Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

Car Recommender System Using Collaborative Filtering and Ontology-Based Conversational Recommender System

Muhammad Radhiva Hibatullah, Z K A Baizal*

School of Computing, Informatics, Telkom University, Bandung
Jl. Telekomunikasi. 1, Terusan Buahbatu - Bojongsoang, Telkom University, Sukapura, Kec. Dayeuhkolot, Kabupaten Bandung, Jawa Barat, Indonesia
Email: [1]radhivahibatullah@student.telkomuniversity.ac.id, [2,*]baizal@telkomuniversity.ac.id
Correspondence Author Email: baizal@telkomuniversity.ac.id
Submitted: **09/01/2024;** Accepted: **25/01/2024;** Published: **27/01/2024**

Abstract−The development of the automotive industry in Indonesia is increasing, especially in automobiles. Due to the increasing number of car brands in Indonesia, it is difficult for users to decide which car suits their functional requirements. Therefore, to overcome this problem, we propose a ontology-based Conversational Recommender System (CRS) using Collaborative Filtering. CRS as a framework aims to have users interact with the system so that the system obtains information related to users functional requirements, ontology-based aims to organize domain knowledge with specific concepts, and Collaborative Filtering improve the accuracy of recommender products in developing recommender systems. The evaluation results include system performance with 85.39% accuracy and user satisfaction getting positive feedback from various factors. This shows that the car recommender system is effective and efficient in providing recommendations according to the functional requirements of users.

Keywords: Recommender System; Ontology; Conversational Recommender System; Collaborative Filtering; Knowledge-based Recommender System

1. INTRODUCTION

In recent years, the automotive industry in Indonesia has experienced significant growth, driven by increased traffic density, rising purchasing power among users, and overall economic development. As cars have become essential for Indonesians in their daily activities, the multitude of available car brands has made it challenging for users to navigate and choose a vehicle that aligns with their functional requirements. To address this challenge, the development of a recommender system for cars based on functional requirements has become crucial.

A recommender system for cars based on functional requirements aims to predict user preferences by leveraging information obtained from various sources [1], [2]. Past research, such as the work by Prabowol et al. [1], utilized item-based Collaborative Filtering to recommend cars based on specifications, employing a ranking pattern and attributes matching approach. Similarly, Boteju and Munangsihe [2] employed a Neural Network Model to provide personalized recommendations by collecting data from users and vehicle sellers. However, despite these efforts, many users still struggle to grasp the intricacies of car specifications, necessitating a more user-friendly approach. Prasetyo et al. [3] discuss the use of Item-Based Collaborative Filtering to suggest smartphone accessories to customers. This approach focuses on item relationships to provide accurate recommendations. The authors present a methodology to prove the system's effectiveness, highlighting potential benefits such as increased sales and improved customer satisfaction.

In response to this need, we propose an ontology-based Conversational Recommender System (CRS) and Collaborative Filtering. CRS is a framework to assist users in understanding and selecting cars based on their functional requirements [4]. The CRS incorporates two navigation strategies, i.e., Navigation By Asking (NBA) and Navigation By Proposing (NBP) [5]. NBA involves presenting users with repetitive questions to gather information, ultimately leading to tailored recommendations. On the other hand, NBP collects user feedback on the recommended products, further refining the suggestions. The integration of ontology into the CRS framework aims to organize domain knowledge with specific concepts, enhancing the accuracy of recommendations to align with user functional requirements [6], [7]. The ontology model comprises three classes, functional requirements, products, and specifications [5], creating a structured and hierarchical recommender system.

Building on the foundation laid by previous studies, Theosaksomo and Widyantoro [8] developed a chatbot using a CRS to provide accurate recommendations, our proposed CRS framework emphasizes user interaction to gather information related to functional requirements. This study draws inspiration from various research efforts, including Kun Zhou et al. [9], who focused on recommending high-quality products through interactive conversations, and Bouihi and Bahaj [10], who developed a recommender system for e-learning applications based on the semantic web. Furthermore, the potential applications of Conversational Recommender Systems expand beyond the automotive industry. Cordero et al. [11] explored the use of CRS in medical diagnosis using Fuzzy Rules, demonstrating the effectiveness of CRS in telemedicine. Additionally, Aziz et al. [12] employed an Ontology-based knowledge modeling framework to identify hazards in the process industry, showcasing the versatility of ontology in diverse domains.

Hawalah [13] leveraged ontology to classify Arabic texts, illustrating the utility of ontology in information categorization. Chen et al. [14] presented a sophisticated model for diagnosing and treating diabetes based on ontology, emphasizing its role in providing a shared vocabulary for specific domains.

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

In this context, we proposed ontology-based CRS not only addresses the specific requirements of users in the automotive industry but also aligns with broader trends in leveraging conversational systems and ontology in various domains. The positive evaluation results from Baizal et al. [15] further reinforce the effectiveness of CRS in enhancing recommendation accuracy, query refinement, and user satisfaction.

