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Efficiency in academic evaluation: data envelopment analysis systematic review

Nor Faezah Mohamad Razi[1], Norhayati Baharun[1], Suraya Masrom[2]
[1]Mathematical Sciences Studies, College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Perak Branch, Tapah Road, Malaysia
[2]Computing Science Studies, College of Computing, Informatics and Mathematics, Universiti Teknologi MARA Perak Branch, Tapah Road, Malaysia

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ABSTRACT

Education 5.0@UiTM is transforming Universiti Teknologi MARA (UiTM). This new approach emphasizes flexible learning paths that teach life and cross-disciplinary skills. To make higher education future-ready, universities must adapt fast to the significant global and technical changes caused by the 4th Industrial Revolution and transition from content-based to individualized learning. To ensure students meet Education 5.0@UiTM standards and corporate needs, the evaluation process must be reviewed. Competency-based academic achievement evaluation outperforms grades. This assessment is rarely systematically analyzed. This study was conducted to thoroughly explore the selection of input and output factors in determining student achievement efficiency using the data envelopment analysis (DEA) approach. The study reviewed publications from Scopus, Google Scholar, and Science Direct and found six themes for input variables: human resources, facilities condition and equipment, finance, curriculum, students characteristics, and community resources. output variables included student achievement, satisfaction, graduation rate, employment, research, and community resources. In DEA analysis, input and output selection affects scope, aim, production frontier, efficiency scores, accuracy and completeness. So, characterizing student achievement requires choosing relevant input and output variables. This study can enhance student evaluation processes to prepare college graduates for the next industrial revolution.

Corresponding Author:

Nor Faezah Mohamad Razi
Mathematical Sciences Studies, College of Computing, Informatics and Mathematics,
Universiti Teknologi MARA Perak Branch
32610 Seri Iskandar, Perak, Malaysia
Email: norfaezahmohamadrazi@gmail.com

1. INTRODUCTION

Comparing current learning to earlier learning is really different. Teaching techniques were once exclusive to the classroom, but that is no longer the case. Students' reliance on teachers has been somewhat diminished as a result of the current educational revolution. Traditionally, teachers' primary goal has been to transfer knowledge to students in the classroom. However, that goal has now enhanced the role it plays as a repository of acquired information. Because of this, students need to study independently rather than being spoon-fed information. Students' ability to adjust to Education 5.0 will be strengthened by doing this.

Beginning in 2019, Universiti Teknologi MARA (UiTM) started actively promoted Education 5.0, with the goal of changing the university's teaching and learning processes to better comply with the needs and expectations of today's students [1]. Education 5.0 was promoted by UiTM from 2019 onwards in an effort to modernize the university's pedagogical practices to meet the demands and expectations of today's students. The goal of the Education 5.0@UiTM initiative is to enhance the learning process by implementing cutting-edge technologies like augmented reality, virtual reality, and gamification. The plan also stresses the value of incorporating real-world experiences and developing soft skills.

In order to make the higher education ecosystem future-ready, we must not only respond quickly to the rapid global and technological developments brought on by the 4th Industrial Revolution but also to look into the quality of its content. Soeprijanto and Femalia [2] stated that aiming to build a quality education; it needs to perform comprehensively including the teacher availability, the availability of facilities and infrastructure, as well as the curriculum and learning system. It is worth noting that the concept of Education 5.0@UiTM is still in its early stages, and its implementation may vary across different institutions. Therefore, to achieve this agenda in ensuring that the students produced can have quality that is in line with Education 5.0@UiTM and further generate students that match the needs of employers, the evaluation process is the major area that has to be investigated. The focus of earlier evaluation techniques was grade accomplishment. The higher the grade, the better the student is regarded. Grade is the primary predictor of a student's achievement, according to numerous past studies [3]–[5]. Employers continue to complain that a high grade does not guarantee that a student will perform well in their career, even when considering the level of academic success.

The way of students now values the learning are from experience, challenge, space to express and create, flexibility, be given voice, connectedness and learning that instigate change. Therefore, there is a need for the higher institution management specifically educators to identify further on factors that can be taken into account to develop a competent student so that the students produced is holistically a quality student. To be competent is to have the knowledge and abilities necessary to carry out one's duties successfully.

Students in higher education must acquire a variety of skills in order to become competent in their field. Several studies from various nations have begun to ensure that their students are well trained in a variety of skills in order to generate competent students. Wong *et al.* [6] carried out a study to determine the abilities necessary of future Graphic Design graduates in Malaysia. They divided skills into 29 subcategories according to five components: i) cognitive competence; ii) functional competence; iii) personal competence; iv) ethical competence; and v) meta-competencies.

