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Recommending Mathematics Learning Applications for Students: A Comprehensive Approach Using Multi-Attribute Utility Theory (MAUT)

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Abstract:

Selecting the right mathematics learning application is crucial for supporting students' learning processes, but this is often hampered by a wide variety of choices without objective guidance, potentially leading to less effective selections. This descriptive quantitative study describes the implementation of the Multi-Attribute Utility Theory (MAUT) method to recommend mathematics learning applications that align with student needs. MAUT flexibly and comprehensively considers various weighted criteria, making it effective for decision-making with complex preferences. Eight criteria were used to evaluate ten mathematics learning applications: (1) user review count, (2) storage capacity, (3) rating, (4) user count, (5) application usage cost, (6) answer accuracy, (7) ease of use (UI/UX), and (8) step-by-step solutions. Data were collected through questionnaires distributed to 20 respondents. The calculation process in the MAUT method was carried out through several stages: determining the relative weights for each criterion, constructing a decision matrix, performing normalization on the decision matrix, and calculating the final utility value for each alternative. Based on the calculation results using the MAUT method, the recommended application order is as follows: Photomath, Question.AI, Cymath, QANDA, Gauthmath, Check Math, Symbolab, Mathos AI, Mathway, and Math Workout. This study is expected to provide a practical contribution by helping students and educational institutions choose the most optimal mathematics learning application, and to serve as a basis for the future development of a more structured recommendation system.

Keywords: Decision support system, Multi-Attribute Utility Theory (MAUT), mathematics learning application, students, recommendation.

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Introduction

As a fundamental discipline, mathematics plays a central role in supporting the development of various fields such as science, technology, engineering, and economics (Jazuli, 2021). Mastery of mathematical concepts is an essential competence that helps students develop logical thinking skills, solve problems systematically, and adapt to the increasingly complex demands of the era (Siswanto & Meiliasari, 2024). However, many students still face significant challenges in understanding complex mathematical material (Asri et al., 2024). This finding is consistent with research by Agustina et al. (2021), which shows that students in Indonesia often struggle to master basic mathematical concepts, have low mathematical literacy in problem application, and face major obstacles in exact science courses at the university level, which ultimately impacts their motivation and academic achievement.

Along with the rapid development of technology, various mathematics learning applications have emerged, offering innovative solutions to overcome students' learning difficulties (Rijoly et al., 2024). These applications utilize interactive features, visualizations, and artificial intelligence (AI) to present material in a more engaging and easy-to-understand manner. For example, Photomath and Mathway can solve mathematical problems by simply scanning an image, while Mathos AI uses an adaptive learning algorithm to tailor material to the user's ability (Febrina & Mahmud, 2024). This trend aligns with data from Straits Research, which noted that the global educational application market reached USD 6.01 billion in 2024 and is projected to surge to USD 33.51 billion by 2033, with a Compound Annual Growth Rate (CAGR) of 21.04% during the 2025–2033 period, reflecting a high and sustained demand for technology-based learning solutions (Warade, 2025).

Although many learning applications are available, students often face difficulty in determining which application is most effective for supporting their learning process (Cahyawati & Gunarto, 2021). This is due to the diverse features and characteristics offered by each application. In this context, there are several key aspects that are generally considered by students when choosing a learning application. Applications with an intuitive and easy-to-use interface are often chosen as they are perceived to increase comfort and efficiency during the learning process (Febrina & Mahmud, 2024). In addition, an application's ability to explain the problem-solving process systematically and in detail is also an important criterion, as it helps students understand the steps more deeply (Karim et al., 2022).

The accuracy of the answers provided by an application is a crucial factor, as the precision of the solution is highly determinative of success in correctly understanding mathematical concepts and procedures (Muzammil et al., 2023). Moreover, the application's storage capacity is also an important consideration, especially for students with limited-spec devices; lightweight applications that do not consume much memory are certainly preferred as they do not burden the device (Mandarani & Putra, 2020). The popularity of an application, reflected by the number of downloads and positive reviews, is often used as an indicator of trust and credibility (Ramadani, 2024), while ratings on digital platforms are frequently used to assess overall quality and user satisfaction (Yunita et al., 2023). Finally, the cost of using the application cannot be ignored, given that not all features are available for free and some premium features can only be accessed by paid users (Hakim, 2020).

