An Experimental Study on Providing User Control in E-Commerce Recommendation through Conversational System

Seth Owirodu, Yuchuan Lin, Sheng Tan
Department of Computer Science
Trinity University
San Antonio, Texas, USA
email: {sowirodu, ylin, stan}@trinity.edu

Zhou Tong
Department of Computer Science
Wheaton College
Norton, Massachusetts, USA
email: tong_tony@wheatoncollege.edu

***Abstract*—Recommender Systems(RS) are gaining importance across different domains, especially in e-commerce. Existing RS work mainly focuses on improving accuracy while neglecting other concerns associated with commercial RS, such as lack of transparency, little or no user control, and absence of diversity. In this paper, we aim to address those concerns by implementing a conversational system based e-commerce RS using real-world product data. We also conducted a month-long user study with over a hundred participants to investigate how users respond to the conversational system as a control mechanism to mitigate the abovementioned problems. Results show that the majority of the users give positive responses to the conversational system based control mechanism. The post-study questionnaires indicate that better control, transparency, and diversity can be achieved utilizing our system. By considering users' perspectives, this work contributes to a better understanding of how we can utilize the conversational system to mitigate transparency and diversity issues associated with RS.**

Keywords—Recommender System; Conversational System; Transparency; User Control; E-commerce.

I. INTRODUCTION

In the past decade, the Recommender System (RS) has played an increasingly important role across different domains of the online services such as e-commerce, social media, banking, news, music, and video [1]. The main task of RS is to help the user navigate through an overload of information by providing personalized recommendation to particular users based on explicit or implicit information [2]. For example, recommendations account for about 60% of all video clicks from the home page on Youtube [3], while the recommended items account for around 35% of the total customer purchase on Amazon [4]. Thus, the deployment of RS can not only alleviate the problem of information overload but also make significant contribution to the overall success of the service [5].

In most of these practical applications, RS has been improving over the years by aiming for better recommendation accuracy. However, many researchers have become aware that other than accuracy, existing RS failed to address several other concerns adequately, such as diversity and transparency. For example, RS can create "filter bubbles" that prevent users from accessing more diverse content and lead to potential polarization views [6]. Moreover, RS generally keeps the recommendation process "behind the scenes" which lacks of transparency which allow for very little accountability [7]. Additionally, RS rarely offers users any explicit way to direct or participate in the recommending process [8]. Without providing diversity and transparency, it can greatly diminish user trust and satisfaction which increase the bias of the RS.

Among all the concerns discussed above, the user control has the most direct impact compared to others. This is because by enhancing user control, it is possible to mitigate other problems, including diversity, transparency, and accountability. In particular, by allowing users to participate in the recommendation process, the RS can be more responsive and align with user interests, which leads to better recommendation accuracy [9]. User control also requires RS to be more transparent and accountable through the process [10]. In addition, it increases the diversity of recommendation results by providing user the opportunity to explore beyond default options or known interests [11].

Much researches has been done to implement different mechanisms for increasing user control of the RS [12]. PeerChooser enables the user to increase the weight of the active user represented by nodes in calculating recommendations [13]. TasteWeights allows the user to adjust the weight of different parameters to change their importance in the recommendation process [14]. PARIS achieve user control by utilizing interactive mechanism like drop-down lists and checklists [15]. There is also a large body of work leveraging conversational systems (i.e., chatbots) to help users interact with the RS [16]. Such mechanism allows users to give feedback about the recommendation results through conversational systems [17].

Conversational systems or dialogue systems are designed to serve the user through conversation for various purposes given the context [18]. In recent years, with the significant advancement in natural language processing, deep learning, and cloud computing, conversational systems have already been used in applications across various domains [19]. Compared to other interactive mechanisms, the conversational system has several advantages [20]. First, conversational systems are intuitive and have a much lower learning curve. Second, conversational systems can be easily customized for various purposes without affecting the interface. Those advantages make the conversational system an ideal interactive mechanism to enable user control for RS.

