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Conversational Recommender System based on Functional Requirement using Knowledge Graph for Building Personal Computer

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Abstract−When a person wants to build a personal computer, this person needs to browse many kinds of computer components. Besides that, this person needs to consider the compatibility between hardware and an affordable price. This will be a problem for people who are still unfamiliar with the computer, due to their lack of understanding of how compatibility between computer components works and the time-consuming nature of market research. To deal with this problem, the recommender system will assist in finding and matching compatibility efficiently based on the functional requirements of the user. The recommender system will issue various products based on the preferences and interests of the user, but some recommendations still need to be checked for compatibility. With the help of developing a Conversational Recommender System by utilizing the Knowledge Graph, it will be easier to construct the relationship between component compatibility. We propose this research by using Knowledge Graph as alternative from ontology to build Conversational Recommender system in Building Personal Computer. This research will involve the user to prove whether the recommendations from this system meet the needs and accuracy of the recommendations requested. The main results of this study will issue a recommendation for the development of personal computers by considering compatibility using the Conversational Recommender System using the Knowledge Graph approach, this research resulting a potential accuracy with perceived efficiency and informative recommendation according to customer satisfaction.

Keywords: Compatibility; Conversational Recommender System; Graph-Database; Knowledge Graph; Personal Computer

1. INTRODUCTION

When buying a product, many potential customers have difficulty choosing from the various options available. Customers sometimes don't have time to look for information regarding a product according to their needs [1]. Therefore, an application called a recommender system was developed to help potential customers find the product they want faster, with personalized recommendations [2].

Currently, the need for Personal Computer (PC) is very dominant to help a person's various jobs, especially among adults [3][4]. Some people find it difficult to buy and build a PC because of varying specifications and needs. It is necessary to review the compatibility and technical requirements of each component of a PC [5]. This problem gave rise to the development of a Conversational Recommender System (CRS) where customers can find an item according to their functional requirements [6]. There is previous research related to multi-domain framework to build a CRS based on functional requirements [6]–[8] and also a CRS based on technical specifications [9].

It started with CRS research using the Functional Requirements framework by Baizal et al., [7] with this research led to a superior CRS using Functional Requirements compared to flat models (interaction models based on technical features that are widely used on e-commerce sites). In 2019, it was continued by Ayundita et al., who conducted research on the Conversational Recommender System by comparing the basis functional requirement and technical feature in a product using the ontology approach with the laptop domain [9].

As technology continues to advance, the demand for more efficient and accurate recommender systems also increases. In particular, the use of a conversational interface in a recommender system has become a popular research topic in recent years. The use of a conversational interface allows for a more natural and interactive way for customers to express their needs and preferences, making it easier for the system to understand and provide personalized recommendations[10].

We use knowledge graph method instead of Ontology as previously [6][7][9]. This is supported by the fundamental concept and application of knowledge graph in the form of database instead of the ontology [11]. This supported by the concept Computational model by Baizal et al., for example, by adapting the Navigation By Asking (NBA) concept to the knowledge Graph structure in this study. For the evaluation of this study, the concept of Compound Critiquing on Conversational Recommender System is used as a reference for evaluation. Evaluation is carried out with an aspect of recommendation accuracy, query refinement, and user satisfaction as a user response to the CRS implemented [12].

The knowledge graph used in this study represents entities and relations between products and their specifications. The use of a knowledge graph allows for more precise relationships between products, making it easier for the system to understand and provide accurate recommendations [13]. Additionally, the knowledge graph is used to consider compatibility for each component of the PC, which is a crucial aspect when building or buying a PC.

This research provides a new approach for building a conversational recommender system for PC products, using a knowledge graph as a representation of entities and their relations. The approach is able to consider compatibility between components, which is crucial when building or buying a PC. The aim of the evaluation is to demonstrate that this approach can provide accurate recommendations, refine queries, and increase user satisfaction.

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The results of the evaluation will show that the use of a knowledge graph in combination with functional requirements allows for a more precise and personalized recommendations for customers [12]. Additionally, the compatibility consideration for each component can improve the overall customer experience when building or purchasing a PC. Furthermore, this approach can be expanded to other domains and products, making it a versatile and valuable tool for e-commerce and customer service [5].

