EFFECT OF EMBODIMENT IN HUMAN-AGENT NEGOTIATIONS

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EFFECT OF EMBODIMENT IN HUMAN-AGENT NEGOTIATIONS

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To my precious family and my loved.

ABSTRACT

With the current advancement in artificial intelligence, intelligent systems interacting with humans are becoming more prevalent in our lives. One of the challenges is building socially intelligent agents who can effectively negotiate with their human counterparts. While designing such agents, it is essential to consider humans' bounded-rationality, emotions, facial expressions, arguments, and gestures. Apart from this, the perception of a physically embodied agent might be different from the virtually embodied one. It might influence human negotiators' decisions and responses.

Accordingly, this thesis focuses on the effect of bidding strategy, gestures, and embodiment in human-agent negotiations where the human participants negotiate with a humanoid robot. Our experimental results show that taking the human opponent's bidding behavior into account while generating an offer improves the robot's negotiation outcome. Another important observation is that an agent designer should be careful while designing gestures compatible with the agent's behavior since the gestures may also negatively affect the negotiation result. Furthermore, the experimental results showed that the social welfare was higher when the negotiation was held with a virtual robot rather than a physical robot. We observed that human participants made more collaborative moves during the negotiation in the virtual setting compared to the physical environment.

With the current progress in artificial intelligence, intelligent systems interacting with humans are becoming more common in our lives. One of the challenges in this area is to create socially intelligent agents that can negotiate effectively with their human rivals. When designing such factors, it is important to consider people's limited rationality, emotions, facial expressions, arguments, and body movements. Other than that, the perception of a physically embodied agent may

differ from a virtually embodied one. This difference can affect the decisions and interactions of human negotiators.

Accordingly, this thesis focuses on the influence of the bidding strategy of the smart agent, body movements, and physical embodiment on negotiation in human-agent negotiations negotiated by humans and humanoid robots. Our experimental results show that when the robot considers the bidding behavior of the human competitor while creating the bid, it improves the bargaining outcome for the robot. Another important observation is that body movements can affect the outcome of the negotiation positively as well as negatively. Therefore, agent designers need to be careful when designing body movements appropriate for the agent's behavior. In addition, it has been observed that social welfare is higher if the negotiation is carried out with a virtual robot instead of a physical one. It is noteworthy that the participants in the virtual environment adopt a more collaborative approach during the negotiation compared to the physical environment. In addition, the participants found the physical robot and body language more appropriate and stated that the robot act created a more human-like perception.

ÖZETÇE

Yapay zekadaki mevcut ilerlemeyle birlikte, insanlarla etkileşime giren akıllı sistemler hayatımızda daha yaygın hale gelmektedir. Bu alandaki zorluklardan biri, insan rakipleriyle etkili bir şekilde müzakere edebilecek sosyal akıllı etmenler oluşturmaktır. Bu tür etmenleri tasarlarken, insanların sınırlı rasyonelliğini, duygularını, yüz ifadelerini, argümanlarını ve vücut hareketlerini dikkate almak önemlidir. Bunun dışında, fiziksel olarak cisimleştirilmiş bir etmenin algılanması, sanal olarak cisimleştirilmiş olandan farklı olabilir. Bu farklılık, insan müzakerecilerin kararlarını ve etkileşimlerini etkileyebilir.

Bu doğrultuda, bu tez, insanlar ile insansı robotların müzakere ettiği insan-etmen müzakerelerinde, akıllı etmenin teklif stratejisinin, beden hareketlerinin ve fiziksel cisimleştirmenin müzakere üzerindeki etkisine odaklanmaktadır. Deneysel sonuçlarımız, robotun teklif oluştururken insan rakibinin teklif verme davranışını dikkate almasının, robot için pazarlık sonucunu iyileştirdiğini göstermektedir. Bir diğer önemli gözlemimiz ise, beden hareketleri müzakere sonucunu olumlu etkileyebileceği gibi olumsuz da etkileyebilir. Dolayısıyla, etmen tasarımcılarının etmenin davranışına uygun beden hareketlerini tasarlarken dikkatli olması gerekmektedir. Ayrıca, müzakerenin fiziksel bir robot yerine sanal bir robotla gerçekleştirilmesi durumunda sosyal refahın daha yüksek olduğu gözlemlenmiştir. Sanal ortamda katılımcıların müzakere sırasında fiziksel ortama göre daha işbirlikçi yaklaşım benimsediği dikkat çekmektedir. Bunun yanı sıra, katılımcılar fiziksel olan robotla beden dilini daha uygun bulmuşlardır ve robot etmenin daha insansı bir algı oluşturduğunu belirtmişlerdir.