Although there are existing studies for conversational RS,

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they mainly focus on how to improve the recommendation results by refining the user preferences [16]. Moreover, since those work mainly aim for recommendation accuracy improvement, they fail to address other concerns for the RS, such as transparency and diversity, especially under the e-commerce setup. In this study, we try to answer the following research question: **how do people view the conversational system as the control mechanism for e-commerce RS, which underlying algorithms do they prefer, does it improve the diversity and transparency of the RS?** We focus on the e-commerce application since it is among the most used domains for both RS and conversational system. Also it is essential to understand user's perspective on how to improve the transparency and diversity of RS utilizing conversational system.

To answer the question, we first build a mockup e-commerce website that leverages real-world customer data and integrates both the recommender and conversational systems. Then, we conduct a month-long user study by allowing participants to freely explore the website and interact with the RS through a conversational system. We customize the RS so users can play around with the underlying recommendation algorithms/parameters and get the updated recommendation results on the fly. We also collect the user feedback to gain insights into the user's perspective on the conversational system as a control mechanism over RS. This study contributes to a better understanding of how the conversational system can be utilized to mitigate the concerns, such as transparency and diversity associated with RS.

The rest of this paper is organized as follows. Section II discusses the related work of E-commerce RS, interactive RS, and conversational system. Section III describes the design details of the system. In Section IV and Section V, we describe the experiment setup and results of the user study. Finally, Section VI and Section VII discussed the limitations and summarize the results of this study.

II. Related Work

A. E-commerce Recommendation Systems

Over the last decade, there has been a growing interest and research effort towards RS for e-commerce websites. This is because RSs have a tremendous impact on both users and e-commerce providers. The products are recommended based on various factors, such as popularity, customer demographics, product rating/comment, and customer's past purchase/browsing history [21]. A RS usually includes three key components: acquire data from customers, compute and rank the recommendation, then present the recommendation results [22].

In general, e-commerce RS can be divided into four categories: content-based filtering, collaborative filtering, hybrid, and social network-based. Content-based filtering RS recommends items similar or closely related to the items the user has purchased previously [23]. The techniques used in content-based filtering approaches include: traditional information retrieval methods (e.g., TF-IDF, LDA) and advanced machine learning methods (e.g., Bayesian, decision tree, ANN) [24]. The major limitation of content-based filtering is overspecialization, limited content analysis due to a lack of keywords [25].

Collaborative filtering RS recommends items based on the items previously preferred or purchased/browsed by other users [23]. In particular, most of the systems can be further sorted into two types: heuristic-based (e.g., KNN, graphy theory, SVM) and model-based (e.g., Bayesian, Clustering, linear-regression) [26]. This approach also has several drawbacks, such as sparsity problem, gray sheep problem, and scalability problem [26].

In order to avoid the shortcomings of above mentioned systems, hybrid RS has emerged to take advantage from the previous two approaches. It is done by combining content-based filtering and collaborative filtering RS together in various ways, such as weighted, switching, mixed, feature combination and cascade [27]. Recently, by leveraging the fast-growing of social network applications, social network-based RS has been proposed to utilize data from other aspects, such as user preferences, social connections to improve recommendation accuracy and overcome major challenges including cold-start problem and sparsity problem [28].

B. Interactive recommendation systems

Since the first introduction of RS in the mid-1990s, the majority of the research efforts have been dedicated to improve the system performance and accuracy [29]. Recently, more and more work has been done to improve the overall quality of RS in other aspects, such as diversity, novelty, context, and serendipity [30]. In particular, RS should also take into consideration of factors including transparency and controllability [31] to further increase the societal value and user trust [32]. Thus, research on human factors by developing interactive RS has gained increasing interest. For the RS, there are three distinctive phases where the user interaction with the system could happen: preparation (preference selection), computation (recommendation computation), presentation (results presentation).

The majority of the existing RS utilize implicit user preferences when generating recommendation results. This means the user has no control over which preference will be used or prioritized compared to others. Since user's preferences are highly complex, contextual, and even contradictory under specific scenarios [33], it is crucial to give the user the freedom to choose and prioritize their preferences in order to improve controllability. For example, the system proposed by Schaffer *et al.* [34] allows user to adjust the weights of different input parameters to change their corresponding importance in the recommendation process.