The main contribution of this research is operating framework CRS with functional requirements and using different methods by using Knowledge Graph as a representation of entities and relations between their products with PC specification domains and being able to consider compatibility for each component [14]. Knowledge Graph is proposed to make it easier to build relationships between products with more precision [15].

2. RESEARCH METHODOLOGY

Consideration and preparation are needed when building a CRS, particularly when using a Knowledge Graph-based approach. The Knowledge Graph and database structures will be based on the Neo4j platform, as proposed by Miller et al. [11].

2.1 Conversational Recommender System

A Conversational Recommender System (CRS) is a recommendation system that adopts the mechanism of repeated interactions between the system and the user to recommend products. This CRS is inspired by the interaction between customer conversation and professional salesman support, by repeatedly asking questions from the system to obtain recommendations [6]. To increase the accuracy of recommendations in CRS, it will be assisted by a query refinement model with two navigation models: Navigation by Asking (NBA) and Navigation by Proposing (NBP). NBA will ask iterative questions to eliminate items to gradually obtain the user's preferences, while NBP will adapt to the user's preferences at the moment based on the user's feedback [6][7].

2.2 Knowledge Graph

Knowledge Graph (KG) is a process of analyzing, and choosing decisions in various forms, starting from gathering facts, revealing relationships with others, and building new insights using a recommender system based on KG [16]. It will provide relationships between users and items that are integrated into various data sources to improve the accuracy of the recommender system. KG can be formally defined as follows:

$$\mathcal{KG} = \{(h, r, t) \mid h, t \in \mathcal{E}, r \in \mathcal{R}\} \quad (1)$$

On the Equation. (1) $\mathcal{E}$ as entities and $\mathcal{R}$ as triplet relation (h,r,t), indicates a fact r with h as head entity until t as tail entity [13].

2.3 Graph Database Concept

The Graph Database at this time is one of the implementations of the knowledge graph in the form of a database, in contrast to databases in general such as Relational Database Management System RDBMS, which are still in the form of tables to combine their respective relations using Primary Key and Foreign Key, while the Graph database consists of edges (entity) and vertices (relation) The focus of the Graph database is intended as a tool to facilitate modeling. In addition to describing each entity, there are properties that provide a unique identity, as follows:

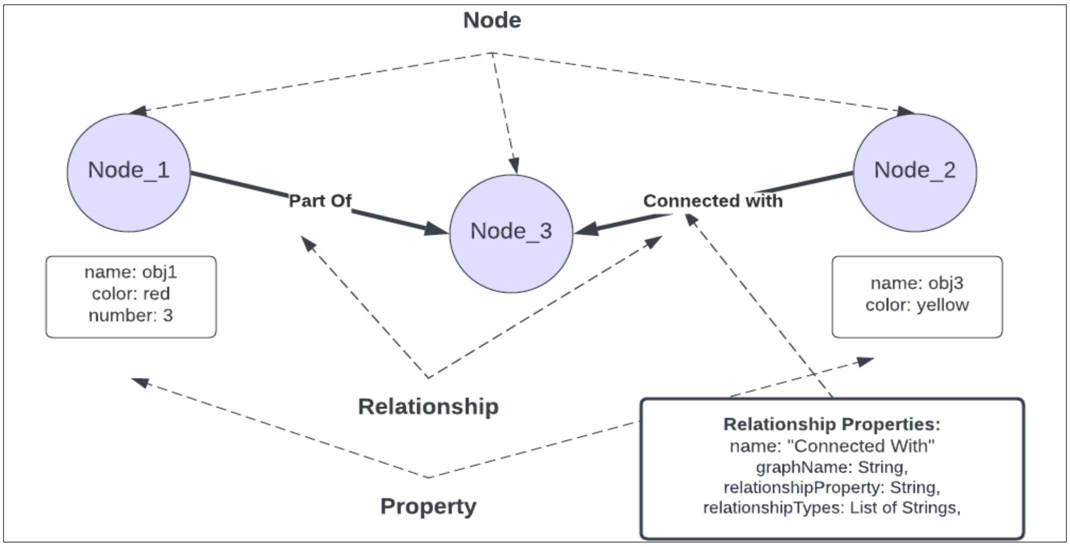

Figure 1. Attribute Graph Concept

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From Figure 1 a Graph is an object that has nodes and relationship. Nodes have properties and organized with relationship, which also have properties as the identity of the object [13].