With numerous aspects to consider, an approach that can objectively integrate all these elements is needed so that the decision-making process for choosing a learning application can be done rationally and measurably. Without a proper guide, a subjective

and undirected selection of an application can actually hinder the learning process, as students may choose an application that does not fit their needs or learning style. This not only reduces learning effectiveness but can also decrease overall learning motivation (Harianto et al., 2024).

To address the problem of selecting the right learning application, a Decision Support System (DSS) approach becomes a relevant solution. A DSS is a computer-based system designed to support every phase of the decision-making process, from problem identification and data and strategy selection to the evaluation of available alternatives (Sarwandi et al., 2023). Furthermore, a DSS functions to process data into information that can be used to solve semi-structured problems and assists decision-makers in handling unstructured issues, particularly in management contexts, to improve the quality of the decisions made (Suhartini et al., 2024). In the context of choosing a learning application, a DSS can process data from various criteria to generate recommendations for the most optimal application.

In line with the increasing application of DSS in education, a number of studies have discussed the selection of learning applications using decision-making methods. For example, Karim et al. (2022) applied the Elimination and Choice Translating Reality (EDAS) method to select a mathematics learning aid application, while Febrina & Mahmud (2024) used the Preference Selection Index (PSI) method to evaluate AI-based learning media.

In the context of implementing a Decision Support System (DSS), selecting the right method is key to producing accurate recommendations that meet specific needs. One widely used method is the Multi-Attribute Utility Theory (MAUT), a systematic approach that evaluates a number of alternatives based on various relevant attributes (Munjal et al., 2022). In this method, each alternative is assessed based on predefined criteria, and each criterion is given a weight according to its importance to the decision-making goal (Handayani, 2022). The value of each attribute is then converted into a uniform utility scale to facilitate aggregation among alternatives (Jin et al., 2021). MAUT is effective for handling complex and multi-criteria problems because it can accommodate different preferences quantitatively and in a structured manner (Munjal et al., 2022). According to Trisudarmo et al. (2024), MAUT is suitable for the selection of multidimensional learning applications. Based on this, this study chose MAUT for its systematic and quantitative framework, which facilitates a comprehensive and consistent evaluation of alternatives while integrating user preferences for various relevant criteria.

The Multi-Attribute Utility Theory (MAUT) method has been widely applied to support decision-making in various fields. This method is used in various cases such as determining the best employee (Nuroji, 2022), selecting honorary staff (Hondro, 2022), choosing top-tier students (Kayati et al., 2022), selecting learning media applications during the pandemic (Pradana et al., 2023), selecting Tahfidz Islamic Boarding School (Ilmiyah et al., 2023), recommending smartphones (Sinaga et al., 2024), selecting chatting applications (Rohayani et al., 2024), choosing student concentrations in the Informatics Engineering study program (Budiman et al., 2024), e-voting systems for OSIS chairperson selection (Trisudarmo et al., 2024), selecting cryptocurrency exchange platforms (Putra & Utami, 2024), selecting the best nurses in preventing and controlling infections in hospitals (Dewi et al., 2024), and so on. From the previous research explained above, it can be concluded that the MAUT method has not been specifically used to select mathematics learning applications based on student preferences. Therefore, this research is expected to help students make more rational and systematic decisions. The final result

of the application recommendation will truly reflect the needs and expectations of students in improving the effectiveness of mathematics learning.

Methods

This research is a descriptive quantitative study that aims to systematically and objectively explain the process of selecting mathematics learning support applications for students. The method used is Multi-Attribute Utility Theory (MAUT), which was chosen to identify the most suitable applications for recommendation based on a quantitative evaluation of various criteria. A descriptive research design was employed to present the characteristics of each application alternative in a measurable way, allowing the results to provide a clear overview of their strengths and weaknesses.

