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Efficiency analysis of prospective mathematics teachers' learning media development using data envelopment analysis

Mirta Fera[*)1], **Nurul Hilda Syani Putri**[1]
[1]Mathematics Education, Universitas Maritim Raja Ali Haji, Indonesia

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ABSTRACT

This study analyzes the efficiency of the learning media development process carried out by prospective mathematics education teachers using the Data Envelopment Analysis (DEA) approach. The sample consists of 30 graduates of the mathematics education study program from 2022–2024, whose final projects on the development of learning media or teaching materials are treated as Decision Making Units (DMUs). The input variables include the grade in the learning media/multimedia course and the duration of the research, while the output variables consist of the percentage scores of content expert validity, media expert validity, teacher practicality, and student practicality. The analysis was conducted using an output-oriented DEA model under the assumptions of Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). The results show that the CRS model identifies 11 DMUs (36.67%) as efficient, whereas the VRS model identifies 16 DMUs (53.33%) as efficient, and the average efficiency scores of both models lie in a high range (≥0.93). The slack calculations indicate that several DMUs still need to improve their output quality, particularly in the components of content validity and teacher practicality. These findings highlight the need to strengthen supervision and systematic mentoring to enhance the content quality and practicality of learning media developed by prospective teachers. This study is limited by the relatively small number of DMUs and its focus on a single study program, so the generalization of the results should be made cautiously, and further research with a larger sample and more diverse DEA model specifications is recommended.

Corresponding Author:

Mirta Fera,
Universitas Maritim Raja Ali Haji
Email: mirtafera0901@umrah.ac.id

Introduction

Issues of education quality often arise not only because the content is difficult, but also because the learning process is not well designed. The quality of this process is strongly influenced by teachers' decisions in planning instruction, choosing strategies, and using media that match students' needs. These decisions play a major role in shaping students' learning experiences in the classroom. Therefore, prospective teachers need to be viewed as the main designers of learning experiences, including how they develop and utilize learning media that will be used in classroom instruction. This perspective is consistent with the notion of teachers as instructional designers who plan learning systematically (Kilbane & Milman, 2015). Decision making in lesson planning should begin with a clear identification of decision makers, criteria, and alternatives, reducing disagreements about the problem definition and goals, in line with general guidelines for structured decision-making methods (Baker et al., 2002).

In mathematics education study programs, the ability to develop learning media is typically facilitated through research-and-development-based final projects, in which students design products that are evaluated in terms of validity, practicality, and effectiveness (Ediyani et al., 2020). In this process, prospective teachers must manage their project time, draw on knowledge from relevant courses, and coordinate with supervisors as well as content or media experts. Various studies have shown that well-designed learning media and multimedia can make learning more engaging and support the achievement of learning objectives more efficiently in the classroom (Ediyani et al., 2020; Krstić, 2021). However, these studies generally focus on media quality and its impact on learning, while there is still little research that specifically examines how efficiently prospective teachers transform the inputs they possess into media products that are ready to be used in class.

In the field of educational research, many quantitative studies focus on predicting student learning outcomes based on various cognitive and non-cognitive factors, such as numerical ability, motivation, and family background (Sasanguie, Van den Bussche, & Reynvoet, 2012). This approach provides important insights into factors influencing achievement, but it has not yet extensively addressed how the performance of individual prospective teachers as learning media developers can be assessed in a quantitative and systematic way. In fact, media-development final projects provide a combination of input data, such as grades in relevant courses and project duration, and output data in the form of validity and practicality scores, which are highly suitable to be analyzed within an efficiency-evaluation framework using approaches such as Data Envelopment Analysis, which has been widely applied to study the efficiency of educational units (Lestari, Sugiono, & Yuniarti, 2015; Shero et al., 2022).

Data Envelopment Analysis (DEA) is a nonparametric approach used to assess the relative efficiency of a decision making unit (DMU) when multiple inputs and outputs are involved simultaneously (Charnes, Cooper, & Rhodes, 1978; Ray, 2004). Unlike statistical analysis, which requires a specific functional form, DEA compares each DMU with the "best-practice frontier" formed from combinations of other DMUs, thereby identifying which units are already efficient and which still have room for improvement. In education, this approach has been widely used to evaluate the efficiency of schools, programs, and institutions by utilizing routinely available data, such as resource indicators and learning outcomes (Lestari et al., 2015; Muniz, Andriola, Muniz, & Thomaz, 2024; Shero et al., 2022).

