Effects of Communication Channels on Explainable Food Recommendation Systems

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1 Introduction

With the increasing integration of artificial intelligence (AI) technologies into everyday life, there is a growing demand for systems that not only provide precise recommendations but can also deliver transparent, understandable explanations [4]. Explainable AI (XAI) has been employed to address this need by making complex algorithmic processes more accessible to the end user, thus promoting user trust and understanding [2]. However, explainability alone does not compose the effectiveness of the content, but also how the explanations are communicated plays a crucial role in how users perceive, engage with, and ultimately accept these recommendations [7]. Previous research has shown that physical presence of a robot

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can increase user engagement by providing a richer, more interactive experience that fosters a sense of connectedness [13]. Moreover, there is a notable effect of different communication channels (e.g., physical embodiment versus purely digital) for users' within personalized meal recommendation systems [15]. However, there is still a gap in understanding how embodiment translates to practical applications, particularly in scenarios where complex, personalized information needs to be communicated efficiently and effectively. To investigate this, we have developed two different interface configurations: (i) one based on a standard web interface accessible with a tablet and (ii) another that complements this tablet interface with a humanoid robot capable of providing food recommendations along with explanations through speech and gestures. The robot introduces physical embodiment and aims to create a more human-like interaction by utilizing multimodal communication. By examining user reactions and interactions with both systems, we aim to determine whether physical embodiment influences user engagement and affects perceptions of the recommendations, including acceptance and satisfaction with the system.

The remainder of this chapter is organized as follows. Section 2 presents related work. Section 3 describes the setup of the study, detailing the components and configurations used. Section 4 provides an evaluation and discussion of the experimental results. Section 5 concludes the paper and suggests future research.

2 Related Work

The increasing adoption of artificial intelligence in day-to-day applications has developed an interest in understanding the most effective ways to deliver personalized and explainable recommendations. In particular, research has focused on the communication mediums: the means of presenting the recommendations and corresponding explanations to the user. Various communication mediums, such as web-based systems [4, 9, 11] and mobile interfaces [3, 14, 16], have been studied for their effects on recommender systems. Moving beyond these conventional mediums, recent research has focused on robots as a promising alternative for recommendation delivery, particularly in scenarios where physical presence may improve effectiveness with enhanced user engagement.

Kamei et al. [9] experiment with robots recommending items based on customers' purchasing behaviors tracked by networked sensors in a shop. Using multiple robots, they show that participants lingered longer near shelves when robots interacted with them, often mirroring previous purchasing behaviors. Herse et al. [6] investigate embodiment's role in social robots' persuasiveness within a service setting. They conduct an experiment comparing a human, robot, and kiosk for restaurant recommendations. The results reveal that human-like embodiment enhances persuasiveness, though only with specific recommendation phrasing. They suggest human-like traits can boost recommendation impact, with a dependence on the choice of language. Sakai et al. [15] conduct an experiment with robots in both virtual and embodied setting with visitors in conversations about food preferences before recommending dishes. While behavioral differences were minimal, the study found that physical robots notably improved satisfaction and agreement with recommendations, suggesting that embodiment has a positive impact on user engagement. Interestingly, in our setting, user engagement is higher when participants interact solely with a conventional tablet interface compared to when they interact with the robot and tablet together.

Embodiment research also takes place in education and negotiation. Çakan et al. [5] study the difference in negotiation styles, when interacting with virtual robots and physically embodied robots. Human participants took the negotiation more seriously against physically embodied robots and made more collaborative moves in the virtual robot setting. Survey responses indicate that participants perceived the robot as more human-like when it is physically embodied.

Köse et al. [10] investigate embodiment and gesture effects in child-robot interactions with a child-sized humanoid robot in an interactive drumming game. They studied three forms of communication: (i) direct interaction with an embodied system, (ii) a sound only, and (iii) a real-time virtual avatar. Through mixed-design measures, data from the experiments reveal that physical embodiment, especially with gestures, significantly enhances interaction quality, performance, and user enjoyment. Ultimately, a physically embodied robot with gesture capabilities enhances the perceived intelligence of the agent and improves engagement in human-computer interactions. In a similar setup, [12] compared various forms of embodied negotiation opponents, to test the hypothesis that the appearance of the robots would change participants' impressions and attitudes. Ultimately, it did not alter the final session results.