2.4 Personal Computer Specification

To understand a Personal Computer, it is necessary to recognize what components are needed to function. There are many component parts in a Personal Computer, therefore, the theory in this chapter will cover the problem boundaries. Personal Computers have components that are connected from input to output, the following is a component diagram at Figure 2. that is connected to the motherboard for a Personal Computer.

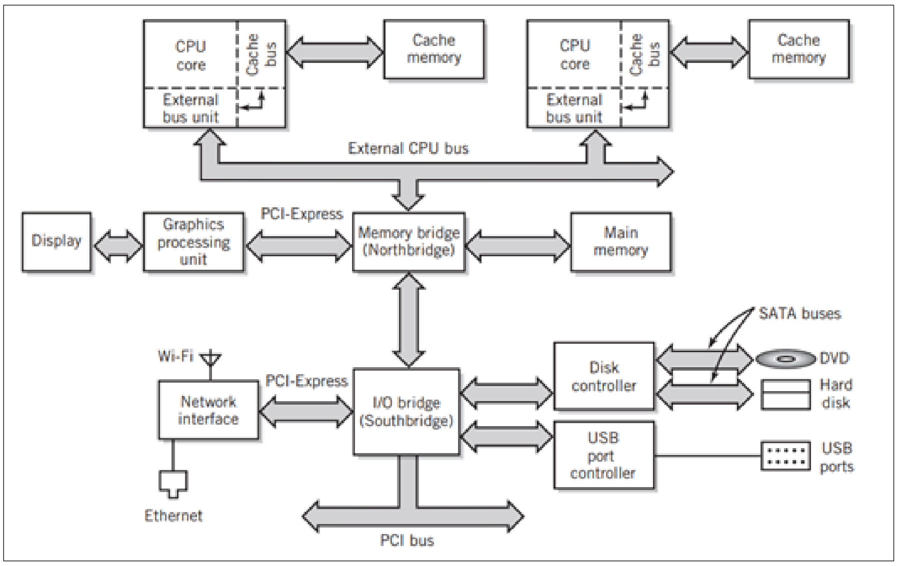

Figure 2. Generalized Bus Interface pada Motherboard.

The diagram in Figure 2 is the bus interface on motherboard in general, the main components that must be considered following the diagram include GPU, CPU, Main memory (RAM), Hard disk, and Motherboard [17].

2.5 Neo4j

Neo4j is an open-source graph database implemented in Java. The founders of Neo4j explain that the graph database has a full transactional database that can accommodate data in the form of a graph rather than a table. The query system in Neo4j uses the Cypher Language, which allows for expressive and easily understandable queries when executing and updating efficiently [11]. Below is an example query from Neo4j.
a. MERGE (p : Person name : 'Daniel Kaluuya')
b. MERGE (m : Movie title : 'Get Out')
c. MERGE (p) − [: ACTEDIN]− > (m)
d. RETURN p, m

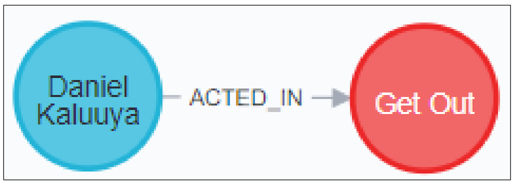

Figure 3. Query Neo4j

From Figure 3 it can be seen that the query results show the relationships between actors and movies from the previous query.

2.4 Implenetation

Implementation is carried out using a web apps platform with backend using node.js and database using Neo4J.

2.4.1 System Schema

The system aims to recommend computer components to be assembled according to user needs. Recommendations will be generated through questions and choices with the CRS framework assisted by NBA [6][8], where the questions are specific about what features are sought and needed. For example, in the case of this recommendation, the system will ask for the intensity of use of RAM, GPU, and CPU, up to the storage size (HDD), and what specific usage will be used on the computer to be built.

