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Selecting Tourism Site Using 6 As Tourism Destinations Framework Based Multi-Criteria Recommender System

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***Abstract*— Batu City is a place with many types of tourism and had many tourists in 2019. However, there was an imbalance of tourist attractions visited from the total number. Tourists are only fixated on famous tourist spots. Therefore, a recommendation system is needed that can provide recommendations for tourists. In this study, we use the Multi-Criteria Recommender System (MCRS) method based on the rating value between users to obtain recommendations from the system regarding selecting tourist destinations. The authors use the 6 As Tourism Destinations (6AsTD) framework for user assessment criteria in this study. The framework consists of six indicators that assess the success of tourism destinations, including attractions, accessibility, amenities, support services, activities, and available packages. The six components are considered the key to the success of a tourist destination under the marketing approach. This study aimed to obtain a recommendation system for selecting tourist destinations using the multi-criteria concept based on the 6AsTD framework. Based on the experimental results, the proposed method has an accuracy rate of up to 72%.**

***Index Terms*—Recommendation, multi-criteria recommender system, tourism destinations, 6AsTD framework.**

I. Introduction

In the industrial era 4.0, people are busy with work that takes up much time, energy, and thoughts. Something fun is needed, one of which is traveling to relieve fatigue and workload. Traveling has many benefits, including reducing fatigue and stress with school for students or work for office workers. After traveling, the body will be ready to carry out work activities. When traveling, humans see the beauty of nature in front of their eyes with their own eyes. However, they can also feel the difference in personality and temperature and see various animals and plant bodies in the country or place visited. Come and feel firsthand the differences in customs, cultural differences, food differences, culinary differences and eating procedures, religious differences, and beliefs of others. In addition, we can still listen to the legends of the area and other anecdotal stories. All of this can increase our insight and knowledge. Every time we take a trip, it will bring new benefits, get new experiences, and gain new knowledge.

Indonesia has many cities offering various tourist destinations [1]. One of these cities is Batu which is a place that has many types of tourism, ranging from nature tourism to educational tours. Batu is also known as a fantastic city that makes tourists feel at home and want to return to travel in Batu. Batu City has a considerable number of visitors every year. Batu City noted that in 2019 the number of tourists who came was 6,047,046 tourists, with 6,035,310 local tourists and 11,736 foreign tourists. However, of the total number, there is an imbalance of tourist attractions visited from data from the statistical agency of Batu City, Selecta found as many as 1,394,270 tourists [2]. From this data, it can be concluded that tourists are only fixated on famous tourist attractions because

That requires a recommendation system that helps recommend new and not well-known tours so that tourist attractions can compete and Batu tourists know that other tours are excellent but have not been visited often. Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be of use to a user. The recommendations relate to various decision-making processes, such as what items to buy, what music to listen to, or what online news to read [3]. The recommendation system can use the classic recommendation method, which only uses one rating. This method has the disadvantage that many items cannot be represented with only one criterion. For example, in an e-commerce system, customers judge products based on several criteria, such as product quality, price, delivery, and after-sales service. Classical collaborative filtering techniques that only use one criterion in several applications are often irrelevant and not relevant. Accommodate the opinions given by users. Therefore, the author uses the Multi-Criteria

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Recommendation System method. This recommendation method does not use only one criterion but uses several measures to get recommendations expected to produce better recommendations than using the single criteria recommendation method [4], [5].

II. Related Work

Hassan et al. explain the neural network pattern where the input layer is in the form of rating criteria 1 to n, and the output layer is R_0 or overall rating. This research was conducted by Hassan and Hamada, implementing a neural network with MCRS. It can be concluded that the multi-criteria method based on neural networks results in increased accuracy compared to the classical recommendation method [6].

Next, Arif et al. in 2019 explained that the 6AsTD Framework uses six variables to assess tourism destinations. The ranking results are distributed to every traveler's mobile device connected to the blockchain network. The system in this study can connect several potential tourists in Batu Tourism City. The system also generates tourist destination ratings and sends them to other users using the Blockchain network [7].

In another study conducted in 2022, the authors proposed a recommendation system for selecting halal tourism using a rating destinations-based MCRS. They implemented the research on halal tourism games so that they used the criteria for halal tourism as a reference for determining the rating. The experimental results in the study show that the average accuracy value of the recommendations is 0.6 [8].

III. Research Method

The author implements the Multi-Criteria Recommendation System (MCRS) method in the form of a game by displaying tourist descriptions and the advantages of tourist attractions, which are implemented into games that have an attractive appearance so that users do not get bored when inputting ratings. This game will be built using the Unity Engine. In this study, the Multi-Criteria Recommendation Collaborative Filtering method is used to provide recommendations for tourist attractions to users. Unlike the traditional recommendation system, which only relies on one assessment criterion, several criteria will adjust the user to get the common recommendations in a multi-criteria recommendation system. So this method is more accurate than the classic recommendation system or single criteria [9].

