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Recommendation System for Selecting Web Programming Learning Materials for Vocational High School Students using Multi-criteria Recommendation Systems

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ABSTRACT

In the independent curriculum, the learning that is carried out focuses on developing character, student competence and honing interests, talents. So the amount of learning material given to students does not have to be complete or less. Apart from that, the independent curriculum no longer burdens students with achieving a minimum score because assessments no longer use Minimum Completeness Criteria (KKM) scores. This makes it difficult for teachers to determine whether the material that has been explained can be understood because grades are not a benchmark for a student's success. In fact, if the teacher does not know a student's understanding, the teacher will have difficulty continuing to the next material. Implementation of the Multi-Criteria Recommender System (MCRS) can make it easier for teachers to predict whether students can progress to the next material and recommend which modules are suitable for these students. The recommendation system that will be built is in the form of web-based learning media so that students can be more interested and can help teachers improve learning outcomes. The method used is collaborative filtering by comparing adjusted cosine similarity, cosine based similarity and spearman rank order correlation. Based on the implementation of MCRS using the collaborative filtering method, it shows that the results of the recommendation system have a good impact on the teaching and learning process. Based on the 3 algorithms implemented, the best prediction result is cosine based similarity because the MAE value obtained is the lowest, namely 1.19 and the accuracy value is 76%.

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1. INTRODUCTION

Curriculum in the field of education is crucial as it serves as one of the indicators of the success of the learning process. Currently, the Ministry of Education in Indonesia is implementing a new policy in the education curriculum called the "Merdeka Curriculum [1]." The Merdeka Curriculum aims to inspire students and encourage them to master competencies that will support them in achieving their aspirations. This curriculum focuses on character development, student competency, and talent nurturing. Therefore, the amount of learning material given to students does not have to be exhaustive or limited [2]. Additionally, the

Merdeka Curriculum no longer burdens students with achieving minimum scores because assessments no longer use the Minimum Passing Criteria (KKM) [3].

The education of Software Engineering (RPL) majors in vocational high schools (SMK) is strategically responsible for preparing students to enter the workforce related to software development. In this regard, understanding web programming well is crucial for RPL students to compete in the ever-changing industrial world [4]. While the new policy is beneficial as it allows students to express themselves more freely, it poses challenges for teachers in determining whether the material has been understood since grades are no longer the standard for student success. If a teacher does not know a student's understanding, they will struggle to proceed to the next topic. Hence, there is a need for evaluation to determine whether students understand the material explained by the teacher. The evaluation should be enjoyable so that students do not feel burdened. Therefore, a system is needed to recommend whether students understand the given material and if the teacher can move on to the next topic.

Based on this, this research will utilize a Multi-Criteria Recommender System (MCRS) as a recommendation system determinant with web programming material as the subject matter. The use of MCRS is highly versatile, such as in insurance, where recommendations consider users' current needs and recommend policies most suited to users [5]. It can also be applied in libraries by recommending books for students who are often confused about which ones to read [6], and recommending thesis titles can aid validation teams when handling numerous submissions [7]. Recommendations can be based not only on titles but also on descriptions or abstracts [8]. During the COVID-19 pandemic, recommendation systems were used to calculate the risk levels of various regions by considering several criteria [9]. In local environments, recommendation systems are also useful, for example, in determining nearby communities based on location, category, and interests [10].

Furthermore, the use of recommendation systems is essential in critical areas such as healthcare services, aiming at disease prevention, reducing treatment costs, and enhancing quality of life [11]. A Multi-Criteria Recommendation System is a recommender system that provides target users with a list of items most relevant to them by ranking item relevance across multiple criteria provided by users. These systems, also known as recommendation engines, have become a significant research area and are now applied in various fields. The techniques behind recommendation systems have evolved over time. Generally, these systems help users find products or services they need (e.g., books, music) through the analysis and collection of other users' activities and behaviors, especially in the form of reviews, and provide the best recommendations [12].

