

Laptop Recommender System Using the Hybrid of Ontology-Based and Collaborative Filtering

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Abstract: In the era of ever-evolving information technology, choosing the best laptop can be a complicated task for many users. The increasing complexity of technical specifications is often an obstacle, especially for users who need help understanding them. In addressing this challenge, we propose a solution: a laptop recommendation system that considers users' preferences and functional needs. We designed this system to help users choose a laptop that suits their daily functional needs. This system uses a form of Conversational Recommender System (CRS) by combining Ontology-Based Recommender System Filtering and Collaborative Filtering (CF). Ontology-Based Recommender System Filtering ensures a strong relationship between functional needs and technical specifications of laptops, making it easier for users to identify the right laptop. At the same time, Collaborative Filtering (CF) can provide diversity to the recommended products by using similar user preference data. We evaluate the accuracy of our system by calculating the success rate of recommendation accuracy with the accuracy metric, and the evaluation results show that the success rate of recommendation accuracy reaches 93.33%. Our system is highly effective in assisting users in choosing a laptop that suits their functional needs. With our laptop recommendation system, users can confidently select the correct laptop without being burdened by technical specifications, thus making their lives easier and more productive.

Keywords: collaborative filtering, conversational recommender system, laptop recommender system, ontology-based recommender system, recommender system

INTRODUCTION

The evolution of technology and the widespread use of the internet have brought about major changes in various aspects of our lives, such as doing work, communicating with others, and engaging in social interactions. Most people now consider laptops essential devices in computing technology. However, with the increasing functionality and variety of laptop types, choosing a product that suits their needs can be challenging for users. One of the complicating factors in laptop selection is the need for more understanding of technical specifications among users. Most people may need to become more familiar with the technical specifications and features they should look for when buying a laptop, especially if they are not experts in the technology field. Therefore, they need help determining a laptop suitable for their daily needs (Laseno & Hendradjaya, 2019; Sharma & Yadav, 2020). In order to help users find a laptop that is suitable for their day-to-day needs, recommendation systems have an important role to play in solving this problem (Iswari et al., 2019).

To provide users with recommendations for items, the recommender system plays an essential role; several methods can be used, such as Content-Based Filtering (CBF), which utilizes data from things that users have liked in previous items; Collaborative Filtering (CF), which uses other similar user profiles to generate recommendations, as well as Hybrid which combines both methods to achieve high-quality recommendations, and so on. Many studies have been conducted on laptop recommendation systems to provide recommendations that match user preferences. For example, research conducted using the RNN method combined with Collaborative Filtering (CF) has achieved an accuracy of 96% (Tjayadi & Mawardi, 2022). In addition, other research on laptop recommendation systems using ontologies has also been conducted, and in this study achieved an accuracy of 84.6% (Ayundhita et al., 2019).

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Therefore, we can use a hybrid approach to improve accuracy in recommending an item to overcome the weaknesses of Ontology-Based methods. In this research, we will develop a Conversational Recommender System (CRS) that combines Ontology-Based and Collaborative Filtering (CF) techniques to achieve higher accuracy and provide a better user experience.

LITERATURE REVIEW

Currently, many recommender systems have provided laptop recommendations that suit the needs of their users. Several previous studies related to the research background exist, and researchers can use these studies as references.

Rusli et al.(Iswari et al., 2019) proposed a product recommender system for ontology-based e-commerce systems. They implemented a recommender system on an ontology-based e-commerce platform by combining Collaborative Filtering (CF) methods, including using the slope one algorithm to provide ratings based on domain ontologies. The researchers used a case study of mobile phone products to demonstrate that the system provides product recommendations and recommends categories based on user preferences.

Ayundhita et al.(Ayundhita et al., 2019) researched a laptop recommender system using an Ontology-Based Conversational Recommender System (CRS). They integrated the recommender system with the Ontology-Based method. The results showed that the accuracy of recommendations based on testing the functionality requirement questions reached 84.6%.

Lee et al.(Lee et al., 2017) proposed an ontology-based tourism recommender system. They used Semantic Web technology and ontology methods to build a tourism recommender system to make it easier for users to get the necessary resources and reduce query loads.

Baizal et al.(Abdurahman Baizal et al., 2017) researched the evaluation of compound critiquing based on the functional requirements of the Conversational Recommender System. This research evaluates the model in terms of recommendation accuracy, query refinement, and user satisfaction. The results show that the approach produced a recommendation accuracy of 89.77% and refined user needs.

