Effects of Agent's Embodiment in Human-Agent Negotiations

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ABSTRACT

Human-agent negotiation has recently attracted researchers' attention due to its complex nature and potential usage in daily life scenarios. While designing intelligent negotiating agents, they mainly focus on the interaction protocol (i.e., what to exchange and how) and strategy (i.e., how to generate offers and when to accept). Apart from these components, the embodiment may implicitly influence the negotiation process and outcome. The perception of a physically embodied agent might differ from the virtually embodied one; thus, it might influence human negotiators' decisions and responses. Accordingly, this work empirically studies the effect of physical and virtual embodiment in human-agent negotiations. We designed and conducted experiments where human participants negotiate with a humanoid robot in one setting, whereas they negotiate with a virtually embodied replica of that robot in another setting. The experimental results showed that social welfare was statistically significantly higher when the negotiation was held with a virtually embodied robot rather than a physical robot. Human participants took the negotiation more seriously against physically embodied agents and made more collaborative moves in the virtual setting. Furthermore, their survey responses indicate that participants perceived our robot as more humanlike when it is physically embodied.

CCS CONCEPTS

• **Computing methodologies** → *Intelligent agents*.

KEYWORDS

Human-Agent Negotiation, Embodiment, Human-Robot Interaction

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1 INTRODUCTION

Negotiation is the process of resolving those conflicts and finding mutually acceptable solutions. It has been capturing the attention of AI researchers for several decades due to its complexity and extensive applicability to effectively resolve real-life problems in our society (e.g., task and resource allocation, commerce, and governance) [4, 12, 28]. Various studies support human-agent negotiations where software agents negotiate with their human counterparts [18, 27, 29]. Apart from designing offering strategies [17, 30], some work focus on investigating the effect of emotion and facial expressions in human-agent negotiation (e.g., adopting angry facial expression versus happy facial expression during the negotiation) [9, 14, 19, 39]. Moreover, some studies address designing natural language processing models and dialogue strategies for human-agent negotiations [8, 25]. As a complement, this work investigates the effect of negotiating with a physically embodied agent versus a virtually embodied agent on both negotiation outcome and interaction. Almost all works in the negotiation literature except some recent studies [3, 35] have been built on an agent framework supporting either disembodiment [13, 32], or virtual embodiment [10, 37]. On the other hand, physical embodiment may influence the social interaction as stated in [23]. Underlying interaction with the human may end up with a different outcome depending on whether the physical or virtual embodiment is adopted [26]. This study aims to fill this gap by investigating the effects of embodiment in human-agent negotiations where an autonomous negotiating agent uses some gestures and arguments to build rapport with and convince a human negotiator.

To achieve this, we utilized the framework introduced in [3] by enriching gestures and moods used by our humanoid robot and creating a digital replica of our humanoid robot along with its environment. Accordingly, we designed and conducted experiments where human participants negotiated with the physical and virtual robots on a given resource allocation problem. According to the empirical results, the participants were inclined to act more competitively against a physically embodied robot as it was sensed as a real competitor. Human participants made more collaborative moves during the negotiation in the virtual setting compared to the physical environment as far as the product utilities (i.e., the higher product is the more efficient outcome for both sides) are concerned, negotiating with the virtually embodied robot ends in better results. All aforementioned insights can be utilized to improve the efficacy of human-agent negotiation frameworks. As suggested by [7], virtual human agent platforms could be used to train human negotiators. It has been shown that human negotiators can improve their negotiation skills through numerous negotiation experiences with a virtual agent. Given the results, a physically embodied robot could be preferred for more challenging training.

2 RELATED WORK

The effect of embodiment on interaction has been studied for decades [1, 5, 16, 20, 21, 23, 24, 40]. This section overviews some leading works and mentions some related human-agent negotiation studies.

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To begin with, Wainer *et al.* investigate the effect of the embodiment of a supporting agent, which aims to help the participants solve the Towers of Hanoi game [40]. They evaluate physical and virtual embodied agents regarding their perception of human participants and social interaction. Their results support that physically embodied robots are perceived as most enjoyable to interact with and considered the most watchful among other setups, although the embodiment type does not affect the task performance (i.e., task completion time). Similarly, Leite *et al.* report that human chess players' enjoyment was higher while interacting with a physically embodied robot over a virtual one [24]. Another study emphasizes the importance of physical embodiment in human-agent interaction and reports empirically that participants rated physically embodied social robots higher in terms of social presence and the quality of the interaction [23]. Moreover, Kiesler *et al.* designed an agent that interviews with human participants about their health and studies the embodiment effect in four different settings [20]. In the first setting, participants were interviewed with a physically embodied humanoid robot and a projection of that robot. In the second setting, a virtual agent and its projection interview participants. According to their experimental results, participants perceived that the physically embodied robot had a more positive personality. Consequently, participants spent more time with the physically embodied robot and liked it more than the virtually embodied software agent.

