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Tourism Destination Recommendation Using Ontology-based Conversational Recommender System

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Abstract: Traveling is one of the human psychological needs. Many choices and lack of information about desired tourist attractions are some of the obstacles in fulfilling the need. One of the technologies to overcome these obstacles is the recommender system which can provide recommendations for the users to choose some interesting tourist attractions from several tourist destinations. A conversational recommender system (CRS) offers a way of recommending tourist destinations in a conversational mechanism. We use ontology as a representation of knowledge to generate conversational interactions, recommendations, and explanation facilities. With this ontology-based CRS, we can overcome cold start problems, and also the system can guide the users to get the desired tourist attractions. In this study, we use a combination of navigation by asking (NBA) and navigation by proposing (NBP) strategy to generate interactions on the CRS. Based on the user study, in general, users find it helpful in finding tourist destinations that suit their needs. It is because the factor of *trust* and *perceived ease of use* comes from the interaction and explanation facilities contained in the system. Besides, *perceived usefulness* directly affects users' interest in utilizing this CRS interaction model in the future.

Keywords: Recommender System, Conversational Recommender System, Ontology, Navigation by Asking, Technology Acceptance

1. Introduction

Traveling is one of the human psychological needs. Many choices and lack of information regarding desired tourist attractions are some of the difficulties to meet this need. However, the rapid development of science and technology can help humans to meet their travel needs. One of the technologies to overcome these obstacles is the recommender system which can provide recommendations of tourist attractions from several tourist attractions in an area. As a result, tourists can be faster and not confused in choosing tourist spots.

Recommender systems emerge as an important tool in the development and management strategies of traveling, e-commerce, and restaurant business [1-3]. Recommender systems emerge as an important tool in the development and management strategies of traveling, e-commerce, and restaurant business [1-3]. The recommender system generates a list of recommendations in one of two ways through collaborative content filtering. There are three basic approaches in recommender systems, i.e. collaborative filtering, content-based filtering, and knowledge-based filtering. The main idea of collaborative filtering is to utilize opinion information or behavior from previous users to predict the behavior of new users [4]. Meanwhile, content-based filtering is an approach based on direct matching between features of recommended activities and the user's interest in each of the features [5]. Collaborative filtering has three problems, i.e. cold start, scalability, and sparsity [6]. Content-based filtering has a drawback where the results of the recommendations given are less diverse because they only refer to the content of the items [7]. Moreover, knowledge-based recommender systems are applied to scenarios where collaborative filtering and content-based filtering approaches cannot be applied. Besides, a knowledge-based recommender system is one of the approaches which can clarify the cold-start problems [8-9].

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A conversational recommender system (CRS) is a type of knowledge-based recommender system. In CRS, there are two main strategies to meet needs, i.e. navigation by proposing (NBP) and navigation by asking (NBA) [10]. In NBP, the system shows a certain product and knows the needs of the user from the feedback given from the recommended product. In NBA, the system inquiries directly about the user's needs. In our previous study, we have developed a framework for developing CRS based on functional product requirements (high-level requirements) by integrating NBA and NBP [11]. Conversation based on functional product requirements is an appropriate approach for users who do not master the detailed technical features of the products [12]. Meanwhile, the combination produces conversation which can mimic a conversation between a prospective buyer and a sales support professional [13].

A potential tourist will be more interested in visiting tourist attractions in an area that he has never visited before. Currently, many tourism recommender systems have been developed. Esmaeili et. al [25] recommend tourist attractions based on users' social relationships in social commerce. Alrasheed, et. al [24] used two levels of the travel industry recommender framework structure to help potential voyagers discover the objective that best matches their inclinations and necessities. The framework consolidates two degrees of suggestions as every client demand goes through two degrees of proposals. The main level includes giving the client a bunch of objections that coordinates her inclinations (because of the inclinations of comparative clients). The subsequent level positions the arrangement of objections dependent on the client inclinations and imperatives.

