Technical Literacy Adaption in Robots

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***Abstract*—Adaptive communication in social robots plays a vital role in improving user engagement and task performance, particularly when addressing diverse levels of technical literacy. This study explored the impact of tailoring robot communication to users' literacy levels. Participants were categorized into low, medium, and high literacy groups based on a pre-interaction questionnaire, and the robot's communication style was adapted accordingly, with simplified instructions and detailed guidance for low-literacy users. Experimental results demonstrated that adaptive communication significantly improved user satisfaction and minimized task completion time across all proficiency levels. These findings highlight the importance of adaptive communication in enabling robotic interactions for individual needs, offering valuable insights for designing inclusive and effective human-robot interaction strategies.**

I. INTRODUCTION

The integration of robots into everyday life presents new challenges, particularly in the area of user interaction. Social robots, in particular, require effective communication to fulfill their intended roles in domains such as healthcare, education, and entertainment. However, a significant obstacle to the widespread adoption of robots is the varying levels of user technical literacy. As the technical capabilities of robots grow, so too does the complexity of their interactions with humans. This disparity in user literacy can create barriers to effective communication, as users with different levels of technical proficiency may struggle to understand or engage with robots.

The importance of addressing user literacy in Human-Robot Interaction (HRI) is evident in prior research, which highlights how varying levels of technical understanding affect user engagement and task performance. For example, research has shown that individuals with low technical literacy may struggle with complex instructions or system interfaces, leading to disengagement and frustration [1]. In contrast, users with higher technical literacy might find overly simplistic guidance unhelpful and underwhelming, resulting in decreased engagement and inefficiency. Such challenges underscore the need for adaptive communication systems that can adjust to the user's technical proficiency, enhancing both user experience and task completion.

Existing approaches to HRI have explored adaptivity in communication, emphasizing its potential to improve user satisfaction and performance. However, most current systems focus on either simplifying or complicating interactions without recognizing the full spectrum of user literacy levels. Thus, the novelty of this research lies in its approach to categorizing users into high, medium, and low literacy levels, enabling robots to tailor their communication dynamically. This classification helps the robot adjust its interaction style, providing appropriate levels of detail and complexity based on the user's proficiency.

Furthermore, our study draws on established frameworks in Human-Computer Interaction (HCI) and HRI to ground our adaptive communication model in the existing literature. Research on socially intelligent robots has shown that effective communication is essential to build trust and user engagement, particularly in contexts where users may have limited technical background [9]. By tailoring interactions to suit the user's literacy level, we aim to enhance both the effectiveness and the perceived value of robot interactions, promoting greater acceptance and satisfaction among diverse user groups.

The contributions of this research are twofold. First, we introduce a novel model of adaptive communication based on technical literacy, which expands the current understanding of how robots can interact more effectively with users. Second, we provide empirical evidence of the positive impact of personalized communication on user satisfaction and task performance. These findings build on prior work that emphasizes the importance of adaptivity in robot-user interactions and provide new insights into how robots can be designed to meet the diverse needs of users [10].

This study seeks to answer the question: Does adapting a robot's responses based on a user's technical literacy scores improve user satisfaction and engagement in human-robot interactions? We propose a novel approach that combines established user assessment methods with adaptive communication techniques. We propose a novel method to measure technical literacy, refining traditional methods like the System Usability Scale (SUS) to better categorize users based on their proficiency levels. The robot responses are then tailored to these categories (high, medium, and low), providing personalized guidance that is more likely to engage users effectively. We investigate how this adaptive communication model impacts user satisfaction, engagement, and task comprehension, examining how personalized interactions enhance the overall user experience in human-robot interactions.

II. Related Work

Social robots have been effectively utilized as teaching tools across various sectors, including education, healthcare, and vocational training centers. In health care, robot-assisted learning can improve health literacy and learning motivation in elderly individuals. [5]. In educational settings, robotic programs are used to teach young students, focusing on increasing their technological literacy. [6] Robotics can also be used to teach technological literacy to non-engineering students, acting as a powerful tool for sparking interest in technology among people who may not have a technical background. [8]

During the teaching and learning process, one of the most crucial aspects to consider is the interaction between educational social robots and students. There are two key perspectives for making this interaction effective and seamless: the role of the robot and the role of the people involved. Ultimately, enhancing this interaction is the primary goal. The first perspective focuses on the robot's role in the interaction, examining whether the engagement is personalized or adaptive. Questions arise regarding how robots can modify their behavior to tailor learning experiences for individual students. Various case studies have demonstrated that robots can significantly enhance learning outcomes through personalized interactions [10].