Based on previous research, we will develop an ontology-based recommender system incorporating the Collaborative Filtering (CF) method to recommend laptops based on daily user needs. This research(Ayundhita et al., 2019) will be used as the primary reference in the ontology process(Iswari et al., 2019) and as the direct reference in hybrid methods, hoping to achieve better performance.

Ontology-Based Recommender System

An ontology-based recommender system is an advanced recommendation system that employs an ontology, a formal representation of knowledge in a specific domain, to model the concepts and relationships within it. This approach proves particularly valuable in Semantic Web (SW), Artificial Intelligence (AI), and Systems Engineering (SE), where intricate relationships between objects necessitate modeling and analysis. Using an ontology, the recommender system can deliver more precise and personalized recommendations based on a user's preferences and behavior. The technology has wide-ranging applications, including e-commerce websites, healthcare, and education. In the context of the recommender system, Ontology-Based Recommender Systems are used to help users find items or products that match their needs(Ibrahim et al., 2019; Iswari et al., 2019).

Implementing an Ontology-Based Recommender system involves developing an ontology related to a particular domain or topic, involving concepts, relations, and rules. Researchers evaluate the similarity between user preferences and ontology by using it to model user preferences.

Collaborative Filtering

The recommender system produces individualized recommendations as output or personalizes users to items that interest them. Researchers have categorized recommender systems into several types according to their classification, and one of the types is Collaborative Filtering (CF)(Yera Toledo et al., 2019). Collaborative Filtering (CF) is a popular approach in recommender systems, where the system looks at people with similar tastes in the past and future(Ahmed et al., 2020; Sharma & Yadav, 2020). To implement this method, CF requires historical data on user preferences for items or products consumed(Yehuda Koren et al., 2021).

The calculation of similarity between users in CF involves sophisticated metrics such as cosine similarity or Pearson correlation, which provide a profound dimension of analysis into shared preferences. On the other hand, item-based collaborative filtering introduces users to items or products with characteristics similar to their preferred or high value. Similarity calculations between items are performed based on the user's engaging judgment, adding depth of understanding and providing exciting recommendations.

While collaborative filtering exhibits advantages such as the ability to work without detailed information about the item or product and provide insight into elements previously unknown to the user, it also faces challenges. Users with preferences that are unique or very different from other user groups can need help in

providing satisfactory recommendations. Moreover, the cold start concept becomes an obstacle when new users or items need more historical data to provide accurate recommendations.

Therefore, it is necessary to consider and integrate with other recommendation methods carefully. The right combination can improve the accuracy and effectiveness of the collaborative filtering system, bringing the recommendation experience to a higher level for each user.

Conversational Recommender System

Conversational Recommender System (CRS) is one recommender system that uses an iterative interaction mechanism by explicitly asking (Baizal et al., 2017; Jin et al., 2019). This CRS allows users to provide more detailed information about their preferences through user and system interactions. Currently, CRS is divided into 2, namely CRS, which focuses on the technical specifications of an item, and CRS, which focuses on the functionality of an item (Abdurahman Baizal et al., 2017).

CRS, which focuses on the technical specifications of an item, aims to provide recommendations based on the technical characteristics of the product or service, such as size, weight, color, or material. At the same time, CRS, which focuses on the functionality of an item, aims to provide recommendations based on the functions or benefits of the product or service. In both types of CRS, interaction with the user is crucial to ensure the recommendations align with their preferences and needs.

Ontology Design

This system uses an ontology based on the RDF/OWL standard and ontology building using Protégé software. In ontology-building, four main components are involved: classes, property objects, data properties, and individuals. Fig 3 shows that the ontologies have three main classes: FuncReq, Product, and Specification.