Furthermore, Kose *et al.* compare the effect of physical embodiment, virtual embodiment, and no embodiment on children in a drumming game setup with a humanoid robot [21]. According to the results, children mimicked playing the drums better while interacting with the physically embodied robot using gestures than two other setups. Bainbridge *et al.* show that participants obey orders from physically embodied robots more than virtually embodied ones [5]. According to the questionnaire results, participants rated physically embodied robots more positively and naturally than virtual ones. Moreover, Hoffman *et al.* observed that human participants preferred collaborating with a physically embodied robot in task-oriented scenarios, whereas they preferred the virtually embodied robot in conversational scenarios [16]. On the other hand, they report no significant difference between physical versus virtual embodiment in terms of persuasion and task performance.

In the context of negotiation, Bevan and Fraser examine the effect of handshaking before the negotiation on negotiation outcome through human-human negotiation experiments [6]. In their setting, two human participants are asked to negotiate on a single issue, namely price, by adopting the role of buyer or seller. There are two independent variables in their setting: telepresence and handshaking. For the former case, one of the participants is represented by a humanoid robot (i.e., teleoperated by the human negotiator), while the other participant negotiates with the robot controlled by the other human negotiator. For the latter variable, there are three possible options: (1) no handshake before the negotiation, (2) human participant handshakes with the robot before the negotiation but no feedback is given to the human negotiator controlling the robot, and (3) the same as the previous one but haptic feedback is given to the human controller. Their experimental results show that shaking hands before a negotiation increases social welfare in agreement utilities. The highest level of cooperation is obtained when the participants handshake with haptic feedback. In that study, participants negotiate with each other and a robot. The robot is used to present one of the participants to examine the effect of handshaking before the negotiation. In contrast, our primary focus is studying the effect of physical embodiment on human-agent negotiations, where a human negotiator negotiates with a fully autonomous humanoid robot.

Furthermore, Thellman *et al.* study the effect of physical embodiment in a one-shot ultimatum game (UG) [35]. In their study, either a physically embodied "Nao" robot or a virtually embodied agent offers how they will share a certain amount of money, and human participants should respond either by an acceptance or rejection. While some participants negotiate with the robot, others negotiate with the virtual agent. Their between-subject analysis results show that social presence is essential for human-robot interaction, and being physically or virtually present does not affect the robot's perception in a social sense. In contrast to that study, our work examines the effect of embodiment in a multi-issue negotiation with a more sophisticated fully autonomous negotiating agent using gestures and arguments during the negotiation.

3 HUMAN-AGENT NEGOTIATION

In general, negotiations are about a finite set of n issues $\mathcal{I} = \{1, 2, \ldots, n\}$ [33]. Each issue $i \in \mathcal{I}$ has a range of possible instantiations. In a resource allocation problem, each issue denotes a resource to be allocated in the negotiation (e.g., a list of fruits to be shared). Their values could be the amount of resources to be given to a negotiating party. An outcome is a complete assignment to the set of issues, an offer is represented by o. Preferences are represented by means of linear additive utility functions as shown in Equation 1 where w_i represents the importance of the negotiation issue i for the agent, o_i represents the value for issue i in offer o, and $V_i(.)$ is the valuation function for issue i, which returns the desirability of the issue value. It is assumed that $\sum_{i \in \mathcal{I}} w_i = 1$ and the domain of $V_i(.)$ is in the range of [0,1] for any i. Note that each negotiating party knows only its preferences and does not have access to its opponent's preferences and negotiation strategy.

$$\mathcal{U}(o) = \sum_{i \in \mathcal{I}} w_i \times V_i(o_i) \tag{1}$$

We adopt the Alternating Offers Protocol [2] to govern the interaction between human and agent negotiators. According to the protocol, the human participant makes the first offer in the negotiation. The party who receives an offer can either accept or make a counteroffer. This process continues in a turn-taking fashion until a termination condition is reached (i.e., reaching a deadline or agreement). In our study, a human participant negotiates with a humanoid robot to allocate given resources; consequently needs to specify what resources they want for themselves and their amount. Instead of chat-based communication, speech-based communication is more convenient for humanoid robots. To accomplish this, the robot listens to the human participants constantly and analyzes what it hears in order to extract a structured offer by using regular expressions. By utilizing speech-to-text technology and a negotiation corpus, we reduce mispronounced terms and enable the robot to gather the human participant's intents. We then employ several grammar structures built specifically for the underlying domain.