Related research on MCRS explains the purpose of building multi-criteria recommender systems using CF algorithms with a case study on women's beauty products on Femaledaily.com. It analyzes the results of comparing multi-criteria usage with single-criteria in building recommender systems using collaborative filtering algorithms in a case study on women's beauty products on Femaledaily.com, resulting in an error of 2.4197 [13].

Moreover, other studies provide recommendations for tourists as the city of Batu offers various types of attractions, but tourist spots are often not balanced. MCRS methodology was used with six criteria: attraction, accessibility, amenities, support services, activities, and available packages. Based on a questionnaire given to 157 tourists in Batu, the accuracy of the research reached 72%. Furthermore, the research results indicate that the more tourist destinations known, the higher the accuracy of recommendations using MCRS [14].

Another study focused on using MCRS to recommend products. Although challenging due to each product having many criteria, MCRS usage has shown promise. The study involved three phases: building models and assigning weights, calculating similarity in each criterion and user for decision making, and finally predicting and recommending products. Weighting was done using GA to normalize rank numbers as preferences can vary over time and each user can change continuously. The results show that GA-based MCRS with single or multiple criteria is superior and applicable to any recommendation system [15].

This research will utilize three algorithms from collaborative filtering methods and compare the results of these methods to determine which one yields the highest performance. Testing will be conducted using a confusion matrix, including accuracy, precision, recall, and F1 score.

2. RESEARCH METHOD

2.1 Data

The data used in this research is the test results carried out by students of SMKN 1 Muara Uya, Tabalong Regency, South Kalimantan, majoring in Software Engineering for the academic year 2021/2022. The tests conducted by students are based on the MCRS model approach with several criteria as shown in Table 1, consisting of 40 questions divided into 10 modules.

There are 3 criteria used in this research, as follows:

1. Number of correct answers
2. Completion time (seconds)
3. Score

These criteria support the recommendation process using MCRS. In obtaining recommendations, items that will be the final outcome of the research are certainly required. The items used in this research are materials about web programming. These items can be seen in Table 1.

Table 1. Module Item Data

Item Code	Item Description
M1	Basic HTML
M2	Link and Table
M3	Multimedia Format Display
M4	CSS
M5	Create Forms
M6	Basic Web Client Programming, HTML and Javascript
M7	Getting to know OOP
M8	Looping
M9	Get to know PHP
M10	Creating a Login Form with PHP and MySQL Get and Post

2.2 System Design

In this research, the author implements a recommendation system using the MCRS (Multi-Criteria Recommender System) method with Collaborative filtering algorithm implemented on a web-based platform using JavaScript programming language in web-based learning subjects. This system is aimed to assist teachers in determining whether students can proceed to the next material and which modules are suitable or recommended for the students. It helps teachers identify which topics students have mastered or not yet mastered. This web-based learning platform provides a new learning experience for students to be more interactive during tests.

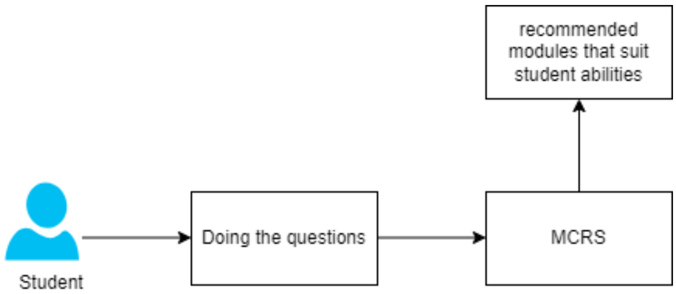

Figure 1. Research Design

In the initial stage, students are asked to work on several available modules. If there are modules that have not been worked on, the system will predict whether the student can work on them. Additionally, from these modules, there are recommendations for which modules are mastered by the student. An illustration of the research design can be seen in Figure 1.

There are two actors who can operate the system in this research, namely students and teachers. Each actor has different activities, which are depicted with use cases. For the teacher actor, it can be seen in Figure 2.