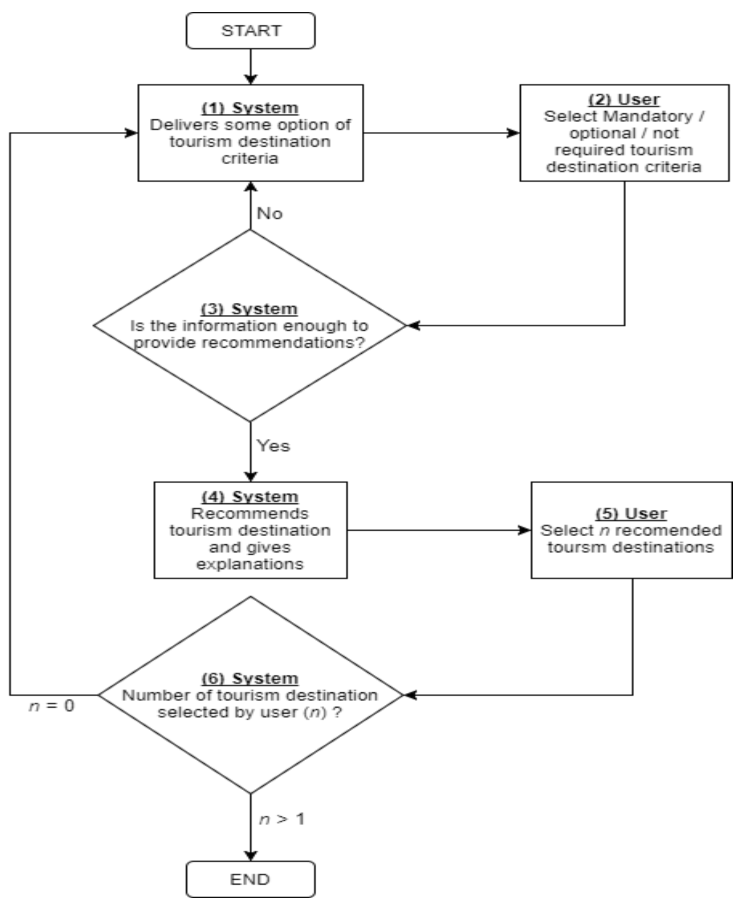

Figure 1. User and system interaction flowchart

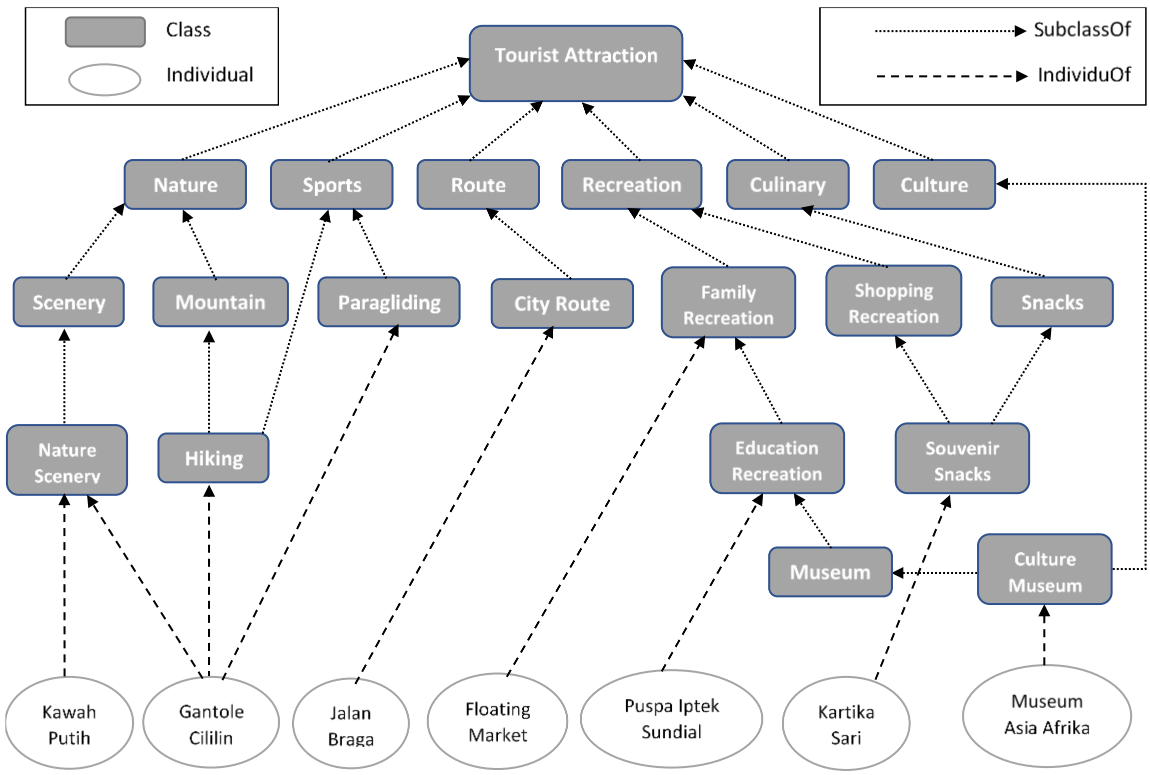

Figure 2. Tourist attraction ontology

Prospective tourists will travel to an area that has never been visited, so they do not know what tourist destinations to visit according to their needs. Therefore, we built a CRS, where users only need to express their needs in high-level requirements, and the system will guide with question and answer mechanism to recommend tourist attractions that suit user needs. With the question and answer mechanism, the system can be courageous as a tourism expert in an area. Our previous CRS framework [11] is a multidomain framework that can be applied in various domains by utilizing ontology as knowledge representation. Ontology plays an important role in representing the domain of the products (smartphone, laptop, car, server, etc.). In this framework, the user model is built during the conversation, and the ontology domain is used to recommend products. The same thing was completed in several studies that made use of ontology [14-16]. In our previous research [11], the proposed framework was successfully adopted for CRS development in the laptop domain [17]. In this study, we apply the framework in [11] to develop CRS in the tourism sector, with readjustment in interaction mechanism and ontology domain.

In the real world, if someone wants to travel to an area which has never been to, then he does not know the characteristics of tourist attractions in that area. In this case, the CRS with interactions based on high-level requirements is a better approach. The developed CRS explores user needs from the point of view of high-level requirements through the conversational mechanism. The navigation strategy takes advantage of the NBA and NBP according to the framework that we have developed, with some readjustments. Besides, it is necessary to adjust the ontology in the tourism sector. In this study, the ontology takes the tourism domain in the Greater Bandung area.

This paper is organized as follows. In Section 2, we introduce the user and system interaction mechanism—strategy for guiding users when the user interacting with the recommender system is discussed in Section 3. Moreover, in Section 4, we present an overview of user perception evaluation by using the technology acceptance model (TAM). In Section 5, we discuss some results of the conversational recommender system for recommending tourist destinations in a conversational mechanism. Finally, the conclusion of the proposed recommendation system in this study is given in Section 6.

2. INTERACTION MODEL MECHANISM