In contrast, our study focuses on recommender systems. We examine how explainable recommender systems are experienced through different interfaces, namely a conventional tablet and a robot combined with a tablet, and how these interfaces affect user engagement, satisfaction, and overall system performance.

3 Research Setup and Hypotheses

In this chapter, we utilize the personalized explainable recommendation framework developed by Buzcu et al. [4], designed to support users in making food choices that meet both health requirements and personal preferences. The interaction between users and system is governed by the protocol illustrated in Fig. 1. The interaction is initiated by a user request consisting of several constraints, and the system provides an explanation along with the given recommendation. The user can provide feedback about recommended recipes and their corresponding explanations or end the interaction by either accepting or terminating the session without any agreement. With the given feedback, the recommendation strategy revises its recommendation, thus engaging in a subtle negotiation. This process lasts until they reach a termination condition.

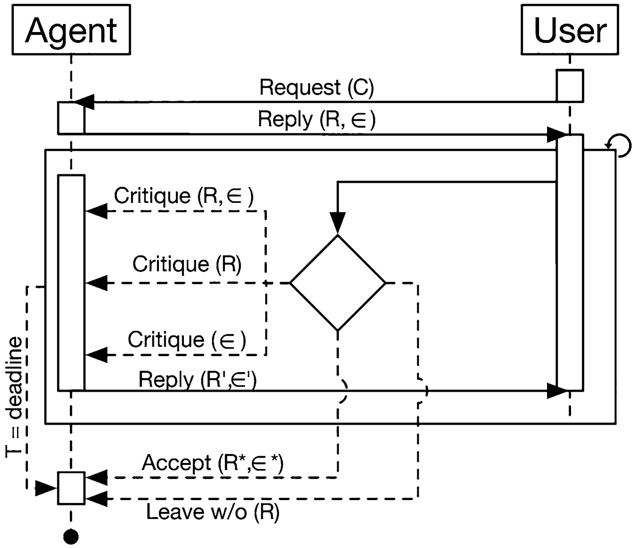


Fig. 1 FIPA description of the negotiation protocol where C corresponds to the user constraints, R is a recipe recommended by the agent, and ϵ is an explanation that comes with the recipe

The recommendation generation process begins with filtering. The system processes each user's dietary restrictions, allergies, and ingredient preferences and filters out items that do not align directly. For instance, vegan users will only receive plant-based recipes. This filtering is enabled by an RDF ontology-based database, which defines complex relationships between food entities and user dietary restrictions to refine the available choices to meet each group of users' requirements. The system evaluates the remaining items using a multicriteria utility function, which rates each option based on (i) *nutritional value*, (ii) *active metabolic rate (AMR)*, and (iii) *user satisfaction scores*. Ultimately, these scores are combined via their respective weights to calculate an overall additive utility score for each item, which determines a heuristic ranking among the filtered options. The highest-ranked item that has not been recently recommended is then selected to be recommended. The system generates post hoc explanations to clarify the reasoning behind the choice from the selected recommendation. This step includes two types of explanations:

- **Item and User-Based Explanations**: Using historical data, a decision tree is constructed to identify the key features that influenced the recommendation in a post hoc manner.
- **Contrastive Explanations**: The system compares the chosen item with a similar alternative that did not meet the decision criteria or was filtered otherwise. This contrast is used to show why the recommended item is a more preferable option by highlighting features.

So far, [4] has implemented the recommendation framework with a web interface. Figure 2 shows the web interface as in the recommendation state. The web interface provides a medium for users to interact with the recommender system with the means of allowed actions in the protocol (see Fig. 1). The interface allows users to see recommended recipes in detail (e.g., name of the recipe, recipe ingredients, nutritional information) along with the explanation of the recommendation and give feedback about both recommendation and explanation. The recipe feedback section consists of options and the recipe ingredients. Users can pick the appropriate option (e.g., "I don't like...," "I ate the following recently...") with preferred ingredients. The explanation feedback can also be given by selecting the preferred option in the explanation feedback section. Users have three options to respond to the given recipe: (i) *accepting the recommendation and ending the session*, (ii) *submitting the feedback and requesting new recommendation*, and (iii) *terminating the session*.