In Ukraine, a project-based pedagogical technology called complex analytical and synthetic work with the text (CASWT) is being developed [7]. This technology aims to enhance students' communicative competencies. Furthermore, a study [8] further disclosed that all parties involved in higher engineering education in the Tampere region hold comparable perspectives on the significance of engineering graduates' skills and personal competencies. In addition, other study [9] discovered that the development of resilience abilities enhances kids' ability to be more tolerant and gain a deeper understanding of their surroundings. It is precisely in the face of these challenges that the advantages of achieving high educational outcomes become evident. While there is ongoing interest in studying how to measure academic accomplishment, the specific factor that determines academic achievement remains unclear and requires additional research.

Performing a systematic evaluation of previous studies is essential. As stated by Robinson and Lowe [10], regular literature reviews are plagued by many problems such as being incomplete, heavily influenced by reviewer bias, and failing to consider variations in study quality. Snyder [11] also added that traditional literature reviews often lack thoroughness and rigor and are conducted ad hoc, rather than following a specific methodology. While systematic literature review (SLR) is a methodical approach to examining existing literature. Furthermore, according to a study [12], SLR involves a rigorous process that involves the selection, categorization, and critical evaluation of prior studies in order to address a specific research question. In the context of SLR, a predefined protocol or plan is established before commencing the review process. It discusses an extensive search method that allows researchers to answer a specific question [13]. The systematic review offers details on the review process (e.g., keywords used, article selection) so that others can replicate the study, confirm the findings, or investigate the generality [14].

While there have been several studies that have attempted to conduct systematic reviews of input and output selection in the field of education using the data envelopment analysis (DEA) method, their primary emphasis has not been on evaluating the efficiency of academic achievement. For instance, previous study [15] concentrated on assessing the efficiency of public primary education institutions. Meanwhile, the research conducted by Ferro and D'elia [16] examined the methodological approaches employed in measuring efficiency within higher education. Furthermore, Contreras and Lozano [17] pointed out that the scarcity of studies focusing on the competency aspect when measuring academic achievement has led to a lack of comprehensive understanding and a failure to systematically synthesize the relevant literature in this area.

The goal of the current review was to find a new way to measure how well college students do in school. By putting together, a list of all the factors that have been used to measure student achievement efficiency, researchers will be able to figure out which factor/s is/are the most important and what lacking in measuring student achievement efficiency. The question raise during the process of knowledge acquisition in the selection of input and output for DEA is: i) In general, how has the literature review on DEA in the higher education field progress for the past 6 year's period?; ii) What are the factors, including the input and output characterization that been used to measure the academic achievement efficiency?; iii) What was the DEA models that been used previously to measure academic achievement in education field?; and iv) How did the integration revolution between DEA model and other methods develop?

These questions arise because there are numerous driving forces currently affecting businesses that are predicted to have a major impact on jobs while also growing skill inequality [18]. Thus, identification of the determinant that can conclude overall student's achievement is the issue that need to take into account since these determinant are very important to offer an education of quality and a solution to the challenges of the 21st century society in general, and of the Education 2030 Agenda in particular [19]. Therefore, in order to respond to the research questions, the review has been conducted by searching for relevant articles. Thus, it is of interest to multiple parties, and not just educators but also stakeholders at the higher education level need to be aware of this issue so that institutions may produce students who are not only academically proficient but also competent in a variety of skills acquired during their studies.

2. RESEARCH METHOD

This study chose a SLR strategy in light of the difficulties posed by the diversity of the body of existing information and the impossibility of using other well-established scientific methodologies, such as meta-analysis, for knowledge synthesis. The definition of research through literature review is to identify, evaluate, and interpret the papers published in a given field of research [20]. Prior to beginning the literature search, the following inclusion criteria were applied. First, it was agreed that only articles that looked at the causes (input variables) and effects (output variables) should be considered in order to assure content relevance. Secondly, to acquire a comprehensive picture of recent (and sufficient) research, the years of publication for the literature search were restricted to 2012-2020. Regarding language, only publications written in English were included in the search criteria.

Two additional reasons encouraged the use of a SLR approach: i) in the case of extensive diversity, literature review is one of the most appropriate research methodologies [21] and ii) a literature review enables the researcher to assess the state of knowledge on a particular issue in depth. The review procedure consisted of four stages: i) identification of literature; ii) literature review screening; iii) eligibility and exclusion; and iv) items abstraction.