The interaction mechanism in the CRS includes dialogue, recommendations, and explanations (why a tourism site is recommended). The generation of this interaction mechanism utilizes semantic reasoning in ontology, which we have developed in previous studies [11]. In our current research, we focused on developing interaction mechanisms tailored to the tourism domain using the CRS framework in [11]. Figure 1 describes the user and system interaction mechanisms. In Step 1, the system provides questions (NBA strategy) for several categories of tourist destinations such as nature, culinary, recreation, sports, culture, and routes which have general categories (upper level in ontology - see Figure 2). Further, the user provides an answer associated with the desired travel category. For each question option (in the tourism category) provided by the system, the user answers whether the tourism category must be fulfilled ($\overline{F_m}$), better fulfilled ($\overline{F_o}$), or not desired ($\overline{F_x}$) as described in Step 2. Next, in step 3, the system determines whether the user's answer is specific enough to recommend tourist attractions. If there are still too many tourist destinations that meet the user's answers, the system returns to Step 1 by providing questions for more specific needs (categories). The more specific category is the node that has a subclass of the previously selected category node ($\overline{F_m} \cup \overline{F_o}$). If the system considers that this information is specific enough for a recommendation, the system provides a recommendation as shown in Step 4. After the system has provided recommendations, the user selects a tourist spot (Step 5). If the user selects several recommended destinations ($n > 1$) then the system has successfully provided recommendations. However, if the user does not choose the recommended tourist spot at all ($n = 0$), the system returns to Step 1 (NBA strategy). Furthermore, the system guides the user to get a more suitable tourist destination.

The ontology consists of a class hierarchy, i.e. the tourist attractions class. This class has subclasses and individuals. The class represents the category of tourist attractions, while individuals represent tourist destinations. In ontology, tourism categories are represented in a hierarchy of classes from general to specific. In CRS, the high-level requirements expressed by the user can be in the form of tourism categories in various levels of the class hierarchy. Each entity in the hierarchy (classes and individuals) is connected by relations *subclassOf* and *individualOf*. Figure 2 depicts the structure of the tourist attraction ontology. In preparing the ontology, we consulted with the West Bandung Regency Tourism Office, West Java. In this figure, we only show a part of the actual ontology due to the limited space in the paper. In the tourist attraction ontology, several classes can have the same subclasses or individuals. For example, hiking is a subclass of sports and mountains. Meanwhile, Gantole Cililin is an individual of nature scenery, hiking, and paragliding.

In ontology, the data properties used for each individual are data regarding the specifications of a tourist destination. Some of the data properties used are as follows.