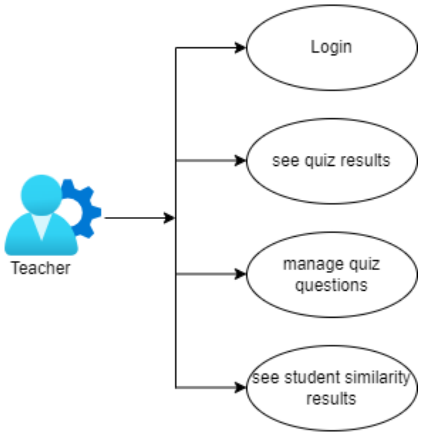

Figure 2. Teacher Use Case

In Figure 2, it can be seen that the teacher actor has four activities that can be performed, namely logging into the system, viewing quiz results, managing the list of questions based on modules, and viewing the similarity results as well as student recommendations. Furthermore, for the student actor, it can be seen in Figure 3.

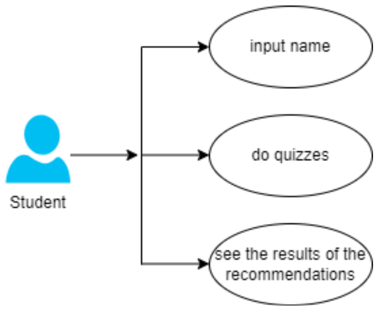

Figure 3. Student Use Case

In Figure 4, it can be seen that the student actor has three activities that can be performed in the system, namely entering their name, working on quiz questions, and viewing recommendations based on the quizzes they have completed. Additionally, system planning is also depicted in the form of an activity diagram, which will illustrate the system in more detail based on the flow performed by the actors.

2.3 Experiment

2.3.1 Multi-Criteria Recommender System

Recommendation systems are decision support tools that suggest something to users that may be relevant to their preferences. Recommendation systems can also assist users in obtaining valuable items from a vast collection available. Then, recommendation systems evolve by adding the number of criteria to improve the accuracy of prediction. Criteria are various attributes that can be combined to describe the quality of items [16].

Recommendation systems typically operate in three stages [17], as follows:

a. Modeling Stage

This stage focuses on preparing the data that will be used for the next two phases. Data preparation includes finding ratings based on criteria and users. The calculations used are in accordance with the selected method.

b. Prediction Stage

This stage aims to predict ratings or scores that are unknown to users through information processed in the modeling phase.

c. Recommendation Stage

This stage is an advanced stage of the prediction phase, where various approaches are used to support user decisions by filtering the most suitable items. The nature of these recommendations is to propose new items to users that are likely to be appealing.

2.3.2 Collaborative Filtering

Collaborative filtering is an algorithm used for recommendation systems. The way collaborative filtering works is by finding similarities among other users' values to predict items that might be of interest or liked. The most important factor in this algorithm is the user's ratings of the products, which serve as the basis for determining recommendations [18]. However, this crucial factor becomes a weakness of this algorithm because it cannot provide recommendations if there are no ratings, or the accuracy will be compromised if there is insufficient input data. Additionally, this algorithm has the advantage that recommendations will still be provided even in less-than-ideal circumstances [19]. This research employs the collaborative filtering method with four algorithms [20] as follows.

a. Adjusted Cosine Silimarity

$$\mathrm{S(i,j)} = \frac{\sum_{u\in U}(R_{u,i}-\bar{R}_u)(R_{u,j}-\bar{R}_u)}{\sqrt{\sum_{u\in U}(R_{u,i}-\bar{R}_u)^2}\sqrt{\sum_{u\in U}(R_{u,j}-\bar{R}_u)^2}} \quad (1)$$

Where:

- *i* are students whose grades will be predicted
- *j* are students whose data is used to make predictions
  sim(i, j) is the similarity value between i and j
- $R_{u,i}$ is the u value of student i
- $R_{u,j}$ is the u value of student j
- $\bar{R}_i$ is the average of all grades from student i
- $\bar{R}_j$ is the average of all grades from student j

b. Cosine Based Similarity

$$\mathrm{S(i,j)} = \frac{\sum_{u\in U} R(u,i)R(u,j)}{\sqrt{\sum_{u\in U}(R_{u,i}-\bar{R}_i)^2}\sqrt{\sum_{u\in U}(R_{u,j}-\bar{R}_j)^2}} \quad (2)$$