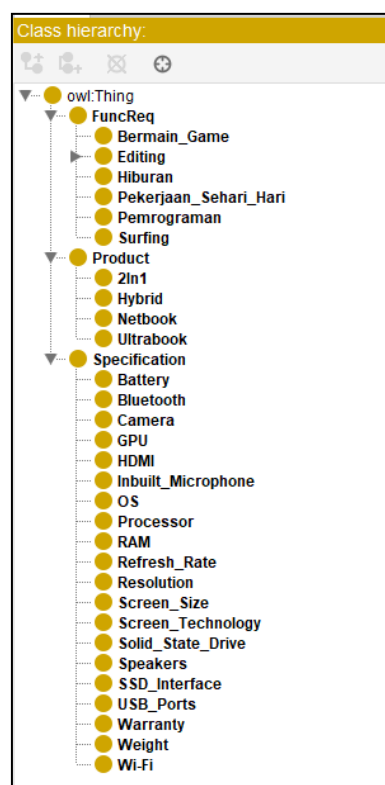


Fig. 1 Ontology Classes Structure

The FuncReq class is a Hierarchy of functional requirements class used to organize various classes and subclasses. This class hierarchy is used to present the functional requirements of users in the laptop domain.

The Product class hierarchy organizes different product types in the laptop domain. This hierarchy reflects the hierarchical relationship between product classes, ranging from a more general level to a more specific level. Using this hierarchy, the types of laptop products can be organized systematically and structured.

The Specification hierarchy is used to organize product specifications in the laptop domain. This hierarchy has the purpose of mapping functional requirements with the corresponding products. Researchers will base the grouping of product specifications on the quality level of the product when creating this class hierarchy.

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Adjusted Cosine Similarity

Adjusted Cosine Similarity is a function to measure similarity based on the angle most widely applied for calculating similarity values, shown in the equation between items. The following is the formula for the Adjusted Cosine Similarity method:

$$\text{sim}(x, y) = \frac{\sum_{u \in i} (R_{u,x} - \bar{R}_u) - (R_{u,y} - \bar{R}_u)}{\sqrt{\sum_{u \in i} (R_{u,x} - \bar{R}_u)^2} \sqrt{\sum_{u \in i} (R_{u,y} - \bar{R}_u)^2}} \quad (1)$$

- $\text{sim}(x, y)$: Similarity value between items x and y
 $u \in i$: The set of all users who rated items x and y
 $R_{u,x}$: User rating on item x
 $R_{u,y}$: User rating on item y
 \bar{R}_u : Average value of user rating

Adjusted Weighted Sum

The Adjusted Weighted Sum function calculates the predicted rating for item y by user x. It does this by considering the average rating of items users rate and using this information to make predictions. If two users give similar ratings for an item, they are considered related (Kumar et al., 2019). The formula for predicting the rating on item y for user x is as follows:

$$P(x, y) = \bar{R}_y + \frac{\sum_{i=1}^n (R_{x,i} - \bar{R}_i) \times \text{sim}(i, y)}{\sum_{i=1}^n |\text{sim}(i, y)|} \quad (2)$$

- $P(x, y)$: Predicted value of item y for user x
 \bar{R}_y : Average rating value of item y
 $R_{x,i}$: User x's rating on item i
 \bar{R}_i : Average rating value of item i
 $\text{sim}(i, y)$: Similarity value between item i and y

Mean Absolute Error

Accurately measuring the recommendation accuracy of a recommender system is necessary to assess its performance and comprehensively understand its ability to provide the right advice to users (Jeevamol & Renumol, 2021). Although this process is not the system's primary focus, calculating recommendation accuracy is important in improving its overall functionality and usability. The accuracy calculation procedure aims to find the error values that may appear in the recommendation system. The approach used in this calculation refers to the Mean Absolute Error (MAE), where the metric used detects the system's accuracy by comparing the predicted ranking with the actual ranking by comparing the expected rating with the actual rating of the item (Hasan & Roy, 2019), as described in the following equation.

$$MAE = \frac{\sum_{i=1}^n |P_{u,x} - R_{u,x}|}{N} \quad (3)$$

- MAE : Mean Absolute Error Value
 $P_{u,x}$: Predicted value of user u for item x
 $R_{u,x}$: Actual value is given by user u for item x
 N : Number of Users

User Preference Modelling

User preference modeling is essential in recommender systems (Ayundhita et al., 2019). The main objective is to provide the right questions and model the user profile based on the feedback provided by the user. Researchers use data processing methods to determine user preferences, which helps identify user preferences and needs in more detail. Some of the frequently discussed cases are as follows:

