Assessing the Decision-Making Process in Human-Robot Collaboration Using a Lego-like EEG Headset

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Abstract

Human-robot collaboration (HRC) has become an emerging field, where the use of a robotic agent has been shifted from a supportive machine to a decision-making collaborator. A variety of factors can influence the effectiveness of decision-making processes during HRC, including the system-related (e.g., robot capability) and human-related (e.g., individual knowledgeability) factors. As a variety of contextual factors can significantly impact the human-robot decision-making process in collaborative contexts, the present study adopts a Lego-like EEG headset to collect and examine human brain activities and utilizes multiple questionnaires to evaluate participants' cognitive perceptions toward the robot. A user study was conducted where two levels of robot capabilities (high vs. low) were manipulated to provide system recommendations. The participants were also identified into two groups based on their computational thinking (CT) ability. The EEG results revealed that different levels of CT abilities trigger different brainwaves, and the participants' trust calibration of the robot also varies the resultant brain activities.

Keywords: Human-robot interaction, Electroencephalogram (EEG), Decision-making, Team collaboration, Computational-thinking ability

1. Introduction

Human-robot collaboration (HRC) has become increasingly popular and influential in recent decades. With the advanced services supported by robots, numerous emerging HRC applications have been developed that encourage humans and robots to work together to achieve common goals. HRC-related tasks are widely deployed in various fields, from conventional assembly line robots to innovative educational robot tutors (Hsu et al., 2022). Given the ever-increasing complexity of task contexts, the use of a robotic agent has been drastically increased, and its character has shifted from a supportive tool to a decision-making collaborator to enhance the communication and facilitate the interaction between humans and robots in collaborative contexts. To satisfy numerous real-world situations, various robotic applications are developed to provide assistance and to support humans in our everyday life. However, despite the best design efforts, the developed robotic agents may not work perfectly under various kinds of HRC conditions. HRC often involves complex contexts and consists of numerous components; as a result, providing perfectly reliable human-robot systems is infeasible in reality. Therefore, it is essential to examine how imperfect automation affects decision-making processes during HRC. Recent research explores the influence of a robot's characteristics (such as level of autonomy and capability) on HRC and examines how these elements may affect human-robot decision-making in collaborative contexts. The results show that a robot with high autonomy has a greater influence on human decisions (Rau, Li, & Liu, 2013); however, the robot errors also significantly impact trust intentions and the consequent interactive behaviors (Nesset, Robb, Lopes, & Hastie, 2021). With regard to enhancing HRC, instead of focusing on developing advanced algorithms to support so-called perfect autonomy, it is critical to investigate the influence of robot capability on HRC in decision-making contexts.

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As the robotic technology is not advanced enough to satisfy all types of real-world situations, a successful HRC occurs when the humans and robots adapt to each other and reach a mutual understanding of the shared goals. During the collaborative processes, humans may reject recommendations from a robot when it would be advantageous or accept suggestions when inappropriate. Prior research devotes considerable endeavors to investigate the influence of robot autonomy in the resultant technology acceptance and task outcomes during HRC. The results reveal that a highly autonomous robot can contribute to better performance in human decision-making than a robot with low autonomy (Rau et al., 2013), and participants achieve better trust calibration when collaborating with a robot with sufficient capability (Schaefer, Chen, Szalma, & Hancock, 2016). However, a recent study (Złotowski, Yogeeswaran, & Bartneck, 2017) shows that the exposure to autonomous robots evokes a negative attitude toward robots than non-autonomous agents. Therefore, to understand different perceptions and examine potential conflicting findings of HRC, in addition to the external factor (i.e., robot capability), close attention should be paid to evaluating the differences of the internal factor (e.g., an individual's knowledgeability). For instance, prior research suggests an individual's previous experience in robotics affects not only trust intention in specific contexts but also overall attitudes toward robots (Sanders et al., 2017). This indicates that individual differences in HRC can have major influences on the resulting human-robot decision-making processes in a given task. However, most of the current work regarding individual differences focuses mainly on the manipulations of system transparency or robot personality (Barnes, Chen, Jentsch, & Redden, 2011; Esterwood, Essenmacher, Yang, Zeng, & Robert, 2021; Matthews, Lin, Panganiban, & Long, 2020). An individual's background (such as knowledgeability or expertise) is rarely discussed, and its potential influences on HRC remain unknown.