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α Utility constant to determine robot moods.

β A proportion of robot's target utility

ΔU Change between opponent's previous and current offer in terms of robot's utility

μ A time parameter that scales the utility change

Θ Coefficient to take proportion of robot's target utility

i Issue

LT Estimated utility lower threshold for robot

R Reservation value

T_{Θ} Predefined negotiation time

t_{cur} Current offer's negotiation time

$T_{deadline}$ Negotiation deadline

t_{prev} Previous offer's negotiation time

TU Target utility

$TU_{Behavior}$ Behavior dependent strategy's target utility

TU_{Hybrid} Hybrid strategy's target utility

TU_{Times} Time strategy's target utility

$U(O_h^{t_{cur}})$ Utility of opponent's offer for robot

$U(O_h^{t_{prev}})$ Utility of opponent's previous offer for robot

$U(O_j^{t_{cur}})$ Utility of robot's next offer

CHAPTER I

INTRODUCTION

Day by day, our society benefits from more advanced intelligent systems solving complex social problems analytically and interacting with humans effectively [3]. With the improvement of intelligent systems and robotics, social robots are becoming an inevitable part of our society, and we will presumably see them almost everywhere in our daily lives [4, 5]. As robots become more human-like, they will become more widely integrated into society.

For instance, humanoid robots are used as a teacher to give a lecture in some studies [6, 5] and are used to help people with memory training by encouraging them to talk about their travel stories [4]. Furthermore, we can recently observe that socially interactive robots have been used to assist children with autism [7]. It can be foreseen that eldercare robots will play a key role in lonely older people's lives [8]. With the emergence of Industry 4.0, we expect to work together with robots to carry out some tasks [9]. As social robots are more integrated into our daily lives, some decisions will presumably require to be decided jointly in such a collaborative environment where conflicts between humans and robots may occur. Humans and robots would interact to resolve conflicts and seek mutually acceptable decisions. To find common ground, we may need to negotiate with robots on task allocations or other daily conflicts. For this reason, there is an immediate need for designing negotiating agents that are specialized in interaction with humans [10, 11].

Although human-agent negotiation has been studied in the literature, most works have been built on chat-based platforms or virtual agent frameworks. However, the physical embodiment is an essential component for establishing meaningful social interaction as stated in [12]. Moreover, underlying interaction with the human may end up with a different outcome depending on whether the physical or virtual embodiment is adopted [13]. It is interesting to study how humanoid robots can negotiate with their human counterparts.

Negotiation is a complex process in which there are a variety of variables affecting its outcome [14]. For example, a party may adopt a particular negotiation strategy, resulting in different outcomes while negotiating with different partners or when employed in various contexts. Due to its complexity and extensive applicability to effectively resolve real-life problems in our society (e.g., task and resource allocation, commerce, governance), it has been taking AI researchers' attention for several decades. Although a variety of automated negotiation systems and approaches have been proposed [14], there are relatively fewer works in the field of human-agent negotiation, which requires considering different dynamics such as bounded rationality, interaction medium, emotions [15], and gestures [16]. While human factors such as facial expressions, emotions, or gestures do not take place in automated negotiation in which intelligent software agents negotiate with each other, these factors play a crucial role in human-human and human-agent negotiations. There are various approaches to design negotiation frameworks for human-agent negotiations considering those factors [17, 18, 19, 20, 21]. While some of those works focus on the effect of emotion in human-agent negotiation (e.g., adopting angry facial expression versus happy facial expression during the negotiation) [11, 22, 23], others investigate negotiating strategies resulting in efficient outcomes while establishing a good relationship with human counterparts [24, 25]. As mentioned above, almost all works in the literature have been built on an agent framework disembodiment (i.e., text-based negotiation), and virtual embodiment is available. This study aims to fill this gap by investigating the effects of gestures and embodiment in human-agent negotiations.