1. Address
2. Description of the place
3. Operating time (opening hours - closing hours)
4. Average time of visit
5. Tariffs
6. Telephone number
7. Rating

3. STRATEGY FOR GUIDING USER

A. *User Model*

For each interaction, question, recommendation, and explanation is generated based on the user model. In providing several questions, the system selects some nodes in the ontology. According to the user's answer, the system stores the nodes in the user model as the user's preference. The system elicits user preferences by asking questions, delivering some recommendations for tourist attractions, and explaining why these tourist attractions are recommended. The interaction model in the system was built by using NBA and NBP approaches to the CRS. The questions posed in the system are in the form of categories of tourist attractions stored in the ontology.

For every interaction, some nodes in the ontology are randomly selected by the system as questions. According to the user's answers to the 24 questions, the system stores the selected node as the user's choice. User choices are defined into 5 variables [9], i.e. $R = (\overline{F_m}, \overline{F_o}, \overline{F_x}$, *Dtype*, *Dproperty*). Here, $\overline{F_m}$ is a collection of tourist destination categories that must be met (functional mandatory), $\overline{F_o}$ is collection of destination categories tourism which is better fulfilled (functional optional), $\overline{F_x}$ is a collection of tourist destination categories that are not desired, *Dtype* is a collection of selected tourist destinations, and *Dproperty* is a collection of properties from selected tourist destinations.

The choice of user R is dynamically updated throughout the interaction process and the changes that occur are preserved in the user model. The user model serves as a history of user choices. Hence the update process is done gradually along the interaction process. Therefore, the user model and ontology become knowledge for the system in generating interaction and providing recommendations for tourist destinations.

B. *The Case in the Interaction Model*

There are several interaction processes in the tourist destination recommender system. In each process, the system provides several questions in the form of tourist destination categories which can be selected by the user. In the testing process, users are asked to assess the system with an adjusted number of questions (1 to 6 questions). The user is requested to fill out a questionnaire asking how many questions per interaction do you think express help needs. By the results of the questionnaire attended by 53 respondents, the maximum number of questions per interaction (*maxq*) which is useful in meeting user needs is *maxq* = 6 (49.1%), then *maxq* = 4 (20.8%), *maxq* = 5 (17%), *maxq* = 3 (9.4%), and *maxq* = 2 (3.8%).

In the recommender system, four cases can arise in the interaction process as follows [10].

1) Initial Interaction (Empty user profile)

On initials interaction, the user profile is still empty. The system provides several questions in the form of tourist destination categories which are still general. The system will give questions to 4 class users at the top level in the hierarchy (in the ontology). This 4 class intake refers to our previous study [11]. The NBA approach is in the form of the category of tourist destinations that must be fulfilled (F_m), category of tourist destinations that are better fulfilled (F_o), and category of tourist destinations that are not desired (F_x). If the user chooses F_m, then a tourist destination must meet each of the selected categories. Furthermore, F_o is met if the category for F_o are also found in F_m, which is used for the utility value. Meanwhile, the chosen F_x means that the category is not required. An example of the initial interaction can be found in Figure 3.

2) No destination selected

If the user does not choose any tourist destinations, the system looks for other nodes that the user could potentially like [11]. This allows the system to generate nodes that have not appeared or been asked. These nodes are in the form of classes (representing the user's needs) that the system hasn't asked for yet but the user might like. The function to find this node refers to a previous study [11].

3) Insufficient user preference to produce recommendation (Specific questions)

The requirements entered by the user are still too general so that more specific questions are brought up by generating candidate nodes from the selected mandatory and optional categories. In this case, the system will look for the subclasses of nodes that the current user likes. Semantic reasoning is in [11]. This is completed so that needs can be more specific. An example of the specific questions can be seen in Figure 4.