2.1. Phase 1: identification of literature

The studies were chosen from a systematic evaluation of electronic databases for research articles, theses, and dissertations, as well as manually examining the reference lists of relevant articles. Search queries were utilized on Scopus, Google Scholar, and Science Direct. At this phase, relevant articles were retrieved from the three search engine databases mentioned earlier. During the search, the terms "academic achievement efficiency," "academic accomplishment efficiency," and "Data Envelopment Analysis" were utilized. Table 1 summarizes the search string criteria.

From this phase, the search returned one journal from Scopus, 18 journals from Science Direct, and 173 journals from Google Scholar, for a total of 192 journals to be evaluated in the subsequent step. In addition, the literature search includes a systematic literature search to determine the extent to which other scholars have conducted research on the topic at hand.

Table 1. Systematic literature review search string

Database	Keywords
Scopus	TITLE-ABS-KEY (("Academic Efficiency*" OR " Academic performance*" OR " Academic Achievement*") AND ("Data Envelopment Analysis*") AND ("Input and Output variables*"))
	TITLE-ABS-KEY (("Systematic review" OR "systematic literature") AND ("Academic Efficiency*" OR " Academic performance*" OR Academic Achievement*") AND ("Data Envelopment Analysis") AND ("Input and Output variables"))
Google Scholar	("Academic Efficiency in higher education*" OR "academic performance" AND "Data Envelopment Analysis " AND ("education*") AND ("Input and Output variables*")
	(Systematic review" OR "systematic literature") AND ("Academic Achievement Efficiency" OR "Academic Achievement" OR "Academic Competence" OR "Academic Achievement Efficiency" OR "academic performance") AND ("Data Envelopment Analysis") AND ("Input and Output variables"
Science Direct	(("academic achievement" OR "academic performance" OR "academic competency") AND ("input and output") AND ("data envelopment analysis"))
	((Systematic review" OR "systematic literature") AND ("data envelopment analysis") AND ("academic achievement" OR "academic performance" OR "academic competency"))

2.2. Phase 2: literature review screening

At this stage, the relevant literature, encompassing all the research, was evaluated to determine its applicability in measuring academic achievement through the use of Data Envelopment Analysis. The result underwent further refinement based on the acceptance and rejection criteria described as: i) Inclusion criteria stipulated that citations should be from a scholarly international publication, published between 2016 and 2022, and focused on the selection of input and output for determining academic achievement efficiency; and ii) Exclusion criteria stipulated that citations cannot be the application of DEA from another field of study. Each article abstract was then reviewed and judged for its theoretical robustness and contribution to the current discussion. Hence, 115 journals were excluded for not complying with the specific criteria for inclusion. Five journals were subsequently eliminated due to duplication.

2.3. Phase 3: eligibility and exclusion

The subsequent stage involves determining eligibility and identifying exclusions. During this phase, a comprehensive review was conducted on the remaining 40 literatures. Out of them, 16 full text articles were discarded since they did not meet the criteria of being empirical articles. Currently, there are 24 literatures that are still pertinent and being utilized for the systematic literature review. The authors downloaded and read the complete texts of all 24 papers. The entirety of the chosen complete articles was examined and summarized. A systematic review was conducted, utilizing an item checklist to organize the following information: author(s), publication title, publication year, nation or region of study, selection of input and output variables, DEA model, and decision making units (DMU). Figure 1 depicts the flow diagram of SLR.

