations are consistent with (2).

Consequently, the DMU with the highest efficiency value is considered the most efficient DMU. The DMU efficiency results will be compared in Phase 3 with the model that was calculated in Phase 1.

Phase 3: to compare between the two models to determine which model has the best educator digital performance.

In this last phase, the results from each model which are the BCC input-oriented super efficiency model and Bi-O MCDEA super efficiency BCC model will be compared to determine which of these models gives the most efficient results. Finally, the chosen model will help this study to make the decision to determine the best digital competency score among educators in statistical subject.

4. RESULTS AND DISCUSSION

4.1. Result in Phase 1 in measuring the efficiency score using BCC input oriented model

The efficiency score of the implementation by using the BCC input-oriented model is shown in Table 3. This research assessed the efficiency of 30 statistical course educators (DMUs) across 11 UiTM campuses using the BCC input-oriented model and lingo software for analysis. The total DMUs that have been evaluated were 30 STA404 educators (DMUs) from 11 UiTM campuses and only 23 were deemed efficient. By taking educator from Melaka (DMU1) deemed efficient with the value of 1 as an example, the input value this educator where the academic qualification (Master's Degree), total hours spent during online distance learning (ODL) is four hours, cost of spending on digital RM4, 169 per semester and total registered class is two. Then, the output value that educators (DMU1) produce is 115 students and total cost e learning is RM350. It shows that this educator had fully utilized its own input value in order to produce the optimum amount of output until it was deemed efficient with the value of 1 by the BCC input-oriented model.

Table 3. The efficiency score of each DMUs using BCC input-oriented model

Campus	DMUs	BCC input-oriented model efficiency score	Findings
Melaka	DMU1	1	Efficient
	DMU6	1	Efficient
	DMU9	1	Efficient
	DMU10	1	Efficient
Samarahan 2	DMU2	0.75	Inefficient
	DMU23	1	Efficient
	DMU24	0.75	Inefficient
	DMU25	1	Efficient
Merbok	DMU3	0.8221924	Inefficient
	DMU4	0.75	Inefficient
Arau	DMU5	1	Efficient
	DMU19	1	Efficient
	DMU20	1	Efficient
Tapah	DMU11	0.8703588	Inefficient
	DMU13	1	Efficient
	DMU14	0.75	Inefficient
	DMU22	1	Efficient
	DMU26	1	Efficient
	DMU27	1	Efficient
	DMU18	1	Efficient
Seremban	DMU12	1	Efficient
	DMU17	1	Efficient
	DMU29	1	Efficient
Shah Alam	DMU8	0.7692779	Inefficient
	DMU30	1	Efficient
Terengganu	DMU8	1	Efficient
Machang	DMU15	1	Efficient
	DMU28	1	Efficient
Johor	DMU16	1	Efficient
Raub	DMU21	1	Efficient

Inefficiency DMUs were highlighted shows that Campus Samarahan 2 (DMU2 and DMU24). While for Merbok campus found that both of its educators were not efficient. Tapah campus (DMU11 and DMU14 found to be inefficient. Lastly Shah Alam campus also has inefficient educators (DMU8). Take Merbok (DMU3) as an example; he/she only manage to score an efficiency score of 0.8221. The efficiency score was close enough to 1; however, it was still not enough to be deemed as efficient. The most inefficient DMUs was Samarahan 2 (DMU2, DMU24), Merbok (DMU4), and Tapah (DMU14) with an efficiency score of 0.75 respectively which was far from efficient. All of these inefficient DMUs determine that the states were not fully utilized their own input value to produce the optimum amount of output value.

The rank of efficient DMUs from the previous model efficiency score by using the SE model was shown in Table 4 represent the ranked efficiency score of efficient DMUs by using the SE model. Since the BCC input-oriented model only gives the maximum value of 1 as an efficient score; therefore, it was difficult to determine the most efficient DMU among all five efficient DMUs. Hence, the SE model was used in this Step 2 of Phase 1 to rank these five efficient DMUs in order to determine the most efficient educator, as shown in Table 4.

Table 4. The ranked efficiency score of efficient DMUs by using the SE model

DMU	CAMPUS	SE model efficiency score	Rank
DMU1	Jasin	1	10
DMU5	Arau	1.25	7
DMU6	Melaka	1	10
DMU7	Kuala Terengganu	1	10
DMU9	Melaka	1	10
DMU10	Melaka	1	10
DMU12	Seremban	1	10
DMU13	Tapah	1.616162	6
DMU15	Machang	2.186667	2
DMU16	Johor	1.138593	9
DMU17	Seremban	18.88889	1
DMU18	Tapah	1	10
DMU19	Arau	1.180328	8
DMU20	Arau	1	10
DMU21	Raub	1.740591	4
DMU22	Tapah	1	10
DMU23	Samarahan 2	1	10
DMU25	Samarahan 2	2.08381	3
DMU26	Tapah	1	10
DMU27	Tapah	1.680525	5
DMU28	Machang	1	10
DMU29	Seremban	1	10
DMU30	Shah Alam	1	10