The same conceptual framework can in fact be applied to prospective teachers who develop learning media, by treating each final project as a DMU that transforms academic inputs and research time into media products that are judged to be valid and practical. Through DEA, it becomes possible to map which prospective teachers have already reached a relatively high level of efficiency and in which output components slack is still found, indicating the need to improve product quality (Shero et al., 2022; Sihombing, Lubis, & Afri, 2023). This information is valuable for study programs to conduct benchmarking among students, design more targeted supervision, and review courses and learning experiences that support instructional design competence.

Based on this gap, the present study treats media- or teaching-material-development final projects produced by mathematics education graduates as DMUs whose efficiency is measured using DEA models under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions (Charnes et al., 1978). Specifically, this study seeks to answer the following questions: (1) What is the level of efficiency of learning media development among prospective mathematics education teachers based on DEA CRS and VRS models? (2) Which DMUs are classified as efficient, and in which output components is slack still observed? and (3) What are the implications of these efficiency findings for final-project supervision and for the development of teacher-education curricula in mathematics education study programs.

Method

The data in this study were collected using a descriptive method that systematically portrays the facts and characteristics of the object under investigation (Sukardi, 2004). The unit of analysis in this research is graduates of the Mathematics Education study program. The research sample consists of 30 Decision Making Units (DMUs), labeled DMU1–DMU30, all of whom are graduates from the 2022–2024 period who meet the following criteria: (1) their final project focuses on the development of learning media or teaching materials, and (2) complete data are available for all input and output variables. Accordingly, these 30 DMUs represent all graduates in that period who satisfy the research criteria, and are therefore considered adequate to describe relative efficiency within the context of this study program. However, because the data come from a single institution, generalizing the findings to broader contexts must be done with caution, and this limitation is reiterated in the discussion and conclusion sections.

Efficiency was measured using Data Envelopment Analysis (DEA). DEA is a nonparametric method used to assess the relative efficiency of a DMU by simultaneously considering multiple inputs and outputs (Charnes et al., 1978; Ray, 2004). In simple terms, DEA compares each DMU with the most efficient combination of other DMUs, thereby indicating whether a given DMU already uses its inputs in a balanced way to generate outputs or still has room to improve its performance. This approach is relevant in educational contexts because it enables study programs to identify which students are relatively efficient and in which aspects of media development improvement is still needed (Lestari et al., 2015; Shero et al., 2022).

The DEA models employed in this study are output-oriented models under the assumptions of Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS). An output orientation was chosen because the main focus of the research is to maximize the quality of media products produced by prospective teachers (in terms of validity and practicality) given the inputs already expended, rather than to minimize inputs. The use of both scale assumptions (CRS and VRS) is intended to compare efficiency when scale is assumed to be constant and when scale variations are taken into account, as is common in efficiency studies in education (Muniz et al., 2024). Efficiency calculations were performed using the Win4DEAP 2 software package, in line with standard practice in DEA studies in the educational field.

The DEA model in this study is based on the CCR and VRS. This model consists of determining for each DMU the maximum ratio between output and input through the use of mathematical programming, with the problem formulation linearized into the following linear programming model (Charnes et al., 1978).

$$Max \sum_{r=1}^{R} u_{rb} y_{rb} \qquad (2)$$

s.t

$$\sum_{i=1}^{I} v_{ib} x_{ib} = 1$$

$$\sum_{r=1}^{R} u_{rb} y_{rb} - \sum_{i=1}^{I} v_{ib} x_{ib} \leq 0$$

$$u_r,\ v_i \geq 0$$

The input variables in this study are the grade in the learning media or multimedia course and the duration of the research project (in months). The grade in the learning media or multimedia course is used as an initial indicator of prospective teachers' academic ability to design and use media, because this course is designed to provide conceptual knowledge and practical skills related to the development of learning media. The use of grades as one of the indicators of performance or academic ability is also common in higher education research, for example in studies examining the relationships among academic competence, learning processes, and final project grades (Tuononen & Parpala, 2021). The importance of mastering the development of valid and practical media in teacher education is likewise emphasized in various studies on learning media development (Ediyani et al., 2020). The second input variable is the duration of the research (in months), based on the research schedule stated in the final project manuscript. This value represents the time resources used by students in planning, developing, and refining the media or teaching materials. Its use as an input in DEA is intended to assess the relative efficiency of how research time, as one of the resources, is utilized to produce quality outputs.