Much work have been proposed to enable user control over the recommendation computation process by either allowing the user to adjust the algorithm parameters/weights [14] or switch between different types of algorithms [35]. Compare to commonly used one algorithm fit all approach, this type of user control gives users the ability to select different algorithms that can tailor to different scenarios. For example, the content-bases filtering approach has the advantage when there is enough domain knowledge on the feature space while the collaborative filtering approach works better under the scenario where there is no overspecialization on user profile and recommend items. Since the algorithm/parameter change over the recommendation computation process yields a bigger impact on the final results, our study will focus on providing the user interaction with the system during this phase.

The presentation control mechanism allows the user to reorder or present the recommendation results in various ways that better fit a specific user and his/her interest under different scenarios [34]. Specifically, system like TalkExplorer [36] uses a cluster map to visualize relations between recommender agents. MusiCube [37] allow the user to rate more items to refine recommendation directly in the recommendation results. On the other hand, work proposed by Jin *et al.* [38] leverage straightforward post-filtering functionalities to refine recommendation results and achieve cognitive load reduction.

C. Conversational systems

Conversational systems or conversational user interfaces are conversational agents that can interact with different users using natural language [39]. The technology is also known as chatbots which humans could interact with [40]. With the rapid development in the area of artificial intelligence, especially the advancement in natural language processing in the recent years, chatbots are capable of performing many labor-intensive task at a much lower cost and has been widely deployed across a varied range of applications, including intelligent customer service for e-commerce, virtual personal assistance, financial dialogue system, physical healthcare, and pedagogical conversational agent [19].

Based on the specific techniques utilized, typical conversational system can be divided into the six categories: template-based, corpus-based, intent-based, RNN-based, RL-based, and hybrid approaches [19]. Because of the advancement in computational power and deep learning algorithms, more and more research have tried to combine several techniques to improve the performance of the chatbots [18]. For example, it is possible to utilize a ranking algorithm to select the optimal response from candidate responses generated by several chatbots leveraging different techniques [41].

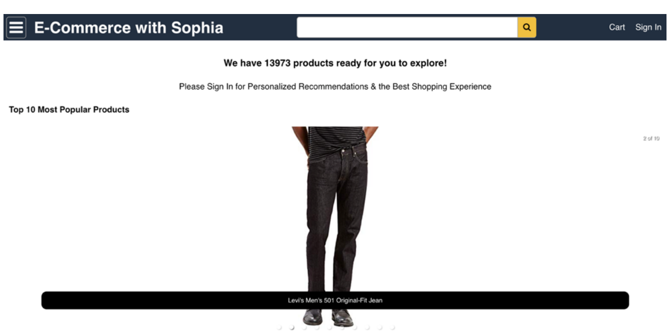

Figure 1. A screenshot of the e-commerce website used for our study.

It is worth noticing that there are existing work attempt to integrate the conversational system with the recommendation system to further improve recommendation performance [17]. It is done by eliciting user preferences and further reduce preference ambiguity through the conversational systems leveraging AI techniques [16]. Although there are many research efforts have been made towards this direction, existing work mainly focuses on how to improve the response from the conversational system or better integration of those two systems [42]. Different from existing work, our study aims to explore the potential of utilizing conversational RS to improve the transparency and controllability of the RS, especially under the e-commerce application scenario.

III. System Design

In this section, we describe the details of how we implemented the system. Specifically, we discuss the data set and frameworks that were chosen as well as how we used them respectively.

A. E-Commerce website and Data set

We implement the e-commerce website using the open-source framework Amazona [43]. The website layout shares high similarities with the popular shopping website Amazon and has been adopted by most e-commerce websites. This way, users can quickly get familiar with the layout and explore the website without much learning curve.

In particular, we made several changes to the website to accommodate our study. First, we change the website from category-based to brand-based. This is because we want the user to focus on the recommendation page without getting overwhelmed by various product category page information. Second, we created two different sections on the home page to display the recommended items based on the underlying recommendation algorithm and randomly selected items which mimic the modern e-commerce website. The website's home page after user login is shown in Figure 1.


```
{
"image": ["https://images-na.ssl-images-
amazon.com/images/I/71eG75FTJJL._SY88.jpg"],
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"vote": "2",
"verified": True,
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"style": {
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        "Color:": "Charcoal"
        },
"reviewerName": "Abbey",
"reviewText": "I now have 4 of the 5 available colors of this
shirt... ",
"summary": "Comfy, flattering, discreet--highly recommended!",
"unixReviewTime": 1514764800
}
```


Figure 2. A sample of the Amazon Review Data

To populate the website, we utilized the Amazon product review data and product metadata of Amazon Review Data (2018) [44] for our implementation. This data set is the updated version of the Amazon Review Data released back in 2014 [45], containing product reviews and metadata from Amazon, including 233.1 million reviews spanning from May 1996 to Oct 2018. The whole dataset has 29 different categories of products in total. A sample of the review data is shown in Figure 2.