Where :

- *i* are students whose grades will be predicted
- *j* are students whose data is used to make predictions
  sim(i, j) is the similarity value between i and j
- $R_{u,i}$ is the u value of student i
- $R_{u,j}$ is the u value of student j
- $R_i$is the average of all grades from student i
- R_j is the average of all grades from student j

c. Spearman Rank Order Correlation

$$\mathrm{sim(i,j)} = \frac{\sum_{u=1}^{n}(R_{u,j}-R_i)(R_{k,j}-R_j)}{\sqrt{\sum_{u=1}^{n}(R_{u,i}-R_i)^2 x \sum_{k=1}^{n}(R_{k,j}-R_j)^2}} \quad (3)$$

Where :
- i are students whose grades will be predicted
- j are students whose data is used to make predictions
  sim(i, j) is the similarity value between i and j
- $R_{u,j}$ is the u value of student i
- $R_{k,j}$ is the k value of student j
- R_i is the average of all grades from student i
- R_j is the average of all grades from student j

The flow of using the collaborative filtering method can be seen in Figure 4.

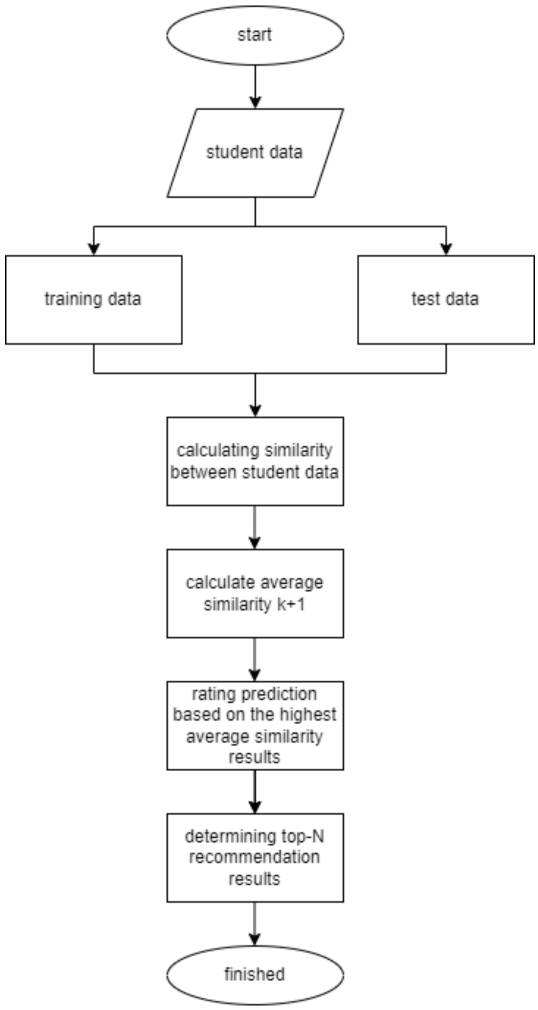

Figure 4. CF flowchart

2.3.3 Confusion Matrix

Confusion matrix is one of the methods used for system testing [21]. The equation for carrying out this test is carried out as follows.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (4)$$

$$Precision = \frac{TP}{TP+FP} \qquad (5)$$

$$Recall = \frac{TP}{TP+FN} \qquad (6)$$

$$F1 = 2\ x\ \frac{precision\ x\ recall}{precision+recall} \quad (7)$$

Where TP represents the number of True Positive samples, TN represents the number of True Negative samples, FP represents the number of False Positive samples, and FN represents the number of False Negative samples in the confusion matrix [22].

2.3.4 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is one of the testing methods used to measure the accuracy of a prediction. The value of MAE indicates the average error between the predicted and actual results [23]. The equation for conducting this testing is as follows.

$$MAE = \sum \frac{|y'-y|}{n} \quad (8)$$

Dimana,
y' = predicted value
y = true value
n = amount of data

A smaller MAE value indicates that the error between the actual and predicted results is lower, which also means that the model can predict well [24, 25].