The alternatives analyzed include ten popular platforms: Photomath, Question.AI, Mathway, Mathos AI, Gauth, QANDA, Cymath, Check Math, Symbolab, and Math Workout. The analysis was conducted to determine the most appropriate application to recommend as a support for the mathematics learning process. The research procedure consists of: (1) developing criteria and a rating scale for each alternative, (2) establishing the preference weights of the decision-maker, (3) implementing the MAUT method to evaluate the alternatives, and (4) formulating the recommendation results.

Each criterion is classified into one of two types: benefit and cost. A benefit criterion is one where a higher value indicates a better alternative, such as an application's rating or answer accuracy. Conversely, a cost criterion is one where a lower value indicates a more desirable alternative, such as storage capacity or application usage cost. This classification is crucial because it affects the value normalization calculation within the MAUT method.

There are eight criteria used in this study. Each criterion is described along with its measurement scale as follows:

a) User Review Count ($K1$)

The number of user reviews reflects user satisfaction and experience with the application on official platforms (e.g., Play Store/App Store).

Rating Scale:

- 1 if the application has fewer than 100.000 reviews.
- 2 if the application has between 100.000 and 750.000 reviews.
- 3 if the application has more than 750.000 reviews.

b) Storage Capacity ($K2$)

Storage capacity indicates the amount of memory required on the device.

Rating Scale:

- 1 if the application requires more than 100 MB of storage.
- 2 if the application requires between 50 MB and 100 MB of storage.
- 3 if the application requires less than 50 MB of storage.

c) Rating ($K3$)

Rating indicates the average star rating given by users on app stores, serving as an indicator of quality and user satisfaction.

Rating Scale:

- 1 if the application's rating is less than 3.5.
- 2 if the application's rating is between 3.5 and 4.2.
- 3 if the application's rating is greater than 4.2.

d) User Count ($K4$)

The user count indicates the application's popularity based on the number of downloads on app stores.

Rating Scale:

- 1 if the application has fewer than 500.000 downloads.
- 2 if the application has between 500.000 and 5.000.000 downloads.
- 3 if the application has more than 5.000.000 downloads.

e) Application Usage Cost (*K5*)

Application usage cost measures the extent to which essential features can be accessed for free without requiring payment.

Rating Scale:

- 1 if the application is fully paid or the free version lacks access to key features.
- 2 if the application is free, but crucial features (such as step-by-step solutions) are only available in the premium version.
- 3 if the application is completely free or its full features are sufficient for student learning needs.

f) Answer Accuracy (*K6*)

Answer accuracy measures the level of correctness and reliability of the answers provided by the application.

Rating Scale:

- 1 if the application frequently gives incorrect or inconsistent answers.
- 2 if the application gives correct answers for most problems but still contains some errors on specific problem types.
- 3 if the application consistently provides correct and accurate answers for a wide range of mathematical problems.

g) Ease of Use (UI/UX) (*K7*)

Ease of use evaluates the quality of the interface and the convenience for users to operate the application.

Rating Scale:

- 1 if the interface is confusing, unintuitive, and requires a long time to learn, with minimal usage guidance.
- 2 if the application is fairly easy to use but still requires some adaptation or has confusing parts for new users.
- 3 if the application is very easy to use, has an intuitive and neat interface, and is supported by clear instructions and smooth navigation.

h) Step-by-Step Solutions (*K8*)

Step-by-step solutions evaluate the completeness and clarity of the problem-solving process presented by the application.

Rating Scale:

- 1 if the application only displays the final answer without showing the solution steps.
- 2 if the application displays partial steps that are incomplete or unclear.
- 3 if the application displays all solution steps completely, systematically, and in an easy-to-understand manner.