2.RESEARCH METHODOLOGY

2.1 Research Stages

During user interaction, the system will ask questions regarding their functional requirements to provide personalized car recommendations. The system will repeat the questions several times to ensure accuracy, and once the functional requirements have been established, the system will offer car recommendations and detailed explanations. The system has been designed to include three modules.

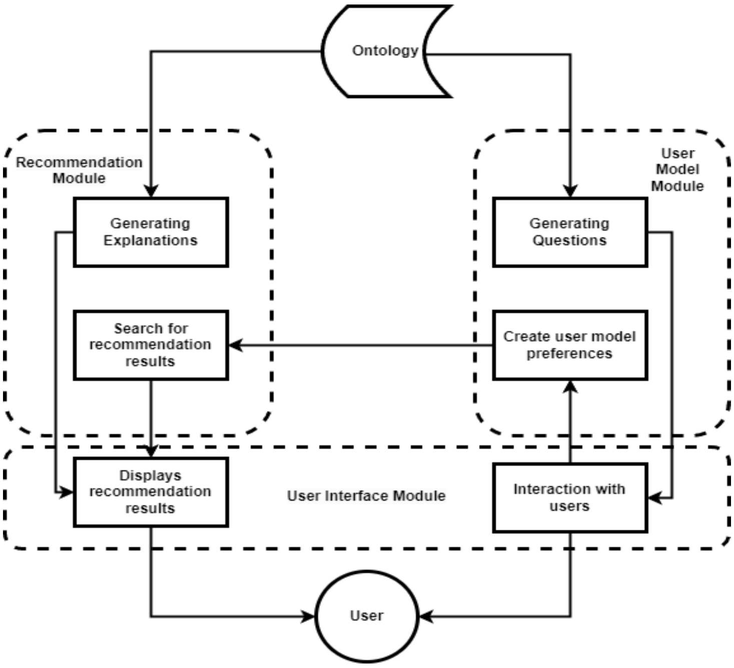

Figure 1. General System Overview

The general system design is depicted in Figure 1, with each module serving a unique purpose. The user preference model module serves as a vital link between the ontology and the system, enabling the generation of questions related to users' functional requirements. This module plays a crucial role in facilitating the development of personalized recommendations for each user. In contrast, the recommendation module aims to suggest products that meet users functional requirements based on their personalized questions. Additionally, the module provides users with comprehensive explanations of the recommended product characteristics, benefits, and drawbacks to enable them to make informed decisions. The user interface module serves as the primary point of interaction between the system and its users. It is responsible for displaying personalized questions based on user preferences and presenting recommendation results clearly and easily. By utilizing this module, the system can provide highly personalized product recommendations tailored to the user specific requirements and interests. With its user-friendly interface and intuitive design, this system offers a seamless and effective solution for anyone seeking personalized product recommendations [4].

Our proposed mechanism for interacting with the Customer Relationship System (CRS) is designed to provide a personalized experience to the user. This is done by engaging them in dialogue through a series of questions aimed at better understanding their needs and functional requirements. The system will ask questions regarding user preferences may influence their product selection. Once users provide their feedback, the system will analyze the data and recommend products that best suit their functional requirement. The system will consider the user's functional requirements factors . The system will also provide an explanation of the recommended items, including their features, advantages and disadvantages. This information will enable users to make informed decisions when selecting products. Next, the system will collect data about the user's functional requirements and use it to improve future recommendations. The system will analyze user data to identify trends and patterns in their preferences, which will help further personalize recommendations. The system will also track users' previous purchases, feedback and reviews to understand their preferences better. For a better understanding of this interaction, see Figure 2, which depicts the communication between the user and the system. The figure shows how the user and the system communicate through a series of questions and responses, leading to personalized product recommendations.

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

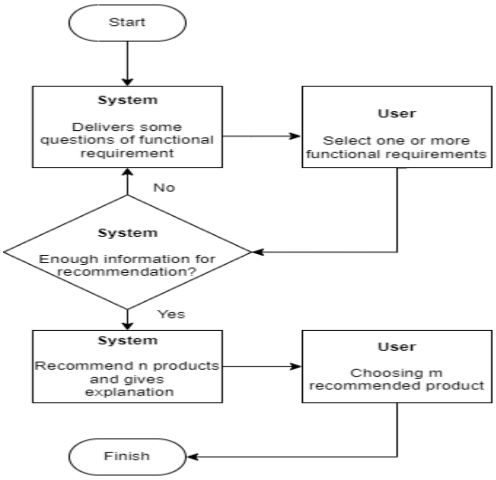

Figure 2. Interaction procedure between user and system

Figure 2 presents a comprehensive depiction of the interaction procedure that takes place between the user and the system. It includes each step involved in the journey, from the beginning to the end, with a detailed explanation of each action. When the user initiates the interaction, the system prompts them with a series of questions that are relevant to the functional requirements. The user is then given the flexibility to select. The user is offered a range of functional requirements to choose from, based on their individual preferences and requirements. These requirements are designed to cater to the user specific requirements and ensure that their experience is tailored to their liking. By providing this flexibility, the user can customize their experience to match their unique preferences, resulting in a more satisfying and efficient interaction. After making a choice, the system will carefully examine the information provided to ensure that it meets the user requirements. Overall this process is designed to be seamless and user-friendly, ensuring that the user requirements are met efficiently and effectively.