The outputs in this study are the quality of the media development products, measured through four indicators: (1) the percentage score of validity assessed by content experts, (2) the percentage score of validity assessed by media experts, (3) the percentage score of practicality assessed by teachers, and (4) the percentage score of practicality assessed by students. These four indicators are treated as output variables in DEA because they represent the level of product quality generated from the use of the input variables—research time and learning media course grades—in line with efficiency studies in education that conceptualize inputs as various educational resources and outputs as performance outcomes resulting from the use of those resources (Muniz et al., 2024). In addition, recent research on learning media development employing R&D approaches or models such as ADDIE and 4D widely positions validity, practicality, and effectiveness criteria as the main indicators of media product quality (Bahari & Setiawan, 2024; Jalil, Prastowo, & Widodo, 2019; Nanda & Agustini, 2023; Wijayanti, Chrisnawati, & Fitriana, 2019). Accordingly, in this study the scores of content expert validity, media expert validity, teacher practicality, and student practicality are treated as direct representations of the quality of media development outcomes produced by each student as a DMU. The descriptive statistics sample for inputs and outputs is presented in Table 1.

Table 1. The descriptive statistics sample of inputs and outputs

variable	max	min	mean
output			
% validity material score	0.98	0.78	0.86
% validity media Score	0.94	0.75	0.87
%Practicality teachers score	1	0.77	0.91
%Practicality students score	0.98	0.70	0.85
input			
Course grade	91	77	83.16
Research duration	33	9	13.97

The values of each variable were obtained through document analysis of the study program archives, which contain data on course grades, the duration of final project completion, and reports of validity and practicality assessments by experts and users (teachers and students). The data were analyzed using Data Envelopment Analysis with output-oriented constant returns to scale (CRS) and variable returns to scale (VRS) models. Through these models, an efficiency score was calculated for each DMU and slack in the output variables was identified, indicating the potential for improving media quality.

Results and Discussions

This section presents the research results. The table below contains information about the distribution of DMU efficiency scores. The author uses Win4DEAP 2 to calculate the efficiency of the Decision Making Unit (DMU) and compare the CRS model and the VRS model in DEA. The cumulative distribution of the efficiency scores for the CRS and VRS models is presented in Table 2.

Table 2. Cumulative Distribution of Efficiency Scores for CRS and VRS Models

Range Skor	CRS	VRS
1,000	11	16
0,900-0,999	17	13
0,800-0,899	2	1
0,700-0,799	0	0
0,600-0,699	0	0
0,500-0,599	0	0
0,400-0,499	0	0
0,300-0,399	0	0
<0,299	0	0
sum	30	30

From Table 2, the analysis results of the CRS model indicate that 11 students (DMU1, DMU2, DMU4, DMU5, DMU6, DMU7, DMU8, DMU10, DMU14, DMU23, DMU30) are categorized as efficient students (score 1) while 19 other students have scores below 1. The average efficiency score of the CRS model is 0,959. The analysis results of the VRS model show that 16 students (DMU1, DMU2, DMU4, DMU5, DMU6, DMU7, DMU8, DMU9, DMU10, DMU11, DMU14, DMU21, DMU23, DMU24, DMU25, DMU30) are categorized as efficient, while 14 students have scores below 1 with the average efficiency score of the VRS is 0,978. In this case, it is noted that the average efficiency score of the VRS model is higher than that of the CRS model, which is consistent with Chamdani (2019), study that states the average efficiency score of the VRS model is generally higher than that of the CRS model.

The difference in the number of efficient DMUs in the CRS and VRS models shows that when the production scale assumption is made more flexible (VRS), more prospective teachers are assessed as being able to use their resources efficiently. This indicates that part of the variation in efficiency is related to differences in scale or in individual capacity to manage research time and to optimize the knowledge acquired from the learning media course.