In addition to educational contexts, it is essential to explore how robots interact with humans in socially acceptable ways. Research has investigated the development of ”robotiquette,” a set of social rules designed to ensure users feel comfortable while engaging with robots [9]. This consideration is vital not only for fostering positive interactions but also for building trust and rapport between students and educational robots, ultimately leading to more effective learning experiences.

The second perspective emphasizes the human side of the interaction. Effective communication involves more than just the robot's capabilities; it also requires human input. The concept of "robot literacy" a study highlights the necessity of educating users on how to coexist with robots, addressing both the opportunities and potential risks associated with everyday human-robot interactions. [1] Another study identified the skills needed for users to interact effectively with voice-based AI systems [11]. Similarly, individuals may require specific skills to engage meaningfully with social robots.

This study focuses on the first approach, emphasizing the importance of making robots more adaptive. Numerous studies have explored this concept; for instance,investigators examined how robots can adjust their interactions based on user responses, emotions, and past interactions across various applications [3], demonstrating that adaptive robots hold significant promise in multiple sectors. This study specifically targets social robots adapting to the technical literacy of users. It proposes a novel approach in which social robots assess the user's technical literacy level and tailor their responses and communication style accordingly. For instance, if a user has low technical literacy, the robot will avoid complex terminology and instead provide simpler, more detailed explanations to ensure comprehension. This tailored approach not only fosters better communication but also builds user confidence in interacting with technology.

This study aims to investigate whether taking a user's technical literacy into account improves the effectiveness of human-robot interactions. Through experimental design, we will assess interactions, comparing adaptive versus non-adaptive communication strategies. This will help determine if users with lower technical literacy benefit more from robots that adjust their responses to suit individual needs, ultimately providing insights into how adaptive interactions can enhance user engagement and learning outcomes in robotic applications.

One of the key tasks in our study is to assess the user's technical literacy level. Some researchers utilized a questionnaire as an evaluation tool for measuring technological literacy. [13] This study emphasizes the importance of question quality in terms of validity, reliability, and difficulty levels, as informed by the Rasch model. Similarly, we will employ questionnaires to assess the technical literacy of users. The process of framing question might involve considering what kind of experimental task we are using.

Additionally, Studies used structured approach which involves selecting appropriate tools, such as the Adapted Technology Acceptance Model (TAM) to gauge perceptions of technology's usefulness and ease of use, helping to identify individuals' comfort levels with various technologies. [15] Moreover, the Attitudes Toward Computer/Internet Questionnaire (ATC/IQ) is employed to explore user attitudes and skepticism regarding technology, effectively revealing potential barriers to effective usage. This insight is crucial for understanding how these attitudes may influence technology adoption and engagement. The Computer Proficiency Questionnaire (CPQ) and Mobile Device Proficiency Questionnaire (MDPQ) further complement this assessment by measuring specific skills in computer and mobile technology use, evaluating practical abilities that range from basic tasks to more advanced functions. By combining data from these questionnaires, we gain a comprehensive view of an individual's technical literacy.

III. Design and Implementation

A. Hardware

This study makes use of cutting-edge hardware and software to develop a smooth and flexible Human-Robot Interaction system. The prime hardware is the Spot robot by Boston Dynamics, selected for its mobility and anthropomorphic design. It is controlled wireless from a tablet. To deal with the large language model that generates the dialogue, a powerful GPU such as the NVIDIA GeForce RTX 4090 is required. The voice of the user is picked up through a microphone, while an external Bluetooth speaker emits generated responses. This combination of hardware ensures that the interactions are clear, responsive, and catered toward the user.

B. Software

The software system uses multiple tools to ensure smooth and dynamic Human-Robot Interaction. Python 3.12 forms the backbone of the custom scripts and control interfaces. To process speech input from users, OpenAI's Whisper model is utilized for real-time conversion from speech into text, allowing the system to dynamically comprehend user commands from speech input. In generating adaptive and intelligent responses, OpenAI's ChatGPT-4.0 is utilized, generating responses based on user input and technical literacy levels. To deliver these responses as speech, Google Text-to-Speech is used to synthesize the responses and return naturally sounding audio. Spot is controlled through a tablet which is equipped with proprietary software that ensures the accurate movements and task executions of the robot.