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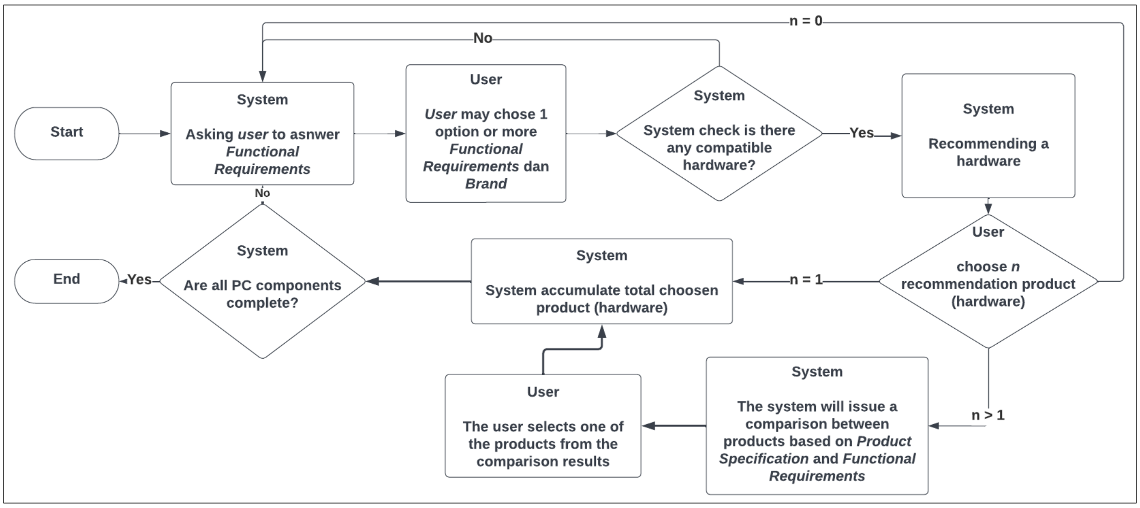

Figure 4. User-system interaction scheme

Figure 4 is a user-system interaction scheme to get a recommendation requested by the user. In the first interaction, the system will issue a preference and requirement question using the CRS framework, then the user will fill in these choices, and after that, the system will check compatibility with other components. If not, the system will provide additional questions until there are enough to recommend, the system will proceed to the stage of making recommendations, and the recommendations that are chosen will be accumulated until all components are met.

2.4.2 Data

The data we use is a PC component dataset that has been crawled in 2017, with the US market including currencies converted from USD to Indonesian Rupiah.

2.4.3 Knowledge Graph Schema

The schema in this Knowledge Graph is divided into two main parts to process the ongoing CRS.

a. FuncReq Class Hierarchy Map: is a mapping for grouping functional requirements for each component item (hardware), more details can be reviewed in Table 1.

Table 1. Rule Class Hierarchy Functional Requirement Example

HARDWARE	FUNCTIONAL REQUIREMENT		PRODUCT SPECIFICATION		
	Level 1	Level 2	Cores Focused	Frequency Focused	Hyperthread
CPU	Gaming	Lightweight Games	Low End	Low End	No
		Casual Games	Medium End	Low End	No
		Competitive Games	Medium End	Medium End	Optional
		...	...	...	...
	Office Work	Multimedia Software	Low End	Low End	Yes
		...	...	...	...
RAM	...	...	...	...	...

b. ProductSpec Class Hierarchy Map: The purpose of this class hierarchy is to describe the functional requirements specifications on a PC by defining and grouping a product with the quality level of the product, for example in Table 2.

Table 2. Rule Class Hierarchy of Product Specifications Example

Component	Class Hierarchy	Technical Specification
CPU	Professional End	CPU Cores > 12 CPU Frequency > 3.2GHz Hyperthreading
	High End	8 < CPU Cores ≤ 12 CPU Frequency > 3.2GHz Hyperthreading
	Medium End	4 ≤ CPU Cores ≤ 8 CPU Frequency < 3.2GHz
	…	…
RAM	High End	Memory Slot: DDR4 Memory Size > 16GB

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	Memory Frequency > 3200MHz
…	…

This mapping then implemented in Neo4j as Figure 5 shown as example, each of nodes are connected based on rules mapping from Table 1 and Table 2.