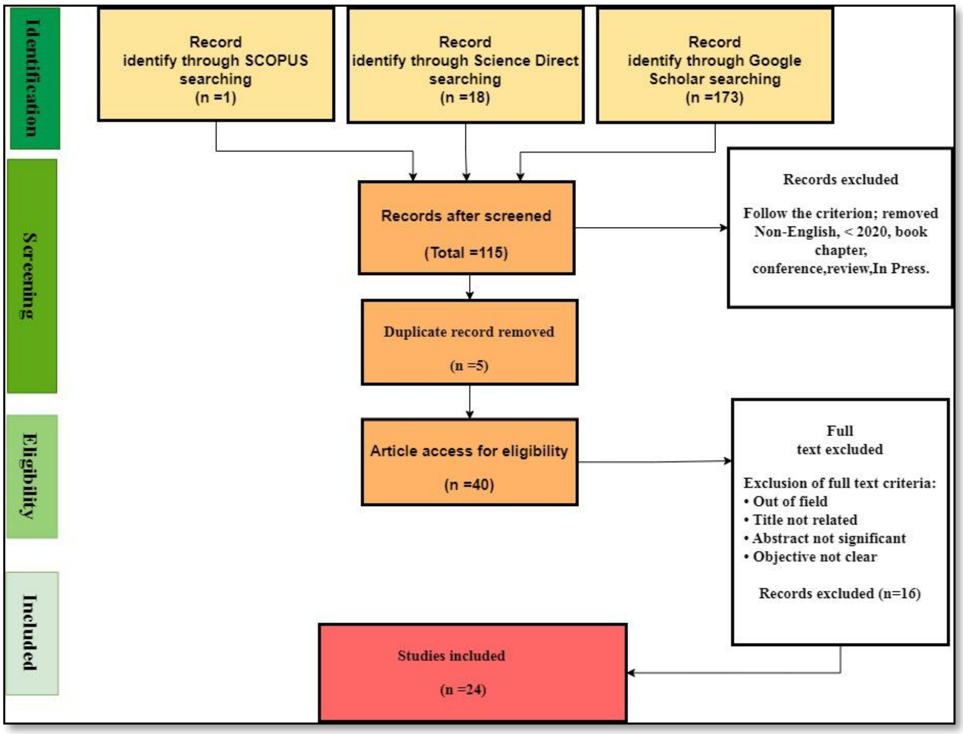

Figure 1. Systematic review flow diagram

2.4. Phase 4: items abstraction

After the eligibility process, the remaining articles were appraised, reviewed, and analyzed; the results are explained in depth in this publication. The focus of the reviews was on specific papers that fit the study topic. Quality appraisal of the remaining 24 articles was carried out using the appraisal tool for cross sectional studies (AXIS) [22]. The appraisal tool comes with an explanatory help text which gives some background knowledge and explanation as to what the questions are asking. The explanations are designed to inform why the questions are important. The appraisal tool has areas to record a "yes", "no" or "don't know" answer for each question and there is room for short comments as well. In ensuring the quality of the articles content, three experts for quality assessment. The 24 articles were then reread to confirm their eligibility.

The papers were then extracted to find topics and sub-themes pertinent to the current study by examining the titles, abstracts, and full texts of the articles (in-depth). Furthermore, a thematic analysis was used to uncover themes connected to research patterns and trends in DEA studies. In the initial phase of the theme analysis, the writers assessed the remaining 24 articles to extract the statements and data pertinent to the study's research issue.

In the subsequent phase, the authors used a coding technique to construct meaningful groups. The abstract data were then turned into useful data and guided by the identification of themes, ideas, or significant concepts for additional related and interconnected data [23]. Ultimately, a total of six themes for input variable and output variables manage to be spotted for categorizing the input and output variables used in DEA analysis namely: i) human resources; ii) facilities condition and equipment; iii) financial; iv) curriculum; v) students characteristics; vi) community resources, respectively for input variables, while i) student achievement; ii) satisfaction; iii) graduation rate; iv) employment outcome; v) research outcomes; and vi) community impact. The abstraction data was discussed later.

3. RESULTS AND DISCUSSION

3.1. The evolution application of DEA all over the world

Application of DEA in the field of education is illustrated in Figure 2, 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.