3. RESULTS AND DISCUSSION

3.1. Research Results

In obtaining data to be processed into a recommendation system, the 40 students were asked to work on questions divided into 10 modules on the website-based system that had been created. The questions to be answered by students are in the form of multiple choice as seen in Figure 5. In the system, it will be calculated how many minutes students take to work on questions in 1 module as a consideration for implementing the recommendation system.

Figure 5. Student Quiz Page

After students have completed all the given questions, at the end, recommendations for modules that students should study will appear, along with modules that they have mastered. These recommendations include material that needs to be reviewed and material that has already been mastered, as shown in Figure 6.

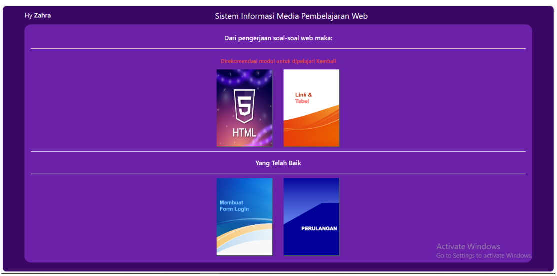

Figure 6. Module Recommendation Display

To see the overall results of students who have worked on quiz questions, subject teachers can log in to the login page as shown in Figure 7 below:

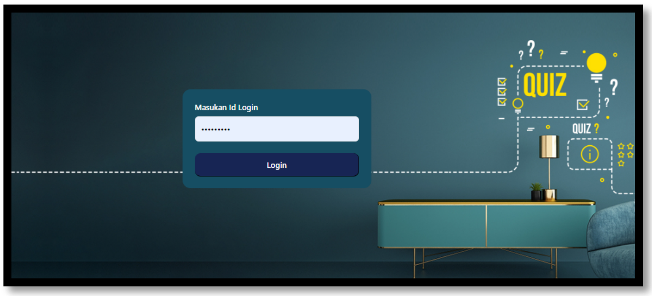

Figure 7. Display of the Teacher Login Page

After logging in, teachers can view the recommendation results of all students who have completed quiz questions as a consideration and follow-up for the teacher in evaluating the taught learning material. The following are the recommendation results for students who have not yet mastered and have mastered the web programming subject along with the similarity scores generated, as shown in figures 8 and 9.

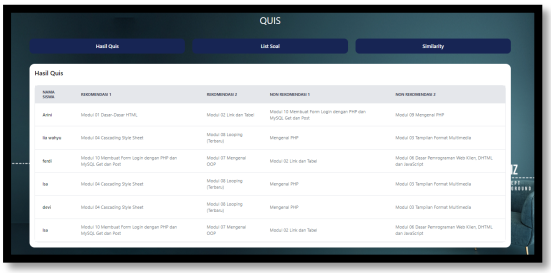

Figure 8. Recommendation Results for All Students

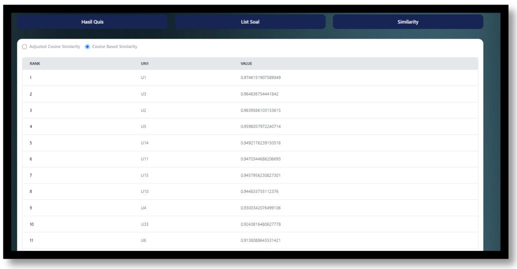

Figure 9. Similarity Results

3.2. Discussion

The testing conducted in this research uses a confusion matrix and MAE (Mean Absolute Error). In the confusion matrix, it calculates accuracy, precision, recall, and F1 score. The data used for testing consists of 5 test data with a training data ratio of 35.

In Table 2, the results for the adjusted cosine similarity algorithm are shown. Each test data has different similarities to the training data. Test data with code Un1 has similarities with U1, and the recommended module to be studied again is the basic HTML module (M1), while the most mastered module is creating a login form with PHP and MySql using get and post methods (M10). Test data with code Un2 has similarities with U18, and the recommended module to be studied again is the basic web client programming module, HTML, and JavaScript (M6), while the most mastered module is looping (M8). Test data with code Un3 has similarities with U6, and the recommended module to be studied again is the link and table module (M2), while the most mastered module is understanding OOP (M7). Test data with code Un4 has similarities with U5, and the recommended module to be studied again is looping (M8), while the most mastered module is the basic web client programming module, HTML, and JavaScript (M6). Test data with code Un5 has similarities with U13, and the recommended module to be studied again is creating a login form with PHP and MySql using get and post methods (M10), while the most mastered module is understanding PHP (M9).