However, the fact that 14-19 DMUs remain inefficient in both models indicates that a considerable number of prospective teachers are still not optimal in converting educational inputs into high-quality media products. This condition is important for the study program because it signals the need to strengthen supervision in the aspects of design, try-out, and revision of learning media, so that students not only complete their final projects

Jurnal EDUCATIO (Jurnal Pendidikan Indonesia)
Vol. 11, No. 2, 2025, pp. 18-25

but also achieve a high level of efficiency in the development process. The detailed efficiency scores of the CRS and VRS DMU data processing results are presented in Table 3.

Table 3. Efficiency Scores Of the CRS and VRS DMU

DMU	CRS Score	VRS Score
DMU1	1.000	1.000
DMU2	1.000	1.000
DMU3	0.917	0.986
DMU4	1.000	1.000
DMU5	1.000	1.000
DMU6	1.000	1.000
DMU7	1.000	1.000
DMU8	1.000	1.000
DMU9	0.971	1.000
DMU10	1.000	1.000
DMU11	0.917	1.000
DMU12	0.922	0.993
DMU13	0.932	0.937
DMU14	1.000	1.000
DMU15	0.861	0.948
DMU16	0.933	0.947
DMU17	0.905	0.910
DMU18	0.988	0.988
DMU19	0.949	0.954
DMU20	0.949	0.954
DMU21	0.981	1.000
DMU22	0.902	0.923
DMU23	1.000	1.000
DMU24	0.976	1.000
DMU25	0.976	1.000
DMU26	0.982	0.989
DMU27	0.919	0.960
DMU28	0.864	0.888
DMU29	0.937	0.976
DMU30	1.000	1.000

The VRS model shows more efficient DMUs compared to the CRS model. This indicates that when differences in scale among students are taken into account, more prospective teachers can be considered efficient in converting their available inputs into high-quality media products. Several previous studies in educational efficiency also report that VRS models tend to yield higher efficiency scores than CRS models, because they relax the strict proportionality assumption and are more sensitive to scale variations in educational settings (Chamdani, 2019; Condez, 2024).

The difference in the number of efficient DMUs between the two models also shows that some students who appear inefficient under the constant returns to scale (CRS) assumption become efficient when returns to scale are allowed to vary (VRS). This indicates that their media development performance is actually good when evaluated relative to a more realistic scale of resource use. Nevertheless, there are still several DMUs that remain inefficient under both models, suggesting that the quality of their outputs particularly in terms of teacher and student practicality does not yet match the time invested and the initial capabilities they possess. The results of the analysis of output slacks calculations using the CRS and VRS models are presented in Table 4.

Every inefficient DMU is associated with slack. Slack represents the degree of inefficiency in the allocation of input or output variables: an efficient DMU has slack equal to 0, whereas slack > 0 indicates either excess input that could be reduced or insufficient output that needs to be improved. In this study, slack values were obtained using a multiple-stage DEA procedure that identifies projection points of efficient DMUs whose input–output combinations are closest to those of inefficient DMUs (Coelli, 1992). In an output-oriented model, such as the one used here, inefficiency (efficiency score < 1) implies that the DMU needs to increase its output levels while keeping its inputs constant.

Table 4. Frequencies of DMUs with Positive Slacks on Output Variables

Output variable	CRS: number of DMUs with slack > 0	VRS: number of DMUs with slack > 0
Validity score – material expert	9	6
Validity score – media expert	5	5
Practicality score – teachers	10	7
Practicality score – students	8	3

The slack data analysis shows that inefficiency in media development mainly arises because output quality is not yet consistent across the four assessed indicators. Several DMUs still exhibit slack in content expert validity scores, media expert validity scores, teacher practicality, and student practicality, and therefore have not reached an efficient position on the DEA frontier. In the CRS model, there are 9 DMUs that still have slack in content validity, 5 DMUs in media validity, 10 DMUs in teacher practicality, and 8 DMUs in student practicality; in the VRS model, these numbers decrease to 6, 5, 7, and 3 DMUs, respectively. This pattern indicates that the most frequent issue does not lie in the correctness of content or media design, but rather in the extent to which the media are perceived as practical and easy to use by teachers and students in the classroom. The use of indicators such as validity and practicality in this way is in line with the study by Suwatra et al., who developed Android-based teaching materials incorporating local wisdom and evaluated their feasibility through expert validity tests and practicality tests in elementary schools (Mudiartana, Margunayasa, & Divayana, 2021).