In order to reduce excessive information that would distract users, we only picked the Clothing and Shoes sub-dataset category with 32.2 million reviews and 2.6 million products. This is because many of the products from the real-world e-commerce website are from those categories and users are more familiar with the brands from those categories. To reduce the sparsity problem of the review data, we used the 5-core review data, a dense subset extracted from the original product review data where each product has at least five reviews.

B. Recommendation system and Chatbot

For this study, we implemented the recommendation engine using Case Recommender [46], which is an open-source a Python framework of several popular recommendation algorithms for both implicit and explicit feedback. This framework aims to provide a rich set of components that allow us to construct a customized RS based on a set of underlying algorithms and rating prediction.

It is worth noting that this study does not seek to tackle the cold start issue in the recommendation system where the system does not contain prior information about a specific user. To resolve this issue, during the registration process, each user is required to enter basic user information (e.g., age, gender) and select their top favorite brands and products from the list the website provides.

In order to generate the recommended items, our system first computes the estimated ratings for all product candidates with the trained model using the default algorithm or explicitly selected by that user. Next, the product candidates are sorted by their estimated ratings. Next, a list containing the top n products with the highest estimated ratings is sent back as the recommended items. Here, the number of recommended products, the recommendation algorithm, and rating prediction are considered parameters controlled by either the user or default setting. The default number of products being recommended, recommendation algorithm, and rating prediction is 5, most popular, and SVD, respectively.

After comparing various chatbot frameworks implemented, we selected the react-chatbot-kit for building our chatbot [47], a React-based open source chatbot framework. The default chatbot framework contains a message parser, a configuration, and an action provider, which allows us to easily configure the interactive conversational system for our study and integrate it with our implementation of the e-commerce website and underlying RS.

To better handle the user control request for the underlying RS, we first designed and implemented several message parsers that can detect different keywords and determine what kind of responses should be returned to the user. Next, we came up with different keywords related to our user control methods or user control in general. All the control keywords are implemented as buttons so users can easily choose from the conversation without typing. After the user clicks the button, specific actions will be triggered (e.g., switching the algorithm, changing the number of items to be recommended). An example of the chatbot implementation is shown in Figure 3.

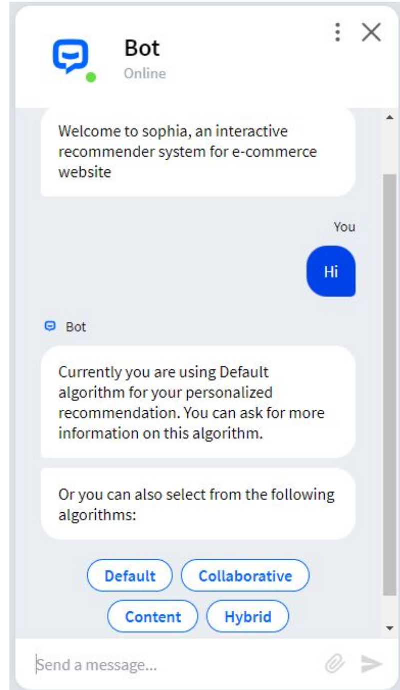

Figure 3. A screenshot of the chatbot used for our study.

IV. Experimental Setup

We studied the user behavior of our system, a conversational system based interactive RS for e-commerce website, where the user can interact with the conversational system to change the underlying algorithms and parameters. The proposed system supports the switching between multiple recommending algorithms, which gives the user the control of the RS and the ability to view the results generated by various algorithms/parameters on the fly. When a user logged into the system, he/she will be assigned the baseline algorithm as his/her initial condition. They will also receive a brief message from the conversational system to inform them about the currently running algorithm and potential options they can switch to.