The goal of the present study is to explore the impacts of the differences in an individual's knowledge levels and a robot's recommendation qualities on HRC. The research questions and the associated hypotheses are listed as follows:

(a) Do an individual's knowledge levels affect her reliance on robot suggestions?

H1: Individuals with high knowledge levels tend to rely more on their own judgments rather than to rely on robot suggestions.

(b) Do a robot's capabilities affect user acceptance of the provided aids?

H2: Users tend to accept more robot suggestions in high capability conditions than the low capability conditions.

To examine the research questions and validate the hypotheses, this study develops a robotic agent that provides decision aids to support human decision-making processes. In this preliminary report, six participants were recruited for the empirical studies. The experimental tasks were adopted from the Bebras computing challenge, which asked participants to perform computational thinking related questions. During the processes, a participant and a robot formed a team to approach the tasks and reach final decisions. As the experimental tasks were related to problem-solving skills, the participants were divided into two groups based on their computational thinking ability test scores. In addition, two levels of robot capabilities (i.e., high vs. low) were used in the experiments to collaborate with the participants. Multiple surveys were adopted to examine the cognitive perceptions toward the robot assistant. A Lego-like EEG headset was used to collect human brain activities during HRC. Compared to the traditional analytical methods (e.g., qualitative interviews or quantitative questionnaires), the EEG device is capable of offering neurophysiological evidence to examine a participant's brainwaves during decision-making. Integrating the EEG headset and questionnaires allows us to measure the real-time brain activities, explore the resultant feedback, and identify the relationship between the brainwaves, decision-making processes, and task outcomes. The present study can serve as an innovative research framework that integrates qualitative, quantitative, and neurophysiological mechanisms to examine the effectiveness of HRC and provides a more comprehensive understanding of human-robot decision-making processes in collaborative contexts.

2. Related Works

2.1. Human-Robot Collaboration (HRC)

HRC consists of a variety of complex designs and involves complicated interaction schemes to satisfy numerous real-world conditions. To overcome the rapid growth in task complexity, advanced robotic systems have been developed to adapt flexible human-robot team structures in order to facilitate HRC across various complex situations. An intelligent robotic agent requires intricate designs involving interdisciplinary knowledge to enhance the effectiveness of HRC as well as task outcome. As current robotic technology is not advanced enough to satisfy all types of real-world situations, how human operators interact with (imperfect) robotic agents in various complicated conditions has become an important issue (Chien, Lewis, Mehrotra, & Sycara, 2013; Lewis, Sycara, & Walker, 2018; Mercado et al., 2016; Sheridan, 2020). For example, misunderstanding the robot's capability may cause users to over-trust in robotic aids (Chien, Mehrotra, Brooks, Lewis, & Sycara, 2012) or under-trust the recommendations (Chien, Lewis, Sycara, Kumru, & Liu, 2020), leading to unexpected outcomes during HRC.

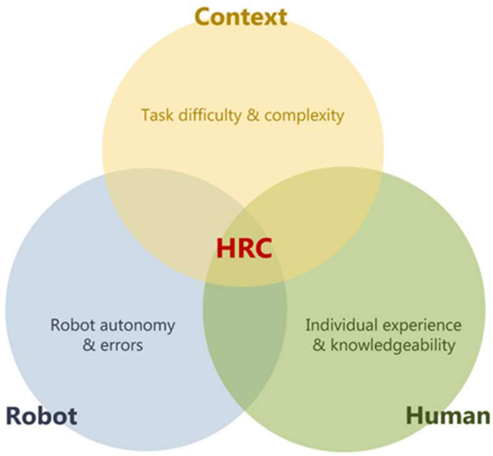

Figure 1. HRC involves multiple fields, robot-related, human-related, and context-related fields.