Apart from the content of the explanations, how they are delivered also plays a crucial role in their effectiveness. Therefore, it is essential to investigate which communication medium/modality would establish more effective interaction with the user when building personalized explainable systems. This chapter mainly focuses on personalized explainable food recommendation systems and examines the effect of communication medium/modality (i.e., the effect of physical embodiment and textual/speech-based communication). Consequently, this chapter aims to investigate the following research hypothesis through user studies. For sake of readability, hereafter, tablet (touch-screen-based devices) only is referred to as a conventional interface:

- **Hypothesis 1 (H1)**: Incorporating a physically embodied robot into an explainable food recommendation system affects user engagement. *(Metric: Amount of user feedback)*
- **Hypothesis 2 (H2)**: Incorporating a physically embodied robot into a conventional interface shifts the original recommendation perception and acceptance. *(Metric: Recommendation acceptance rate)*
- **Hypothesis 3 (H3)**: Interacting with a physically embodied robot with a conventional interface could result in different satisfaction levels with the personalization of recommendations compared to conventional interfaces.
  (Metric: Qualitative user feedback)

Accordingly, we compare two settings in which the user interacts with the system via only a tablet (only visual and textual data is delivered) in one setting, whereas they interact with a QT robot via speech in addition to the use of a tablet. Note that we utilize the same strategies for recommendation and explanation generation in both settings. Ultimately, we aim to study user engagement, acceptability of the explanations, and communication effectiveness by comparing the interactions with the user when the explanations are delivered by a tablet-based medium or a physical humanoid robot with a tablet interface.