Our system supports four underlying recommending algorithms. Each algorithm is identified to the user using an abbreviation derived from the original name. Users can interact with the conversational system for further information about each algorithm, such as a simple description of what this algorithm is and how it is being used in the RS. The supported algorithms are as follows:

- The *Baseline* algorithm generates the results by selecting the top reviewed items from randomly selected categories/brands. This algorithm was called *Default* and was used as ”non-personalized” algorithm.

- The *Collaborative* algorithm generates the results utilizing collaborative filtering approach. It searches the similar preference user with the current user to find the similar users. After finding a similar user, it then presents the recommendation for the current user according to the preference of similar ones. The algorithm was called *Collaborative* and was used to improve the user experience for new user of the system.
- The *Content* algorithm generates the results leveraging content-based filtering approach. The item recommended by such an approach often indicates textual information where each item is described with the keyword and its weight. Then the items are recommended based on item characteristics and the user's preference. The algorithm was called *Content* and was used to recommend items similar to what the user has liked or purchased in the past.
- The *Hybrid* algorithm generates the results by taking advantage of both content-based filtering and collaborative filtering approaches. It is done by combing the recommendation results from those two approaches. The algorithm was called *Hybrid* and was used to avoid the disadvantages of content-based filtering and collaborative filtering approaches.

Once in the system, users could change the underlying algorithms and rating prediction parameters by interacting with the website's conversational system. The change will take effect immediately after user specification in the conversational system. After the user types in or selects the desired algorithms or parameters, the system will reload the list of recommended items on the current page (if they are on the item recommendation page) and show the results from the newly selected algorithm/parameter. The user's choice will persist throughout the system and affect all the predictions for item recommendations.

The summary of the experiment data is listed as follows: there are 108 users participated in our study over one month period of time; of all the participants, 45 were female, 52 were male, and the rest declined to reveal that information; the age range is from 21 to 50; 95 of them make the algorithm/parameter at least once. We consider switching from one algorithm/parameter to another as a single change event. There is a total of 1315 change events recorded during the experiment.

We also asked all participants to fill in a questionnaire after the experiment. It is used to assess the participants' experience using the proposed system. The questionnaire uses a five-point Likert scale, ranging from 1 to 5, where 1 represents strong disagreement, and 5 represents strong agreement. There are a total of 98 pieces of feedback collected. The questionnaire statements were as follows:

1) I become familiar with the system very quickly.
2) The information provided by the chatbot was sufficient for me to change the underlying algorithms/parameters.
3) I would like use this system in the future on e-commerce website.
4) I like the item recommendation result generated by the system.
5) I have fun when I am using the system.
6) The recommend results contained a lot of variety when switch to different algorithms/parameters.
7) The system has no real benefit for me.
8) I have to invest a lot of effort to obtain different recommendation results.
9) I feel in control of the recommending process.

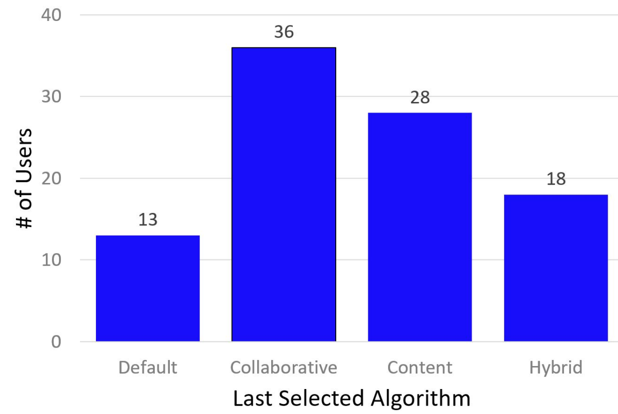

Figure 4. User Preferences of Algorithms

V. RESULTS

In this section, we describe our findings from this study. It contains the results for both algorithm/parameter switching and the questionnaire.

A. User Switch Algorithms

Of the 108 users in our study, 95(87%) changed underlying algorithms at least once, as mentioned before. This means 13 users only use the default algorithm/parameter during the process. These activities likely resulted from users' unawareness of the conversational system on the web page, or the results generated by the default algorithms has already met their expectation. The high percentage of users switching the algorithm/parameter at least once demonstrates that most users utilize the conversational system to adjust underlying algorithms. This also shows the user's willingness to explore RS through conversational system and desire for transparency and user control over RS.