If the information collected is not enough, the system continues the interaction. If the information provided is sufficient, the system directly provides car product recommendations and an explanation. After that, the user selects the recommended car. However, if the user chooses more than one product or does not choose, the system again provides several functional requirement questions to be more specific about the recommended product. After that, the user gives a rating to the recommended product .

2.2 Car Ontology

Widyantoro et al. [4] designed the ontology to have three main classes, functional requirements, products, and specifications. SubClassOf and InstanceOf connect each hierarchical class entity to produce interactions based on functional requirements. Figure 3 showing the specification hierarchy serves as a guide to ensure that functional requirements are accurately matched with their corresponding products. This hierarchy sorts product specifications based on quality levels, ensuring each product meets its intended use. To illustrate, when it comes to transmission specifications, the scale divides them into two distinct categories. automatic and manual types. This helps to ensure that the appropriate transmission is chosen, depending on the product's specific requirements [16], [17].

Figure 4 presents the product hierarchy is a system that simplifies the process of selecting a car that meets the unique functional requirements of each user. This system categorizes car product specifications into several distinct categories, each with its distinctive attributes. For instance, SUVs are designed for off-road exploration, while LCGCs are ideal for transporting children to school.

Figure 5 presents the functional requirements hierarchy primary purpose is to describe user's functional requirements and demands regarding cars. In this hierarchy, various subclasses are interrelated and form a complex structure. In this hierarchy, questions and explanations relate to specific classes and subclasses.

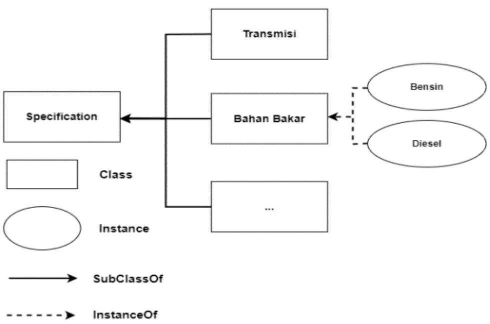

Figure 3. Specification hierarchy

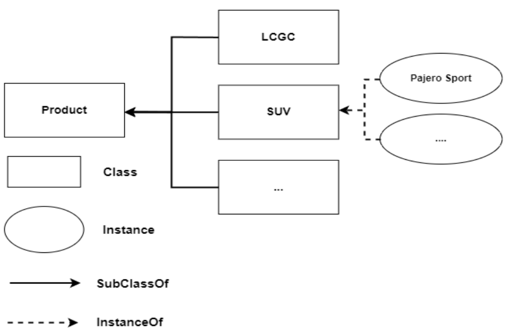

Figure 4. Product hierarchy

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

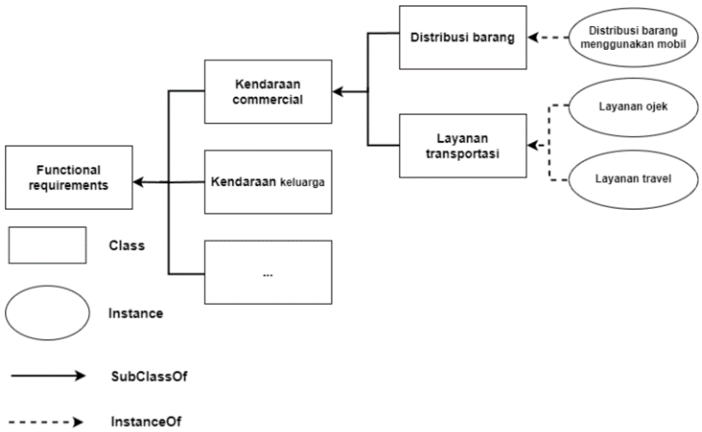

Figure 5. Functional requirement hierarchy

2.3 User Preference Modelling

It is crucial to model user preferences to create questions and build profile models based on feedback. This is relevant for the recommender system, where several interaction cases may arise.

a. Empty user profile
   This case occurs when the user profile is still empty. The system provides several questions in the form of car categories that are still general in nature, the aim is to build a user profile model.
b. Multiple product selection
   This case occurs when the user still has difficulty deciding which product to choose. To assist users in personalizing product choices, the system can use a questioning strategy regarding elements to differentiate between product groups.
c. None of the products selected
   This case occurs when if the user does not select any product. Then, the system looks for other nodes that match the user requirements, this allows the system to generate products that have not appeared or been requested.
d. The recommendations cannot be generated due to the lack of clear and specific requirements defined
   It seems that in some cases, the requirements may still need to be more general. When this happens, the system may ask for more specific functional requirements. The questions asked by the system will likely be related to the users previous answers, in order to gather more information and clarify any uncertainties.

2.3 System Overview

The system presents questions related to functional requirements that can recommend products according to functional requirements. Figure 6 shows the user filling in the questions provided by the system. The system presents questions repeatedly until the information from the user is fulfilled. The system gives questions covering functional requirements such as family car, commercial cars, competitions, and official duties of an agency. The system provides optional answers to users to provide information related to their functional requirements. The system then processes the user responses to generate product recommendations that match their functional requirements.