- a) **Empty User**. Researchers encounter this case when they have not established the user profile and have no information about the user's preferences and needs. Therefore, the strategy is to formulate initial questions to start the interaction and gradually build up the user profile (Ayundhita et al., 2019).
- b) **Lots of Product Choices**. This happens when the user has to choose from various products and takes more time to decide which suits his needs (Ayundhita et al., 2019). In such cases, they tend to choose multiple recommendation options. The strategy to use in situations like this involves asking questions highlighting each product's differentiating elements.
- c) **No Selected Product Recommendations**. This occurs when users have difficulty choosing a product that suits their functional needs. The proposed strategy is to offer functional requirements at one level and then return to operational requirements at the previous level that have not been asked (Ayundhita et al., 2019).
- d) **Does Not Meet the Requirements**. This case illustrates that the initial requirements definition did not generate appropriate recommendations. Therefore, the approach was to request more specific functional requirements for the next level (Ayundhita et al., 2019).
- e) **No Product Match the User's Profile**. This case shows that the definition of requirements needs to be revised to generate the proper recommendations. Therefore, the strategy was to request more specific functional requirements at the next level (Ayundhita et al., 2019).

METHOD

Overview of the Recommender System

In this study, we are developing a conversational laptop recommender system to help users select the best laptop. The initial stage involves data capture, including collecting information related to laptop functionality and individual information such as price and desired laptop functionality. After analyzing user preferences, the system will suggest recommended items using collaborative filtering methods and ontologies. The recommendation results will be rated on each item to match the laptop functions that match the user's needs.

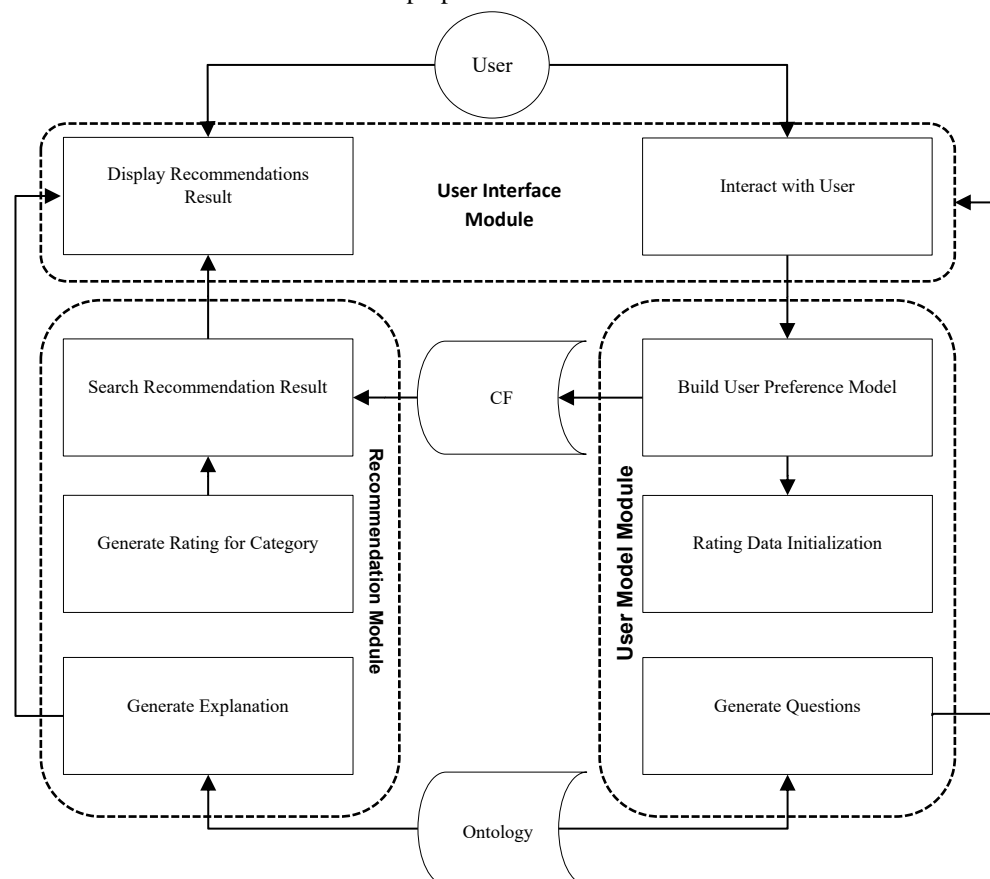


Fig. 2 Overview of the Recommender System

Fig. 1 illustrates that there are three modules in the recommendation system, i.e., User Interface Module (UIM), Recommendation Module (RM), and User Model Module (USM), each serving a specific purpose. Firstly,

the UIM interacts directly with the user by displaying questions from the USM and recommendations from the RM. Additionally, the UIM asks the user for their judgment based on the selected products. Users can actively participate in decision-making using this recommendation system, leading to more personalized and relevant recommendations. Secondly, the RM functions to match products with user profiles and provide detailed specifications and advantages and disadvantages. Thirdly, the USM connects the system with collaborative filtering and ontology to gather relevant information about user preferences, needs, and ratings of related products to recommend.