C. Implementation

The experiment setup was designed to make participants perceive Boston Dynamics' Spot robot as fully autonomous and capable of understanding and responding to human speech. To simulate speech, a Bluetooth speaker was placed on the robot, delivering verbal responses in a way that made it appear as though Spot itself was speaking. Instead of directly integrating a large language model (LLM) into Spot, the Wizard of Oz (WoZ) method was used to simulate these responses, with a researcher discreetly operating the system. The researcher triggered generated speech responses from OpenAI's ChatGPT-4.0, which were played through the external speaker, reinforcing the illusion of Spot's autonomy.

Speech responses were generated dynamically in real-time based on user interactions. A microphone captured the user's spoken input, which was processed using OpenAI's Whisper model to convert speech into text. This textual input was then fed into ChatGPT-4.0, which generated contextually appropriate replies tailored to the participant's level of technical literacy, which is in condition B. But, in condition A technical literacy levels are not used in generating responses from the LLM. The researcher managed this entire process from a computer running Python scripts, ensuring the system appeared seamless and responsive. The generated textual replies were further processed using Google Text-to-Speech (TTS) to produce audio output, which was then played through the Bluetooth speaker on Spot.

The participants were engaged in a series of carefully designed problem solving tasks in which Spot appeared to provide guidance and instructions. One of the more advanced tasks involved helping participants in setting up and using a Python development environment. The task required participants to download and install Anaconda IDE, a popular platform for data science and programming. Spot guided users through the process of downloading the correct version of Anaconda according to their operating system, installing it, and verifying the installation.

Once the IDE was set up, participants were instructed to create a new Python environment within Anaconda. Spot provided step-by-step guidance, which varied based on the participant's technical literacy level. For users with lower literacy levels, Spot's instructions were detailed, breaking down each step, such as navigating the interface. For user's with medium literacy level the instructions were designed to strike a balance between detail and conciseness, assuming some familiarity with basic programming but offering guidance where necessary, and for higher literacy levels the guidance was more concise and technical, assuming familiarity with programming concepts.

After setting up the Python environment, participants were tasked with installing Jupyter Notebook within the IDE. Once Jupyter Notebook was successfully launched, participants were asked to create a new notebook and write a simple Python script to add two numbers and display the result. Spot guided them through writing the script, running the cell, and interpreting the output.

The speech responses during this task were tailored to match the participant's technical literacy level. For example, participants with lower literacy levels received explicit step-by-step instructions and encouragement, while those with higher literacy levels were given brief, jargon-heavy directions to complete the task independently. This adaptive guidance ensured that all participants could complete the task at their own pace, enhancing personalization and making the system flexible for a diverse range of users.

The Wizard of Oz (WoZ) method was pivotal to this experiment, enabling the simulation of highly advanced capabilities without the need for complex integration of LLMs directly into Spot. While participants believed Spot was autonomously processing their inputs and generating its own speech responses, the reality was that a hidden researcher orchestrated the interaction. The placement of the Bluetooth speaker on Spot was crucial to this illusion, ensuring the audio appeared to be coming from the robot itself. The researcher actively managed the pipeline, converting user speech through Whisper, generating replies via ChatGPT-4.0, and delivering audio responses through Google TTS. This approach provided full control over the interactions, allowing the researcher to ensure consistency and alignment with the experimental objectives.

D. System Details

To reproduce this experiment, researchers will need Boston Dynamics Spot robot as the primary hardware component. A Bluetooth speaker should be mounted on Spot to deliver verbal responses, ensuring the illusion of the robot speaking. A computer running Python 3.12 is required for controlling the robot and managing the interaction pipeline. The system utilizes OpenAI's Whisper model for converting user speech into text, and ChatGPT-4.0 for generating contextually appropriate responses tailored to technical literacy levels, so we would need a GPU like NVIDIA GeForce RTX 4090. These responses are converted into audio using Google Text-to-Speech (TTS) and played through the Bluetooth speaker. A microphone is needed to capture participants' speech input, and Spot's native software on the tablet is used for task execution. The tasks should be set up in a controlled environment with a consistent experimental protocol, such as downloading and installing Anaconda IDE, creating a Python environment, installing Jupyter Notebook, and writing and executing a simple script.