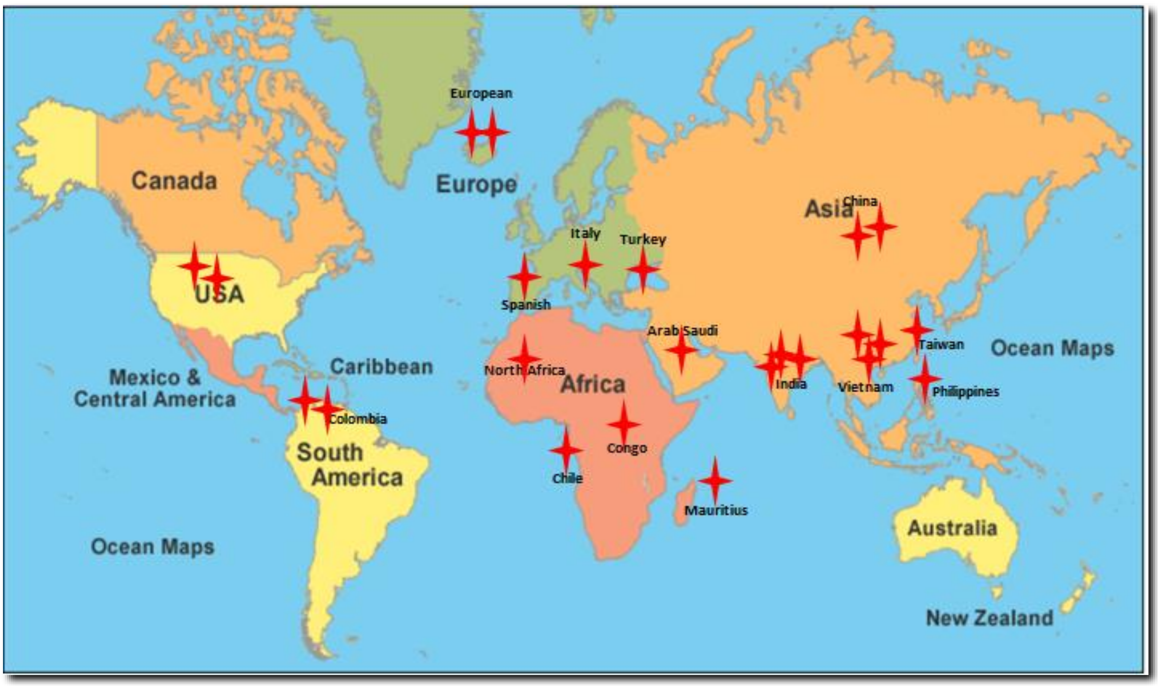

Figure 2. Geographic distribution of contribution countries to apply DEA method

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 as presented in Figure 3. 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.

3.2. Input and output selection in education field

In DEA, the inputs and outputs selection are critical since it dictates the scope and aim of the analysis. Educational outputs are the outcomes of all levels of education (primary, secondary, and postsecondary), whereas input factors are the mechanism by which DMUs attain these outcomes. Thus, the objectives of the evaluation and the availability of data will decide which variables are inputs and which are outputs in a DEA analysis.

The choice of inputs and outputs determines the production frontier and efficiency scores, which in turn inform the analyst's conclusions about the performance of the DMUs. If the inputs and outputs selected are not relevant or appropriate for the analysis, the results will not accurately reflect the performance of the DMUs. Additionally, the inputs and outputs selection affect the number of DMUs that can be evaluated, as well as the complexity of the analysis. For example, if too many variables (inputs and outputs) are selected, the analysis may become too complex and difficult to interpret. On the other hand, if too few variables (inputs and outputs) are selected, the analysis may not be comprehensive enough to accurately reflect the performance of the DMUs.

Thus, the primary purpose of this study is to identify the variables (inputs and outputs) used in prior research to evaluate students' academic achievement efficiency. Therefore, the purpose of this study is to examine in detail and exhaustively the selected articles that evaluate the performance effectiveness in the education sector. By examining the inputs and outputs of earlier research, we can assess whether variables are appropriate or if more variables have yet to be explored to evaluate student academic achievement. Thus, the findings of selection input and output in measuring academic achievement efficiency are compiling as Table 2.

Table 2. Selection of input and output tools checklist

Type	Category theme	Author
Input	Human resource	[24]–[37]
	Facilities	[31], [38]–[40]
	Financial	[24], [25], [28], [33]–[36], [40]–[42]
	Equipment	[25], [33]
	Curriculum	[26], [27], [43], [44]
	Student characteristics	[32]–[34]
	Community resources	[33], [45]
Output	Student achievement	[25], [34], [38]–[40], [43]–[46]
	Satisfaction	None
	Graduates' rates	[32], [35], [45]
	Employment outcomes	[35]
	Research outcomes	[27], [33], [36], [37], [40], [42]

According to Table 2 findings, there is still room for improvement in showing that evaluation methods (finding the variables) are used holistically in measuring academic achievement efficiency. Due to the new problems and rising opportunities presented by innovative practices, graduates of higher education are expected to possess a vast array of abilities beyond the traditional scope. This is due to the fact that growing practices and new difficulties are necessitating individuals who can adapt and innovate in response to changing conditions. Employers increasingly seek applicants with these competencies, as they are seen essential for success in the modern workplace.

3.3. DEA model commonly used in education field

In DEA, there are two primary models: the Charnes, Cooper, and Rhodes (CCR) model and the Banker, Charnes, And Charnes (BCC) model. The CCR model implies constant returns to scale, which indicates that a particular percentage increase in inputs results in an equal increase in outputs. The CCR model is useful for assessing the relative efficiency of DMUs that operate on a comparable scale and employ the same manufacturing technology. The BCC model, on the other hand, allows for variable returns to scale, so making it more adaptable to DMUs of various sizes. The BCC model is useful for comparing the relative efficacy of DMUs with varying production processes and sizes. The choice of DEA model should be based on the characteristics of the DMUs, the selection of inputs and outputs and the goals of the analysis. Therefore, through this study where only focusing on the type of DEA model that used were found out the common model that been used by previous selected studies that related in measuring academic achievement in education field presented as Table 3.