The bidding strategy determines what to offer during the negotiation [12]. In our work, the agent calculates a target utility and makes an offer whose utility is the closest to it. Accordingly, we use the "Hybrid" strategy proposed in [19] that combines well-known time-dependent and behavior-dependent strategies. According to this strategy, the agent considers its opponent's bidding behavior more than the remaining time in the beginning. As the negotiation progresses and the deadline approaches, it pays more attention to the remaining time. Here, the target utility at each turn is calculated as shown in Equation 2 where TU_{Times} and TU_{Times} are estimated by a time-dependent concession function provided by Vahidov [38] and an extension of the Tit-For-Tat Strategy [11], which replicates the opponent's moves to some extent, respectively.

$$TU_{Hybrid} = (t^2) \times TU_{Times} + (1 - t^2) \times TU_{Behavior} \qquad (2)$$

4 DECISION MODULES & GESTURES

Since the study aims to investigate the effect of embodiment in human-agent negotiations, we use a Nao humanoid robot and its virtual replica in this study to represent our negotiating agent, which we refer "Caduceus" [1] in the rest of the paper. This section explains the decision-making module (i.e., bidding and acceptance strategies) and presents the designed gestures and arguments for more humanlike interaction. Algorithm 1 illustrates how *Caduceus* makes its decisions and how its mood changes during the negotiation. At the beginning of each round, *Caduceus* first checks whether the deadline is reached. If so, it ends the negotiation (Line 1–2). Otherwise, it generates its next offer according to its bidding strategy (Line 4). In this study, our negotiating agent employs the "Hybrid" bidding strategy explained in Section 3. If the utility of the opponent's current bid is higher than or equal to the utility of *Caduceus*'s incoming offer (i.e., Happy mood), it accepts the given offer (Line 5–6). Recall that the higher the utility, the more desired the offer is. Otherwise, it makes its counteroffer (Line 8). Recall that its opponent first makes an offer, and *Caduceus* responds with an acceptance or a counteroffer. While making its offer, the agent determines its mood and adopts convenient gestures and arguments (Line 9). As human negotiators' mood changes overtime during the negotiation depending on their opponent's attitude and remaining time, we describe a number of moods for *Caduceus* related to negotiation based on [34] as follows:

Happy: Our humanoid robot is satisfied with its opponent's offer and accepts it if its utility is greater than or equal to the robot's next offer (i.e., $U(O_h^t) >= U(O_c^t)$)

Pleased: If the opponent concedes and the robot's utility has increased significantly (i.e. $\Delta U > 0.25$), but their offer is not still acceptable for the robot (i.e., the opponent's offer utility is less than the acceptance threshold, $U(O_h^t) < U(O_c^t)$), it feels pleased.

Hopeful: The robot adopts a hopeful mood if its opponent concedes, although its utility is not considerably changed (i.e., 0.25 => ΔU >0). This mood is activated if the opponent's offer utility is less than the acceptance threshold, similar to the pleased mood.

Neutral: When the opponent changes its offer's content, but the robot's utility is not changed (i.e., $\Delta U = 0$), its mood becomes neutral.

[1] It is a recognized symbol of commerce and negotiation in Greek mythology.

Algorithm 1: Caduceus's Decision Module

$T_{deadline}$, t: Deadline & the current time ;
O_c^t, O_h^t: Caduceus's counter offer & Human opponent's offer;
O_h: Human opponent's offer history;
$U(O_h^t)$: The utility of human opponent's offer for Caduceus ;
R: Reservation Utility (i.e., minimum acceptable utility);

1 **if** $t >= T_{deadline}$ **then**
2   End-Negotiation() ;
3 **else**
4     $O_c^t \leftarrow$ generateOfferWithHybrid(O_h, t, $T_{deadline}$);
5   **if** $U(O_c^t) \leq U(O_h^t)$ **then**
6   Accept() ;
7   **else**
8   MakeOffer(O_c^t) ;
9   mood ← getMood(O_h,t,R) ;

Dissatisfied: If the opponent makes a selfish move and decreases the robot's utility by a small portion (i.e., -0.25 <= $\Delta U < 0$), it becomes dissatisfied and shows its dissatisfaction by using some arguments.

Annoyed: If the opponent makes a selfish move that reduces the robot's utility significantly (i.e.,$\Delta U <$ -0.25) or makes the same offer twice (i.e., $U(O_h^{t_{cur}}) == U(O_h^{t-1})$), it becomes annoyed and expresses its annoyance using arguments.