HRC raises many research opportunities and the collaborative processes across multiple fields (figure 1), including human-related dimensions, such as individual experience and knowledgeability, robot-related aspects, such as robot autonomy and robot errors, and context-related elements, such as task difficulty and complexity. For instance, a robot with low capability will increase the task difficulty and result in a heavy workload, where the increased workload contributes to a high possibility of over-trusting the automated aids (McBride, Rogers, & Fisk, 2011; Wang, Jamieson, & Hollands, 2011). To study the complex dependent and independent variables in HRC, it is necessary to take the interdisciplinary point of view to systematically examine the factors that influence user intention and the consequent behaviors with a robotic agent. However, the majority of HRC research focuses mainly on the manipulations of system-related factors (such as system reliability or level of autonomy) and applies traditional approaches (such as questionnaires or interviews) to measure users' perceptions. These conventional methods only present little information regarding users' underlying cognitive strategies and may fail to reflect how the users perceive or respond to the events. Therefore, to support a comprehensive overview, a holistic approach that adopts measures from different disciplines to examine the data is necessary.

2.2. Electroencephalogram (EEG)

Computational thinking involves many complex cognitive processes, including the perception of the current situation, the emotional state at the moment of decision making, the influence of past experiences and knowledge, and so on. In previous decision-making studies, the multi-criteria method (e.g., AHP, ANP) is commonly used to collect experimental data. However, this method requires participants to compare many relevant factors, easily making participants feel fatigued and inaccurate experimental data (Piwowarski, Singh, & Nermend, 2020). To address this issue, EEG-based assessments were adopted by (Ahmed, Walid, & Islam, 2020) to measure the mental load under the CT learning environment. More specifically, Ahmed's study implements MATLAB GUI to immediately calculate the theta/beta ratio to differentiate the level of mental load usage of CT and non-CT groups in real-time. Therefore, in the current study, we used electroencephalography (EEG) to collect brain signals from the participants in the experiment.

2.2.1. Neuroscience research method

The commonly used research methods in the field of neuroscience can be divided into two types according to the type of signals collected: electrophysiological signals and hemodynamics. The most common type of electrophysiological signal is the electroencephalogram (EEG), which collects signals from tiny electrical currents transmitted in the brain, and is characterized by a minimum time unit of milliseconds of data accuracy. The drawback is that the measurement process may collect noise such as myofilament signals, which must be further filtered out during the subsequent data processing.

The types of hemodynamics are functional Magnetic Resonance Imaging (fMRI) and functional Near-Infrared Spectroscopy (fNIRS). Because blood is paramagnetic when it is hypoxic and antimagnetic when it is oxygenated, fMRI detects the "BOLD Signal" in the brain by observing the BOLD signal. It features a high spatial resolution, but the temporal resolution is not as precise as that of EEG, which is accurate down to milliseconds. In addition to fMRI, fNIRS also collects signals by monitoring changes in blood oxygen concentration in the brain. However, unlike fMRI, fNIRS does not observe magnetic changes caused by blood oxygen concentration, but rather determines changes in brain activity through the different absorption rates of near-infrared light by oxyhemoglobin and deoxyhemoglobin in brain tissue (Scarapicchia, Brown, Mayo, & Gawryluk, 2017).

Among the three neuroscience research methods, EEG, which has a higher temporal resolution than fMRI and fNIRS (EEG: < 1 msec; fMRI & fNIRS > 1sec) that is able to respond the brain activity in real-time, is more suitable for the HRC situation in this study, so EEG was chosen to collect participants' physiological signals.

2.2.2. Decision-making-related brain regions

Decision-making includes many complex cognitive processes, such as the current situation, the emotion at the decision-making moment, the influence of experience and knowledge, and so on. In this study, the participant's brainwave signals were collected by an EEG headset to observe the cognitive decision-making process during the experiment. Human decision-making is influenced by emotional state, memory, and reward systems, with associated brain regions concentrated in the Prefrontal Cortex (PFC) and the following brain regions: dorsolateral Prefrontal Cortex (dlPFC), Ventromedial Prefrontal Cortex (vmPFC), Dorsomedial Prefrontal Cortex (dmPFC), Orbital Frontal Cortex (OFC), Right Temporo-Parietal Junction (rTPJ).

Looking back at studies on individual decision-making behavior, Li et al. (2021) studied the activation of the decision-maker motivational system (BAS & BIS) when managerial level decision makers perform exploratory decision-making and found that the dlPFC was more active when low motivation subjects performed exploratory decision making than when they maintained exploitation tasks. The findings suggest that the dlPFC brain region is activated when people make more creative decisions, while the vmPFC, vlPFC, and vlPFC, on the other hand, are relatively more active when working in their current state.