Table 2. Adjusted Cosine Similarity Calculation Results

	Un1, U1	**Un2, U18**	**Un3, U6**	**Un4, U5**	**Un5, U13**
M1	4,33	4	3,67	4,33	3.33
M2	4,67	4	1,33	4	3

M3	5,33	3	5,67	4	5,33
M4	6	4,33	5,33	4,67	2
M5	4,67	4,33	4	5	3
M6	6	2,33	3	6	4,67
M7	5,67	4,33	6	5,33	4,33
M8	5	5,67	6	2,67	4
M9	5,67	3,67	5,33	6	6,33
M10	6,67	2,67	4,33	5,67	1

Each result of the confusion matrix testing on the adjusted cosine similarity algorithm can be seen in Table 4. However, before knowing the results of the confusion matrix, it is necessary to classify positive and negative labels as in Table 3, which consists of TP = 22, TN = 16, FP = 6, and FN = 6.

Table 1. Confusion Matrix Adjusted Cosine Similarity

	Negative	Positive
Negative	16	6
Positive	6	22

Table 2. Adjusted Cosine Similarity Test Results

Accuracy	76%
Precision	79%
Recall	79%
F1	79%

Meanwhile, for the MAE testing on the adjusted cosine similarity algorithm, it is 1.88, as seen in Table 5. The MAE result is calculated for each test data, and then the average is taken from all test data.

Table 5. MAE Adjusted Cosine Similarity Test Results

Prediction	**Total MAE**
Un1, U1	4,567
Un2, U18	0,967
Un3, U6	1,2
Un4, U5	1,617
Un5, U13	1,067
Mean of MAE	1,88

In Table 6, the results for the cosine-based similarity algorithm are shown. Each test data has different similarities to the training data. Test data with code Un1 has similarities with U1, and the recommended module to be studied again is the basic HTML module (M1), while the most mastered module is creating a login form with PHP and MySql using get and post methods (M10). Test data with code Un2 has similarities with U26, and the recommended module to be studied again is creating a login form with PHP and MySql using get and post methods (M10), while the most mastered module is understanding OOP (M7). Test data with code Un3 has similarities with U6, and the recommended module to be studied again is the link and table module (M2), while the most mastered module is understanding OOP (M7). Test data with code Un4 has similarities with U30, and the recommended module to be studied again is looping (M8), while the most mastered module is the basic HTML module (M1). Test data with code Un5 has similarities with U13, and the recommended module to be studied again is creating a login form with PHP and MySql using get and post methods (M10), while the most mastered module is understanding PHP (M9).

Table 6. Cosine Based Similarity Calculation Results

	Un1, U1	**Un2, U26**	**Un3. U6**	**Un4, U30**	**Un5, U13**
M1	4,33	3,33	3,67	4,33	3.33
M2	4,67	3	1,33	4	3
M3	5,33	2	5,67	3	5,33
M4	6	3,33	5,33	4	2
M5	4,67	4	4	3	3

M6	6	2,67	3	4,33	4,67
M7	5,67	4,33	6	3,33	4,33
M8	5	4	6	1,67	4
M9	5,67	2,67	5,33	2,67	6,33
M10	6,67	2	4,33	3	1

Each result of the confusion matrix testing on the adjusted cosine similarity algorithm can be seen in Table 8. However, before knowing the results of the confusion matrix, it is necessary to classify positive and negative labels as in Table 7, which consists of TP = 21, TN = 17, FP = 6, and FN = 6.