Data for criteria *K1* – *K5* were obtained through direct observation on official platforms such as Google Play Store and App Store, while data for criteria *K6* – *K8* were collected through an online questionnaire distributed using Google Forms. This

questionnaire was filled out by 20 respondents, all of whom are students at UIN Syekh Wasil with experience using various digital mathematics learning applications.

The data processing steps using the Multi-Attribute Utility Theory (MAUT) method were carried out through the following stages:

- a) Constructing the decision matrix Z , which contains the values of each alternative for each criterion.

$$Z = \begin{bmatrix} z_{11} & z_{12} & z_{21} & z_{22} & \cdots & z_{1j} & z_{2j} & \ddots & z_{i1} & z_{i2} & \cdots & z_{ij} \end{bmatrix}$$

where z_{ij} is the value of the i -th alternative with respect to the j -th criterion.

- b) Normalizing the decision matrix Z to obtain the value v_{ij} , taking into account the type of criterion.

The normalization value for benefit criteria is calculated using the following formula:

$$v_{ij} = \frac{z_{ij} - \min(z_j)}{(z_j) - \min(z_j)} \quad (1)$$

Meanwhile, the normalization value for cost criteria is calculated using the following formula:

$$v_{ij} = \frac{(z_j) - z_{ij}}{(z_j) - \min(z_j)} \quad (2)$$

where v_{ij} is the normalized value of the i -th alternative on the j -th criterion.

- c) Constructing the normalized matrix V with entries derived from the normalization process in point (b).

$$V = \begin{bmatrix} v_{11} & v_{12} & v_{21} & v_{22} & \cdots & v_{1j} & v_{2j} & \ddots & v_{i1} & v_{i2} & \cdots & v_{ij} \end{bmatrix}$$

- d) Constructing the marginal utility matrix U with entries u_{ij} calculated using the following formula:

$$u_{ij} = \frac{e^{(v_{ij})^2} - 1}{1,71} \quad (3)$$

- e) Determining the final utility value. The final utility value is obtained by multiplying the matrix U by the criteria weights. The weight of each criterion is denoted in the matrix DM , whose entries are obtained from the decision maker's assessment. The final value of each alternative is calculated using the following formula:

$$S = U \times DM \quad (4)$$

After the final utility values for each alternative are obtained, all values are sorted from the highest to the lowest. This ranking then serves as the basis for formulating the final recommendation. The alternative with the highest score is considered the most recommended application for mathematics learning for students.

Results and Discussion

Findings

In this section, we present the raw data obtained from direct observation on official platforms such as the Google Play Store and App Store, as well as from the distributed questionnaire, which serves as the basis for the subsequent analysis. The average values from the questionnaire data, along with the maximum and minimum values for each criterion, are presented in Table 1 and Table 2.

Table 1. Raw Data

Alternative	Criterion							
	K1	K2	K3	K4	K5	K6	K7	K8
Photomath	3	3	3	3	3	2,31	2,62	2,54
Question. AI	2	3	2	3	3	2,06	2,65	2,29
Mathway	2	3	2	3	2	2,57	2,14	1,86
Mathos AI	1	3	3	2	3	2,50	2,00	2,00
Gauth	3	2	3	3	2	2,33	2,33	2,33
QANDA	2	3	2	3	2	2,36	2,45	2,55
Cymath	1	3	3	2	3	3,00	2,00	2,00
Check Math	2	3	3	3	2	2,50	2,00	2,25
Symbolab	2	3	3	3	2	2,33	2,00	2,00
Math Workout	1	3	3	2	2	2,50	2,00	1,50

Source: Author's Documentation

Table 2. Maximum and Minimum Values for Each Criterion

Value	Criterion							
	K1	K2	K3	K4	K5	K6	K7	K8
Maximum	3	3	3	3	3	3	2,65	2,55
Minimum	1	2	2	2	2	2,06	2	1,50

Source: Author's Documentation

This study obtained the preference weights for each criterion directly from a single decision maker in the field of mathematics. The weights are shown in Table 3.