Furthermore, the communication channel is one of the issues to be considered in human-agent negotiation. "The way we say" is just as important as "what we say". Accordingly, selecting the best communication channel is vital while designing a negotiation protocol for human-robot negotiation (HRN). Text-based interaction may not be convenient for humans to communicate with a humanoid robot. Instead, communication via speech would be preferable and natural as most people negotiate through speech. Additionally, as the reciprocal interaction of engagement is an inevitable part of human communication [26], a turn-taking fashion interaction would be appropriate for HRN. Apart from speech, gesture in human-human negotiation and human-robot interaction has been investigated for a long time. There are a variety of studies ranging from imitating people's interaction with each other to unique gestures for demonstrating emotion [27, 28]. While analyzing the effect of gestures in human interactions, it would be an erroneous outlook to ignore business and psychology studies. These studies show that understanding and demonstrating gestures are crucial for interactions [29, 30]. In addition to that, using "gesture" would make the communication more natural as it might influence the negotiation process profoundly [31].

In addition, the physical embodiment is an essential part of the social interaction as stated in [12]. For decades, researchers investigate the effect of embodiment on human-agent interaction [12, 32, 33, 34, 35, 36, 37].

Accordingly, this thesis studies the effect of negotiation strategy, embodiment, and gesture in human-agent negotiations. It presents two variants of existing negotiation strategies taking the remaining negotiation time and the opponent's bidding behavior into account. Our experimental results show that taking the human opponent's bidding behavior into account while generating an offer improves the robot's negotiation outcome. Moreover, we design some arguments and gestures in line with the robot's current mood to empower the interaction with the human negotiators. The effect of gestures and the designed strategies has been studied empirically through human-robot negotiation experiments. The lesson we take from the experiment results is that the usage of gestures along with a particular strategy may negatively impact the negotiation outcome. As a result, we recommend that agent designers examine how humans respond to the robot employing specific strategies and gestures before actual negotiations. Furthermore, a digital replica of our robot has been developed to investigate the effect of the embodiment. In the designed experiments, human participants negotiated with the robot in physical and virtual environments. The experimental results showed that the social welfare was higher when the negotiation was held with a virtual robot rather than a physical robot. We observed that human participants made more collaborative moves during the negotiation in the virtual setting compared to the physical environment. In addition, participants found physically embodied robots more human-likely and rated higher in terms of consistency of their gestures.

The rest of this thesis is organized as follows: Section 2 briefly discusses the related works. Section 3 introduces our initial negotiation framework for human-robot negotiation and experimental setting to study the effect of negotiation strategy and gesture as well as presenting the experimental results. Section 4 explains our experimental setting to investigate the effect of the embodiment in human-agent negotiations and discusses the empirical results elaborately. Finally, Section 5 concludes the thesis with the future work.

CHAPTER II

RELATED WORK

Agent-based negotiation has been widely studied for several decades, and a variety of negotiation frameworks have been proposed so far [38, 39, 40, 41, 42, 43, 44, 45]. Most of these works focus on automated negotiation where two or more software agents negotiate with each other on behalf of their users. Recently, the need for AI systems interacting with humans arises in the research on human-agent negotiation systems. Ficici *et al.* developed a situated multi-agent game environment named Colored Trails (CT) where players can be humans, agents, or both [20]. It is a configurable and extensible system used by the research community that investigates multi-agent decision making. As Lin and Kraus denoted in their vision paper [16], designing human-agent negotiation systems requires taking different dynamics into account. First, human negotiators get used to adopting a natural language to specify their offers instead of creating their well-structured bids through drop-down menus. Therefore, a chat-based negotiation framework called "NegoChat" was proposed by Avi *et al.*, where a negotiating agent and a human negotiator can negotiate by exchanging their bids in English [17]. Another human-agent negotiation framework called "IAGO" allows human negotiators to express their emotions through emoji as well as exchanging additional predefined arguments during their negotiation [18]. In another study, the researchers developed a virtual agent framework in which a negotiating agent can express its emotional states such as being *angry* and *happy* during the negotiation [22]. As a communication medium plays a significant role in human interactions, Divekar *et al.* introduced a framework where a virtual agent communicates with human negotiators through speech [46]. Complementary to those works, our work focuses on the effect of physical embodiment and gestures in human-agent negotiation.

Our study introduces a robot-human negotiation framework where a humanoid robot negotiates with its human counterpart through speech while using additional arguments and gestures.