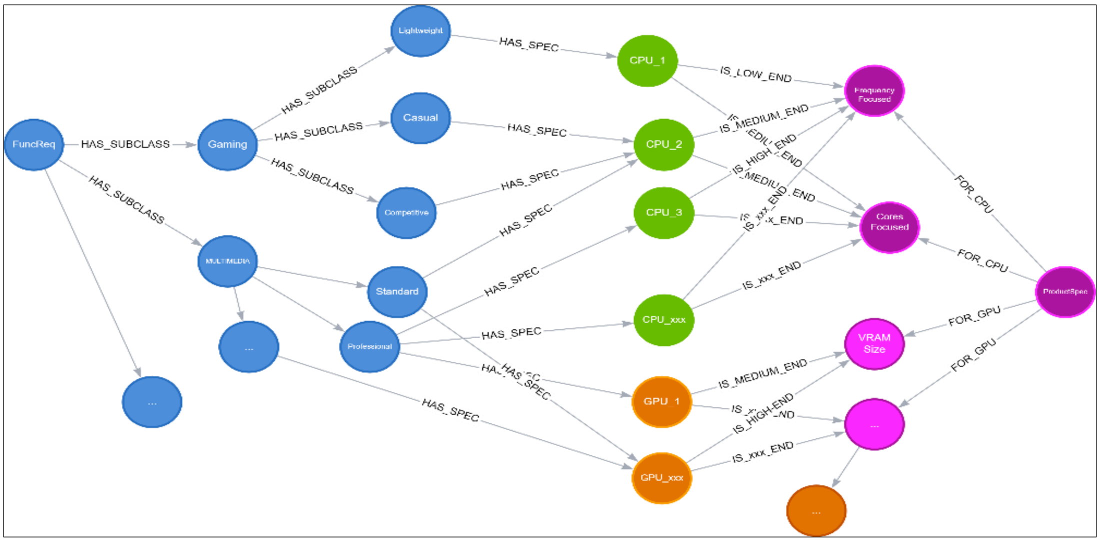


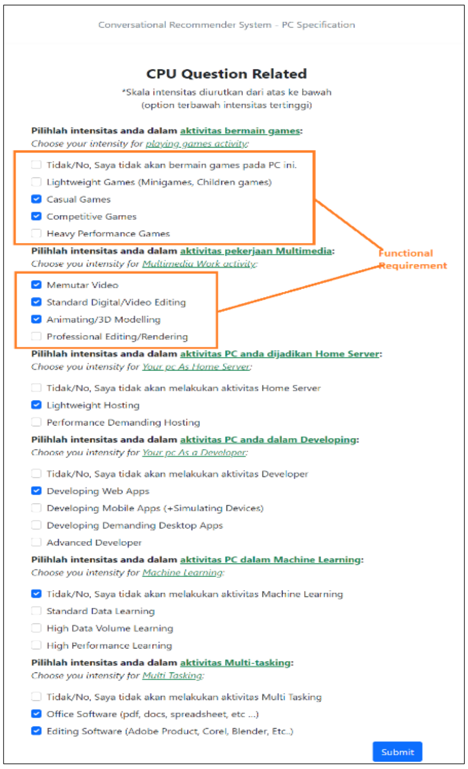
Figure 5 Knowledge Graph Mapping based on rules.

3. RESULT AND DISCUSSION

The evaluation process considers both system performance and user satisfaction. The participants in this evaluation are 60 individuals who are capable of using web-based applications.

3.1 System Result

The initial interaction is displayed as a collection of questions from **Error! Reference source not found.** that can be filled out one or more. After that, it can display a product that has been recommended based on Functional Requirements and compatibility in **Error! Reference source not found.**. then all the options if completed will be totaled like Figure 8.