Table 3. Decision Maker's Preference Weights

Criterion							
K1	K2	K3	K4	K5	K6	K7	K8
0,10	0,10	0,10	0,10	0,10	0,15	0,15	0,20

Source: Author's Documentation

From Table 3, the decision maker's preference weight matrix can be constructed as follows:

$$DM = [0,10 \ 0,10 \ 0,10 \ 0,10 \ 0,10 \ 0,10 \ 0,10 \ 0,15 \ 0,15 \ 0,20]$$

Analysis

In this stage, the implementation of the MAUT method for creating recommendations for mathematics learning applications for students will be presented.

a) Constructing the Decision Matrix Z

Each entry in the decision matrix Z represents data from Table 1. The number of rows corresponds to the number of alternatives used, while the number of columns corresponds to the number of criteria used.

$$Z = \begin{bmatrix} 3 & 3 & 3 & 3 & 3 & 2,31 & 2,62 & 2,54 & 2 & 3 & 2 & 3 & 3 & 2,06 & 2,65 & 2,29 & 2 & 3 & 2 & 3 & 2 & 2,57 & 2,14 & 1,86 & 1 & 3 & 3 & 2 \\ 3 & 2,50 & 2 & 2 & 3 & 2 & 3 & 3 & 2 & 2,33 & 2,33 & 2,33 & 2 & 3 & 2 & 2,36 & 2,45 & 2,55 & 1 & 3 & 3 & 2 & 3 & 3,00 & 2 & 2 & 2 & 3 \\ 3 & 3 & 2 & 2,50 & 2 & 2,25 & 2 & 3 & 3 & 3 & 2 & 2,33 & 2 & 2 & 1 & 3 & 3 & 2 & 2 & 2,50 & 2 & 1,50 \end{bmatrix}$$

b) Normalizing the Decision Matrix Z

In this step, the decision matrix is normalized by calculating the utility value for each entry. *Benefit* criteria are calculated using Formula (1), while *cost* criteria are calculated using Formula (2). In this study, all criteria are of the *benefit* type. The results of these calculations are presented in Table 4.

Table 4. Normalized Decision Matrix Z

Alternative	Criterion							
	K1	K2	K3	K4	K5	K6	K7	K8
Photomath	1	1	1	1	1	0,27	0,95	0,99
Question.AI	0,5	1	0	1	1	0	1	0,75
Mathway	0,5	1	0	1	0	0,54	0,22	0,34
Mathos AI	0	1	1	0	1	0,47	0	0,48
Gauthmath	1	0	1	1	0	0,29	0,51	0,79
QANDA	0,5	1	0	1	0	0,32	0,69	1,00
Cymath	0	1	1	0	1	1	0	0,48
Check Math	0,5	1	1	1	0	0,47	0	0,71
Symbolab	0,5	1	1	1	0	0,29	0	0,48
Math								
Workout	0	1	1	0	0	0,47	0	0

Source: Author's Documentation

c) Constructing the Normalized Matrix V

Each entry in the normalized matrix represents data from Table 4. The number of rows corresponds to the number of alternatives used, while the number of columns corresponds to the number of criteria used.

$$V = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 0,27 & 0,95 & 0,99 & 0,50 & 1 & 0 & 1 & 1 & 0 & 1 & 0,75 & 0,50 & 1 & 0 & 1 & 0 & 0,54 & 0,22 & 0,34 & 0 & 1 & 1 \\ 0 & 1 & 0,47 & 0 & 0,48 & 1 & 0 & 1 & 1 & 0 & 0,29 & 0,51 & 0,79 & 0,50 & 1 & 0 & 1 & 0 & 0,32 & 0,69 & 1,00 & 0 & 1 & 1 & 0 & 1 & 1 \\ 0 & 0,48 & 0,50 & 1 & 1 & 1 & 0 & 0,47 & 0 & 0,71 & 0,50 & 1 & 1 & 1 & 0 & 0,29 & 0 & 0,48 & 0 & 1 & 1 & 0 & 0 & 0,47 & 0 & 0 \end{bmatrix}$$