IV. Evaluation

This study employed a between-subjects design to evaluate the impact of robotic adaptability based on user technical literacy. Two experimental conditions were established: in Condition A, the robot dynamically adapted its responses to align with the participant's assessed technical literacy level (categorized as low, medium, or high), while in Condition B, the robot provided standardized responses, disregarding the participant's technical literacy level.

To assess the participants' technical literacy, a set of 10 questions was prepared (which were related with the experimental task the users were about to perform). Based on their answers, participants were divided as low , medium and high technical literacy levels. Systematically we assigned participants to six distinct subgroups, representing combinations of technical literacy levels and interaction conditions: A1 (low technical literacy with adaptive robot interaction), A2 (medium technical literacy with adaptive robot interaction), A3 (high technical literacy with adaptive robot interaction), B1 (low technical literacy with non-adaptive robot interaction), B2 (medium technical literacy with non-adaptive robot interaction), and B3 (high technical literacy with non-adaptive robot interaction). Each subgroup consisted of two participants, totaling 12 participants per condition, ensuring balanced representation across technical literacy levels.

A. Task Details

Participants undertook a series of progressively challenging technical tasks designed to assess their ability to engage with and benefit from the robot's guidance. The tasks included:

1) Installing Anaconda: Participants initiated the experiment by downloading and installing the Anaconda software distribution. This task involved selecting the correct operating system version, navigating through the installer, and ensuring a successful setup of the platform.

2) Creating a Python Environment: Using the Anaconda Navigator interface, participants created a new Python environment. This step required familiarity with selecting appropriate options, such as specifying a Python version and managing dependencies. It tested participants' ability to configure a development environment.

3) Launching and Using Jupyter Notebook: Participants were guided to open Jupyter Notebook via Anaconda Navigator. They created a new notebook file and set up a workspace for coding. This phase evaluated participants' proficiency in navigating the interface and preparing for computational tasks.

4) Performing a Basic Computation: Participants executed a simple arithmetic operation (e.g., 1+1) within the Jupyter Notebook. This task ensured participants could write and run code, marking the completion of the experimental workflow.

For Condition A, the robot tailored its instructions based on the participant's technical literacy. For low-literacy participants, the robot broke down steps with detailed explanations, while high-literacy participants received concise guidance. In Condition B, the robot provided uniform instructions irrespective of literacy level.

B. Measures

Data collection included both quantitative and qualitative measures.

1) Quantitative Measures: obtained through measurement during the experiment which involves Task Completion Time: Total time taken to complete the assigned tasks in minutes. And Number of Failures: Instances of incorrect task execution or failure to follow instructions.

2) Qualitative Measures: obtained from post experiment survey which involves User Satisfaction: Likert scale responses to statements such as "I think that I would like to use this system frequently." Perceived Ease of Use: Participant agreement with statements like "I thought the system was easy to use." Confidence: Self-reported confidence in using the system, e.g., "I felt very confident using the system." Engagement: Evaluated through questions such as "The interaction between me and the robot was really good." Open-Ended Feedback: Participants provided insights into what they liked or disliked about the system and suggested improvements.

C. Participant

The study involved 12 participants, balanced across conditions and technical literacy levels. Gender representation included 4 female participants and 8 male participants.(shown in figure 2)

Fig. 1. Participant interacting with the robot

The technical literacy levels were balanced with 4 participants in each category: low literacy (2 in A1, 2 in B1), medium literacy (2 in A2, 2 in B2), and high literacy (2 in A3, 2 in B3). This demographic balance ensured the robustness of statistical analysis and the interpretation of results.