For the study of social decision-making, Bitsch et al. explored its link to the rTPJ and found that the rTPJ tends to show higher neural responses when interacting with a noncooperative person, which provides an indicator of identifying improper behavior in human cooperation (Bitsch, Berger, Nagels, Falkenberg, & Straube, 2018). This study would like to observe whether the finding can legitimately apply to Human-Robot interaction.

From the above studies, it is known that PFC is considered the brain region related to the general decision-making behavior, and rTPJ is the brain area related to social decision-making. Therefore, this study collects EEG signals in the Prefrontal Cortex and Temporo-Parietal Junction areas.

3. Methodology

To study the relationship between an individual's knowledgeability and a robot's capability in decision-making during HRC, we developed a platform that encouraged participants to collaborate with the robotic agent during the experimental sessions. The experimental tasks were adopted from the Bebras computing challenge (www.bebraschallenge.org) that focuses on computational thinking and problem-solving skills. Multiple surveys were used to examine participants' cognitive perceptions. An EEG headset was applied to measure the changes in participants' brain activities during HRC.

3.1. Apparatus

A website was developed for conducting the experiments (figure 2), where the participant was asked to collaborate with the robotic agent (figure 3) to perform the experimental tasks. A robot assistant was used on the website to provide recommendations to the participant. Two levels of robot capabilities (high vs. low) were manipulated to examine how the aid quality influenced the participant's decision-making and the resultant technology acceptance. Based on the task difficulty in our experiments, the robot with high capability was capable of answering more complex questions than the low capability robot. This manipulation is close to the actual situation, where humans generally encounter more difficulties in responding to challenging tasks than simple ones.

3.2. Experimental Tasks: The Bebras Computing Challenge

For the experimental tasks, we adopted the questions from the International Challenge on Informatics and Computational Thinking, known as the Bebras computing challenge. The Bebras computing challenge aims to enhance students' computational thinking (CT) abilities. The materials focus on introducing informatics concepts as well as promoting problem-solving skills, including the ability of abstraction, algorithm thinking, decomposition, pattern recognition, and generalization. The questions are described in concise but comprehensive formats, which encourage participants to focus on practicing computational and logical thinking. A total of 18 experimental questions were retrieved from the Bebras computing challenge in 2014 and 2015. By referring to the correct rate of each question in the Bebras computing challenge, the retrieved questions came with two difficulty levels (easy vs. hard). The easy questions are those with the correct rate higher than 50%, whereas the hard questions have the correct rate lower than 50%.

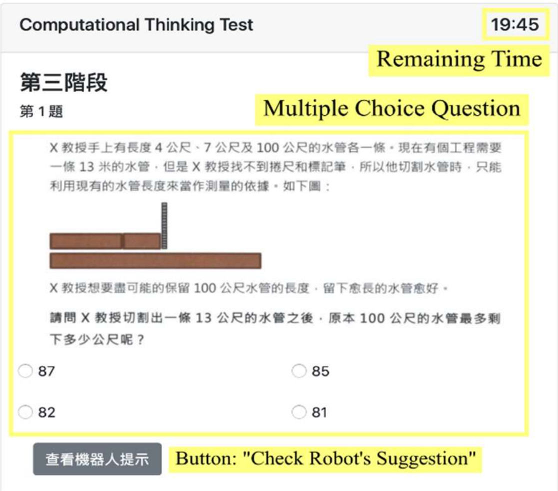

Figure 2. The developed website for the experiments.

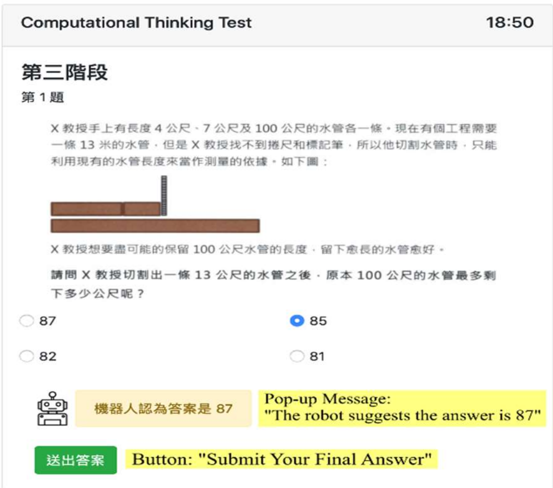

Figure 3. The developed website, after the user submitting the initial response, the robotic agent provides the associated recommendation.