d) Constructing the marginal utility matrix U

After the decision matrix is normalized, the next step is to construct the marginal utility matrix U . Each entry in matrix U is calculated using Formula 3, and the results are as follows:

$$U = \begin{bmatrix} 1,0048 & 1,0048 & 0 & 1,0048 & 0,4452 & 0,1661 & 1,0048 & 0 & 1,0048 & 1 & 0 & 0,2002 & 0,0278 & 0,0729 & 0 \\ 1,0048 & 1,0048 & 0 & 1,0048 & 0,1433 & 0 & 0,1488 & 1,0048 & 0 & 1,0048 & 1,0048 & 0 & 0,0503 & 0,1719 & 0 \\ 0,5076 & 0,1661 & 1,0048 & 0 & 1,0048 & 0 & 0,0627 & 0,3596 & 1,0048 & 0 & 1,0048 & 1,0048 & 0 & 1,0048 & 0 \\ 1,0048 & 0 & 0,1488 & 0,1661 & 1,0048 & 1,0048 & 1,0048 & 0 & 0,1433 & 0 & 0,3893 & 0,1661 & 1,0048 & 0 & 0 \\ 1,0048 & 1,0048 & 0 & 0,0503 & 0 & 0,1488 & 0 & 1,0048 & 1,0048 & 0 & 0 & 0,1433 & 0 & 0 & 0 \end{bmatrix}$$

e) Determining the final utility value/ matrix S .

The final utility value is obtained by Formula 4.

$$S = [0,8340 \ 0,5578 \ 0,2664 \ 0,3527 \ 0,4363 \ 0,4819 \ 0,4819 \ 0,4174 \ 0,3554 \ 0,2225]$$

After applying the MAUT method, the next step is to formulate recommendations based on the analysis results. The ranking of alternative recommendations is obtained from the matrix resulting from the multiplication of the normalized matrix with the decision maker's preference weight matrix.

Table 5. Recommendation Ranking

Alternative	Final Utility Value	Recommendation Rank
Photomath	0,8340	1
Question.AI	0,5578	2
Mathway	0,2664	9
Mathos AI	0,3527	8
Gauthmath	0,4363	5
QANDA	0,4819	4
Cymath	0,4819	3
Check Math	0,4174	6
Symbolab	0,3554	7
Math	0,2225	10
Workout		

Source: Author's Documentation

Based on Table 5, Photomath obtained the highest utility value and is the primary recommendation, followed by Question.AI, Cymath, QANDA, Gauthmath, Check Math, Symbolab, Mathos AI, Mathway, and Math Workout. This ranking is dynamic because it is influenced by the decision maker's preference weights. Therefore, Photomath may not necessarily be the best choice if there are changes in location, time, or evaluation criteria. This demonstrates the flexibility of MAUT, where the final results are highly dependent on the data and preference weights, so any changes to these factors can shift the ranking of alternatives.

Conclusion

The findings of this study show that the MAUT method can be used to recommend mathematics learning applications that meet the needs of students. The calculation process involves several stages: determining the relative weights for each criterion, constructing a decision matrix, normalizing the matrix, and calculating the final utility value for each alternative. Based on these results, Photomath is the most recommended application as it obtained the highest utility value, aligned with the decision maker's preference weights.

The implementation of this method was performed manually using Microsoft Excel, which is time-consuming and risks input errors. Therefore, for future development, it is recommended to build a web or mobile-based application that can automate the MAUT process. Such a system would allow for faster, more accurate, and more user-friendly analysis for students, lecturers, and educational institutions.

This study is limited by the number of criteria used. For subsequent research, it is suggested that the scope of criteria be expanded to include other aspects, such as technological innovation (artificial intelligence) and user data security. These additions are expected to provide a more comprehensive assessment of the quality and usefulness of mathematics learning applications.

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