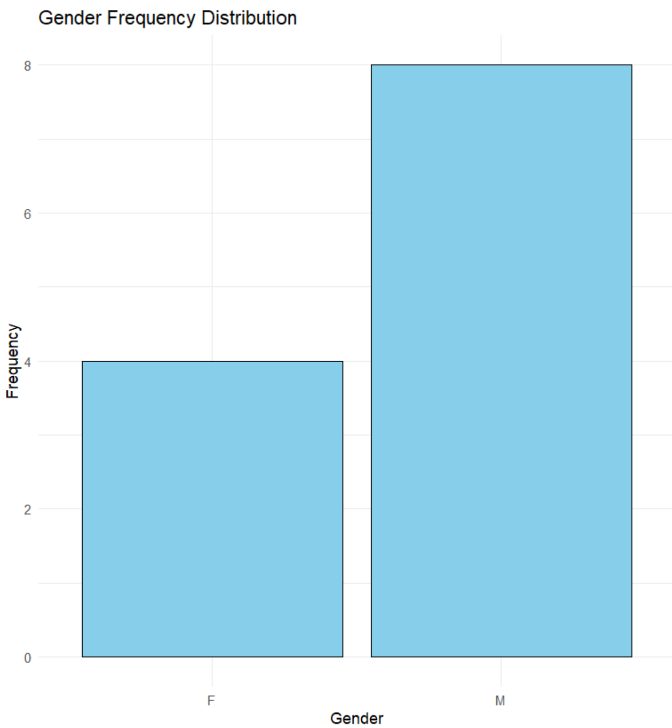

Fig. 2. Gender frequency distribution

V. Results

We aimed to explore the effects of adaptive communication by robots, tailored to users' technical literacy levels, on three key factors: task completion time, user satisfaction, and user engagement. Our hypotheses were based on the expectation that users would take less time on a technical task when the robot's responses match their technical literacy level. Additionally, we anticipated that both high and low technical literacy users would report higher satisfaction when communication was aligned with their literacy level. Furthermore, we also hoped that adaptive communication would lead to greater user engagement, increased interaction time, and an overall improvement in human-robot interaction (HRI).

In addition to these factors, we wanted to assess whether differences in technical literacy levels (low, medium, high) would impact task completion time, user satisfaction, and user engagement.

To test these hypotheses, we conducted a two-way analysis of variance (ANOVA) to examine the effects of two main factors: the adaptive condition (adaptive vs. non-adaptive communication) and technical literacy levels (low, medium, high). The analysis focused on three key metrics: task completion time, user satisfaction, and user engagement.

A. Completion time

We conducted a two-way analysis of variance (ANOVA) to examine the effects of two factors on task completion time: the adaptive condition (adaptive vs. non-adaptive) and technical literacy levels (low, medium, high). The results revealed a significant main effect of the adaptive condition on task completion time, F(1, 6) = 103.26, p = 5.29e-05 (p ¡ 0.001). This indicates that the way the robot adapts its responses significantly impacts task completion time, with participants in the adaptive condition likely performing tasks faster than those in the non-adaptive condition. The illustration is explained in the box plot. (Fig 3)

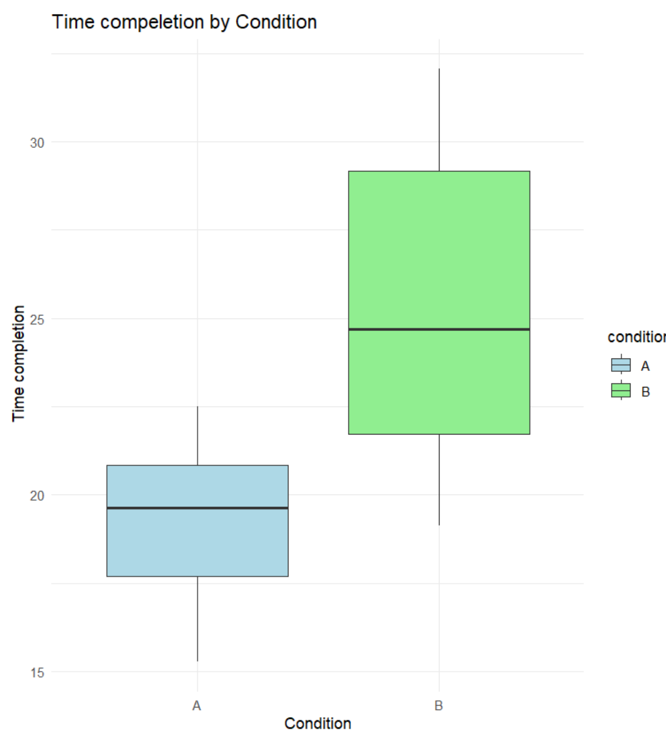

Fig. 3. Time completion across conditions

Additionally, there was a significant main effect of literacy level on task completion time, F(4, 6) = 37.06, p = 0.000229 (p ¡ 0.001). This suggests that task completion time varies significantly across different literacy levels, with users of higher technical literacy likely completing tasks more quickly than those with lower literacy levels.The illustration is explained in the box plot. (Fig 4)