Chatbots have been suggested to effectively interact with humans and support guidance during collaboration (Ischen, Araujo, Voorveld, van Noort, & Smit, 2020; Zarouali, Van Den Broeck, Walrave, & Poels, 2018). Therefore, the chatbot-based robotic agent is adopted in our experiment, where two types of robot capabilities were used. The robotic agent with high capabilities was able to conquer all the easy questions but encountered some challenges in processing the hard questions (i.e., providing accurate suggestions to all easy questions; for the hard questions, if the correct rate of the question in the Bebras computing challenge is lower than 30%, incorrect suggestions were provided in our study). With regard to the robot with low capabilities, more errors were observed in this group, where the robot was unable to process hard questions and had certain difficulties in resolving the easy questions (i.e., providing incorrect suggestions to all hard questions; for the easy questions, if the correct rate of the question in the Bebras computing challenge is lower than 60%, incorrect suggestions were provided in our study). Additionally, in this preliminary study, the wrong suggestions were assigned and delivered in a fixed order.

3.3. EEG

In this study, an EEG headset was used to collect the participant's brainwave patterns which allowed us to investigate the cognitive activities during the experiments. Eight electrodes were used in this study to measure a participant's emotional state, memory, and reward systems in decision-making processes. Six electrodes (Fp1, Fpz, Fp2, F3, Fz, and F4) were placed in the frontal cortex to capture cognitive-related brain activities (figure 4). The other two electrodes (CP5 and CP6) were used to collect information regarding the visual and somatosensory systems from the temporal-parietal junction.

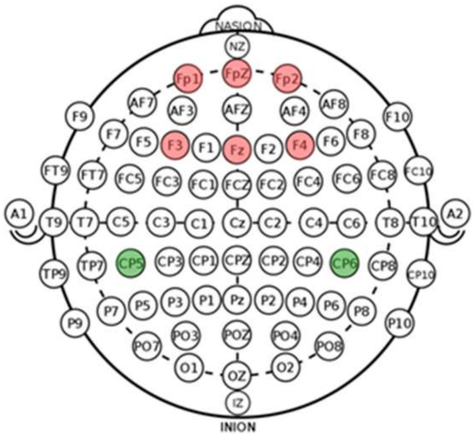

Figure 4. EEG electrode map.

Figure 5. The participant with the EEG headset.

The participants' brainwaves were collected and digitized at a sampling rate of 250Hz through the Lego-like EEG headset (figure 5). The Lego-like EEG headset is a cost-efficient system that allows us to appropriately allocate the electrodes to the needed locations to measure the associated brainwaves (Chuang & Lin, 2019; Lin, Chen, & Chen, 2019). Previous neuroscience research indicates that when the brain is aroused and vigorously engages in mental activities, it generates beta waves with low amplitude and high frequency. As beta waves can represent the arousal state and involve conscious thought (Abhang, Gawali, & Mehrotra, 2016), it was therefore measured in our user studies to examine the logical thinking related signals. The beta waves can be identified into three frequency bands by using Fourier Transform, where different amounts of waves are associated with distinct cognitive activities (table 1). Additionally, compared to the beta signal, the alpha wave has a slower frequency and higher amplitude, which represents the non-arousal state (e.g., a participant is taking a rest after completing a task).

Table 1. Characteristics of brainwaves.

Brain Wave Type	Frequency	Activities
Alpha	8~12 Hz	Relax and recharging
Low beta	12~15 Hz	Quiet, focused, and introverted concentration
Mid-range beta	15~20 Hz	Increases in energy, anxiety, and performance
High beta	18~40 Hz	Stress, anxiety, paranoia, and high arousal

The Bebras computing challenge helps students develop computational thinking abilities, which focuses on the learners' logical thinking and problem-solving skills across various learning states. These processes require participants to constantly maintain the beta states to tackle the questions. Therefore, to recognize participants' cognitive states and brain activities, our study measured two α and β brainwaves that are significantly associated with a human's consciousness and cognitive processes.