Frustrated: When one of the three conditions is met, the robot becomes frustrated: when the utility of its opponent's offer is less than the reservation utility (i.e., $U(O_h^t) < Reservation$); when the current negotiation time is greater than 75%, and the opponent's offer utility for the robot is less than the half (i.e., $t > 75\%$ & $U(O_h^t) <=$ 0.5); or when its opponent makes the same offer thrice or more (i.e., $U(O_h^t) == U(O_h^{t-1}) == U(O_h^{t-2})$).

Worried: As the deadline approaches, the robot hurries its opponent forward. Different predefined negotiation times. *Caduceus* used to inform the opponent three times on 40%,60%, and 80% of the negotiation time.

We enriched the gesture set defined in [3]. As seen in Figure 1, 14 different gestures are prepared for expressing the current moods. In line with those gestures, *Caduceus* picks one of the convenient arguments from the prepared argument set in Table 1:

5 METHODOLOGY

To study the effect of the robot's embodiment (i.e., physical or virtual) in human-agent negotiations, we set up a user experiment where the human negotiator negotiates with a virtually and physically embodied agent in a resource allocation scenario. Accordingly, we suggest and examine two hypotheses as follows: **Hypothesis 1 (H1):** *The utility of the negotiation outcome reached by human negotiators would be significantly different when they negotiate with a virtually embodied agent than that of when they negotiate with a physically embodied agent.* **Hypothesis 2 (H2):** *The human negotiator would perceive the physically embodied agent as more humanlike than the virtually embodied agent.*

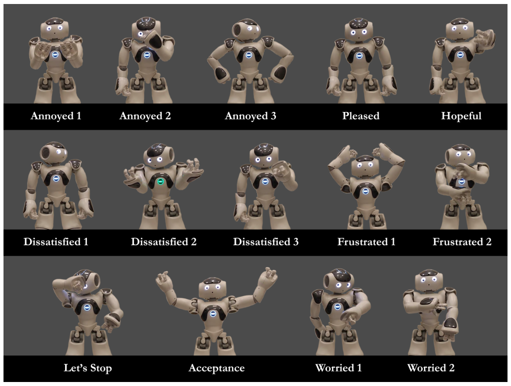


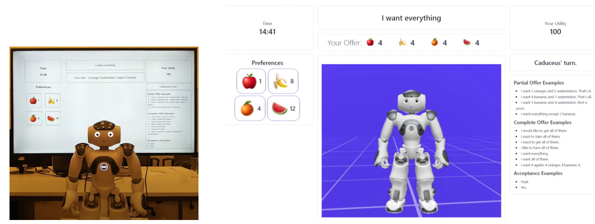
Figure 1: Designed gestures for expressing Caduceus' moods

Table 1: Predefined arguments for expressing Caduceus' moods

Mood	Arguments
Happy	Great! I accept your offer!
Pleased	It is getting better but not enough. That sounds good, but you can give me a bit more.
Hopeful	Let me think about it. It is getting better, but not enough. I appreciate your offer. It would be great if you concede a bit more. Sounds good; we are almost there.
Neutral	Let's talk about other options.
Dissatisfied	No, I can't accept that, unfortunately. Sorry, I can't accept that. That is not going to work for me! I'm sorry, but I could not agree to your offer. I really can't agree with your offer.
Annoyed	No, It is not acceptable! I wish you did not make this offer. How am I supposed to accept this offer? I don't like your offer. You should revise it. I hope we can find a deal today!
Frustrated	Do you really think that is a fair offer? It is not acceptable at all. I am very disappointed with your offer. It is not acceptable at all. Your offer is not acceptable. Please put yourself in my shoes. We cannot reach an agreement. Let's try to be more collaborative.
Worried	The deadline is approaching. Let's find a deal soon. We are running out of time. Let's be more cooperative to find a deal. Hurry up! We need to find an agreement soon.

5.1 Experimental Setup

To test the aforementioned hypotheses, we created a virtual replica of our physically-embodied agent along with our framework. Note that the agent employs the same negotiation strategy, speech recognition method, gesture, and argument sets in both settings. As Figures 2a and 2b show our experimental setups, participants can see their preference profiles (lower left-hand corner), the current offer (top center) along with their utility (upper right-hand corner), remaining time (upper left-hand corner), and some auxiliary sentence structures for possible actions (lower right-hand corner) on the TV screen while negotiating with Caduceus. It is worth noting that virtual and physical setups are almost identical. Official Nao tool called Choregraphe [31] is used to generate robot gestures for both setups. For virtual setup, each gesture is prerecorded and then used by our negotiation tool to represent the virtual *Caduceus*. The physical robot that is used during the experiments is also the same model and version in the Choregraphe so the gestures are identical in both settings. The details of the experimental protocol are explained elaborately in the following section.