Figure 3. Example of initial interaction

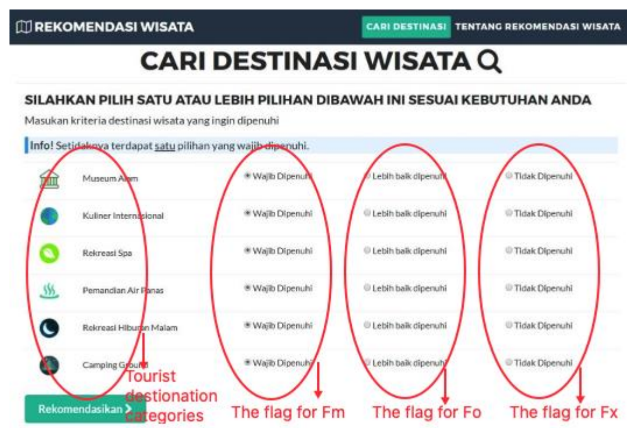

Figure 4. Example of specific questions

C. *Recommendation Task*

The system recommends products that meet F_m, F_o, F_x, *Dtype*, *Dproperty* in the user model. The main problem in recommending tourist destinations is determining whether individual tourist destinations meet the high-level requirements (category). Therefore an algorithm is needed to check the suitability of individual tourist attractions with user needs (classes in ontology). We make use of the *isSatisfyInd* and Algorithm recommend in [11]. We define the function *satisfiedDestinations* to return the set of tourist destinations that meet mandatory user requirements (F_m). Let D be a set of tourist destinations, where $D \subseteq I_{destination}$ (the set of individuals of destinations) and F_m be a set of mandatory functional requirements. The elements of F_m are individuals of functional requirements (I_{func}). Therefore, tourist destinations in D meet F_m are obtained by,

$$satisfiedDestinations(Fm, D) = \{d \in D \mid \wedge_{fm_i \in Fm}\, isSatisfyInd(d, fm_i)\} \quad (1)$$

D. Explanation Facilities

The system recommends tourist destinations based on user choices contained in the user model. This model serves as a history of user choices during the interaction process. The mandatory functional requirement ($\overline{F_m}$) is used as a necessary value in recommending tourist destinations, while the optional functional requirement ($\overline{F_o}$) is used to determine the level of suitability of tourist destinations with user choices symbolized by the utility value. The more $\overline{F_o}$ is fulfilled in the tourist destination, the higher the utility value that exists in that tourist destination. Tourist destinations are obtained by tracing the nodes and their relationships in the ontology.

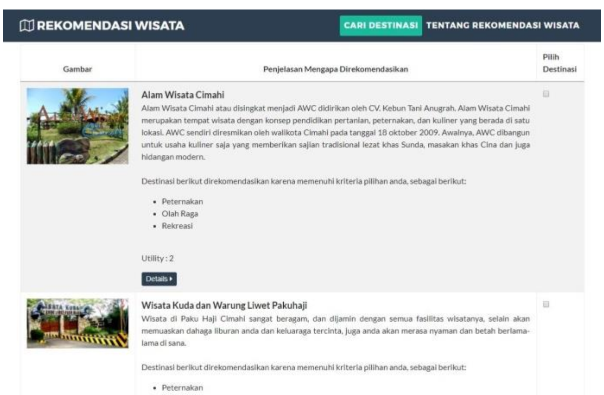

Figure 5. The example of recommendation and explanation facility

The explanation facilities that exist in the system make it easier for users to make decisions. The explanation is built by tracking the user's choices contained in the user model. Recommended tourist destinations are represented in a list sorted based on the utility value contained in each tourist destination. If the utility value is the same, the system compares the rating of the tourist destination. Figure 5 is an example of the explanation facilities which exist in the system. This figure also represents the reason why the tourist destination is recommended.

4. USER PERCEPTION EVALUATION

In this study, we adopt the technology acceptance model (TAM) to analyze and understand the factors that influence the acceptance of a technology [28]. In this case, TAM is used to analyze the influence of the interaction-based tourism recommendation system (CRS) on user perceptions through a user study. We involved 53 students as respondents with a return rate of 80%. In TAM, several factors of user study are used as follows.

1. *Perceived Usefulness* (PU): a factor that indicates the extent to which users feel that the interaction model is quite useful in solving problems [18].

2. *Perceived Ease of Use* (EOU): a factor that indicates the extent to which users feel that the interaction model does not require a lot of effort [18].

3. *Perceived Enjoyment* (PE): a factor that indicates the extent to which users feel attracted, comfortable, and guided by the interaction model offered [19].

4. *Trust* (TR): a factor that indicates the extent to which users trust the recommendations given by the system, where the explanation facility plays a role [20].

Moreover, each factor has several items which turn into a list of questionnaires as summarized in Table 1. Answers to 23 questions are in the form of a 5-point scale from Strongly Disagree (1), Disagree (2), Neutral (3), Agree (4), and Strongly Agree (5).