3.3. Cognitive Measurements

In addition to the EEG measures, to evaluate the cognitive effects of different experimental conditions, multiple questionnaires were adopted to capture the participants' attitudes and perceptions towards the tasks and robotic agent during HRC. The negative attitudes toward robots scale (NARS; Nomura, Suzuki, Kanda, & Kato, 2006) which includes three dimensions (negative attitudes toward situations of interaction with robots, negative attitudes toward the social influence of robots, and negative attitudes toward emotions in interaction with robots) was adopted to measure negative attitudes toward robots (e.g., I feel that if I depend on robots too much, something bad might happen). The robotic social attributes scale (RoSAS; Carpinella, Wyman, Perez, & Stroessner, 2017) was used to identify participants' judgments of the social attributes of robots regarding the dimensions of warmth, competence, and discomfort (e.g., Using the scale provided, how closely are the words below associated with the category robots?). The NASA-TLX survey (Hart & Staveland, 1988) was applied to assess participants' perceived workload during the experimental tasks, which includes six constructs, mental demand, physical demand, temporal demand, performance, effort, and frustration (e.g., How hard did you have to work to accomplish your level of performance?).

3.4. Participants and Procedures

The experiment followed a within-group design. Six student participants were recruited from the university community balanced among conditions for gender (avg. age=21.67). None had prior experience with robot control, although most were frequent computer users. The experiments were conducted in a usability lab that created a quiet atmosphere for the experiment. Additionally, earplugs were provided to the participants to minimize any unforeseen environmental noise that might affect the EEG signals. Participants took a pretest (approximately 20 minutes) to examine their level of CT ability, in which three easy and three hard questions from the Bebras computing challenge were included in this phase. After completing the pretest, the participants were divided evenly into two groups (high CT vs. low CT) based on their test scores. The participants then began the first 20-minute experimental session in which a participant and a robotic agent formed a team for the computational thinking tasks (another six questions). Participants were informed that the robot recommendations were fairly but not perfectly reliable (i.e., imperfect automation). For the experimental scenario, the participant needed to perform a series of calculations and select an answer from the multiple-choice question (figure 2). After submitting the initial response, the robot teammate was present and provided its recommendation to the participant (figure 3). After comparing the initial response and robot recommendation, the participant could either remain or change the former decision and submit the final decision. At the conclusion of the session, participants completed the NASA-TLX workload survey (Hart & Staveland, 1988), negative attitudes toward robots scale (Nomura et al., 2006), and robotic social attributes scale (Carpinella et al., 2017) to measure the perceived task load and human intentions toward the robotic agent. To avoid language issues, Chinese versions of the instruments were also used in our study. After a brief break, the other task load condition was run, accompanied by repeated questionnaires (figure 6).

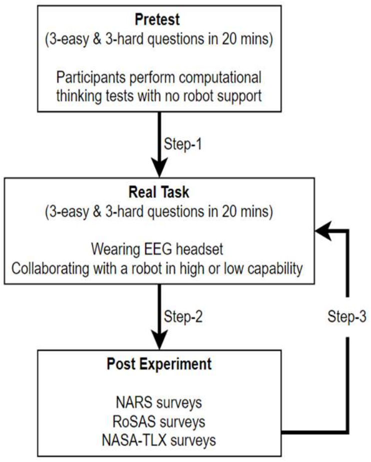

Figure 6. Experiment procedure.

4. Results

Six participants were recruited for the present study. As the preliminary analysis included small sample size, we therefore provided the descriptive statistical results (i.e., mean values) to reveal the potential effects among the experimental conditions. The participants' performance was calculated based on the Bebras scoring system (table 2). For example, in a hard question, a correct answer is worth 12 points, whereas an incorrect answer is negative 4 points. Given the difficulty of our experimental tasks (three easy and three hard questions in each phase), the score range was from -18 to 54 points.

Table 2. Bebras scoring system.

	Correct answer	**Incorrect** answer
Easy question	+6 points	-2 points
Hard question	+12 points	-4 points

The pretest CT score was used to identify the participants into two groups (high vs. low CT ability), where the average score of the high CT group was 16.67 and 6.00 for the low CT group. For the real tasks, the high CT group outperformed the low CT group regardless of the robot capability (table 3). As expected, the results revealed that the robot with low capability significantly decreased the task performance. This was especially prominent for the high CT group, as the participants over-trusted the robot recommendations and reached suboptimal task outcomes (i.e., from 16.67 to 6.00 points).