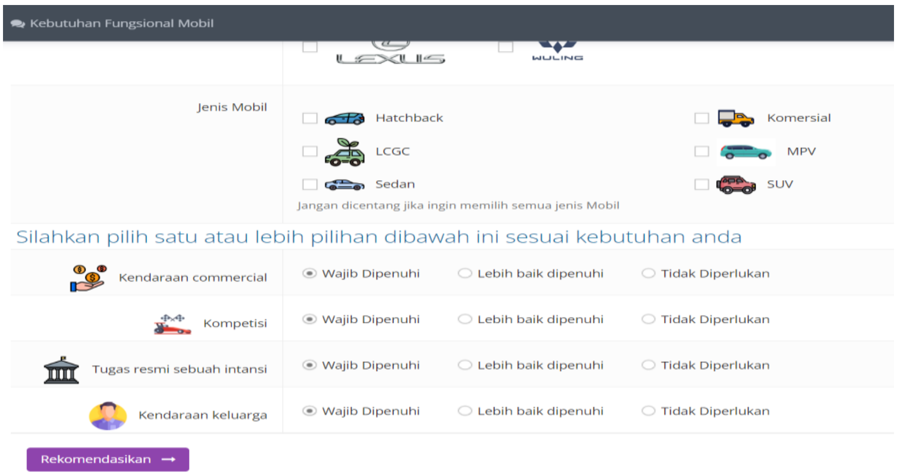

Figure 6. Initial user and system interaction

The user selects questions related to functional requirements. Figure 7 shows that if there are still many recommended products, the system presents more specific questions related to functional requirements.

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

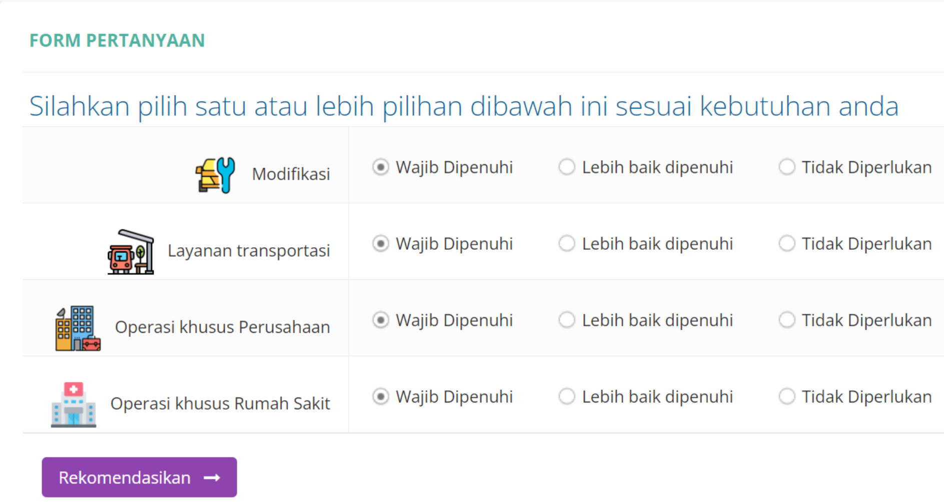

Figure 7. Questions to refine the requirement

Tailoring a car to individual functional requirements, it is important to ask personalized questiones. These questions enhance the adjusment process. For example, if a user is looking for car modifications, or if their primary use involves providing transportation services, refining these questions allows for the creation of a personalized car that precisely fits each user's requirement and preferences. The system obtains information from the user and displays a list of recommendations according to the functional requirements, as shown in Figure 8. Users can select recommendation results that match their functional requirements.

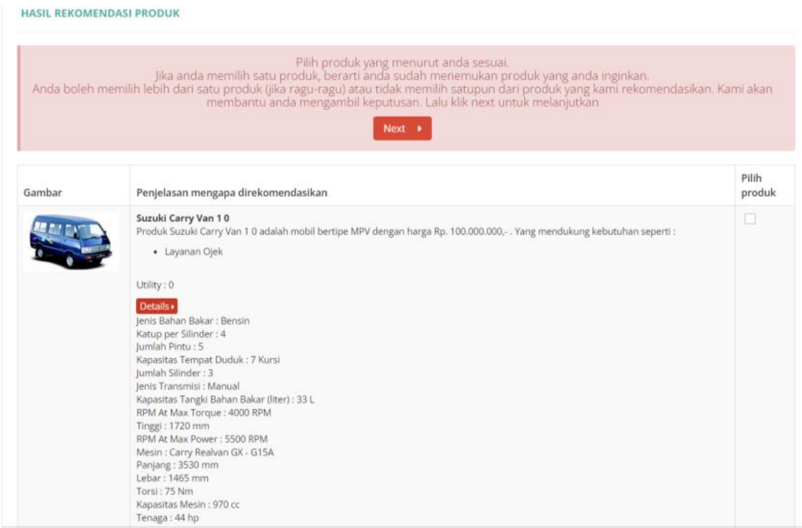

Figure 8. List Recommendation

2.4 Cosine Similarity

Cosine Similarity is a mathematical function used to measure the similarity between two items. It is a commonly used algorithm for computing similarity values in recommender systems, data mining, and information retrieval. In contrast to other similarity measures, Adjusted Cosine Similarity takes into account the user rating patterns and item biases, which makes it more accurate in determining the similarity between two items [3]. The formula for Adjusted Cosine Similarity involves the dot product of the ratings of two items, normalized by the ratings of the users who rated both items. This normalization step is crucial because different users may have different rating scales, and some users may provide more ratings than others. Therefore, the Adjusted Cosine Similarity is a robust and efficient method for calculating the similarity between items in large datasets.