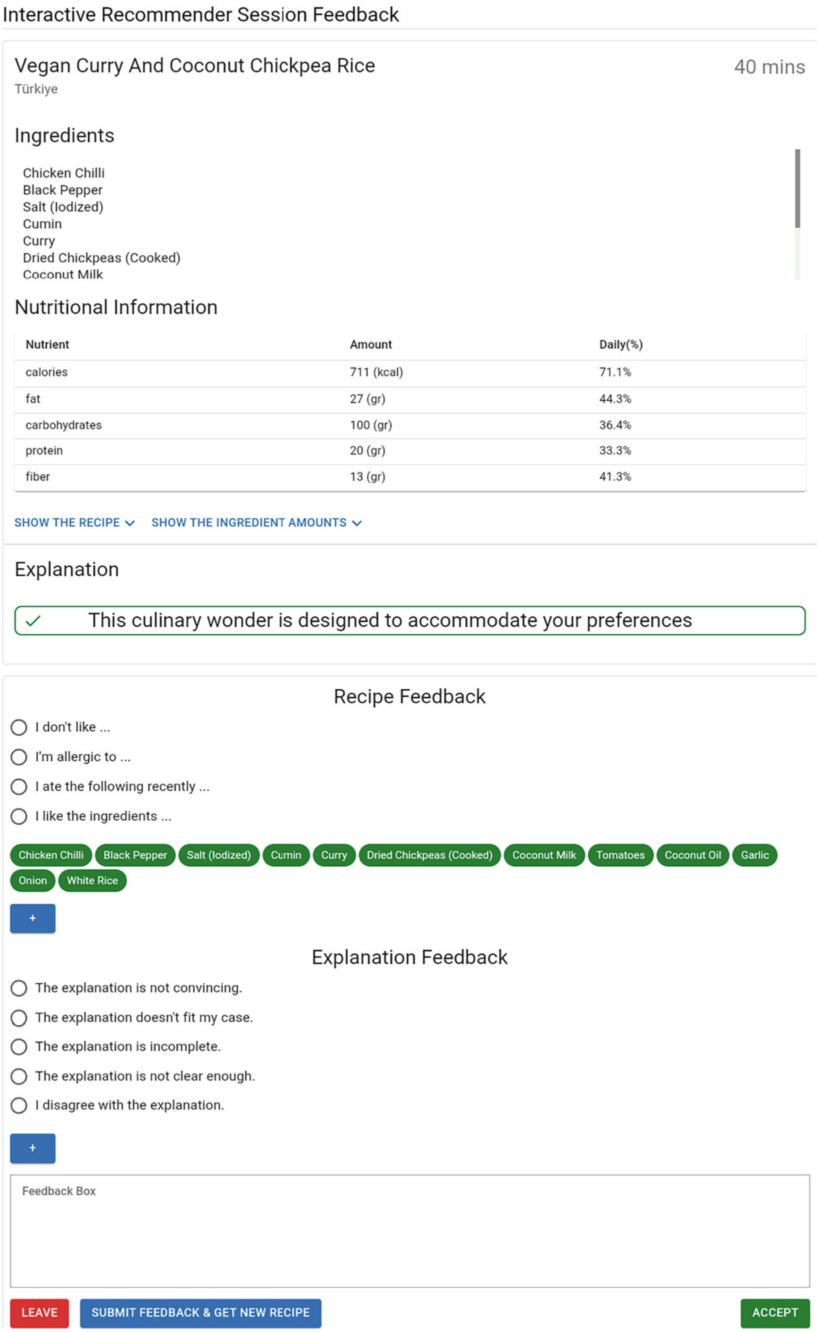


Fig. 2 Tablet web interface

4 Experimental Evaluation

In this section, we first introduce our methodology (Sect. 4.1) and discuss our results with the experimental settings (Sects. 4.2 and 4.3).

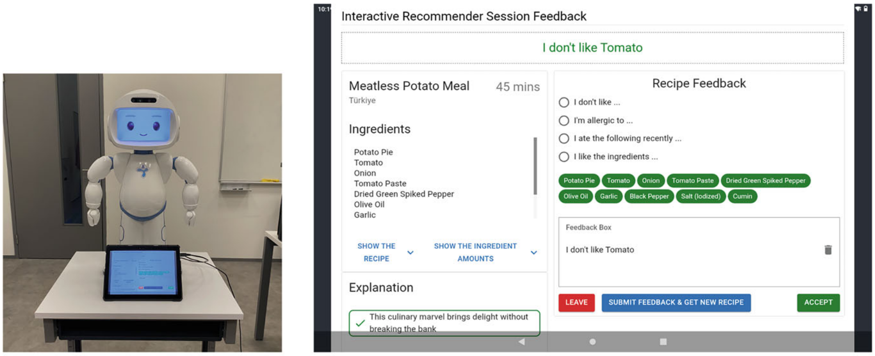
4.1 Methodology

In order to test our hypotheses, we utilize a QT robot[1] supporting various interaction services such as text to speech, speech to text, emotions display, and gestures. Human-robot interaction requires speech communication, emotions, and gestures to capture the users' attention and create a more human-like interaction. On the other hand, grasping the provided material within the dialogue and reasoning them may require some visual deliverables. That is, if we provide the same context in the form of visual and textual, it might be easier for a human user to evaluate. While determining what content should be delivered in textual format via tablet and what content to be delivered by the robot via speech, we conducted a pilot user study where the users give feedback about the effectiveness of communication. We observed that users had difficulty in understanding the details of the given recipe or keeping in mind the related details affecting their decisions. We found out that utilizing speech-based dialogue for short explanations and structured user feedback creates a rapport between system and users. Therefore, we employ the speech-based interaction for the following tasks:

- Greeting the user (e.g., "Hello! My name is QT. I am a nutritionist! I am here to help you about your food selection! Can you hear me?")
- Providing the name of the recipe and its corresponding explanations verbally (e.g., "Great! I can hear you too! Now I recommend you Meatless Potato Meal. Because I think this culinary marvel brings delight as an affordable option. Did you like this recipe?")
- Receiving structured feedback (e.g., "I am curious to hear your thoughts! Would you like to give me a feedback before we continue?")

On the other hand, the content of the full recipe is displayed on the tablet screen as shown in Fig. 3b so that the users can assess the recommendation. Moreover, the robot also uses gestures and expresses feelings, emotions via facial expressions alongside the recommendations to add human likeliness to the system for a more fluent experience. Furthermore, the user can track the interaction states from the tablet interface by displaying the speech recognition outputs simultaneously and options for structured explanations. It is worth noting that both settings (only tablet versus robot and tablet) provide the same content to the users. The only difference

[1] https://luxai.com/humanoid-social-robot-for-research-and-teaching/



(a) (b)

Fig. 3 Robot with tablet session setup and tablet interface

is that some of the visible content changes with the interaction state in the robot setting, while all information is displayed on the tablet in the only tablet setting.