(a) Physical setting **(b) Virtual setting**

Figure 2: Human-agent negotiation settings

5.2 Experiment Protocol

In our experiments, human participants are asked to negotiate with the "Nao" humanoid robot named *Caduceus* in both physical and virtual settings (i.e., within-subject design). To minimize the learning effect, we counterbalance the negotiation session order. Half of the participants negotiate with the physically embodied *Caduceus* and then negotiate with the virtually embodied *Caduceus* while the other half negotiate in reverse order. Note that there is a 5-minute break between two negotiation sessions.

As a role-playing game, participants are asked to negotiate according to a given resource allocation scenario. According to the given scenario, participants and *Caduceus* are lucky customers in a supermarket who will receive free fruits as a reward. Eligibility of this reward requires finding an agreement on how they will share fruits between them. There are four types of fruits, and there are four of each fruit type. Each participant should collect at least 40 points; otherwise, they will receive zero points. There is also a time limitation for this game. They need to reach an agreement in 15 minutes (i.e., deadline). If they cannot reach an agreement within 15 minutes, they fail the negotiation and receive zero points. Since it is essential to introduce an incentive for taking the underlying negotiations seriously, we promise them to give a 5$ gift card from a well-known supermarket brand if they negotiate well and encourage them to maximize their score. Table 2 shows preference profiles of *Caduceus* and its human counterpart for both sessions. Note that the participants know only their scores and are informed that *Caduceus* does not know their scores either. The outcome utility space is plotted in Figure 3 to show that each party has the equivalent agreement space where there are 625 possible outcomes in this scenario. All participants experienced with the same negotiation scenarios [2].

Before each negotiation session, the interaction protocol is explained to the participants via a demo video. Besides, they have a training session where they negotiate on a more straightforward problem for 5 minutes to get familiar with the negotiation process. During their negotiation, participants communicate with *Caduceus* via speech in both virtual and physical settings. In addition, we prepared an interface displaying some necessary information that makes

[2]We would like to state that the experiment protocol adopted in this study was approved by the Ethics Committee of our university, and informed consent was obtained from all participants.

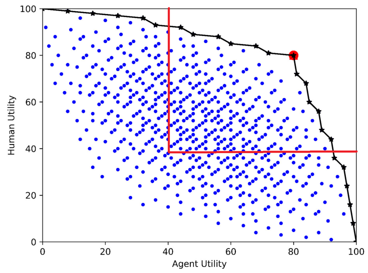


Figure 3: Outcome utility space of the grocery scenario

Table 2: Preference profiles for negotiation sessions

	First Negotiation		Second Negotiation	
Items	**Caduceus**	**Participant**	**Caduceus**	**Participant**
Watermelon	4	12	12	4
Banana	1	8	8	1
Orange	12	4	4	12
Apple	8	1	1	8

a human participant's life easier, as seen in Figure 2. Figure 4 shows the environment we conducted the experiments. As seen, the participant sits across *Caduceus* so that it can observe the *Caduceus*'s gestures and the display screen. Before their second negotiations, they are told that their preferences are utterly different, although only the order of the scores is changed, and the value distribution of the scores remains the same for a fair evaluation. In order to analyze the negotiation results, the framework automatically logs the negotiation results (i.e., whether or not they reach an agreement; if so, the utilities of the negotiation agreement for both sides), the number of rounds to complete each session as well as duration, offer exchanges during the negotiation and the percentages of participants' moves. After completing both sessions, they fill out two questionnaire forms regarding their first and second negotiation session.

Figure 4: Experimental setting for human-robot negotiation

5.3 Participants

We have recruited 52 participants (i.e., bachelor and graduate students from the faculty of Engineering, and departments of Communication Design, and Aviation); 40 males, 12 females; aged between 18 and 42) for our human-robot experiments. Since the medium of instruction in our experiments is English, we asked participants to rate their English level on a scale of 1-7 (1 for the beginner; 7 for advanced). The average English level of participants is 5.65.