When the efficiency and slack results are read together, it appears that many prospective teachers are already able to meet the validity standards set by experts but have not yet fully succeeded in translating these designs into comfortable learning experiences for users. In other words, they have mastered the conceptual and basic technical aspects of media development but still need support in the stages of implementation, classroom observation, and product refinement based on feedback from teachers and students. This pattern is consistent with findings from several studies on the development of teaching materials based on local wisdom, which show that products are declared valid and practical by experts, then subjected to limited classroom trials to observe students' responses and make further revisions so that their use in the field becomes truly effective (Damopolii et al., 2024; Sriyati et al., 2021).

For teacher education programs, these findings imply that improvement does not necessarily require increasing the input load, but rather strengthening students' ability to maximize the outputs they have already designed. Study programs can, for example, increase the number of media try-out sessions with teachers and students, provide clearer space for product revision cycles, and incorporate practicality and user experience as key components in the assessment rubric for media development final projects. Such an approach is in line with the study by Bakhri, Tsuroya, & Pratama (2023) who developed Android-based learning media using QuickAppNinja for elementary school teachers and showed that the use of digital media through structured design and trials can enhance teachers' digital literacy and support instructional activities.

The variation in efficiency scores among students also indicates that success in media development depends not only on technical skills in using tools or applications but is strongly influenced by reflective and adaptive capacities in responding to real learning situations. Efficient prospective teachers tend to be able to read classroom needs, interpret user feedback, and gradually adjust media designs until they approach the ideal condition on the efficiency frontier. These findings align with recent analyses of digital teacher education, which emphasize that pedagogical–technological competence and the ability to adapt technology use to students' learning needs contribute directly to students' perceived learning value (Dang et al., 2024; Val & López-Bueno, 2024). These findings describe the situation in a single study program that is the focus of this research. Therefore, when the results are compared or applied to other study programs or institutions, caution is required and further research in different contexts is needed to support such generalization.

Conclusions

This study analyzed the efficiency of prospective mathematics teachers in developing learning media by applying Data Envelopment Analysis (DEA) using CRS and VRS models to final project data from the mathematics education study program at Universitas Maritim Raja Ali Haji. The results show that some students have already achieved a good level of efficiency in designing and developing learning media, while others still have room to improve their validity and practicality scores. These findings suggest that efficiency in learning media development is related not only to technical skills in using media, but also to prospective teachers' ability to make careful decisions and align media design with pedagogical goals, classroom needs, and stakeholder expectations

For teacher education programs, these findings offer several practical implications. First, study programs need to provide more structured guidance and feedback during the planning, development, and evaluation of learning media, especially for students whose efficiency levels are not yet optimal. Second, mapping efficient and inefficient students can be used as a basis for benchmarking good practices in learning media design, for example by using efficient students' final projects as exemplars, discussion materials, or peer learning resources in relevant courses. Third, integrating decision-support tools such as DEA into the curriculum can help prospective teachers more systematically reflect on how they allocate time, effort, and resources in developing learning media, so that they are better prepared to design effective instruction in real classroom settings.

This study has several limitations that should be considered when interpreting the findings. The data come from a relatively small number of DMUs and from a single mathematics education study program at one university, so the results cannot be directly generalized to other study programs, institutions, or subject areas. In addition, the efficiency analysis is based on a specific set of input and output variables, namely the duration of the final project, course grades, and the percentage scores of validity and practicality assessments; other aspects of teacher competence, such as creativity, adaptability, or long-term impact on students' learning outcomes, are not directly captured in the model. Therefore, the conclusions of this study should be understood as a contextual picture of a single study program, and any generalization to broader contexts should be made with caution.

In line with these limitations, future research is recommended to involve a larger and more diverse group of prospective teachers from various universities and study programs, and to add other indicators that more comprehensively represent teacher competence and the quality of learning media. Subsequent studies may also compare different DEA model specifications or combine DEA with qualitative approaches, such as interviews or portfolio analysis, to deepen understanding of how prospective teachers make decisions when developing learning media. At the policy level, the use of efficiency analysis of this kind can be further explored as a tool to support continuous improvement of teacher education curricula, particularly in courses that emphasize instructional design and the integration of technology into the learning process.

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