4.2 Experiment Setup

The primary objective of our experiment is to analyze the effects of different communication channels on the efficiency of the recommender system. As described above, we have two communication settings of our food recommender: *QT robot with tablet* and *only tablet*. Therefore, our study comprises two subject groups: One only experienced the tablet, whereas the other experienced the robot with the tablet in order to get a food recipe recommendation along with its explanations. We employ between-subject design for our experimental setup to reduce (i) learning effect, (ii) cognitive overload, and (iii) comparison bias so that each participant interacted with only one setting. During our experiment, each participant goes through the steps depicted by Fig. 4:

1. **Preexperiment Survey**: Participants fill out a survey to provide demographic information and their initial perceptions of robots and technology. This survey includes questions about age, gender, education level, and familiarity with technology.
2. **Experiment Sessions**: Participants (i) are informed about the underlying setting through a brief explanatory video, and (ii) practice with a short demo version to familiarize how to interact with the system effectively. Then they start the experiment choose a food preference profile from a pool of predefined profiles (e.g., vegetarian, fast-food lover, sports). According to the chosen profile, the system makes recommendations along with their explanations. Note that the content of the recommendations is generated in the same way for the same

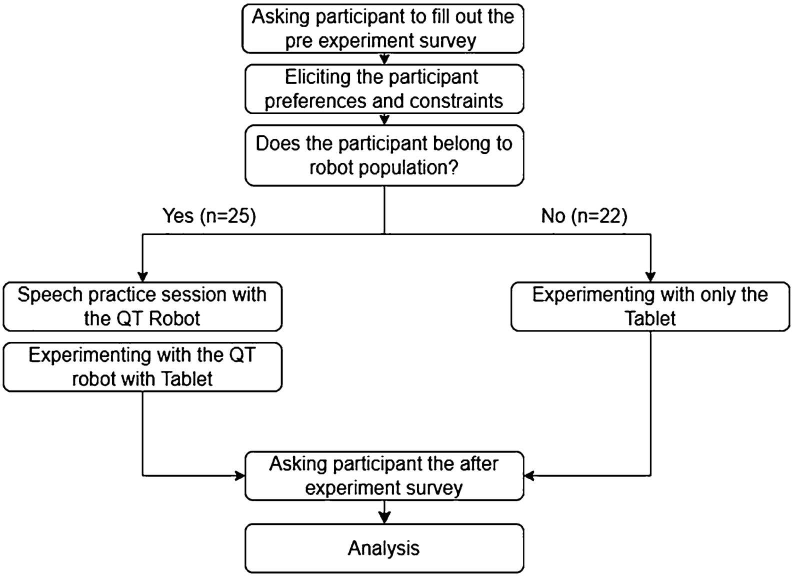


Fig. 4 Experiment procedure

profile. Only the communication channels are different for different subject groups.

3. **Post-experiment Survey**: After their interaction with the system, they fill out post-experiment survey regarding the quality of the recommendations and explanations as well as the likability of the interaction.
4. **Informal Interviews**: At the end of the experiment, participants are interviewed informally to gather qualitative data on their experiences.

In the experiments, we used a 5-point Likert scale to measure participants' responses. After collecting the data, we assessed the distribution to determine the appropriate statistical tests for analysis. Using the Kolmogorov-Smirnov test of normality, we found that our data did not follow a normal distribution. This lack of normality precludes the use of parametric tests, which generally assume a normal distribution of data. The previous lead to select Mann-Whitney U Test, a nonparametric alternative suitable for comparing differences between two independent groups without assuming normal distribution.

The study was conducted at Özyeğin University and involved 59 participants, including students and employees. Participation was voluntary, with optional credits for social sciences students. In order to validate participants' attention, we included a question inside the preexperiment survey that asks, "If you are paying attention, please select 2." Nine participants failed this test. Moreover, three participants had to end the experiment due to personal circumstances. Thus, 47 participants were evaluated for the experiment. Participants were divided into two groups. The robot