The role of gestures in human communication and thinking has been studied extensively [47]. For instance, Xu *et al.* investigate the effects of a humanoid robot's body language to express the underlying mood where the robot plays a teacher role [48]. To the best of our knowledge, in the context of teaching robots in classrooms, it is the first work that studies the body language of a humanoid robot interacting with multiple people. They created 41 co-verbal gestures to display either a positive or negative mood. Their experimental results show that robot mood expressions affect students. The robot teacher received a higher lecturing quality rating while lecturing in a positive mood than lecturing in a negative mood. Regarding the effect of a robot's gesture, another study focuses on the effect of a robot tutor's gesture in teaching foreign words to young children (i.e., 4-6 aged) [49]. They used a Nao humanoid robot to teach foreign words to kids and conducted a user experiment to study how iconic gestures influence the learning process. Their results showed that gestures have a positive effect on long term memorization of foreign words. Moreover, they observed that children engage more and provide more correct answers when those iconic gestures are used.

Another work on the effect of gestures in human-robot interaction examines whether the robot's gestures positively affect the perception of the robot's instructions [50]. In their experimental setup, a humanoid robot describes the location of the items in a kitchen, and the human participants try to find them out. They conducted a between-subject experiment in which some participants get instructions via only speech, whereas others are instructed through both gestures and speech. Their results supported that using both gestures and speech has a more positive effect on the participant's performance. Similarly, in our work, when the agent employs a behavior-based negotiation strategy, it is observed that participants received higher utility on average. The gestures might help understand the decisions of the robot.

Moreover, Thomaz *et al.* propose a model of turn-taking for a humanoid robot to interact with people [26]. They conducted the "Simon Says" experiment with human subjects to collect data. They mainly focused on human response delay data. The human and robot interacted with speech, gaze, and gestures in their experiments. They emphasized that the minimum necessary information needed for the human to respond appropriately in line with the robot's instructions is an essential factor in human-robot interaction. They observed that the usage of gestures and speech affected the human participants' delay. Complementary to this work, we aim to use the most appropriate gestures in line with the robot's mood during the negotiation to establish a smooth interaction flow.

Apart from this, the effect of embodiment on interaction has been studied for decades [32, 12, 33, 51, 34, 35, 36, 37]. In this section, we overview some leading works and also mention some related human-agent negotiation studies. 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 [32]. They evaluate both 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). Another study emphasizing the importance of physical embodiment in human-agent interaction, report empirically that participants rated physically embodied social robot higher in terms of social presence and the quality of the interaction [12]. Moreover, Kiesler *et al.* design an agent that interviews human participants about their health and study the embodiment effect in four different settings [33]. In the first setting, participants were interviewed with a physical embodied humanoid robot and also with a projection of that robot. In the second setting, a virtual agent and its projection interview participants. According to their experimental results, a physically embodied robot is perceived as having a more positive personality. Participants spent more time with the physically embodied robot and liked it more than the virtually embodied software agent.

Leite *et al.* report that human chess players enjoyed more while playing chess with a physically embodied robot than with a virtual one in their experiments [51]. 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 [34]. According to the results, children mimicked playing drums better while interacting with the physically embodied robot than two other setups. According to the survey responses, children enjoyed interacting more with the physically embodied robot, especially when it used its gestures.

Bainbridge *et al.* show that participants obey orders from physically embodied robot more than virtually embodied one [35]. According to the questionnaire results, participants rated physically embodied robot more positively and more natural than the virtual one. Moreover, Hoffman *et al.* observe that human participants preferred collaborating with a physically embodied robot in task-oriented scenarios whereas they preferred the virtually embodied robot in conversational scenarios [36]. On the other hand, they report that there is no significant difference between physical versus virtual embodiment in terms of persuasion and task performance. Furthermore, Artstein *et al.* investigate the impact of embodiment on human participants' decision [37]. In their experimental setup, participants interact with a Nao humanoid robot and a static image of a virtual human. According to their results, although participants rated their rapport higher in physically embodied setup than virtually embodied one, the embodiment type did not influence the participants' decisions during the interaction.

In our work, we examine whether physically embodiment influences the human negotiator's decisions or behavior in negotiation. There are a few studies investigating the effect of embodiment in human-agent negotiation. To begin with, Bevan and Fraser examine the effect of handshaking before the negotiation on negotiation outcome through human-human negotiation experiments [52]. 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 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) [53]. In their study, either a physically embodied 'Nao' robot or a virtually embodied agent makes an offer regarding 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 negotiation is more sophisticated - multi-issue negotiation with a fully autonomous negotiating agent using gestures and arguments during the negotiation. It is worth noting that the interaction with the agent is too limited in that study. Apart from this, there is no other study investigating the effect of physical embodiment in human-robot negotiation to the best of our knowledge.