The ranks of efficient DMUs were created in Table 4 after 23 efficient DMUs have been analyzed using the SE model. Accordingly, the most efficient DMU were educators from the Seremban campus (DMU17), with an efficiency score of 18.88889. The efficiency score of educators in Samarahan 2 campus (DMU23) was significantly higher than the efficiency score range of 1 to 2.08381 for educators from Arau campus (DMU5 and DMU19) at 1.25 and 1.180328, respectively, Tapah campus (DMU13) at 1.616162, Machang (DMU 15) at 2.186667, Johor (DMU 16) at 1.138593, and Raub (DMU21) at 1.740591. As a result, it can be reported that the most efficient DMU was DMU17, an educator from the Seremban campus. The first goal of this study is to determine the optimum educator efficiency utilizing the BCC input-oriented super efficiency model, which has been met.

4.2. Result in Phase 2 in measuring efficiency score using Bi-O MCDEA BCC input-oriented model

This study presents the results from Phase 2 of the implementation process, specifically derived from Steps 1 and 2 of this phase. In Step 1, the efficiency score for each educator was calculated using the Bi-O MCDEA BCC model. These efficiency scores, obtained through the Bi-O MCDEA BCC model, are detailed in Table 5.

The efficiency scores were derived from the implementation using LINGO software, where the scores (represented as d_j). These scores were then converted into actual efficiency scores by using the formula $(1 - d_j)$. An efficiency score of 1 indicates that a DMU is efficient; otherwise, the DMU is considered inefficient. Out of the thirteen DMUs evaluated, only two were found to be efficient: Kedah (DMU2) and Pulau Pinang (DMU9). The number of efficient DMUs identified by the Bi-O MCDEA BCC model was fewer compared to the BCC input-oriented super efficiency model, which had previously identified five efficient DMUs.

Table 6 presents the ranked efficiency scores of the efficient DMUs using the super-efficiency (SE) model. The Bi-O MCDEA BCC model assigns a maximum efficiency score of 1, making it challenging to distinguish between multiple efficient DMUs. Therefore, the SE model was employed in Step 2 of Phase 2 to rank these efficient DMUs and identify the most efficient statistical educator during COVID-19, as shown in Table 6. After evaluating the two efficient DMUs with the SE model, their ranks were determined and presented in Table 6. According to the table, the educator from the Tapah campus (DMU13) was the most efficient, with an efficiency score of 1.059427. The efficiency score of the educator from Kedah (DMU2) was slightly higher than that of the educator from Raub (DMU21), who received an efficiency score of 0.9999998.

Table 5. The efficiency score of each DMUs using Bi-O MCDEA BCC input-oriented model

DMU	Campus	Bi-O MCDEA BCC input-oriented (d_j)	Result ($h=1-d_j$)
DMU1	Jasin	0.7264055	0.2736
DMU2	Samarahan 2	0.8419099	0.1581
DMU3	Merbok	0.3095547	0.6904
DMU4	Merbok	0.7665872	0.2334
DMU5	Arau	0.7242186	0.2758
DMU6	Melaka	0.902899	0.0971
DMU7	Kuala Terengganu	0.8396196	0.1604
DMU8	Shah Alam	0.4828646	0.5171
DMU9	Melaka	0.8324668	0.1675
DMU10	Melaka	0.4460023	0.5540
DMU11	Tapah	0.6814388	0.3186
DMU12	Seremban	0.6903515	0.3097
DMU13	Tapah	0	1
DMU14	Tapah	0.4519777	0.5480
DMU15	Machang	0.7397449	0.2603
DMU16	Johor	0.5486434	0.4514
DMU17	Seremban	0.6769242	0.3231
DMU18	Tapah	0.5581789	0.4418
DMU19	Arau	0.3918714	0.6081
DMU20	Arau	0.463581	0.5364
DMU21	Raub	0	1
DMU22	Tapah	0.5139776	0.4860
DMU23	Samarahan 2	0.8482986	0.1517
DMU24	Samarahan 2	0.8733552	0.1267
DMU25	Samarahan 2	0.3156285	0.6844
DMU26	Tapah	0.4216318	0.5784
DMU27	Tapah	0.6437005	0.3563
DMU28	Machang	0.5615397	0.4385
DMU29	Seremban	0.5857435	0.4143
DMU30	Shah Alam	0.7472702	0.2527

Table 6. The ranked efficiency score of efficient DMUs by using the SE model

DMU	Campus	SE model efficiency score	Rank
DMU13	Tapah	1.059427	1
DMU21	Raub	0.9999998	2

4.3. Result in Phase 3 in comparing and determination of the best statistical educator during COVID-19 between the two models used

In phase three, both models' results were compared side by side so that the difference between the two models' results was more visible. Hence, the summary of efficient DMUs for Phase 1 and Phase 2's implementation was tabulated as shown in Table 7.