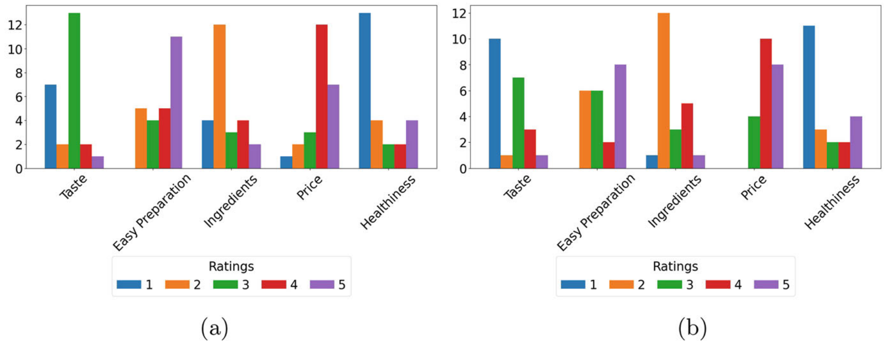


Fig. 5 Histogram analysis of the preexperiment survey for each group. (**a**) Robot with tablet. (**b**) Tablet only

with tablet group consisted of 25 participants: 15 male, 10 female; 20 bachelor's, 4 master's, and 1 PhD student; 9 aged 18–21, 12 aged 22–25, 3 aged 26–30, and 1 aged 36–40; 13 from engineering, 2 from mathematics, and 10 from social sciences. The only tablet group included 22 participants: 13 male, 9 female; 16 bachelor's, 5 master's, and 1 PhD student; 7 aged 18–21, 13 aged 22–25, and 2 aged 26–30; 13 from engineering, 1 from mathematics, and 8 from social sciences. The university ethics committee approved the study.[2]

Finally, Fig. 5 presents a histogram analysis of the questionnaire results, where participants rated factors on a scale from 1 to 5, with one indicating the highest importance. The analysis reveals that, in both groups, the healthiness of a recipe is considered to be the most vital factor in choosing it (52% for robot with tablet group and 50% for tablet-only group). In contrast, 44% of participants within the robot with tablet group rated ease of preparation as the least important factor, and 36% of the participants voted equally price and easy preparation to be the least important factor. The users' priorities on the decision criteria for choosing different recipes are similar for both groups.

4.3 Results and Discussions

Within the analysis of self-explanatory systems, success is commonly measured through two categories of metrics: objective and subjective [8]. On one hand, objective metrics are derived from participants' actions during their interactions with the system, including measures like success rate (e.g., percentage of accepted

[2] Participant data is anonymized and securely stored. They can withdraw anytime without consequences. The study follows ethical guidelines to ensure no physical or psychological harm to participants.

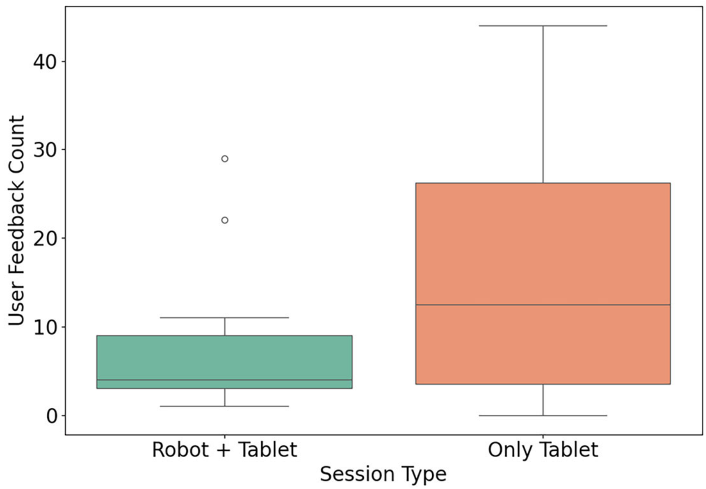


Fig. 6 Amount of feedback per type of session

recipes), the number of interaction rounds per session, or feedback during sessions. Subjective metrics, on the other hand, are gathered from qualitative data such as the post-experiment surveys (see Fig. 8), where participants rate aspects such as perceived effectiveness, satisfaction, and ease of use. These subjective ratings assess whether the incorporating of the robot affects the user satisfaction with the recommendations, explanations, and the general working of the system.