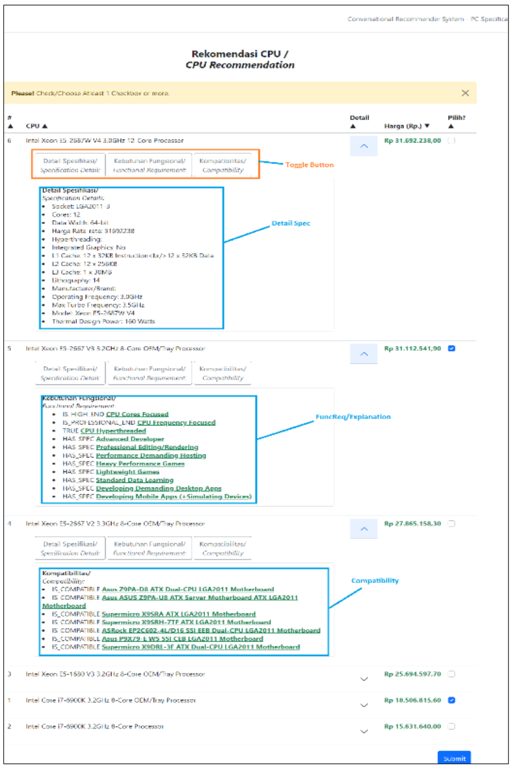


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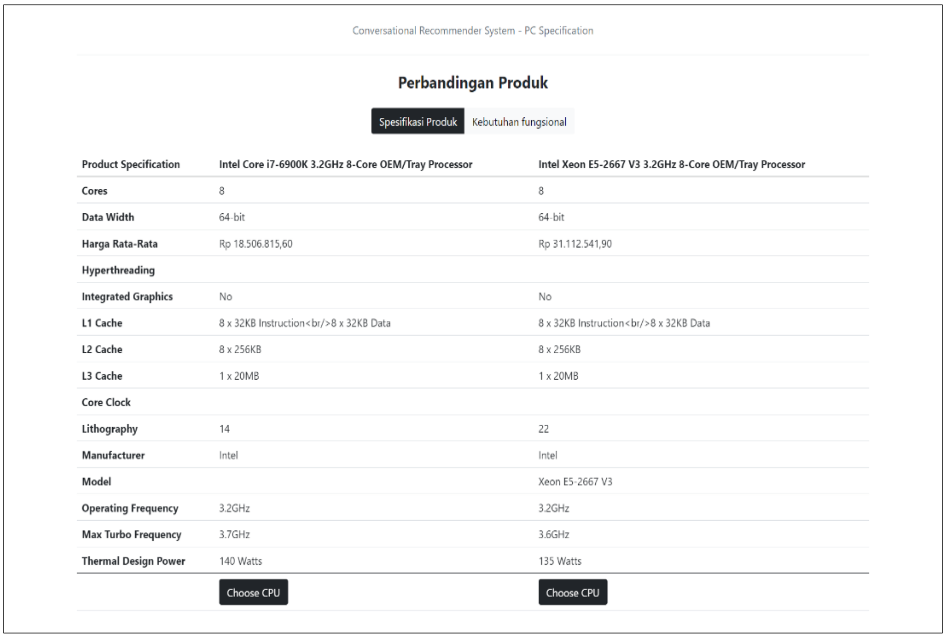
Figure 6. Initial Interaction

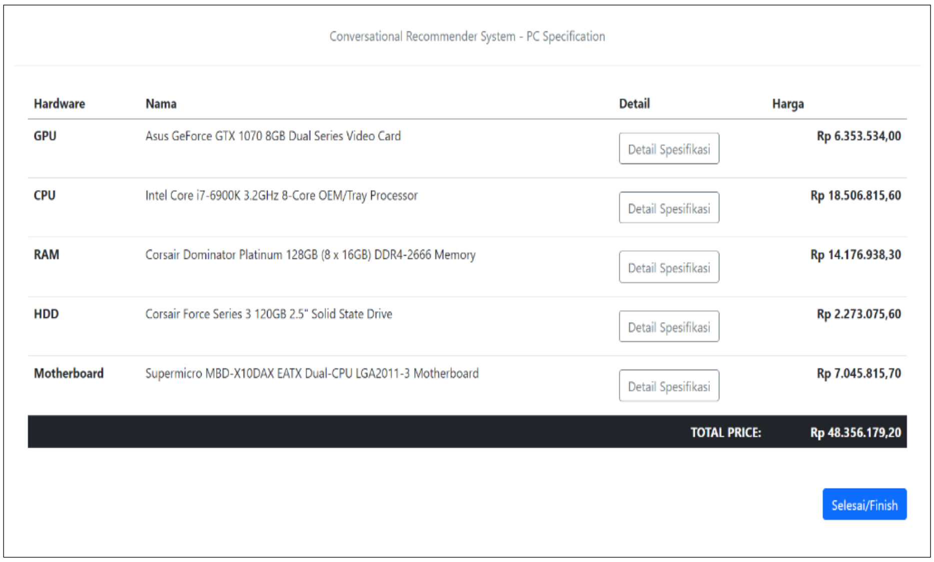
Figure 7. Product Result with Explanation

In **Error! Reference source not found.**, there are many questions that can be expanded upon. This will result in a collection of Functional Requirements that provide a recommendation. The process continues to another page at **Error! Reference source not found.** where the user can choose the item they want. The user can also choose multiple items, which will lead to a comparison of each item on Figure 8.