B. User Algorithm Preferences

Here, we study the user preferences of the algorithm. Among the users who tried different algorithms, the collaborative was the most favored algorithm, followed by Hybrid, content, and default algorithms. Figure 4 shows the number of users who switched algorithms at least once and selected one of the algorithms as their final choice (i.e., the algorithm user chose as the active algorithm at the end of the experiment).

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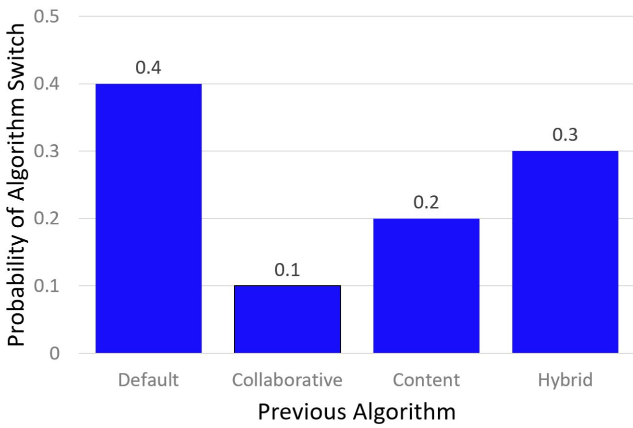

Figure 5. Likelihood to Switch Algorithm

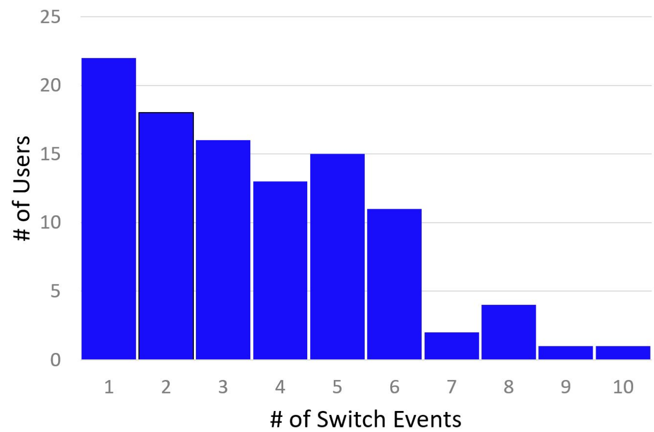

Figure 6. Events Count for User Switch

It is easy to observe that users prefer other algorithms over the default ones. This is because the users knew the default algorithm was non-personalized and could not generate more accurate or personalized results. We can also observe that the user prefers the collaborative filtering-based approach more than the content-based and hybrid approaches. It is likely because the users who switched algorithms at least once are willing to try various options on the parameters. This observation provides insights to support the idea of users' desire for transparency and user control of the recommendation systems.

As we discussed before, most users chose to switch from non-personalized algorithms and try different ones. Figure 5 shows the probability of users in each algorithm who tried a different algorithm afterward. As we can see, users who choose the default algorithm have the highest probability of switching algorithms, followed by hybrid, content, and collaborative. This observation also suggests users' awareness of the non-personalized results generated by the default algorithm. Combining these results with the users' final choice, we can infer that most users are satisfied with the collaborative algorithm. The content algorithm has the next satisfactory rate, followed by the hybrid algorithm.

C. Algorithm Switching Behavior

We also study the user switching behavior by measuring how many times each user switched their algorithms, and the results are shown in Figure 6. The x-axis shows how many switches have been made; the y-axis shows the number of users who made that amount of switches. We only showed the number of switches less than 10 times, which accounts for 97% of the users. The vast majority of the users switched algorithms no more than 6 times. However, there exist users who logged over 95 switches during the experiments. Most users switch just several times. For example, only around 20% of users switched more than 6 times.

The most common pattern for switching was for the user to switch from the default to another algorithm or try the other three algorithms and stop the switching. The median number of switching is 4; after 6 switches, there is a significant drop-off in the number of users. This is because 4 to 6 switches are enough for most users to try other personalized algorithms and decide which one is their favorite. It is worth noticing that most users experiment with the switch early in their use of our system, conduct several switches and then leave the system alone.