Table 3. The DEA models commonly used by previous studies

Author	Objectives of the study	DEA model BCC	CCR
[25]	To discover the efficiency of Spanish schools while simultaneously considering DEA and multivariate analysis.	★	
[44]	This research uses a three-phase technique to identify and forecast the efficiency of academics in engineering programs.		★
[27]	To evaluate the technical proficiency of 30 academic from the departments of Chilean university and to identify the main factors influencing their performances.	★	★
[28]	The present study that analyzed the higher education technical efficiency in the Indian states.	★	★
[30]	The main objective of this study is to analyze activity-wise performance assessment in the departments.	★	★
[31]	To evaluate the efficiency or the academic departments productivity within a university using Data Envelopment Analysis.	★	★
[38]	To evaluate the comparative effectiveness of 28 countries that participated in PISA 2015 and TALIS 2013 based on student performance and teacher quality	★	★
[39]	To fill the gap by investigating the causal nexus between the inputs and performances in the different types of secondary schools and tries to further establish an efficiency score using the DEA approach.	★	★
[42]	To assess the research efficacy of Chinese higher education institutions by using a sample of 105 universities	★	★
[34]	To evaluate the efficiency levels and analyze their determinants in Congolese higher education. Efficiency is evaluated using a semi-parametric approach and a sample of forty-nine higher education establishments spread across three departments of the country.	★	★
[46]	To investigate the technical efficiency of schools and its correlation with their managerial practices by employing a two-stage methodology.	★	
[35]	To assess education sector's efficiency by comparing 28 European Union states at different levels of education using the mathematic approach of data envelopment analysis.	★	
[37]	To develop a strategy that prioritizes performance and effectively allocates research funding to multiple universities with the aim of enhancing research productivity.	★	

3.4. The DEA integrated model

The DEA integrated model is a non-parametric method that doesn't make any assumptions about how the production process works. This makes it a useful tool for figuring out how efficient something is in many different situations. As researchers and professionals in different fields started to use DEA more, they began to realize that it had some flaws, especially when it came to dealing with noisy or incomplete data and figuring out which inputs and outputs were the most important to the effectiveness of DMUs.

Researchers and practitioners have sought to enhance the accuracy and utility of the DEA model by integrating it with various supplementary methods. Zuluaga-Ortiz *et al.* [43] combine a DEA model with a partial least squares (PLS) method to propose a function that objectively assesses the connections between students' secondary school knowledge and their university achievements. Segovia-Gonzalez *et al.* [25] 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. Nauzeer *et al.* [39] 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 [34] also used the same method to find the determining factors of the efficiency of Congolese higher education establishments.

Next is with multiple criteria decision making (MCDM), where Wang *et al.* [47] used integration between DEA and MCDM method to find input and output selection to examine which determinants significantly affect their performance. By applying a DEA model and the multiple correspondence analysis (MCE) technique, Agasisti and Munda [48] ranked European countries based on the efficiency of their compulsory education spending. The analysis ranked the countries using several common variables drawn from the academic literature. Lastly, integrated with Machine Learning revealed the study by La Hoz *et al.* [44] used a three-phase method to evaluate and forecast the academic efficiency of engineering programs university profiles are created non-hierarchical cluster analysis was carried out through the k-means algorithm [49], [50]. Meanwhile a study by Falasca and Kros [41] used Ward's method which one of the clustering approach that tends to produce groups with fairly similar number of entities

Thus, by combining with other approaches such as machine learning, statistical analysis, or survey research, DEA can provide a complete and efficient tool for analyzing educational systems and enhancing student achievement. By integrating these methodologies, educators and policymakers may find areas of inefficiency and best practices, acquiring a greater knowledge of the factors that drive student accomplishment. Overall, combining DEA with other methods can result in a powerful tool for evaluating educational systems and improving student achievement. By identifying areas of inefficiency and best practices, educators and policymakers may make educated choices regarding resource allocation, curriculum design, and instructional improvements, leading to better academic achievement for students.