$$cosim(p,q) = \frac{\Sigma_{u\in i}(R_{u,p} - \bar{R}_u) - (R_{u,q} - \bar{R}_u)}{\sqrt{\Sigma_{u\in i}(R_{u,p} - \bar{R}_u)^2}\sqrt{\Sigma_{u\in i}(R_{u,q} - \bar{R}_u)^2}} \quad (1)$$

$cosim(p,q)$	:	Similarity measure for item p and q
$u \in i$	:	The collection of all users who provided ratings for items p and q
$R_{u,p}$	:	Rating given by user for item p
$R_{u,q}$	:	Rating given by user for item q

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

$\bar{R}_u$: Average rating given by users.

2.4 Weighted Sum

Weighted Sum is a method used to predict the rating a user (p) would give to an item (q) based on the average ratings of similar items. It is calculated by taking the weighted average of the ratings of similar items that have been rated by the user and adjusting it to account for any biases or inconsistencies in their rating behavior [18]. The formula used for this calculation is as follows.

$$A(p,q) = \bar{R}_q + \frac{\sum_{i=1}^{n}(R_{p,i} - \bar{R}_i) \times cosim(i,q)}{\sum_{i=1}^{n}|\ cosim(i,q)|} \quad (2)$$

$A(p,q)$: Estimated rating for item q based on preferences of user p
$\bar{R}_q$: Average rating attributed to item q
$R_{p,i}$: The rating given by user p to item i
$\bar{R}_i$: Average rating value for item i
$cosim(i,q)$: Similarity measure for item i and q

2.4 Mean Absolute Error

The calculation of recommendation accuracy, although not the primary focus of a recommender system, is essential in evaluating its performance and comprehending the accuracy of the recommendations [19]. The accuracy calculation procedure aims to identify any errors that may arise in the recommender system. The approach employed for this calculation involves the Mean Absolute Error (MAE), a widely accepted method in the field that is described in the following equation.

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

MAE : Mean Absolute Error Value
$A_{u,p}$: Estimated rating for item p based on preferences of user u
$R_{u,p}$: The specific rating provided by user u for item p
N : The total user count

3. RESULT AND DISCUSSION

The evaluation considers the system's performance in providing recommendations and user satisfaction [14]. We involved 89 participants, including those with knowledge of car specifications.

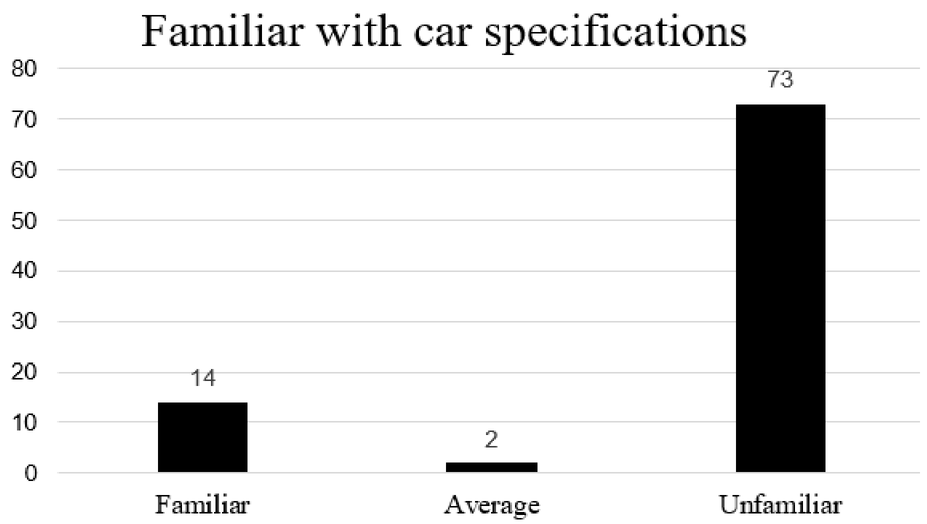

Figure 9. Participants who are familiar with car specifications

According to the data represented in Figure 9, participants have been categorized into three groups based on their familiarity with car specifications. The first group, which consists of 14 individuals, is categorized as Familiar with car specifications. The second group, comprising two individuals, is labeled as Average in their familiarity with car specifications. The final group, which has a significant majority of 73 individuals, has been categorized as Unfamiliar with car specifications. These findings suggest that a large proportion of the participants in this study lack knowledge about car specifications. After getting participants, we evaluated the results for system performance in recommending cars and user satisfaction in using the recommender system.