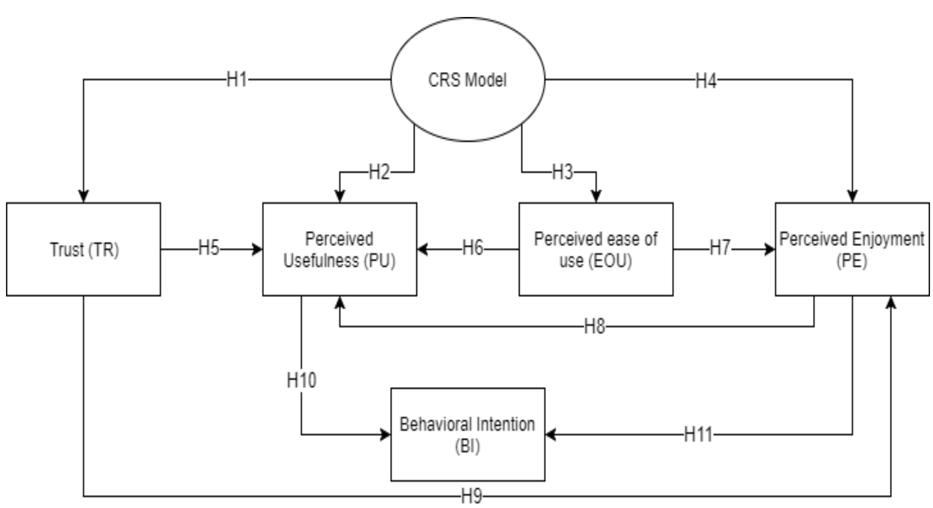

Figure 6. Hypothesis model

TABLE I. QUESTIONNAIRE

Code	Perceived Usefulness (PU)
PU1	The interaction model in the system provides better quality searches for tourist destinations.
PU2	The interaction model saves me time in searching for tourist destinations.
PU3	The interaction model makes it easy for me to find the most suitable tourist destination.
PU4	The interaction model in the system can provide better search results for tourist destinations.
PU5	The interaction model is quite helpful in the process of finding tourist destinations.
PU6	Overall, the interaction model is very useful in finding tourist destinations.
Perceived Ease of Use (EOU)	
EOU1	The system with the interaction model is easy to use.
EOU2	The interaction model on the system is run without the need for effort. It doesn't take much effort to understand.
EOU3	I think the interaction model will also be easy to use for other people.
EOU4	Every step of the interaction is self-explanatory and easy to understand.
EOU5	It is easy for me to master the system with this kind of interaction model.
Trust (TR)	
TR1	I believe in the tourist destination recommendations provided by the system.
TR2	I believe the explanation provided by the system about the reasons why tourist destinations are recommended.
TR3	I believe that the order of the recommended list of tourist destinations suits my needs.
TR4	The explanation facilities provided by the system made me believe that the recommended tourist destinations were under my needs.
Perceived of Enjoyment (PE)	
PE1	The interaction model in this recommendation system is quite interesting.
PE2	With the existing model interaction, it makes me feel comfortable using this system.
PE3	The interaction process in the system is quite satisfying
PE4	The interactions in this system make me feel guided in expressing my needs.

A. *Hypotheses Model*

To analyze the influence of the conversational recommender system (CRS) based on the interaction model in increasing the user's positive perception and also the factors that influence it, we define the 11 hypotheses as follows [10], see Figure 6 for linkage of these hypothesis model.

H_1: The CRS model increases trust.

H_2: The CRS model improves perceived usefulness.

H_3: The CRS model increases ease of use.

H_4: The CRS model improves perceived enjoyment.

H_5: Trust positively affects perceived usefulness.

H_6: Ease of use positively affects perceived usefulness.

H_7: Ease of use positively affects perceived enjoyment.

H_8: Perceived enjoyment positively affects perceived usefulness.

H_9: Trust positively affects perceived enjoyment.

H_{10}: Perceived usefulness positively affects behavioral intention.

H_{11}: Perceived enjoyment positively affects behavioral intention.

Zanker [20] has proven that the explanation facilities in the recommendation system can improve the perceived ease of use, trust, and perceived usefulness. Here, we evaluate the effect of the CRS model to increase the perceived ease of use, trust, perceived usefulness, and perceived enjoyment.

To test the hypotheses H_1 - H_4, testing was conducted by using a questionnaire that involved 53 users. Users of the CRS model tested were between the ages of 16-23 and familiar with web-based applications. Each user tries to use two types of interaction models. The first model is the CRS model that has been developed, and the second model is a general model whose interaction model is commonly used in e-commerce sites. Both models use the same interface and data. The difference between the two models only lies in the strategy of each interaction case.