Interaction Flow

Fig. 2 illustrates the interactions between the user and the system, from the first interaction to the final decision. When the user initiates the interaction, the system presents a set of functional requirements. The user then selects the requirement that best matches their needs. Afterward, the system assesses whether the data collected is sufficient to provide helpful information. Based on the information obtained, the system will offer laptop product recommendations and explanations. If the required information is missing, the system will continue the conversation to gather additional details. Once the system has provided the recommendations, the user will make a choice and select a laptop product. The system will consider its recommendations successful if the user chooses one laptop product. However, if the user selects more than one or fails to make a choice, the system will prompt them with more functional questions.

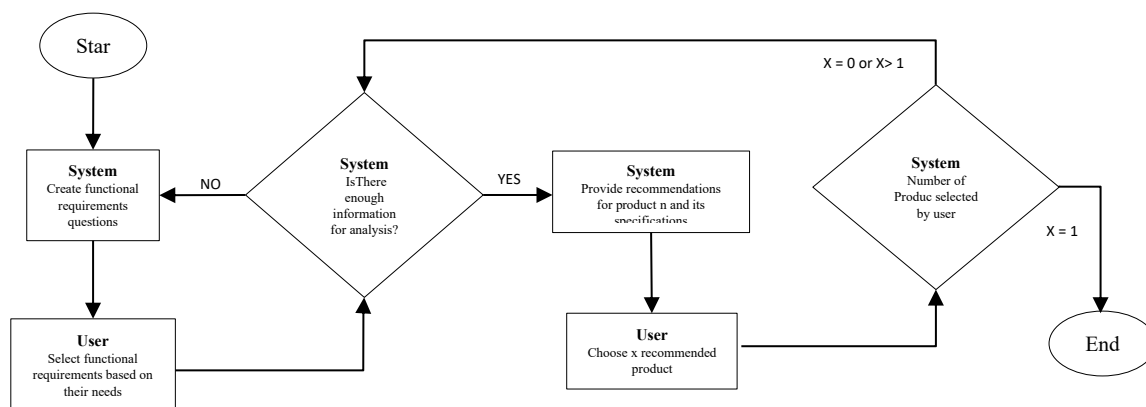


Fig. 3 illustration of user and system interactions

RESULT

Implementation Matrix Item-Based

The process of calculating recommendation accuracy is a critical aspect in the evaluation of the performance of a recommender system. While it may not be the system's primary focus, it provides valuable insights into the accuracy of recommendations, which is vital for understanding the system's effectiveness. The accuracy calculation procedure aims to find the value of errors that may arise in the recommender system. The approach used in this calculation refers to the Mean Absolute Error (MAE), as described in the following. Researchers experimented with data entered from as many as five users and five products with varying rating magnitudes. For example, When users access the website and choose one of the products, the "Microsoft Surface Laptop 3 1873," they can see it in Fig 4.