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

3.1 Matrix representation for the implementation of item-based

The accuracy of recommendations generated by a recommender system is a critical aspect to evaluate the system's performance. While not the primary focus of the system, accurately assessing the quality of recommendations is essential. The primary goal of the accuracy calculation procedure is to identify and quantify any errors that may arise in the system. The Mean Absolute Error (MAE) approach is used by researchers to calculate the accuracy of recommendations [20]. To conduct the MAE approach experiments, data entered by five users and five products with varying rating magnitudes are utilized. This approach helps researchers to understand the accuracy of the recommendations and identify areas for improvement. The system will search for products in the same category as those rated by users, which are not included in the recommendation process. This will create a table similar to Table 1.

C1 : HRV 1.5 L S CVT
C2 : Civic RS 1.5 L
C3 : BRV S MT
C4 : Raize 1.0 Turbo G CV
C5 : Xpander GLS CVT

Table 1. The user's appraisal rating to the product

	U1	U2	U3	U4	U5
C1	4	3	5	2	1
C2	0	5	2	1	1
C3	3	2	2	2	5
C4	4	3	5	4	4
C5	2	1	0	3	5

Table 2 is a comprehensive representation of the outcomes of the adjusted cosine similarity calculation, which is based on the sim(P1, P2) formula. This calculation has been performed for every product, and the results have been presented in a clear and organized manner in the table. By reviewing the information in the table, one can gain a deeper understanding of how the adjusted cosine similarity calculation works and how it can be used to compare various products in a systematic and effective manner.

Table 2. Comparing different products using a similarity matrix

	C1	C2	C3	C4	C5
C1	1	0.08	-0.42	-0.71	-0.53
C2	0.08	1	-0.29	-0.52	-0.54
C3	-0.42	-0.29	1	0.33	0.62
C4	-0.71	-0.52	0.33	1	0.26
C5	-0.53	-0.54	0.62	0.26	1

Table 3 shows the method used to estimate product prediction values based on user preferences. We used the Adjusted Weighted Sum formula to calculate these values, which factor in the weight of each user's input. The resulting values indicate the likelihood of a product being preferred by a user. Please refer to the table for more information on the calculation process.

Table 3. Result of prediction

	U1	U2	U3	U4	U5
C1	2.85	3.44	3.75	2.66	1.30
C2	1.10	3.67	2.28	1.46	0.50
C3	2.68	1.55	1.91	2.36	4.49
C4	3.67	2.43	2.32	3.84	4.75
C5	2.82	1.38	2.19	2.91	4.61

To complete the process, we need to calculate the Mean Absolute Error (MAE). This involves finding the average of the absolute errors, which is the difference between the actual rating value and the predicted rating value. Table 4 displays the errors in ascending order for each sortie.

Table 4. Displays the outcomes for the Mean Absolute Error (MAE**).**

Recommendation from (n)	Recommender products	MAE
Recommendation 1	C4	0.43
Recommendation 2	C5	0.50
Recommendation 3	C3	0.55
Recommendation 4	C2	0.73
Recommendation 5	C1	0.76

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

3.2 Evaluation of system recommendation results

When assessing the effectiveness of a recommender system, it is essential to measure its success rate accurately. One standard method of doing so is by evaluating the accuracy of the recommendations, which can be achieved by tracking the percentage of successful interactions. An interaction is successful when the user can select the recommended car in the CRS, indicating that the system has provided a satisfactory recommendation. This approach helps ensure the recommender system works as intended and provides users value.

$$Accuracy = \frac{number\ of\ successful\ recommendation}{number\ of\ recommendation} \tag{4}$$

Figure 10 shows that 85.39% successfully recommend products that match the functional requirements of users. Meanwhile, 14.61% still needed products that fit their functional requirements.

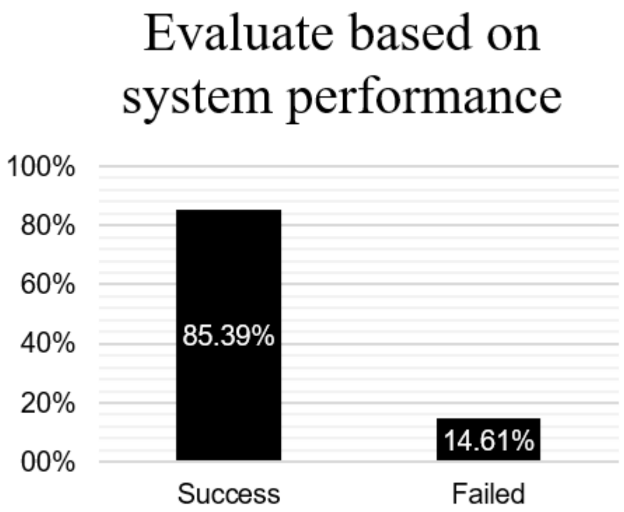

Figure 10. Evaluation of system recommendation results

The system is designed to deliver results with exceptional accuracy and efficiency. CRS as a framework seamlessly to provide users with reliable recommendations and valuable insights. This level of precision ensures that users can trust the system's outputs and make informed decisions based on the recommendations. The system's ability to enhance decision-making processes and improve overall user experience is a testament to its effectiveness and reliability. With its user-friendly interface and intuitive design, the system boasts a smooth and seamless user experience, making it a go-to tool for users seeking reliable and efficient results.