Product Specification	Intel Core i7-6900K 3.2GHz 8-Core OEM/Tray Processor	Intel Xeon E5-2667 V3 3.2GHz 8-Core OEM/Tray Processor
Cores	8	8
Data Width	64-bit	64-bit
Harga Rata-Rata	Rp 18.506.815,60	Rp 31.112.541,90
Hyperthreading		
Integrated Graphics	No	No
L1 Cache	8 x 32KB Instruction 8 x 32KB Data	8 x 32KB Instruction 8 x 32KB Data
L2 Cache	8 x 256KB	8 x 256KB
L3 Cache	1 x 20MB	1 x 20MB
Core Clock		
Lithography	14	22
Manufacturer	Intel	Intel
Model		Xeon E5-2667 V3
Operating Frequency	3.2GHz	3.2GHz
Max Turbo Frequency	3.7GHz	3.6GHz
Thermal Design Power	140 Watts	135 Watts

Figure 8. Comparing Product



Hardware	Nama	Detail	Harga
GPU	Asus GeForce GTX 1070 8GB Dual Series Video Card	Detail Spesifikasi	Rp 6.353.534,00
CPU	Intel Core i7-6900K 3.2GHz 8-Core OEM/Tray Processor	Detail Spesifikasi	Rp 18.506.815,60
RAM	Corsair Dominator Platinum 128GB (8 x 16GB) DDR4-2666 Memory	Detail Spesifikasi	Rp 14.176.938,30
HDD	Corsair Force Series 3 120GB 2.5" Solid State Drive	Detail Spesifikasi	Rp 2.273.075,60
Motherboard	Supermicro MBD-X10DAX EATX Dual-CPU LGA2011-3 Motherboard	Detail Spesifikasi	Rp 7.045.815,70
		TOTAL PRICE:	Rp 48.356.179,20

Figure 9. Final Interaction

The last interaction shows all the items that the user has chosen and displays the total price for all of the items, as seen in Figure 9.

3.1 Evaluation Based on System Performance

The user will go through a series of systems to get recommendations, then the interactions in them will be stored by the system as a measure of the success of the recommended items. Recommendations will be evaluated by users using a questionnaire and calculated with Equation (2).

$$\text{Recommendation Accuracy} = \frac{\text{Total Successful Recommendation}}{\text{Total Recommendation}} \quad (2)$$

Based on the results of Figure 10. users with Male gender have a dominant accuracy score of 91.22% compared to the score of Female users 78.86%. This system has a success rate of 82.24% for familiar users, and 73.38% for unfamiliar

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users. Overall, the system has a success rate of 82.68%, which shows that the system can help users find the desired PC.