4. DISCUSSION

This review aims to put together in a systematic way the findings of input and output selection in DEA methods. Many conclusions may be taken from the included studies throughout the overview of the study process. The bulk of research that match the inclusion criteria are done on the Asian continent, it may be inferred. Vietnam and India, for example, expressed an interest in researching the evaluation of academic achievement using the DEA method. Despite the fact that this DEA approach is being developed in all nations throughout the world, there is no baseline for establishing the selection of inputs and outputs. As a result, researchers can continue to investigate the appropriateness of input and output selection in predicting student academic achievement.

Other than that, the findings revealed that most of DEA studies used universities [26], [32]–[34], [36], [37], [40]–[42], [44], [47] as DMUs while the others used such as students [44]–[46], schools [25], [29], faculties [27], [39], departments [30], [31], and countries [24], [28], [35], [38]. This finding highlights the versatility of DEA in assessing the efficiency of various types of organizations or entities, not just universities. DEA can be applied to any decision-making unit that has multiple inputs and outputs, and its applications have been extended to various fields. By using DEA, decision-makers can identify the best practices of efficient DMUs and improve the performance of inefficient DMUs.

The findings of the review also revealed various selection on input and output been used to evaluate academic achievement efficiency. Full-time teachers [24], [26], scientific researchers [26], number of classroom [39], expenditure [24], [28], personnel and non-personnel funds [30], [41], number of students registered [27], [39], number of course offered [27], number of faculty members [28], [30], [31]. There were also studies used student competency [43], [44] and academic performance [45], such as Fall term GPA, High school and SAT score Spring term GPA College as input variables. Meanwhile for output variables, the findings from this study revealed that mostly output variables that been used by previous researchers are number of research produces [26], [27], [30], progress research index [26], total enrolled students [28], [30], pass out students [28], [29], [32], number of school and classes [29], research grant [31], teaching hours [31] and commonly used is academic performance consist of grade [38], and score [41].

In addition, selected evidence also revealed that the total number of input and output used in to generate multiple outputs as depicted in Figure 3. It was found that, total number of input and output variables is not standardized. The highest number of input used by [43] involved 17 variables and least number of input variable used is [30], [45], where each of the study use one input variable respectively. The number of inputs and outputs that can be included in DEA analysis relies on the size of the DMUs and the characteristics of the data. Generally, the total number of inputs and outputs that can be selected for DEA is not limited. However, the number of inputs and outputs that should be selected depends on the specific problem and the availability of data. In practice, the number of inputs and outputs is often limited by the data collection process, the cost of collecting data, and the computational complexity of the analysis.