Since we mainly investigate to what extent the embodiment affects the interaction of the human negotiators with the designed negotiating robot from different perspectives, a fair evaluation requires a certain amount of experience in both settings. Sometimes, participants can find an agreement immediately after a few rounds. In such a case, they would not have enough experience with the developed environment, so we cannot detect the impact of the presence even if it exists. In our previous human-robot negotiations, we observed that, on average, participants completed their negotiation around five rounds. Therefore, we decided to eliminate the records of the participants who completed one of their negotiations in less than five rounds. As a result, our analysis considers only 30 (23 males, seven females, aged between 18 and 36) participants' negotiation sessions. The reader may wonder why we do not ask the participants to repeat the negotiation to satisfy the minimum number of interactions. If you allow the participants to repeat the same negotiation session in this case, the learning effect from their previous negotiations would change their negotiation behavior; therefore, this bias effect is avoided by filtering those records. Note that counterbalance groups are not affected by this elimination.

6 EXPERIMENTAL RESULTS

After conducting the experiments, applying a convenient statistical test is essential. Since our experimental setting is a within-subject design, we could apply a two-tailed dependent sample t-test. To check the applicability of this test, we first apply the Kolmogorov-Smirnov normality test and Levene's Test (i.e., homogeneity of Variance) [22]. If the data distribution passes these tests, the dependent sample t-test is applied; otherwise, a non-parametric statistics test, namely the Wilcoxon-Signed Rank test. All statistical tests results are given at the 95% confidence interval (i.e., $\alpha = 0.05$).

We first compare the negotiation performance of the participants/agents in both settings. It is worth noting that all negotiation sessions ended with an agreement. Figure 5 shows the average utilities gained by both parties separately and the average normalized products of utilities where the orange and blue color bars denote their scores in physical and virtual environments, respectively. As far as the individual agent utility (i.e., *Caduceus*'s utility) is concerned, it is seen that *Caduceus* received higher utility by little difference on average when it was virtually embodied (0.66 versus 0.69). When we applied the Kolmogorov-Smirnov normality test on physically and virtually embodied agent scores, results show that they are distributed normally ($p = 0.43$, $p = 0.25$ for physical and virtual settings, respectively). We also tested the homogeneity of variance, and the homogeneity requirement was met (f-ratio = 0.47, p = 0.49). Therefore, we applied the two-tailed dependent sample t-test. However, the results are not statistically significantly different on agent utility under the two-tailed dependent sample t-test with a 95% confidence interval (t=-1.63 and p=0.11). When the average utility gained by the human participants was investigated, we observed that their averages were close to each other in both environments (0.80 vs. 0.81). Since these utilities are not normally distributed according to the Kolmogorov-Smirnov, we applied a non-parametric statistics test, namely the Wilcoxon-Signed Rank Test. We have observed no statistically significant effect of physical embodiment on the user utilities (Z=-0.085, p = 0.92). Our statistical test results do not reject the null hypothesis, so there is no statistical support for **H1**.

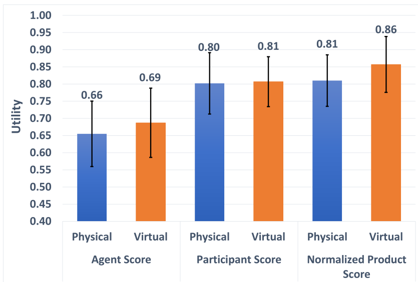


Figure 5: Avg. individual utilities and normalized product scores

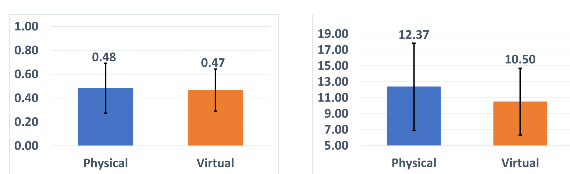
Moreover, the normalized utility product, which denotes the social welfare of the outcomes, is calculated by dividing the product of utilities of *Caduceus* and its human counterpart by the Nash Product (i.e., maximum utility product in the outcome space). In our scenario, the Nash Product is equal to 0.64. When we applied the Kolmogorov-Smirnov normality test to the normalized utility product results, they were distributed normally (p = 0.17, p = 0.06, for physical and virtual settings, respectively). We also tested the homogeneity of variance, and the homogeneity requirement was met (f-ratio = 1.13, p = 0.29). Therefore, we applied the two-tailed dependent sample t-test. Although the averages of the utility products in physical and virtual settings are close to each other (0.81 versus 0.86, respectively), their means are statistically significantly different (t=2.209, p = 0.03), according to this test. Embodiment has a medium-large effect on normalized utility product (Cohen's D = -0.59, %95 confidence interval [-0.994 -0.185]). That is, the agreements were better for both parties when the negotiation was held in a virtually embodied setting. According to our observation, **participants' tendencies towards cooperation and negotiability increase while they are negotiating with the virtually embodied robot**. Interactions become more severe, and competitiveness increases during physically embodied negotiations. As a result, the social welfare of the negotiation outcomes are higher when human negotiators negotiate with a virtually embodied agent.