First and foremost, we consider the users' feedback to the system's recommendation. Recall that the feedback is comprised of any verbal (robot with tablet session) or nonverbal (only tablet session) user response to a given recommendation, which we take as an indicator of engagement levels across groups. Meanwhile, it is difficult to compare the quality of feedback, and we can still consider the amount of feedback where the higher number means the user is engaged more with the system since they actively partake. This gives us a quantifiable measure of user engagement while testing *H1*. Figure 6 shows the boxplot of the feedback counts per group. We note that there is a significant statistical difference between the groups ($p = 0.04 < 0.05$) where the tablet group provided more feedback to the system. We observe that the users engaged more in the tablet-only group in contrast to the robot with tablet group, thus satisfying the *H1* (on average, 14.72 vs. 6.52, respectively).

On the other hand, higher acceptance counts could indicate that users find the recommendations more convincing, so they might be more willing to adopt them. Acceptance counts are defined as the number of times users explicitly agree with a food recipe. Ultimately, the comparative study between the groups would allow us to assess whether physical embodiment affects users' acceptance of the system's recommendations. Our results indicate that the users accepted 68% of the recommendations, whereas tablet acceptance was 95%. Consequently, we note that this supports the *H2* as we found a significant difference among the two groups.

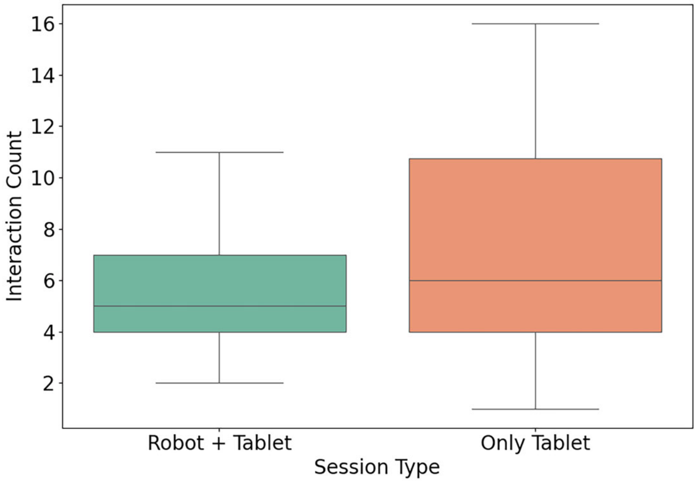
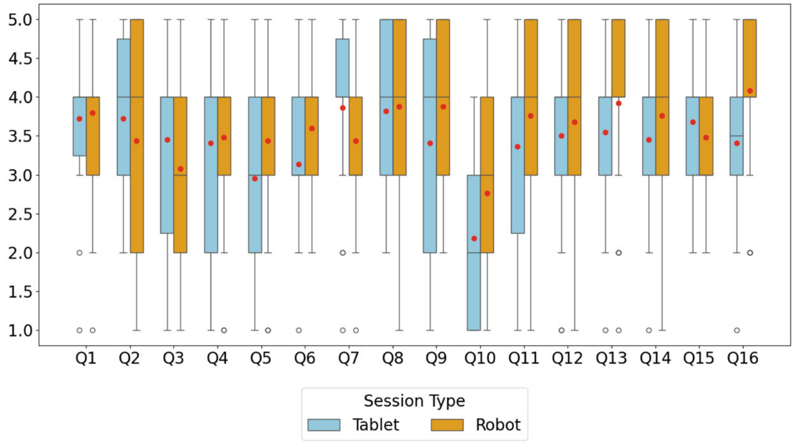


Fig. 7 Amount of interaction per type of session

The acceptance rate and feedback counts could be related to the fact that robots are scrutinized by humans since embodiment brings additional expectations from the system [1]. This could also signal a cognitive load (i.e., may get tired from interacting with the robot)and more tendency to terminate the interaction.

Finally, we consider the number of turns between the groups, as shown in Fig. 7. Here, we define turns as each time a user responds to a recommendation. As a side observation, we noticed a minor difference between the groups ($p = 0.72$, 6.76 vs. 5.94 interactions on average). This may suggest different engagement levels, potentially influenced by user expectations and the mentioned cognitive load during interactions.