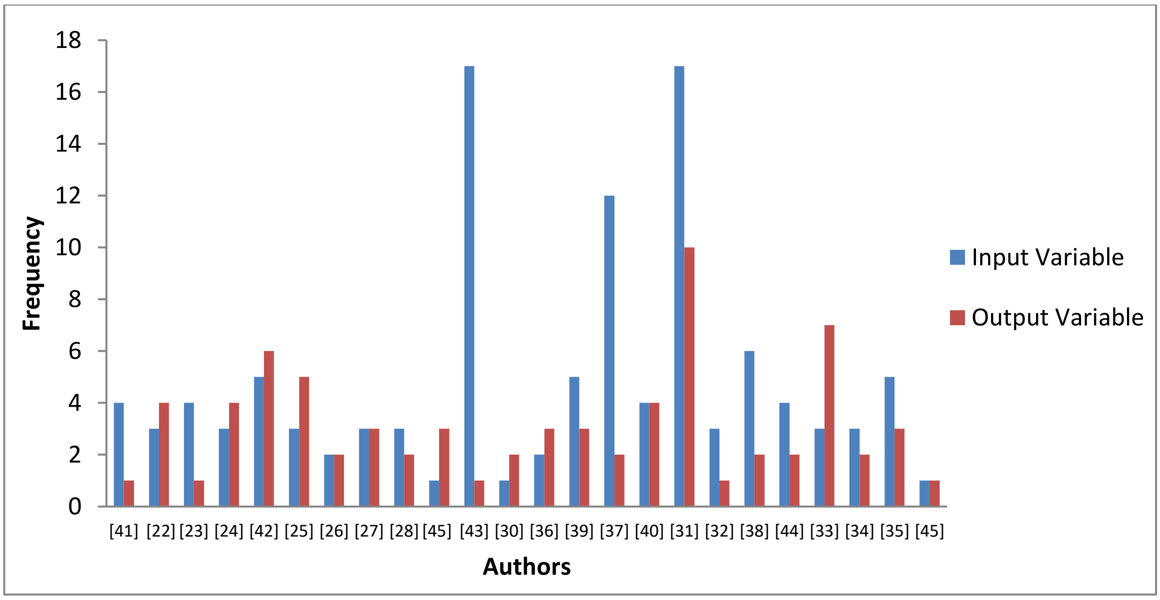

Figure 3. The total number of input and output used in previous studies

Even though DEA capable to handle multiple input and outputs, yet selecting too many inputs or output can make the interpretation become complex and difficult Therefore, it is important to select inputs and outputs that are relevant to the problem being analyzed and can be easily measured it is because the key limitation in evaluating academic achievement is the selection of appropriate input and output parameters [33]. In summary, the input and output selection in DEA is critical because it influences the scope and aim of the analysis, the production frontier and efficiency scores, and the accuracy and comprehensiveness of the results.

In this paper also reveals that most of the previous studies used the popular combination of DEA models namely CCR and BCC model as illustrated in Table 3 to assess the relative of DMUs. Four studies used the single BCC model are the studies done by [25] to discover the efficiency of Spanish schools, examined the technical efficiency of schools and its association with their managerial practices [46], to measure education sector's efficiency by comparing 28 European Union states at different levels of education [35] and to construct a performance-based method for a central planner to distribute research funding to different universities to better stimulate the research output [37]. Meanwhile, the CCR model seeks to identify the frontier of such efficient DMUs, which represents the most efficient performance among the entire DMUs. However, none of this study found used CCR model alone.

5. CONCLUSION

This research paper systematically reviews literature using the DEA method to determine academic achievement efficiency by selecting input and output factors. The author emphasizes that defining a quality student requires a holistic approach and cannot solely be based on grades. This paper suggests that using DEA can help universities identify which students are performing well and which are not. Furthermore, this study highlights a current gap in utilizing student characteristics as input and output variables within the DEA model, despite the growing demand for students to possess a diverse set of competencies, which is a concern. Therefore, the paper suggests that future research should focus on including student competencies as input variables and using additional variables such as student satisfaction as output variables. Furthermore, the paper suggests that integrating DEA techniques with other approaches such as simulation, statistical techniques, and machine learning can improve the accuracy and effectiveness of the model. By addressing these limitations, the DEA method can provide more robust and comparable results. Overall, the paper emphasizes the importance of offering quality education to meet the challenges of the 21st century society and suggests ways to improve the DEA method for this purpose.

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BIOGRAPHIES OF AUTHORS

Nor Faezah Mohamad Razi is a senior lecturer in Universiti Teknologi MARA (UiTM). She is the Resource Person for Fundamentals of Research. She received her BSc in Statistics and MSc in Applied Statistics from UiTM in 2009 and 2012, respectively. Currently she pursues her PhD study in Decision Science area. Her research interest in structural equation modeling (SEM), DEA and Educational technology. She can be contacted at norfa122@uitm.edu.my.

Norhayati Baharun is an Associate Professor of Statistics, Universiti Teknologi MARA Perak Branch, Tapah Campus. She received her PhD in Statistics Education from the University of Wollongong Australia in 2012. Her career started as an academic from January 2000 to date at the Universiti Teknologi MARA that specialized in statistics. Other academic qualifications include both Master Degree and Bachelor Degree in Statistics from Universiti Sains Malaysia and Diploma in Statistics from Institute Teknologi MARA. She is also a certified Professional Technologist (Ts.) (Information & Computing Technology) of the Malaysia Board of Technologist (MBOT), a Fellow Member of the royal statistical society (RSS), United Kingdom, a Professional Member of association for computing machinery (ACM), USA, and a certified neuro linguistic program (NLP) Coach of the Malaysia Neuro Linguistic Program Academy. Her research interests continue with current postgraduate students under her supervision in the area of decision science now expanding to a machine learning application. She can be contacted at norha603@uitm.edu.my.

Suraya Masrom is the head of machine learning and interactive visualization (MaLIV) Research Group at Universiti Teknologi MARA (UiTM) Perak Branch. She received her Ph.D. in Information Technology and Quantitative Science from UiTM in 2015. She started her career as a lecturer at UTM after receiving her master's degree in computer science from Universiti Putra Malaysia in 2001. She transferred to the Universiti Teknologi MARA (UiTM), Seri Iskandar, Perak, Malaysia, in 2004. She is an active researcher in the meta-heuristics search approach, machine learning, and educational technology. She can be contacted through email at suray078@uitm.edu.my.