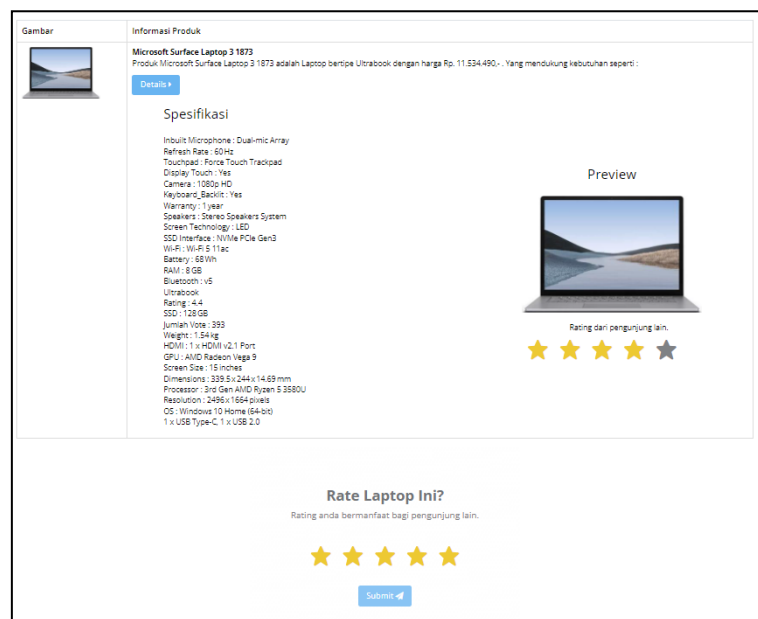


Fig. 4 Example of products selected by the user

The system will look for products with the same category as those that users have rated, and those users see are not included in the recommendation process. Therefore, we can organize the information into a table, as shown in Table 1, which includes User (U) and item (IT). The table explains that IT1 refers to Microsoft Surface Laptop 3 1873, IT2 refers to Hp 14s FQ1092AU, IT3 refers to Hp 255 G9 840T7PA, IT4 refers to Dell Inspiron 3525, and IT5 refers to Microsoft Surface Pro X.

Table 1 Buyer's Rating of the Product

	U1	U2	U3	U4	U5
IT1	5	1	4	1	5
IT2	1	4	1	0	4
IT3	3	1	1	1	5
IT4	2	2	3	5	0
IT5	1	0	1	5	2

Table 2 provides a detailed analysis of the adjusted cosine similarity calculation, which is performed by measuring the similarity between item m and item n.

Table 2 Similarity Matrix Between Products

	IT1	IT2	IT3	IT4	IT5
IT1	1	0.065	0.736	0.736	-0.631
IT2	0.065	1	0.448	-0.809	-0.555
IT3	0.736	0.448	1	-0.800	-0.058
IT4	0.736	-0.809	-0.800	1	0.600
IT5	-0.631	-0.555	-0.058	0.600	1

Table 3 shows the calculation of product prediction values with users using the Adjusted Weighted Sum formula equation. We use the Adjusted Weighted Sum formula to calculate the likelihood of users favoring a product.

Table 3 Prediction Result

	U1	U2	U3	U4	U5
IT1	3.326	2.064	2.695	3.326	4.588
IT2	2.139	0.749	1.444	2.139	3.529
IT3	2.331	1.017	1.674	2.331	3.646
IT4	2.501	1.488	1.995	2.501	3.515
IT5	1.941	0.535	1.238	1.657	2.193

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In the final step, we must calculate the MAE, where the error is the difference between the actual and predicted rating values. Table 4 displays the errors in ascending order. During the final stage of our analysis, we must calculate the MAE to measure the accuracy of our predictions. To do this, we compare the actual rating values with the predicted ones and calculate the difference between them. The resulting errors are then arranged in ascending order and presented in Table 4 for easy reference and analysis.

Table 4 MAE results in ascending order

Order of Recommendation	Recommended products	MAE
Recommendation 1	IT3	0,806
Recommendation 2	IT5	1,049
Recommendation 3	IT1	1,356
Recommendation 4	IT2	1,488
Recommendation 5	IT4	1,606

Evaluation

The recommender system will be evaluated in the evaluation stage to determine its efficiency and quality. This evaluation is critical to decide on how well the system can work. In this research, the researcher evaluated the system performance and user satisfaction as indicators of the resulting performance. In this way, complete information can be obtained about the quality of the system and the extent to which the system can meet the needs and expectations of users.

a) System Performance Evaluation

In this research, system performance evaluation is carried out using accuracy metrics. The accuracy metric tests the accuracy of the recommendations provided by the system. In the evaluation stage, each user rates each recommendation on a scale of 1 to 5. Researchers classify recommendations that receive a rating of 1 to 3 as unsuccessful recommendations, while they classify recommendations that receive a rating of 4 or 5 as successful recommendations. The classification results are used to calculate the accuracy value using the formula:

$$\text{Accuracy} = \frac{\text{Total Successful Recommendations}}{\text{Number of Recommendations}} \quad (4)$$