Fig. 1 shows the steps for implementing MCRS based on the 6AsTD framework. The first step begins with determining the criteria using the 6AsTD framework. Then the second step is taking reference rating data from tourists in Batu City. We carry out the data collection process by distributing questionnaires to tourists. The questionnaire represents questions to tourists about their rating on each criterion owned by a tourist destination. The third step is a computational calculation using the MCRS method. The computation consists of a similarity calculation stage, similarity ranking calculation, rating prediction for each criterion, and ranking of recommendation results. The final stage of the implementation of MCRS is the visualization of the recommendation ranking results into the application user interface. At this stage, we use the Unity game engine. Unity is a game engine that can visualize the results of recommendations through the displayed user interface and virtual environment [10].

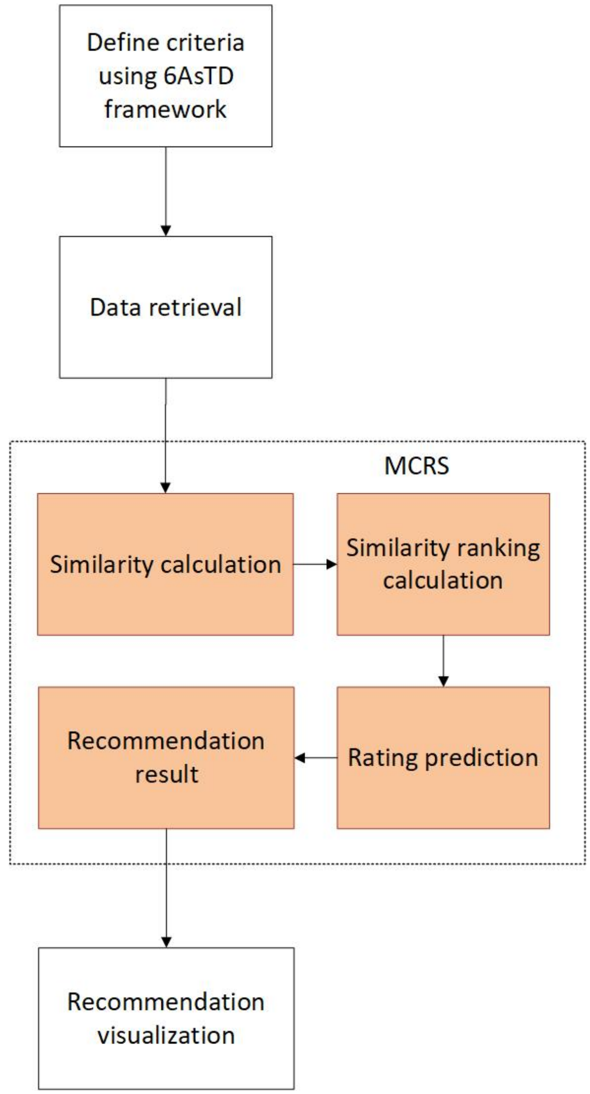

Fig. 1. Steps to implement MCRS

A. 6AsTD Framework

This research used 6AsTD as a framework for obtaining data and assessment information of destination attributes of tourism destinations conducted by tourists [7]. The basic model was first introduced in 2000 in the book Destination Management Systems: Criteria for Success - An Exploratory Research [11], in which 6 A-dimensions are considered the key to the success of tourist destinations under the marketing approach. Since then, many other authors have adopted these six dimensions in tourism research. 6AsTD consists of attractions, accessibility, amenities, ancillary services, activities, and available packages, as shown in Fig. 2.