Table 3. Real task test scores before and after consulting robot's recommendations.

	High robot capability		**Low** robot capability	
	Initial answer	Final answer	Initial answer	Final answer
High CT group	24.67 points	27.33 points	16.67 points	6.00 points
Low CT group	10.00 points	12.67 points	-2.00 points	-2.00 points

The survey result of RoSAS (table 4) showed the participants were able to identify the difference of robot capability. The high capability robot received higher ratings than the low ability agent, regardless of the CT conditions. In addition, while collaborating with a low capability robot, the perceived workload was slightly increased compared to the high capability group

Table 4. Survey results.

	NARS (range: 14~70)		RoSAS- Competence (range: 9~54)		NASA-TLX (range: 0~100)	
	High capability	**Low** capability	**High** capability	**Low** capability	**High** capability	**Low** capability
High CT	35.00	34.00	47.33	42.67	68.11	70.00
Low CT	30.33	33.33	36.67	31.33	69.00	69.67

To examine the decision-making process (figure 7), we divided the collected EEG data into three phases (each within a 5-second time interval). Based on the human-robot interactive events, phase-1 represented the brain activities right before submitting the initial answer; phase-2 characterized the perceptions right after receiving the robot recommendation; phase-3 revealed the brain waves before submitting the final answer.

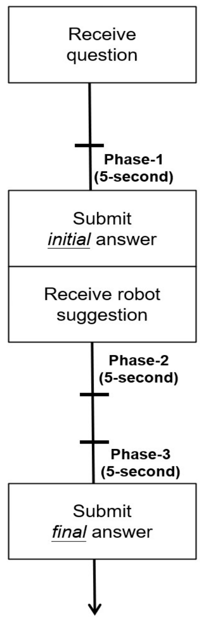

Figure 7. EEG data were divided into three phases.

Due to the system malfunction, one of the participants in the high CT group was removed, and the channel CP5 was also excluded from the EEG data analysis. However, since CP5 is used to collect visual signals and has relatively limited influence on cognitive activities in the decision-making process, removing this channel therefore yields little effect on the results of the brainwave analysis. In other words, to identify the differences between high and low CT groups, the preliminary EEG results (figure 8) utilized seven EEG channels to analyze the data obtained from two high CT participants and three low CT participants. A darker color represented higher EEG signal amplitude. Figure 8 presented the average band power of the EEG channels in each phase and compared the differences of brain activities between the high (*N*=12, 6 trials * 2 participants) and low (*N*=18, 6 trials*3 participants) CT groups. The beta power of the high CT group was significantly higher than the low CT group in the right dorsolateral prefrontal cortex (R-dlPFC), revealing that the high CT group can focus better on problem-solving and decision-making. Additionally, the brain activity of the high CT group varied along with the phase transitions, which may exhibit more effective energy management, i.e., spent less energy before the first submission and paid more attention to determine whether the robot-suggested answer was correct.

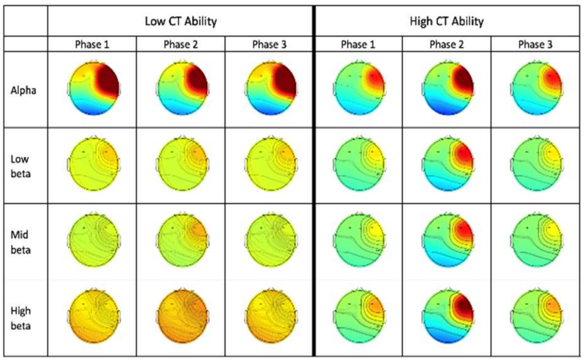

Figure 8. EEG topographic maps for high vs. low CT ability groups in different phases.

To identify participants' (over)trusting intentions during HRC, we further examined and compared two participants' decision-making patterns. Participant #2 and participant #3 were selected for this analysis. This is because these two participants were both from the high CT group but demonstrated greatly different reliance behaviors toward the robot assistant (table 5). Participant #2's test scores were heavily dropped from the initial 30 points to -2 points when collaborating with the robot with low capability. However, this effect was observed in participant #3, where the participant's test score was not affected by the robot with low capability, and conversely, the test score was increased from 22 to 38 points in the high robot capability condition. These observations indicated the differences between overreliance and appropriate reliance on robot aids.