Users are asked to fill out the questionnaire provided after using the two existing models. For hypotheses H_5 - H_{11}, linear regression was performed, which focused on the user's answer to the CRS model. The regression equation adopted is as follows [10]:

$$PU = a + b_5(TR) + b_6(EOU) + b_8(PE) + \varepsilon \quad (2)$$

$$PE = a + b_9(TR) + b_7(EOU) + \varepsilon \quad (3)$$

$$BI = a + b_{10}(PU) + b_{11}(TR) + \varepsilon \quad (4)$$

where a = constant, b_i = coefficient with index i according to the hypothesis contained in the model hypothesis and ε = random error.

B. *Validity dan Reliability Testing*

In the initial step, validity testing was performed on 23 questions using the extraction of the principal components (varimax rotation method with Kaiser Normalization) and we have obtained 17 questions from 23 questions. According to Zanker [20], if the loading factor value > 0.40, then the factor can be understood and accepted to be formed into a fundamental scale in factor analysis.

TABLE II. THE QUESTIONS WHICH ARE SELECTED BASED ON FACTOR ANALYSIS

	Component				
	Factor 1 (EOU)	Factor 2 (BI)	Factor 3 (PU)	Factor 4 (TR)	Factor 5 (PE)
PU1	0.160	0.160	0.756	0.293	0.074
PU3	0.578	0.100	0.402	0.131	-0.339
PU4	0.403	-0.04	0.720	0.062	0.288
PU5	0.289	0.082	0.784	0.304	0.138
Cronbach's Alpha of PU = 0.804					
EOU1	0.806	0.015	0.118	0.032	0.130
EOU2	0.574	0.313	0.436	0.029	0.184
EOU3	0.738	0.108	0.297	0.143	0.014
EOU4	0.723	0.224	0.240	0.163	0.194
EOU5	0.609	0.233	-0.19	0.303	0.481
Cronbach's Alpha of EOU = 0.854					
TR1	-0.09	0.475	0.282	0.672	0.160
TR2	-0.07	0.356	0.271	0.639	0.340
TR3	0.266	0.143	0.109	0.768	-0.007
TR4	0.351	0.134	0.155	0.784	0.123
Cronbach's Alpha of TR = 0.851					
PE1	0.020	0.094	0.097	0.080	0.836
BI1	0.062	0.809	0.107	0.291	0.015
BI2	0.188	0.865	-0.03	0.231	0.023
BI3	0.332	0.605	0.017	0.047	0.478
Cronbach's Alpha of BI = 0.825					

To select the questions to be used in the analysis, we use factor analysis, as shown in Table 2. Here, all loading factors for all questions are greater than 0.40. Questions that contain inconsistent user answers will not be involved in further analysis. Moreover, the results of the reliability test are represented by the Cronbach Alpha value. O'Rourke [3] discussed that a Cronbach Alpha score of 0.50 or more is sufficient for the study, whereas 0.70 is the recommended value, and 0.80 is the desired value [3,28]. All Cronbach Alpha values obtained are greater than 0.80, as summarized in Table 2.

5. RESULTS AND DISCUSSION

A. The Influence of the Interaction Model on User Perceptions

Because we used a sample of users, we made use of the t-test to test whether the mean grade of user's perception towards both CRS and General models was significantly different. To evaluate the significant differences between the mean CRS model and the general model, the *t*-test method was performed. It can be seen from Table 3 that the overall average value of the CRS model is greater than the general model, except in the average EOU, the general model has a greater value than the CRS model. It is shown that H_1, H_2, and H_4 are accepted.

TABLE III. T-TEST TO EVALUATE MEAN OF GRADE OF USER'S PERCEPTION TOWARD BOTH MODELS

Factor	**Model**	**Mean**	**T**	**df**	**p-value (2-tailed)**
PU	CRS model	4.1557	2.891	52	0.006
	General model	3.8349			
EOU	CRS model	3.9321	-2.138	52	0.037
	General model	4.1208			
TR	CRS model	4.1274	3.292	52	0.002
	General model	3.8396			
PE	CRS model	4.1321	2.241	52	0.029
	General model	3.8679			