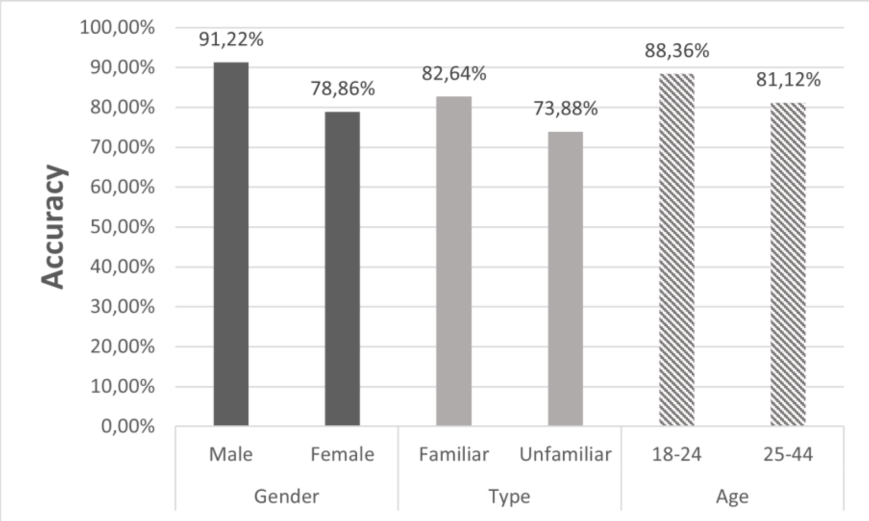

Figure 10. System Performance Result

3.1 Evaluation Based on User Satisfaction

After using the system, the user will be prompted to fill out a questionnaire consisting of 10 questions in Table 3. To help analyze the questionnaire results, it will be assisted with 6 statement classifications as follows: 1) Easy to Use / Usability (ETU), 2) Informative (INF), 3) Perceived Efficiency (PE), 4) Ease of Understanding (EOU), 5) Perceived Quality of Recommendation (PRQ), 6) Trust (TR)[12]. From these statements, there are 2 negative type questions, Q5 and Q10, to compare disapproval.

Table 3. Evaluation Questionnaire

ID	Factor	Question
Q1	INF	I get PC specification product information easily
Q2	PE	I get the recommendations that I want quickly.
Q3	TR	One day, I will buy and build a PC according to the recommendations based on the systems here.
Q4	TR	I would use this system again if I wanted to build a PC.
Q5	ETU	I find it difficult to find a product that suits my requirements.
Q6	ETU	I have no problem using this system.
Q7	EOU	Options can be easily understood.
Q8	EOU	I understand very well all the preference choices given to this recommender system.
Q9	PRQ	I like the way recommendations given.
Q10	PRQ	I do not like the way the system interacts.

The results obtained from a questionnaire can be seen in Figure 11, indicating that the negative statement Q5 and Q10 received scores of -0.68 and -0.51. This indicates that the average user does not agree with the negative statement, while the others have an average score of 0.77 indicating agreement.

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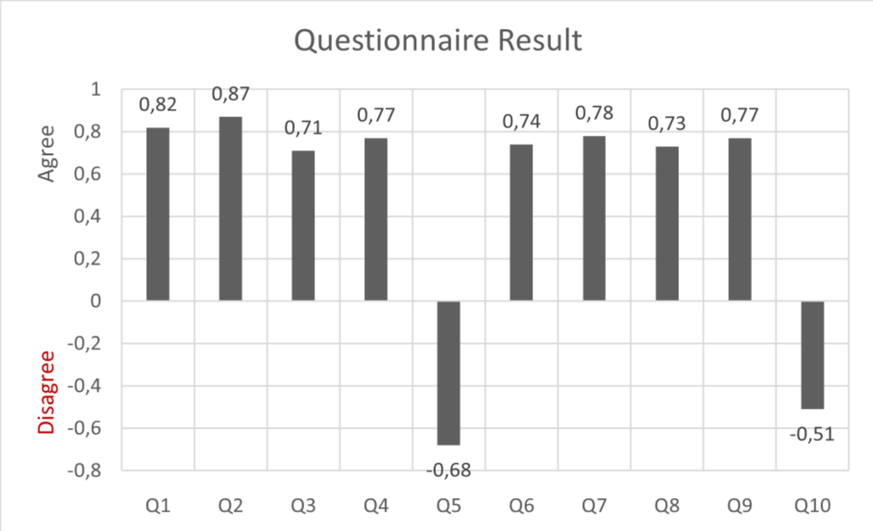

Figure 11. User Satisfaction Result

4. CONCLUSION

With the experiment, we see that the proposed CRS (Content-Based Recommender System) achieved a system performance score of 82.68%. This indicates that the proposed CRS can recommend a product with sufficient accuracy. Additionally, it is supported by the response of users to the 6 types of questions for user satisfaction, with the highest score on the "perceived efficiency" (PE) factor at 0.87% and the "informative" (INF) factor in second place. This indicates that users are satisfied with the recommendations and information provided about the products obtained from the CRS system. For further research, it is expected that the current CRS framework can be further developed to cater to various needs in order to make product recommendations more accurate.

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