Figure 8 illustrates the results of our post-experiment survey questions with regards to our subjective metrics. We link some of the questions to *H3* (Q1, Q11, Q12, Q13, Q14, and Q16) that assess various aspects of recommendation satisfaction and personalization between the groups. These questions provide insights into participants' perceived relevance and accuracy of the recommendations, which reflects the user satisfaction with the system's communication method when compared between the groups. Q1 ($p = 0.69$, on average, 3.73 vs. 3.80) gauges initial liking for the recommended items, setting a foundation for perceived quality, and Q11 ($p = 0.26$, 3.36 for the tablet only vs. 3.76 for the robot with tablet) assesses alignment with the scenario, highlighting satisfaction with situational appropriateness. Q12 ($p = 0.54$, 3.5 vs. 3.68) and Q13 ($p = 0.20$, 3.54 vs. 3.92) measure participants' perceptions of how accurately and personally the system recognized and incorporated their individual preferences. Finally, Q14 ($p = 0.24$, 3.46 vs. 3.76) and Q16 ($p = 0.03$, 3.41 vs. 4.08) focus on the perceived effectiveness of the personalization process, specifically regarding dietary



Q1 I liked the recommended recipes.
Q2 I enjoyed using the recommender system.
Q3 Given interface was comfortable to navigate.
Q4 I liked the explanations that were given.
Q5 I find the given explanations convincing.
Q6 I find the given explanations intuitive.
Q7 The interaction with the recommender was fluent.
Q8 I enjoyed the interaction with the recommender.
Q9 I would like to engage in such an interaction in the future.
Q10 The interaction with the recommender was frustrating for me.
Q11 The recommendations were right for the given scenario.
Q12 Rate the food recommendation system's ability to recognize your food preferences accurately.
Q13 Recommendations were personalized according to my preferences.
Q14 Rate the effectiveness of the food recommendation system in personalizing food recommendations based on your profile.
Q15 What is your opinion about the duration of the experiment?
Q16 How well did the food recommendation system address your specific dietary preferences and constraints?

Fig. 8 Post-experiment survey results for only tablet and robot with tablet

preferences and constraints. Ultimately, *H3* is only partially supported since we found a significant difference for Q16.

Besides the mentioned questions, we observe no significant difference among the questions. However, we would like to note that there was a higher average for the robot with tablet group among Q4 ($p = 0.92$, 3.41 vs. 3.48), Q5 ($p = 0.16$, 2.95 vs. 3.44), Q6 ($p = 0.09$, 3.13 vs. 3.60). These results could signal that the explanations had a slightly higher impact among the participants when they are delivered in an embodied manner. On the other hand, users reported higher scores in Q2 ($p = 0.66$, 3.73 vs. 3.44) and Q3 ($p = 0.27$, 3.45 vs. 3.08). The frustration with the interaction measured by Q10 ($p = 0.12$, 2.18 vs. 2.76) and higher average for the robot supports our finding with the objective metrics. This indicates that either system was not perceived particularly more interesting than the other.

During our unstructured interviews, it became clear that the design of the state machine communication in the robot with tablet configuration may cause impatience for some participants. This aligned with the survey results for Q10 (Fig. 8) where 7 out of 25 participants gave a score of more than 3. The slower pace of interaction combined with occasional speech recognition issues made the session seem less fluent compared to the tablet-only configuration. It was observed that the simple nature of the tablet-only setup made it easy for users to provide feedback, which explains why engagement remained high. In addition, some participants struggled to engage with the system due to their varying levels of English, which may have impacted their ability to fully engage. These challenges highlight the need for more user-friendly communication strategies and better support for non-native speakers.

5 Conclusion and Future Work

This chapter investigated the effects of different communication mediums, a tablet-only interface, and a robot-enhanced setup on the user experience within a personalized food recommendation system. Differences were observed in the frequency of user engagement between the two setups, indicating that the choice of communication medium can significantly impact how actively users participate in interactions. Acceptance levels also varied across the setups, suggesting that communication medium influences users' willingness to adopt the system's recommendations. On the other hand, we looked at how users perceived the system's alignment with their preferences and needs, focusing on their satisfaction with the interaction. The robot-enhanced setup affected user satisfaction minimally. Satisfaction remained largely consistent across both setups, suggesting that physical embodiment alone did not significantly enhance users' contentment or sense of alignment with the system's functionality. These findings emphasize the importance of selecting suitable communication mediums to optimize user experience and perceived effectiveness in recommendation systems. Future designs may benefit from simplifying communication flows in embodied setups to minimize user impatience, enhancing response fluency, and implementing strategies that address language barriers. These improvements could further increase accessibility and engagement across diverse user backgrounds, supporting the development of more intuitive and responsive interactive systems.

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