Table 7. The summary of efficient DMUs for two models used

Phase	DEA model	Total of efficient DMUs	List of efficient DMUs	Most efficient DMU
1	BCC input-oriented super efficiency model	23	DMU1, DMU6, DMU9, DMU10, DMU13, DMU22, DMU26, DMU27, DMU18, DMU12, DMU17, DMU29 DMU30, DMU8, DMU15, DMU28, DMU16, DMU21, DMU23, DMU25, DMU5, DMU19, DMU20	DMU17 (Seremban)
2	Bi-O MCDEA super efficiency BCC model	2	DMU13, DMU21	DMU13 (Tapah)

Table 7 presents the summary of efficient DMUs for the BCC input-oriented super efficiency model and Bi-O MCDEA super efficiency BCC model. 23 DMUs were deemed efficient for the BCC input-oriented super efficiency model and two DMUs were considered efficient for the Bi-O MCDEA super efficiency BCC model. However, both models concluded for the most efficient DMU, whereas the BCC input-oriented super efficiency model concluded that educator from Seremban (DMU 7) campus were the most efficient among all

DMUs. Contradictory, using Bi-O MCDEA super efficiency BCC model had concluded that the most efficient educator was from Tapah (DMU13). Since both models demonstrated different implementation results, two types of approaches were taken into consideration in order to determine which model presents more accurate and efficient results. Then, the most accurate and valid model helped to determine the best statistics educator during COVID-19 in this study.

The initial approach involved comparing the number of DMUs classified as efficient by both models. A model that identified fewer DMUs as efficient was considered more stringent and, thus, potentially more accurate in evaluating and implementing the efficiency standards described by researchers [26], [27]. By comparing both models, it was shown that the five DMUs were deemed efficient for the BCC input-oriented super efficiency model, and two DMUs were deemed efficient for the Bi-O MCDEA super efficiency BCC model, as stated before. Hence, it can be said that the Bi-O MCDEA super efficiency BCC model was more accurate in the implementation process since it come up with two efficient DMUs compared to the BCC input-oriented model produce 17 efficient DMUs. This statement was proven to be true by [27] who improvised the DEA models to be more accurate by increasing the discriminatory ability of DMUs, resulting in a reduced number of efficient DMUs.

The second approach was to compare the similarity and correlation between the results of both models. By comparing both models, it was shown that there was a similarity in terms of the type of DMUs that were deemed efficient. Both models had educators from Tapah (DMU13) and Raub (DMU21) as part of the efficient DMUs. However, for the Bi-O MCDEA super efficiency BCC model, another 21 DMUs were not deemed as efficient. This was due to the fact that the Bi-O MCDEA super efficiency BCC model decreased the number of efficient DMUs to determine the most efficient DMU accurately according to studied by [27], [28]. Hence, for the second approach, the Bi-O MCDEA super efficiency BCC model still managed to achieve the most accurate result compared to the BCC 46 input-oriented super efficiency model.

Therefore, by considering these two approaches of discussion, this study decided to choose the Bi-O MCDEA super efficiency BCC model to determine the most efficient educator in digital competency in statistical course during online learning because it was more accurate in evaluating and implementing the input and output of digital competency. Hence, based on Table 6, the Bi-O MCDEA super efficiency BCC model concluded that educator from Tapah (DMU13) was the most efficient DMU among all DMUs.

5. CONCLUSION

The efficiency analysis conducted using the BCC input-oriented and Bi-O MCDEA models offers valuable insights into the academic performance of educators across various campuses. Of the 30 DMUs evaluated, 23 were identified as efficient in the BCC input-oriented model, demonstrating their ability to maximize output while effectively utilizing input resources. In contrast, the Bi-O MCDEA BCC input-oriented model identified only two DMUs as efficient, indicating a difference in evaluation criteria between the models. The application of the SE model further refined the analysis by identifying the most efficient educator among the high performers. However, it is important to recognize that efficiency scores are relative and may not fully capture the complexities of educators' digital competencies in online learning environments. The study focus on a specific set of campuses and educators limits the generalizability of the findings to the broader context of educators in Malaysia. Despite these limitations, the study makes a valuable contribution by recognizing exemplary educators and highlighting key factors that influence academic achievement.

To build on the findings of this study, further research could investigate the impact of digital learning on academic achievement, focusing on aspects such as engagement strategies, online resources, and assessment methods. This could provide a deeper understanding of the factors that contribute to academic success in digital environments. Additionally, the integration of machine learning techniques with DEA could enhance the precision and depth of efficiency analyses, offering more nuanced insights for educators, policymakers, and institutions. These avenues of research could provide valuable guidance for improving educational practices and policies, particularly in the context of evolving digital learning landscapes.

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C : **C**onceptualization
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

ETHICAL APPROVAL

Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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