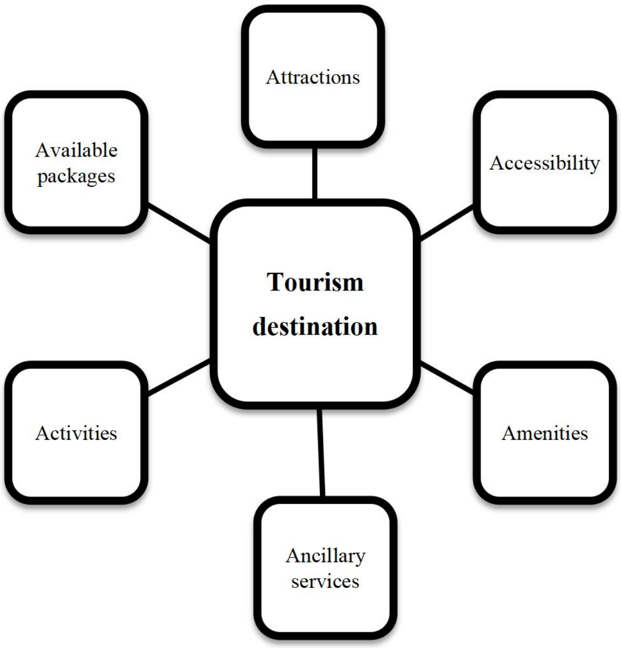

Fig. 2. 6AsTD Framework

B. Multi-Criteria Collaborative Filtering based Recommender System.

With increasing real-world applications, improving recommendation techniques using multiple rating criteria has become an essential topic for its next-generation recommendation system. For example, Yahoo's movie recommendation system displays each user's rating for four categories: story, action, direction, and visual [4]. This additional information about user preferences is likely to help increase the recommendation system's accuracy. Some systems choose to model a recommendation system with an overall rating for each criterion. However, some plans do not include the overall rating in their recommendation system. Formula-based recommendation utility using the overall rating can be seen in (1) [12]. The equation shows the formula in the MCRS method, where R is the rating from the $Users$ against all criteria belonging to the $Items$. In this study, we position potential tourists as $Users$ and tourism destinations as $Items$ choices.

$$R : Users \times Items \rightarrow R_0 \times R_1 \times \ldots \times R_n \quad (1)$$

The working principle of the collaborative filtering algorithm is to provide item predictions that match the user's criteria based on the level of similarity with other users. The collaborative filtering algorithm aims to suggest new items that have never been known by the user based on the interests of previous users who have almost the same level of similarity. The general similarity between users $sim(u,u')$, cosine base similarity is most commonly used in collaborative filtering algorithms. Where in (2), $I(u,u')$ is the item that gets a rating from the user u and u' and $R(u,i)$ is the rating from the user for the item.

$$sim(u,u') = \frac{\sum_{i \epsilon I(u,u')} R(u,i)R(u',i)}{\sqrt{\sum_{i \epsilon I(u,u')} R(u,i)^2}\sqrt{\sum_{i \epsilon I(u,u')} R(u,i)^2}} \quad (2)$$

The next step to getting a recommendation is to determine the overall similarity by evenly distributing the similarity of all criteria with equation 3. Where $sim_{avg}(u,u')$ is the average similarity criteria between user u and user u'.

$$sim_{avg}(u,u') = \frac{1}{n+1}\sum_{c=0}^{n} sim_c(u,u') \quad (3)$$

Predicting the rating can be done by getting a rating from the user with the highest similarity average. After getting the criteria rating from the user with the highest similarity average, the recommendation sequence can be found by ranking the R_0 value (overall rating) [4].

IV. RESULT

This study uses a multi-criteria recommender system to select tourist destinations in Batu City. In this test, several trials will be carried out by changing the parameter for the number of destination ratings entered by the user. This test determines whether the number of destinations the user knows affects system accuracy. In this study, we use 157 reference data, representing the rating criteria values assessed by each tourist on 14 tourist destinations in Batu City.

At the testing stage, the data to be tested is actual data from the user, filled in for a few tours and then calculated using the multi-criteria method. The results of the user's original recommendations will be compared with the recommendations from MCRS. The next step is to calculate the accuracy, precision, and recall value using (4), (5), (6), and (7) [13], [14], [15].

Table 1.
MCRS Confusion Matrix

		MCRS Results	
		Recommended	Not Recommended
Real Data	Recommended	TP (True Positive)	FP (False Positive)
	Not Recommended	FN (False Negative)	TN (True Negative)

There are 3 test assessments, namely:

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

$$F1\ score = 2 \times \frac{precision \times Recall}{precision + Recall} \quad (7)$$

A. Accurate Results of Two Destinations Input

Table 2.
Results of Two Destinations Input

TP = 57 FN =68 FP = 68 TN = 157	Recall	0.456
	Precision	0.456
	Accuracy	0.611
	*F*1 Score	0.456

In Table 2, it is known that testing is carried out on 25 users, where the data being tested is data from taking a questionnaire but only filled in with 25 tourist inputs. Accuracy results obtained from testing five tourism inputs are 0.611.

B. Accurate Results of Three Destinations Input

Table 3.
Results of Three Destinations Input

TP = 62 FN = 63 FP = 63 TN = 162	Recall	0.496
	Precision	0.496
	Accuracy	0.640
	F*1* Score	0.496

In Table 3, it is known that testing is carried out on 25 users, where the data being tested is data from taking a questionnaire, but only three input tours are filled in. Accuracy results obtained from testing three tourism inputs are 0.640. This result has slightly increased accuracy when compared to the two tourist inputs.