We investigate the bidding behavior of each participant in our experiments. In the literature, Thomas proposes the Thomas-Kilmann Conflict Mode Instrument based on the degree of assertiveness (i.e., satisfying own concerns) and cooperativeness (i.e., satisfying other person's concerns) of humans [36]. Accordingly, we study the assertiveness and cooperativeness of the participants. Since assertiveness measures the individual attempts to satisfy their concerns/preferences, we group the offers made by each participant and take their averages separately for both settings. When we applied the normality test on physically and virtually embodied assertiveness, results show that they are distributed normally (p = 0.1, p = 0.2 for physical and virtual settings, respectively). We also tested the homogeneity of variance and met the requirement of homogeneity. (f-ratio = 0.00002, p = 0.99). Therefore we applied the two-tailed dependent sample t-test. As seen, there is no statistically significant difference in the assertiveness of the participants on average in virtual and physical settings (0.83 and 0.84, respectively) according to the dependent t-test (t=0.47, p=0.64). However, when we investigate the assertiveness of the participants at the individual level, we can observe that some participants tended to offer higher utilities for themselves in the virtual environment compared to the physical environment, others acted in the other way around. Without a doubt, there are individual differences. Cooperativeness is the measurement of the individual attempts to find a mutual agreement. We consider the percentages of cooperative moves made by the human participants in order to estimate their cooperativeness level as seen in Equation 3 where definitions of those "moves" can be found in [15].

$$Cooperativeness = \%_{Fortunate} + \%_{Nice} + \%_{Concession} \quad (3)$$

When we applied the Kolmogorov-Smirnov normality test on physically and virtually embodied cooperativeness, results show that they were distributed normally (p = 0.58, p = 0.51 for physical and virtual settings, respectively). We also tested the homogeneity of variance, and the homogeneity requirement was met (f-ratio = 0.15, p = 0.69). Therefore, we applied the two-tailed dependent sample t-test. When we applied a two-tailed dependent t-test on the cooperativeness of the participants in the physical and virtual setting, we found that participants had more cooperative moves when negotiated against virtually embodied robots (t=2.178, p=0.04). On average cooperativeness level of human participants while negotiating with the physically embodied robot, *Caduceus*, was 0.51, whereas it was 0.57 while facing the virtually embodied robot. It is observed that **human participants act more competitively against a physically embodied agent than a virtually embodied one.**

As far as the normalized agreement time is concerned, shown in Figure 6, the parties reached agreements slightly faster when *Caduceus* was virtually embodied (on average agreement time for physical embodiment: 0.483 versus for virtual embodiment: 0.467). When we applied a two-tailed dependent sample t-test, we have not observed a statistically significant effect of using different embodiment on agreement time (t=-0.35, p = 0.72). Similarly, there is no statistically significant difference in the number of rounds to reach an agreement (t=-1.64, p=0.11). However, the participants agreed on slightly lower rounds (on average 10.2 versus 12.13).



(a) Normalized time **(b) Rounds**

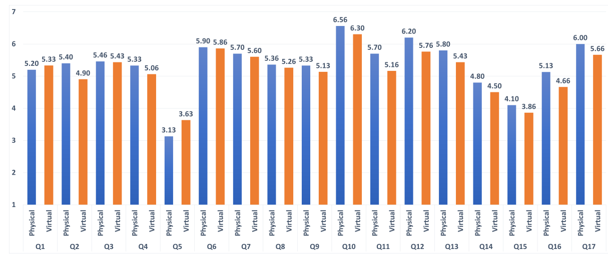
Figure 6: Average agreement time and negotiation round

6.1 Analysis of Questionnaire

Subjective evaluation of the system was done through the questionnaire filled in by the participants at the end of the experiment. The Likert questions are on a 7-point scale (1 for strong disagreement, four is for neutral, and 7 for strong agreement). The questionnaire consists of 17 questions about their first and second negotiation sessions. Since asking these questions after their first negotiation may influence their attitude in their second negotiation, we asked the questions at the end of their experiment. In addition, participants are asked about the experimental setup in general. The means and standard deviations of their responses to those questions are as follows: (i) I understand the experimental instructions. They were clear. (Average: 6.86 ± 0.36); (ii) The demo session shown before the experiment was instructive. (Average: 6.86 ± 0.36); and (iii) Since our communication channel was speech, I found the interaction humanlike. (Average: 5.23 ± 1.43). It can be seen that the instructions and interaction protocol were clear.