The t-test has been proved that the mean of user's

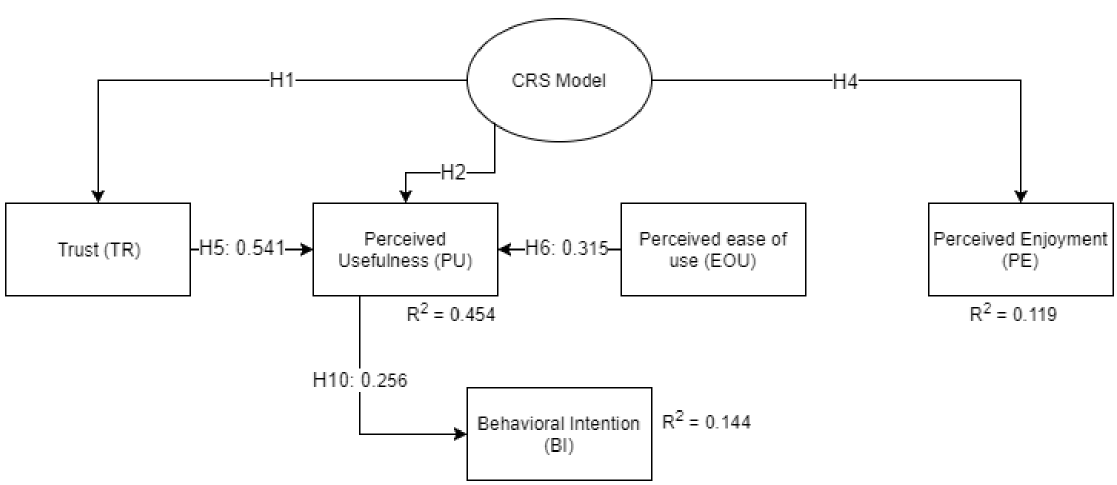

Figure 7. Accepted hypotheses model

perception obtained was significantly different for the three factors (PU, TR, PE), with hypotheses H1, H2, and H4 ($p \leqslant 0.05$). It means that H1, H2, and H4 are accepted. For hypothesis H3 (factor EOU), the mean of EOU of the CRS model is significantly smaller than the general model ($p \leqslant 0.05$). This is because the users think that the general model is easier and more practical in the interaction process. It can be concluded that the CRS model can improve the user's perception of perceived usefulness (PU) ($p = 0.006$), trust (TR) ($p = 0.002$) and perceived enjoyment (PE) ($p = 0.029$).

B. Factors Affecting Users to Adopt Interaction Models

Linear regression is used to evaluate the influence between factors and analyze the influence of factors in adopting the CRS model. The analysis is represented by the hypothesis H_5 - H_{11}. Firstly, the path hypothesis is analyzed based on user perceptions. To evaluate the fit value of the hypothesized model against existing data, the fit model generated by LISREL path analysis is used. Liao et al. [19] studied that the goodness of fit index (*GFI*) value > 0.80. Meanwhile, Al-Maghrabi et al. [21] stated that the p-value < 0.05 represents a good fit model.

After conducting Structural Equation Modeling (SEM) using LISREL path analysis where the path hypothesis is made to represent the linear regression (1) - (3), we have p-value = 0.00257, and $GFI = 0.90$. These results ensure that the suitability of the data and the hypothesis model is quite good.

The accepted path hypothesis can be seen in Figure 7, where each side represents the coefficient (b) of each independent variable. With a significance value of 0.05, we have trust ($p = 0.0001$) and perceived ease of use ($p = 0.023$) which have a significant effect on perceived usefulness (PU) (*H5* and *H6*). It means that trust and perceived ease of use on the CRS model make users feel helped in finding tourist destinations. Besides, the perceived usefulness factor ($p = 0.038$) significantly affects behavioral intention, which means that perceived usefulness makes CRS model users feel like using this interaction model in the future, especially in searching for tourist destinations.

The coefficient of determination (R2) value indicates how much contribution or influence the independent variable on the dependent variable in the model. From Figure 7, we have PU = 0.454 or 45.4%, which means that trust and ease of use affect perceived usefulness by 45.4%, while the rest is influenced by other variables outside of this regression model. Likewise, perceived enjoyment and personal intentions are 11.9% and 14.4%, respectively.

6. CONCLUSION

According to H_1 - H_4 testing ($p \leqslant 0.037$), the CRS interaction model can increase trust, perceived usefulness, and perceived enjoyment (H_1, H_2, and H_4) compared to the general model. Meanwhile, on H_3, the ease of use for the general model is greater than the CRS model because users think this model is easier to use. In testing H_6 - H_{11}, we have the p-value = 0.00257 and $GFI = 0.90$ in the accepted hypothesis model. This value has been shown that the suitability of the data and the hypothesis model is quite good. Moreover, from the accepted path hypothesis, ease of use only affects perceived usefulness, while the behavioral intention is directly influenced by perceived usefulness. In general, users find it helpful in finding tourist destinations that suit their needs. This is because trust and perceived ease of use come from the interaction and explanation facilities contained in the system (H_5 and H_6). Besides, perceived usefulness in the form of recommendations for tourist destinations offered by the system has directly affected users' interest in using this CRS interaction model in the future (H_{10}).

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