C. Accurate Results of Four Destinations Input

Table 4.
Results of Four Destinations Input

TP = 70 FN = 55 FP = 55 TN = 170	Recall	0.560
	Precision	0.560
	Accuracy	0.685
	*F*1 Score	0.560

In Table 4, it is known that testing is carried out on 25 users, where the data being tested is data from taking a questionnaire but only filled in 4 tourist inputs. Accuracy results obtained from testing four tourism inputs are 0.685. This result has slightly increased accuracy when compared to the three tourist inputs

D. Accurate Results of Five Destinations Input

In Table 5, it is known that testing is carried out on 25 users, where the data being tested is data from taking a questionnaire, but only five tourist inputs are filled in. Accuracy results obtained from testing five tourism inputs are 0.727. This result has slightly increased accuracy when compared to the four tourist inputs. All test schemes show that the recommendation system in this study has an average accuracy of 0.666.

Table 5.
Results of Five Destinations Input

TP = 79 FN = 48 FP = 48 TN = 177	Recall	0.622
	Precision	0.622
	Accuracy	0.727
	*F*1 Score	0.622

E. Recommendation Visualization

In this study, we visualize the results of the recommendations by implementing them into a game system built using the Unity game engine. Fig. 3, 4, and 5 show the results of the visualization of recommendations in the form of a game user interface.

Fig. 3. User Input Visualization

Fig. 4. Recommendation Result Visualization

Figure 3 shows the user interface display and a means for the system to obtain tourist destination rating data entered by the player. They enter rating data based on the number of stars, where the more stars that are clicked, the higher the rating given. While Fig. 4 shows an example of the results of the visualization of recommendations for the choice of tourist destinations. Where the asterisk indicates the recommendation rank, the more stars, the higher the recommendation rank. Furthermore, Fig. 5 shows an example of one of the virtual environments from tourism destinations recommended by the system.

Figure 5. Example virtual environment visualization of each recommendation

F. Comparison study

To show the differences in the results and research positions, we show the comparison in Table 6. In this paper, we try to compare the results of this study with several related studies discussed in the previous chapter.

Table 6.
Comparison with Previous study

References	Method	Application	Accuracy
[6]	Neural Network Based MCRS	General Recommendation System	-
[7]	Blockchain and 6AsTD Framework	Tourism Destinations Rating System	-
[8]	Rating Destinations Based MCRS	Halal Tourism Game	0.600
Current Study	6AsTD Based MCRS	General Tourism Recommendation System	0.666

Table 6 compares this study and several studies on previous recommendation systems taken from the method, application, and accurate results. Where paper [6] uses the Neural Network-Based MCRS method, paper [7] uses the Blockchain and 6AsTD Framework, paper [8] uses the Rating Destinations Based MCRS, while our research uses 6AsTD Based MCRS. Each paper also discusses recommender systems in various applications. In comparison, this study produces a higher level of accuracy than paper [8] which is 0.666.

V. Conclusion

This study resulted in a recommendation system for selecting tourist destinations in Batu City using the MCRS recommendation system based on the 6AsTD Framework. The experimental results show that the system makes recommendations to users with the highest accuracy in 5 destination inputs, as shown in Fig. 6. In this experiment, two input destinations have the lowest accuracy value, 0.611, and five have the highest accuracy, 0.727. The experimental results show that the more tourist destinations are known, the higher the accuracy of the MCRS recommendations will be.

This study uses 157 references data taken from the results of questionnaires to tourists in Batu City. For further research, we plan to use more reference data to increase the experimental results' accuracy. Furthermore, the MCRS method can be developed using other similarity calculations such as Pearson Correlation, Kendal Tau, and others. The aim is to get a performance comparison from the results of the MCRS recommendations.

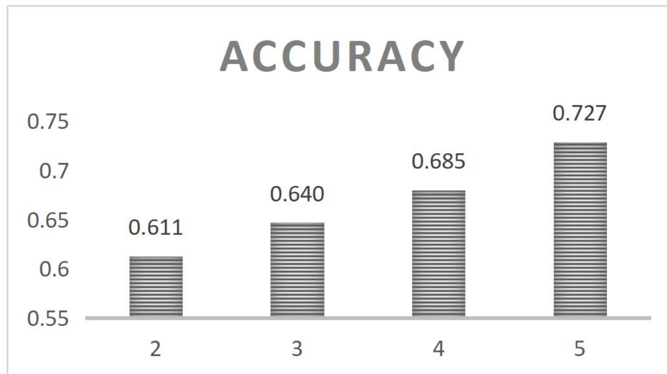

Fig. 6. Percentage Difference Accuracy of Each Test

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