3.3 Evaluation of user sastifaction results

We conduct an evaluation of user satisfaction alongside system performance by using questionnaires. The aim of this evaluation is to analyze the impact of product functionality on how users perceive the system. We examine several factors in detail, including ease of use (EOU), informativeness (INF), perceived efficiency (PE), ease of understanding (EOU), perceived quality of recommendation (PRQ), and trust (TR).

Ease of use (EOU) measures how easy it is for users to operate the system and perform tasks without encountering any difficulty. Informativeness (INF) evaluates how informative the system is in terms of providing users with relevant and useful information. Perceived efficiency (PE) measures the user's perception of the system's speed and responsiveness in performing tasks. Ease of understanding (EOU) examines how well users can comprehend the system's interface and functionality. Perceived quality of recommendation (PRQ) evaluates how well the system's recommendations match the user's requirements and preferences. Trust (TR) measures the user's confidence in the system's recommendations, accuracy, and reliability. You can find the detailed questions related to each of these factors in Table 5.

Table 5. Question description

ID	Factors	Information
US1	PE	I am currently able to locate the product with ease
US2	INF	I find it easy to obtain product information.
US3	TR	I have selected a product in the system that I plan to purchase someday.
US4	TR	If I intended to purchase a vehicle, I would utilize this system.
US5	ETU	I am unable to locate a product that matches my specific requirements
US6	ETU	I didn't encounter any difficulties when using this system.
US7	EOU	The questions provided are easily comprehensible

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

ID	Factors	Information
US8	EOU	I have comprehended the question that was asked without any confusion
US9	PRQ	I am satisfied with the product choices I made.
US10	PRQ	I am not satisfied with the interaction system provided.

Figure 11 shows that users felt assisted by the car recommender system using this ontology-based CRS framework. US5 and US10 show that some users have difficulty finding products that match their functional requirements and less engaging interactions.

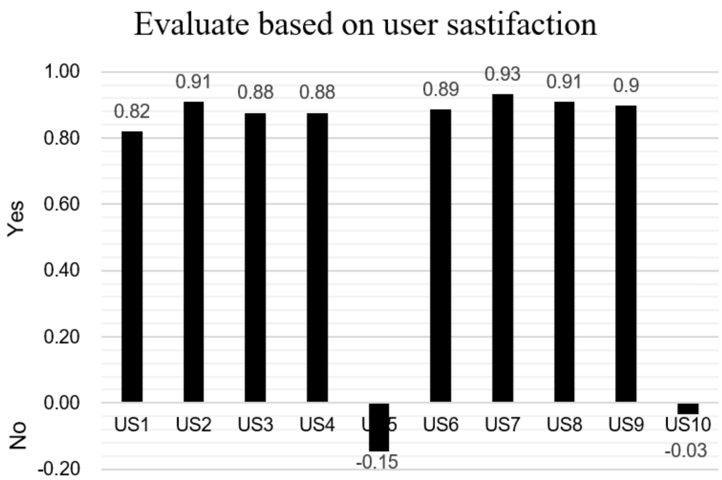

Figure 11. Evaluation of user satisfaction results

4. CONCLUSION

The evaluation report for the car recommender system shows that it has performed exceptionally well, achieving an accuracy rate of 85.39%. The system has been put through a series of rigorous tests to ensure that it provides users with recommendations that suit their functional needs. The results of the evaluation indicate that the system is highly effective in providing recommendations that are relevant and useful to users. Users have expressed their satisfaction with the system's performance, citing its efficiency and effectiveness in providing personalized recommendations. Car recommender systems have become a reliable tool for users who are looking to buy. The system provides users with a comprehensive list of recommendations based on their specific requirements, making it easier for them to make an informed decision. Collaborative Filtering is a technique that is used to improve the accuracy of the designed recommender system. It helps to identify patterns in user behavior and preferences, which are then used to generate more accurate recommendations. This technique has been proven to be highly effective in improving the system's performance and ensuring that users receive recommendations that are tailored to their needs.

REFERENCES

[1] Prabowol, Gusti, Muhammad Nasrun, and Ratna Astuti Nugrahaeni. "Recommendations for Car Selection System Using Item-Based Collaborative Filtering (CF)." 2019 IEEE International Conference on Signals and Systems (ICSigSys). IEEE, 2019.

[2] P. Boteju and L. Munasinghe, “Vehicle recommendation system using hybrid recommender algorithm and natural language processing approach,” in ICAC 2020 - 2nd International Conference on Advancements in Computing, Proceedings, Institute of Electrical and Electronics Engineers Inc., Dec. 2020, pp. 386–391. doi: 10.1109/ICAC51239.2020.9357156.