Tabel 3. Confusion Matrix Cosine Based Similarity

	Negative	Positive
Negative	17	6
Positive	6	21

Table 8. Test Results Cosine Based Similarity

Accuracy	76%
Precision	78%
Recall	78%
F1	78%

Meanwhile, for the MAE testing on the cosine-based similarity algorithm, it is 1.19, as seen in Table 9. The MAE result is calculated for each test data, and then the average is taken from all test data.

Table 9. MAE Cosine Based Similarity Test Results

Prediction	**Total MAE**
Un1, U1	2,1
Un2, U26	0,85
Un3, U6	1,2
Un4, U30	0,75
Un5, U13	1,07
Mean of MAE	1,19

In Table 10, the results for the Spearman rank order correlation algorithm are shown. Each test data has different similarities to the training data. Test data with code Un1 has similarities with U1, and the recommended module to be studied again is the basic HTML module (M1), while the most mastered module is creating a login form with PHP and MySql using get and post methods (M10). Test data with code Un2 has similarities with U18, and the recommended module to be studied again is the basic web client programming module, HTML, and JavaScript (M6), while the most mastered module is looping (M8). Test data with code Un3 has similarities with U26, and the recommended module to be studied again is creating a login form with PHP and MySql using get and post methods (M10), while the most mastered module is understanding OOP (M7). Test data with code Un4 has similarities with U30, and the recommended module to be studied again is looping (M8), while the most mastered module is the basic HTML module (M1). Test data with code Un5 has similarities with U26, and the recommended module to be studied again is creating a login form with PHP and MySql using get and post methods (M10), while the most mastered module is understanding OOP (M7).

Table 10. Spearman Rank Order Correlation Calculation Results

	Un1, U1	**Un2, U18**	**Un3. U26**	**Un4, U30**	**Un5, U26**
M1	4,33	4	3,33	4,33	3,33
M2	4,67	4	3	4	3
M3	5,33	3	2	3	2
M4	6	4,33	3,33	4	3,33
M5	4,67	4,33	4	3	4
M6	6	2,33	2,67	4,33	2,67
M7	5,67	4,33	4,33	3,33	4,33

M8	5	5,67	4	1,67	4
M9	5,67	3,67	2,67	2,67	2,67
M10	6,67	2,67	2	3	2

Each result of the confusion matrix testing on the Spearman rank order correlation algorithm can be seen in Table 12. However, before knowing the results of the confusion matrix, it is necessary to classify positive and negative labels as in Table 11. It consists of TP = 15, TN = 13, FP = 9, and FN = 9.

Tabel 4. Confusion Matrix Spearman Rank Order Correlation

	Negative	Positive
Negative	13	9
Positive	9	15

Table 12. Spearman Rank Order Correlation Test Results

Accuracy	61%
Precision	63%
Recall	63%
F1	63%

Meanwhile, for the MAE testing on the Spearman rank order correlation, it is 1.69, as shown in Table 9. The MAE result is calculated for each test data, and then the average is taken from all test data.

Table 13. MAE Spearman Rank Order Correlation Test Results

Prediction	Total MAE
Un1, U1	4,57
Un2, U18	0,97
Un3, U26	1,12
Un4, U30	0,75
Un5, U26	1,02
Mean of MAE	1,69

4. CONCLUSION

This research proposes to develop a recommendation system to assist teachers in assessing students' abilities. Additionally, students can also identify which modules they have mastered and which ones they need to review. In this case, web programming material with 10 modules is used as the basis for recommendations, considering 3 criteria: the number of correct answers, completion time in seconds, and score.

By employing collaborative filtering method and comparing 3 algorithms, it was found that the cosine-based similarity algorithm is the best as it has the lowest Mean Absolute Error (MAE) value of 1.19. On the other hand, the algorithm with the highest error is the adjusted-based similarity with an MAE value of 1.88. However, looking at the confusion matrix values, both adjusted-based similarity and cosine-based similarity algorithms have the same accuracy. Meanwhile, the Spearman rank order correlation has the lowest value compared to other algorithms.

Suggestions for further research are hoped for. This study can be conducted with a larger dataset involving a greater number of students to ensure that the obtained recommendations are more diverse. Additionally, this research can be developed with different algorithms to compare the recommendation outcomes, thus adding newer analyses.

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