B. User satisfaction

The second test We conducted is a two-way analysis of variance (ANOVA) to examine whether user satisfaction differs between adaptive and non-adaptive conditions and whether it is influenced by different technical literacy levels. The results revealed a significant main effect of adaptation condition (adaptive vs. non-adaptive) on user satisfaction, F(1, 6) = 17.29, p = 0.006 (p ¡ 0.05). The illustration is explained in the box plot. (Fig 5) On the other hand, user satisfaction was not significantly affected across different technical literacy levels, F(4, 6) = 2.00, p = 0.214. This indicates that user satisfaction is influenced by the adaptation condition but does not depend on the technical literacy level. The illustration is explained in the box plot. (Fig 6)

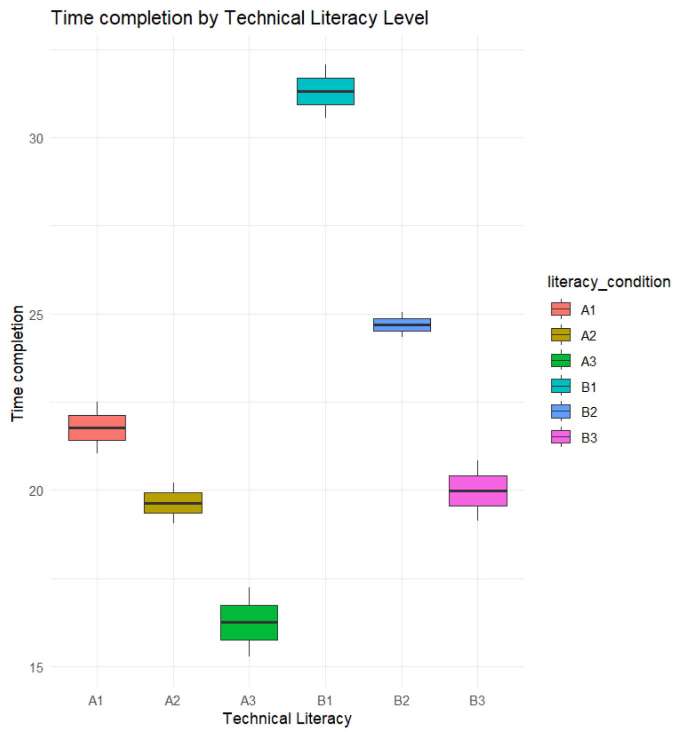

Fig. 4. Time completion across technical literacy levels

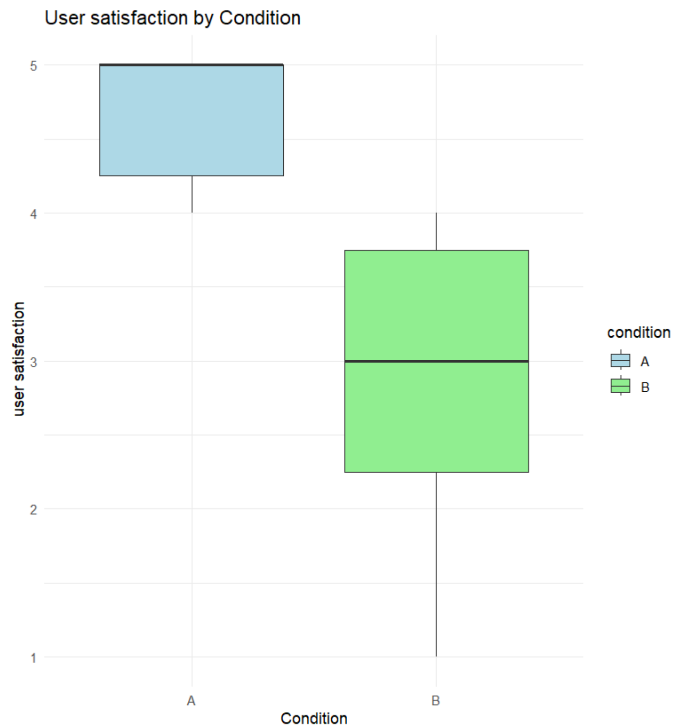

Fig. 5. User Satisfaction across conditions

C. User Engagement

Lastly, We conducted a two-way analysis of variance (ANOVA) to examine the effects of the adaptive condition (adaptive vs. non-adaptive) and technical literacy levels (low, medium, high) on user engagement. The results revealed a marginal main effect of the adaptive condition on user engagement, F(1, 6) = 4.455, p = 0.079 (p ¡ 0.1). This suggests that the adaptive condition might influence user engagement, though the effect is not statistically significant at the conventional threshold (p ¡ 0.05). The illustration is explained in the box plot. (Fig 7) On the other hand, there was no significant main effect of literacy level on user engagement, F(4, 6) = 1.818, p = 0.244 (p ¿ 0.05). This indicates that user engagement does not vary significantly across different technical literacy levels.The illustration is explained in the box plot. (Fig 8)