Figure 7 shows the negotiation and embodiment-related survey questions and the average rating of the participant's responses. The responses are grouped according to what embodiment they face in the negotiation session. The resulting average ratings of the more positively structured statements are above 4 points (i.e., neutral), whereas the responses to the negative-structured statements, such as Q5, are below 4 points. The questions where we found a statistically significant difference are boldfaced (i.e., Q2 and Q12). When we applied the normality test on responses to Q2 results, they were distributed normally (p = 0.13, p = 0.29 for physical and virtual settings, respectively). The homogeneity requirement was also met (f-ratio = 1.43, p = 0.23). When the two-tailed dependent t-test is applied, we found that embodiment has a statistically significant effect on the participant's response to "*Caduceus* negotiated with me like a human negotiator." (Q2) (t=-2.62, p=0.013). Embodiment has a small-medium effect on Q2 (Cohen's D = 0.36, %95 confidence interval [-0.027 0.744]). In the case of Q12, we applied the Wilcoxon-signed Rank test. It also has a statistically significant effect on responses to "*Caduceus*' gestures were mostly consistent with the situation" (z=-1.96, p=0.05). As a result, participants perceived Caduceus as more humanlike (on average 5.4 versus 4.9) and found *Caduceus*' gestures more consistent compared to virtual (on average 6.2 versus 5.76) when it was physically embodied. Embodiment has a small-medium effect on Q12 (Cohen's D = 0.4, %95 confidence interval [0.012 0.788])). Those results support **H2**. According to the question, "I was frustrated with *Caduceus*' attitude during the negotiation." (Q5), it can be observed that the robot's attitude did not frustrate the participants for both physical and virtual versions (on average, 3.13 and 3.63, respectively). Moreover, regarding the question, "*Caduceus* paid attention to my gestures during the negotiation." Q(15), participants think that the robot does not consider their gestures (on average, 4.1 and 3.86, respectively). Indeed, *Caduceus* did not consider their gestures during the negotiation.

During our unstructured interview at the end of the experiment, some participants stated that they enjoyed negotiating physically embodied *Caduceus* more than virtually embodied one. Some positive comments received from the participants are "*Caduceus' gestures are understandable.*", "*I wanted to negotiate with a physically embodied robot twice.*", and "*I felt like physically embodied Caduceus was more than a robot.*". We received a few negative comments such as "*Domain does not suit to negotiation with a robot.*" and "*I focused on the screen to maximize my utility instead of Caduceus*".



Q-1 Caduceus negotiated in a fair way.
Q-2 **Caduceus negotiated with me like a human negotiator.**
Q-3 Caduceus guessed my preferences accurately.
Q-4 Caduceus tried to find the best deal for both of us.
Q-5 I was frustrated with Caduceus' attitude during the negotiation.
Q-6 I am satisfied with my negotiation performance.
Q-7 Caduceus' attitudes were important for my next offer during the negotiation.
Q-8 While Caduceus was making its offers, it consider my negotiation behavior.
Q-9 While Caduceus was making its offers, it consider remaining time.
Q-10 I enjoyed negotiating Caduceus.
Q-11 It was easy to communicate with Caduceus.
Q-12 **Caduceus' gestures were mostly consistent with the situation.**
Q-13 I paid attention to Caduceus.
Q-14 Caduceus' gestures affected my decisions during the negotiation.
Q-15 Caduceus paid attention to my gestures during the negotiation.
Q-16 Caduceus was convincing during the negotiation.
Q-17 I was likely to engage in negotiation with Caduceus.

Figure 7: Average scores of questionnaire responses

7 CONCLUSION

We envision that human-agent collaboration considerably impacts society's productivity and well-being if the underlying infrastructure for such cooperation is carefully designed. The embodiment may implicitly influence human counterparts' behaviors. The choice of agent's embodiment could be made based on the expected engagement and collaborativeness. Accordingly, this work empirically investigates the effect of physical embodiment on human-agent negotiations. Experimental results showed that social welfare was higher when the negotiation was held with a virtually embodied robot rather than a physically embodied robot. Participants were more inclined to collaborate and reach an agreement while negotiating with the virtually embodied robot. While negotiating with the physically embodied robot, interactions grew tenser, and competitiveness increased based on our negotiation traces. Human participants made more collaborative moves during the negotiation in the virtual setting. Lastly, questionnaire results showed that participants perceived our robot as more humanlike and the robot's gestures more consistent with the underlying situation in the physical setup. As future work, we plan to study the effect of the embodiment on human-robot negotiations by involving different types of humanoid robots to see whether the cooperativeness of the human participants towards other humanoid robots varies concerning their appearance. Studying essential measures of individual variations such as the Big Five, assertiveness, and cooperativeness would be interesting.

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