[3] B. Prasetyo, H. Haryanto, S. Astuti, E. Z. Astuti, and Y. Rahayu, “Implementasi Metode Item-Based Collaborative Filtering dalam Pemberian Rekomendasi Calon Pembeli Aksesoris Smartphone,” Eksplora Inform., vol. 9, no. 1, pp. 17–27, 2019, doi: 10.30864/eksplora.v9i1.244.

[4] Z. K. A. Baizal, D. H. Widyantoro, and N. U. Maulidevi, “Query refinement in recommender system based on product functional requirements,” 2016 Int. Conf. Adv. Comput. Sci. Inf. Syst. ICACSIS 2016, pp. 309–314, 2017, doi: 10.1109/ICACSIS.2016.7872760.

[5] Z. K. A. Baizal, D. H. Widyantoro, and N. U. Maulidevi, “Computational model for generating interactions in conversational recommender system based on product functional requirements,” Data Knowl. Eng., vol. 128, Jul. 2020, doi: 10.1016/j.datak.2020.101813.

[6] A. Razia Sulthana and S. Ramasamy, “Ontology and context based recommendation system using Neuro-Fuzzy Classification,” Comput. Electr. Eng., vol. 74, pp. 498–510, 2019, doi: 10.1016/j.compeleceng.2018.01.034.

[7] R. V. Karthik and S. Ganapathy, “A fuzzy recommendation system for predicting the customers interests using sentiment analysis and ontology in e-commerce,” Appl. Soft Comput., vol. 108, p. 107396, 2021, doi: 10.1016/j.asoc.2021.107396.

[8] Theosaksomo, David, and Dwi H. Widyantoro. "Conversational recommender system chatbot based on functional requirement." 2019 IEEE 13th International Conference on Telecommunication Systems, Services, and Applications (TSSA). IEEE, 2019.

Journal of Information System Research (JOSH)
Volume 5, No. 2, Januari 2024, pp 573−582
ISSN 2686-228X (media online)
https://ejurnal.seminar-id.com/index.php/josh/
DOI 10.47065/josh.v5i2.4785

[9] K. Zhou, Y. Zhou, W. X. Zhao, X. Wang, and J.-R. Wen, “Towards Topic-Guided Conversational Recommender System,” Oct. 2020, [Online]. Available: http://arxiv.org/abs/2010.04125
[10] B. Bouihi and M. Bahaj, “Ontology and rule-based recommender system for e-learning applications,” Int. J. Emerg. Technol. Learn., vol. 14, no. 15, pp. 4–13, 2019, doi: 10.3991/ijet.v14i15.10566.
[11] P. Cordero, M. Enciso, D. López, and A. Mora, “A conversational recommender system for diagnosis using fuzzy rules,” Expert Syst. Appl., vol. 154, 2020, doi: 10.1016/j.eswa.2020.113449.
[12] A. Aziz, S. Ahmed, and F. I. Khan, “An ontology-based methodology for hazard identification and causation analysis,” Process Saf. Environ. Prot., vol. 123, pp. 87–98, 2019, doi: 10.1016/j.psep.2018.12.008.
[13] A. Hawalah, “Semantic ontology-based approach to enhance arabic text classification,” Big Data Cogn. Comput., vol. 3, no. 4, pp. 1–14, 2019, doi: 10.3390/bdcc3040053.
[14] L. Chen et al., “OMDP: An ontology-based model for diagnosis and treatment of diabetes patients in remote healthcare systems,” Int. J. Distrib. Sens. Networks, vol. 15, no. 5, 2019, doi: 10.1177/1550147719847112.
[15] Z. K. Abdurahman Baizal, Y. R. Murti, and Adiwijaya, “Evaluating functional requirements-based compound critiquing on conversational recommender system,” 2017 5th Int. Conf. Inf. Commun. Technol. ICoIC7 2017, vol. 0, no. c, 2017, doi: 10.1109/ICoICT.2017.8074656.
[16] M. Guia, R. R. Silva, and J. Bernardino, “A hybrid ontology-based recommendation system in e-commerce,” Algorithms, vol. 12, no. 11, pp. 1–19, 2019, doi: 10.3390/a12110239.
[17] Iswari, Ni Made Satvika, Wella Wella, and Andre Rusli. "Product Recommendation for e-Commerce System based on Ontology." 2019 1st International Conference on Cybernetics and Intelligent System (ICORIS). Vol. 1. IEEE, 2019.
[18] Z. Li, M. Hua, Q. Wang, and Q. Song, “Weighted sum-rate maximization for multi-IRS aided cooperative transmission,” IEEE Wirel. Commun. Lett., vol. 9, no. 10, pp. 1620–1624, 2020, doi: 10.1109/LWC.2020.2999356.
[19] J. Jeevamol and V. G. Renumol, An ontology-based hybrid e-learning content recommender system for alleviating the cold-start problem, vol. 26, no. 4. Springer US, 2021. doi: 10.1007/s10639-021-10508-0.
[20] T. O. Hodson, “Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not,” Geosci. Model Dev., vol. 15, no. 14, pp. 5481–5487, 2022, doi: 10.5194/gmd-15-5481-2022.