VI. Discussion

The results show that adaptive communication can improve task completion time and user satisfaction. Specifically, robots that adjust their communication based on the user's technical literacy level appear to enable users to perform tasks more efficiently and be more satisfied with the interaction. The finding that technical literacy levels significantly impact task performance indicates that tasks should be adapted to the user's ability to ensure optimal engagement and efficiency. This suggests that, in real-world applications, robot systems should be designed to dynamically adjust to the user's literacy level for improved interaction outcomes.

On the other hand, the robot's adaptive nature did not necessarily achieve significant improvements in user engagement. Although there was a marginal effect suggesting a possible influence of the adaptive condition, the majority of participants did not report a substantial difference in engagement levels between the adaptive and non-adaptive conditions. Many participants described the robot as ”friendly,” and appreciated the way the system explained each task. Additionally, the robot's physical appearance, including features like its paw, seemed to capture the participants' attention and add an element of excitement to the interaction. However, despite these positive experiences, the adaptive nature of the robot did not necessarily alter the overall engagement level.

There are limitations in this study that should be acknowledged. First, the sample size was relatively small (12 participants per condition), which may have limited the statistical power to detect smaller effects, particularly in user engagement. Another limitation is the lack of diversity in the tasks. While the tasks chosen were relevant for assessing technical literacy, they may not have fully captured the range of user engagement or satisfaction in real-world applications. The tasks were also relatively short and may not have provided enough opportunity for participants to engage deeply with the robot.

Furthermore, the method used to assess technical literacy level—based on only 10 questions related to the task—could be improved. This approach may not fully capture the breadth of an individual's technical knowledge, and a more comprehensive assessment might lead to more accurate grouping and a