D. Questionnaire Results

Figure 7 summarizes user feedback and perception about the system and interaction effectiveness. The feedback of Q1(M=4.00, SD=0.85) and Q8(M=2.45, SD=1.15) show that the proposed system is relatively easy to use and does not require much effort for the user to learn. It is worth noting that among all the users, the younger users (35 years or younger) gave overall higher ratings on Q1 and lower ratings on Q8. On the other hand, the older users (40 years or older) gave overall lower ratings on Q1 and high ratings on Q8. This is likely because e-commerce websites have widely adopted the conversational system, and younger users are already taking advantage of this feature and are familiar with how to interact with it.

The quality of item recommendation Q4(M=3.85, SD=0.92), information variety Q6(M=3.65, SD=1.25), and information sufficiency Q2(M=3.95, SD=0.82) all received positive feedback from the users. This indicates that the proposed system provides an easily understood explanation for the user to explore different algorithms. Meanwhile, it also produces enough transparency and variety on the generated list of recommended items based on different algorithms.

The feedback on Q3(M=4.15, SD=0.74), Q7(M=1.68, SD=0.88), Q9(M=4.08, SD=0.72) show the effectiveness and usefulness of the proposed system. The overall positive feedback of those statements demonstrates that the proposed system increases the user control and transparency of the recommendation system and has the potential to improve the user experience further if adopted by other similar systems. It is worth noticing that the feedback on Q5 (M=4.12, SD=0.63)

Questions	Mean	SD
Q1: I become familiar with the system very quickly.	4.00	0.85
Q2: The information provided by the chatbot was sufficient for me to change the underlying algorithms/parameters.	3.95	0.82
Q3: I would like use this system in the future on e-commerce website.	4.15	0.74
Q4: I like the item recommendation result generated by the system.	3.85	0.92
Q5: I have fun when I am using the system.	4.12	0.63
Q6: The recommend results contained a lot of variety when switch to different algorithms/parameters.	3.65	1.25
Q7: The system has no real benefit for me.	1.68	0.88
Q8: I have to invest a lot of effort to obtain different recommendation results.	2.45	1.15
Q9: I feel in control of the recommending process.	4.08	0.72

Figure 7. Results of Post Study Questionnaire

is also overwhelmingly positive. This is because the conversational system is intuitive and enjoyable to interact with, which can further facilitate the user's control over the RS compared to other interactive mechanisms.

VI. Discussion

The user study and post-study questionnaire show that integrating the conversational system with RS for e-commerce websites is very promising for better user control and transparency. However, there are still several limitations of our study.

First, our study mainly focused on the RS's user control and transparency aspects; we did not thoroughly evaluate other aspects of the RS. For example, we could use RMSE to evaluate the accuracy of the RS. Besides the accuracy, many other metrics can be used to further evaluate an RS in various aspects, including the relevancy metrics like recall and precision.

Second, our RS cannot correctly handle the cold start issue, which means our system performs poorly for users with no information stored in the system. We plan to solve this issue in future research by using additional data sources, such as social network data or choosing the most prominent groups of analogous users [48].

Third, the conversation system could be improved. By only using partial pattern matching, we have not yet fully utilized the power of the conversational system. In the future, we would like to build a more intelligent conversational system by combining NLP and deep learning techniques. So our system can better understand the user's intention and provide a more appropriate response.

Last, due to the limited time, we could not provide additional user control options other than underlying algorithms for the study. For future work, we would like to add other options, such as different rating predictions (e.g., SVD, SVD++, ItemKNN, UserKNN), different hyperparameters, and a different number of recommending items. By providing more user control options, we can gain more insights into the user perspective on our system.

VII. Conclusion

RS plays a vital role across different domains of online services. Despite the fast accuracy improvement over the years, modern RS for e-commerce still fails to address issues, such as lack of transparency and user control. In this paper, we implement an e-commerce RS using real-world product data and integrate a conversational system to enable user control over the recommendation process. We also conduct a user study and questionnaire to gain more insights into the question: how do people view the conversational system as the control mechanism for e-commerce RS. The results show that a majority of the user consider the conversational system an excellent interface to achieve user control and transparency for e-commerce RS. We also find that the collaborative filtering-based algorithm is the most preferred algorithm, while many users agree that our system can improve the diversity and transparency of the RS.

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