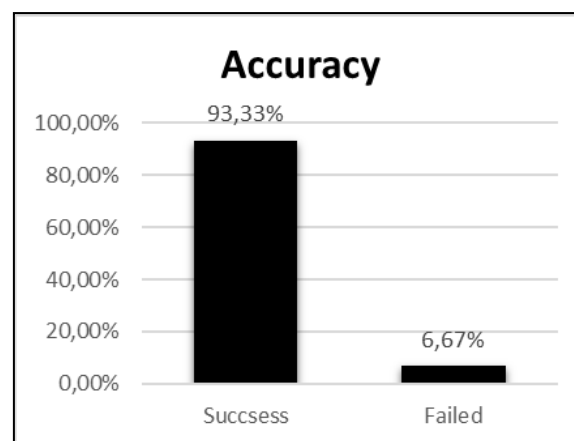


Fig. 5 Result of Recommendation Accuracy

As Figure 5 illustrates, the overall accuracy of the system reached 93.33%. Meanwhile, the unsuccessful ones reached 6.67%. This result is better than previous research (Ayundhita et al., 2019), which only relied on ontology with an accuracy of only 84.6%. Further evaluation can be done to identify aspects of improvement to increase the accuracy of the system's recommendations.

b) User Satisfaction Evaluation

In developing a recommender system, user satisfaction evaluation is an important aspect. This study used a questionnaire to interact with users through 10 questions from Table 5 to obtain more accurate results. Our

analysis focuses on six main factors, i.e., Usability (US), informativeness (INF), Perceived Efficiency (PE), Ease of Understanding (EU), and Perception of Recommendation Quality (PRQ).

Table 5. Explanation of questionnaire

ID	Factor	Question
S1	PE	I am able to find a laptop that I like
S2	INF	I find it easy to find information on my laptop computer
S3	TR	When I buy a laptop one day, I will choose it from this application
S4	TR	If I buy a laptop one day, I will use this application again
S5	US	Finding a laptop that suits my needs is difficult.
S6	EU	I had no difficulty using this system
S7	EU	The questions and answers provided by the application are easy to understand.
S8	EU	I can easily understand the questions given by the application
S9	PRQ	I like the interaction in this application
S10	PRQ	I like the product I have chosen

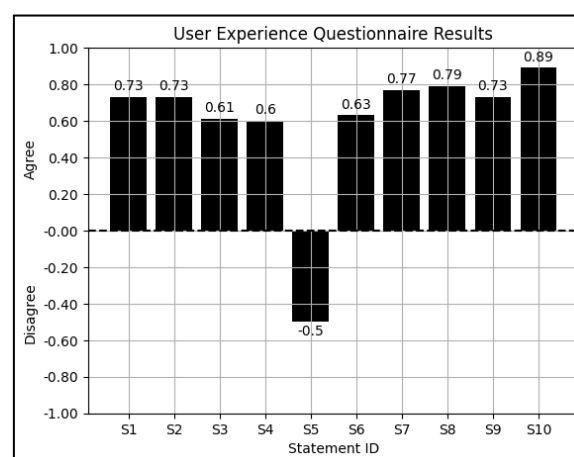


Fig. 6 Result of User Experience Questionnaire

Based on the information in Fig. 6, statement ID S5 scored negatively. Although most users disagreed with this statement, the results were positive for the other Statement IDs, indicating agreement. This suggests that the six factors relating to Usability (US), informativeness (INF), Perceived Efficiency (PE), Ease of Understanding (EU), and Perception of Recommendation Quality (PRQ) have delivered promising results.

DISCUSSIONS

We evaluated the success of this model by calculating a matrix based on the responses of 75 respondents. This assessment focuses entirely on system performance and user satisfaction. It should be noted that improving system performance contributes positively to overall user satisfaction. Fig. 4 and Fig. 5 illustrate that the recommender system using the Hybrid method which combines functional requirements methods and collaborative filtering increases the success rate, thereby increasing user satisfaction with the system.

CONCLUSION

This research uses ontology and Collaborative Filtering methods to provide laptop recommendations, considering similar user data. The Item-Based Collaborative Filtering algorithm is accurate, especially when users give limited ratings and low errors (MAE 0.809026). The combined method has the potential to provide more diverse laptop recommendations. The evaluation showed a recommendation accuracy of 93.33%, in line with the

expectation that integrating these methods is beneficial in helping users select the desired laptop. The system as a whole can increase user satisfaction with the recommendations provided.

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