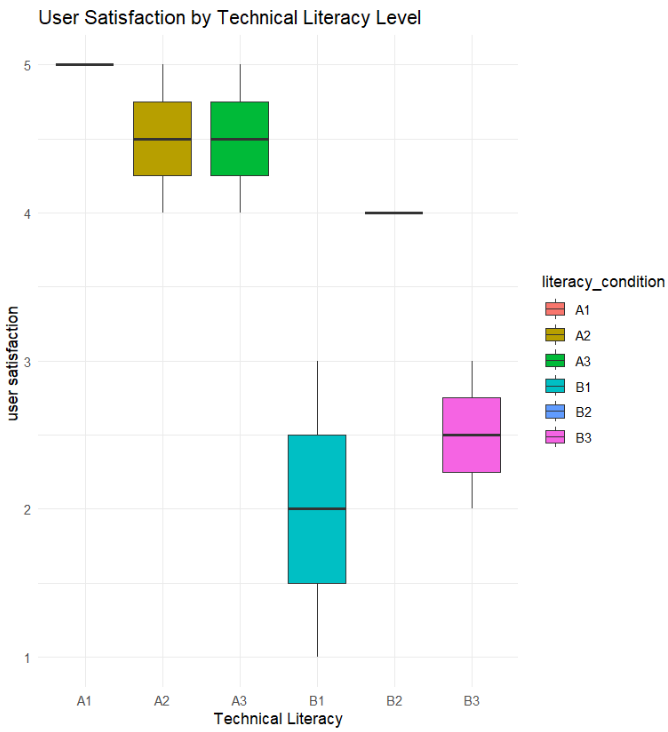

Fig. 6. User Satisfaction across technical literacy levels

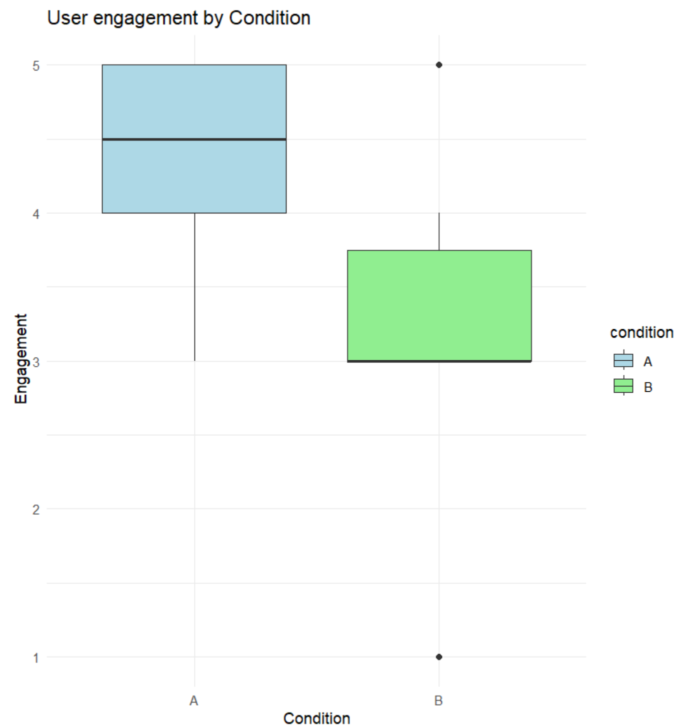

Fig. 7. User Engagement across conditions

better understanding of how different levels of literacy impact the results. Additionally, the robot's response time was slow at times, which may have affected the overall user experience, particularly for participants in the adaptive condition who were waiting for tailored responses. Improving the response time would likely enhance the interaction and overall engagement in future studies.

Future research could explore the long-term effects of adaptive robot communication on user engagement and satisfaction. It could also investigate other adaptive communication factors, such as voice tone or emotional cues, and their interaction with technical literacy levels. Additionally, examining user motivation and increasing the diversity of participants would help further understand how adaptive communication can benefit different user groups in human-robot interactions.

VII. CONCLUSION

In conclusion, our study highlights the potential for adaptive robots to meet the needs of users with varying levels of technical literacy, by providing customized guidance that enhances learning and interaction outcomes. Through an experimental design, we evaluated the effectiveness of adaptive communication and demonstrated their capacity to improve user experiences in robotic applications.

By comparing adaptive and non-adaptive conditions, the study revealed that adaptive communication significantly enhances task performance and user satisfaction, primarily by tailoring responses to align with users' technical literacy levels. Participants in the adaptive condition completed tasks more efficiently and reported greater satisfaction compared to those in the non-adaptive condition. These findings underscore the importance of personalized interactions in enhancing engagement and learning outcomes, emphasizing the critical role of tailoring robotic systems to meet individual user needs effectively.

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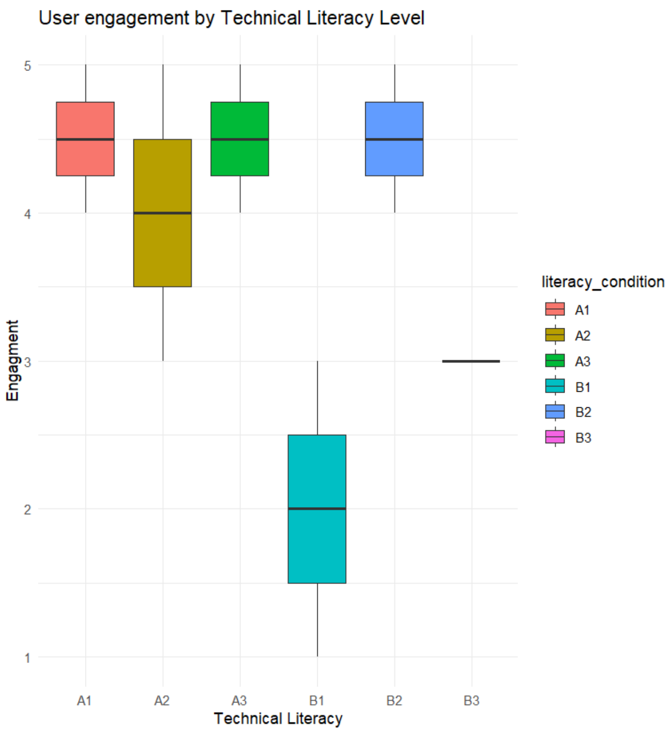

Fig. 8. User Engagement across technical literacy levels

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