Table 5. Real task test scores before and after consulting robot's recommendations.

	High robot capability		**Low** robot capability	
	Initial answer	Final answer	Initial answer	Final answer
Participant #2	22 points	22 points	30 points	-2 points
Participant #3	22 points	38 points	22 points	22 points

Similar results can be seen from the EEG topographic maps (figure 9). Although both participants followed the robot's suggestions, participant #3 (right in figure 9) was able to identify the correctness of the provided suggestion and submit the correct answer, whereas participant #2 (left in figure 9) accepted and submitted the wrong answer. The map revealed that higher EEG signal amplitude was observed in participant #3 across all the brain waves and phases. The brainwaves were especially active at the right dlPFC in phase 2 (the moment right after receiving the robot recommendation). Since the electrodes located in the prefrontal cortex are used to capture decision-making related signals, this pattern may suggest that the participant was going through a decision-making process and validating the robot's suggested answer. Given the variances between these two participants, their EEG topographic maps provided supplemental and strong support to explain the differences in their reliance behaviors.

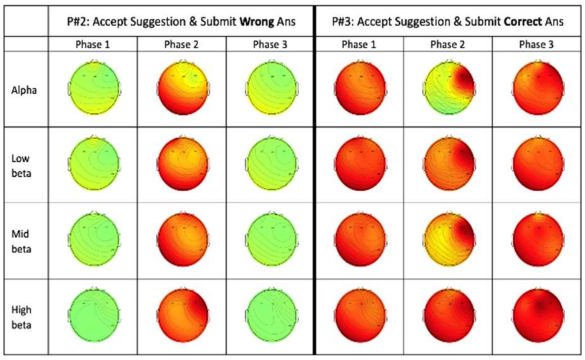

Figure 9. EEG topographic maps of participant #2 and #3.

5. Discussion and Conclusion

The present study examines the human-robot decision-making process in collaborative contexts, where the participants and the robotic agent formed a team for the experimental tasks. In the reported user studies, participants performed CT-related tasks while assisted by a robotic agent, with either high or low capability to process the questions. As shown in the RoSAS questionnaire, the perceived competence was higher in the robot with high capability than in the low capability agent. This observation suggested that participants were aware of the capability changes regarding the provided recommendations and were able to identify the differences between the conditions. However, as expected, the results confirmed that the change in system capability primarily affected the overall task performance. The low capability condition heavily decreased the task outcomes, especially for the participants with high CT ability. The change in robot capability also influenced the perceived workload. Compared to the high capability group, the workload ratings were higher while receiving assistance from a low capability robot. In addition, while participants recognized the high capability robot was more competent than the low capability agent, the NARS questionnaire showed an interesting result, where the high CT group had slightly higher negative attitudes toward the robot with high capability (although the rating difference is relatively small).

In addition to the survey results, the EEG device can support neurophysiological evidence to examine a participant's brainwaves when making decisions. The adopted Lego-like EEG headset provided us with an inexpensive means to collect and analyze the participants' brain activities during their decision-making processes. The results revealed an individual's CT ability did affect their brain activities when performing the CT-related tasks. More importantly, the EEG analysis (i.e., topographic maps) supported strong evidence that allowed us to compare participants' cognitive intentions and resultant behaviors.

The present study develops an innovative framework that integrates qualitative, quantitative, and neurophysiological approaches to effectively examine decision-making processes during HRC. This framework can serve as basic research guidelines to enhance human-robot team collaboration as well as optimize the effectiveness of collaborative decision-making. The present research serves as a pilot study, which mainly focuses on examining the feasibility of the developed research framework and methodology. Despite the small sample size in our pilot experiments, the preliminary results are sufficient to enable us to validate the appropriateness of the research designs. In our upcoming formal studies, more participants will be recruited and their EEG data will be normalized to compare the differences in their brain activities during the decision-making process. The research findings would allow us to better understand general principles pertaining to human trust in robot recommendations during decision-making processes and examine how trust mediates reliance on HRC. In addition, through the research findings, we could develop robotic agents of different capabilities that can best support the participants with diverse expertise and increase the efficiency of HRC.

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7. References

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