CHAPTER III

STUDYING THE EFFECT OF GESTURES

To study the effect of negotiation strategy and using gestures in human-robot negotiation, we present a speech-based negotiation protocol and a compatible negotiation strategy employing variants of well-known negotiation tactics. In the following sections, we first describe how the human participants interact with the robot and how the robot makes its offers according to its strategy during their negotiation. After describing the initial gestures designed for this study, the experimental setting and results are explained elaborately.

3.1 Negotiation Protocol

A negotiation protocol governs the interaction among agents during their negotiation. Human-agent negotiation frameworks so far support text-based communication although the medium (e.g. *speech*, *vision* or *text*) plays a crucial role in human communication [5]. Human negotiators find speech-based interaction more natural to interact with their partners and mostly use gestures to convince their partners or show how they feel [54]. Accordingly, this work studies the effect of the gestures in human-robot negotiations governed by the speech-based human-robot negotiation protocol (SHRNP) [2] depicted in Figure 1.

In this framework, a humanoid robot Nao named *Jennifer* negotiates with a human negotiator to come up with a mutual agreement. According to SHRNP, the negotiation is formed as a sequence of rounds where each round consists of three type of actions: *notification*, *bidding* (i.e., rejecting and making a counteroffer), and *acceptance*. In the notification phase, Jennifer is waiting for her human counterpart's notification for be ready to make his offer. When the human negotiator notifies that he is ready for his offer, Jennifer pays attention and translates the speech to a set of words. For the conversation's fluidity, our framework aims

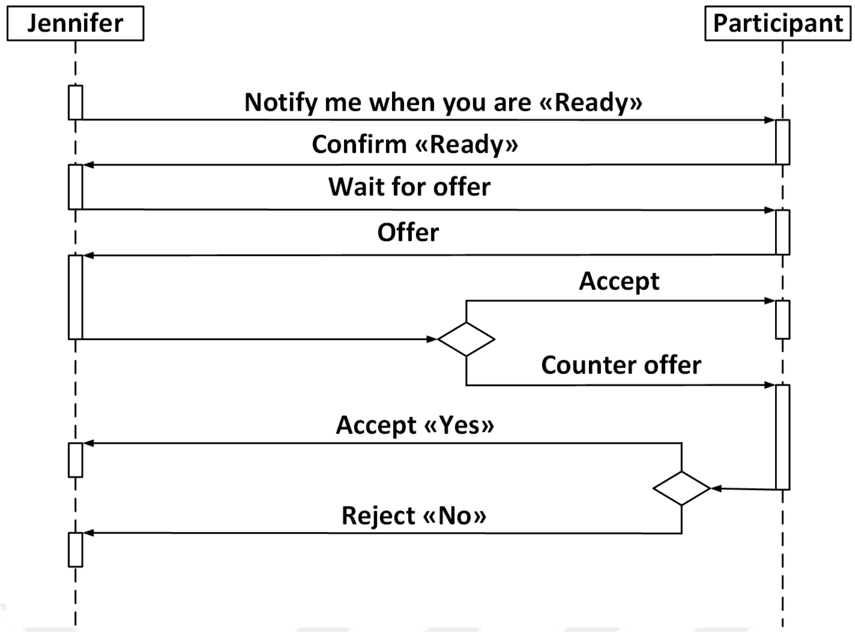


Figure 1: FIPA Representation of Speech-based Protocol [2]

not to restrict the user with a set of predefined words. Therefore, Jennifer uses dictation instead of grammar-based speech recognition. Afterward, she converts the human negotiator's sentence into a structured offer (i.e., a vector of values) by applying several heuristics. After evaluating the offer, Jennifer decides whether to accept the given offer or not. If it is an acceptable offer according to her strategy, she accepts, and the negotiation ends. Otherwise, she makes her counter-offer via speech. Then, human negotiators evaluate whether Jennifer's offer is acceptable or not. They can accept Jennifer's offer and terminates the negotiation successfully, or he can go for another round. This interaction is repeated in a turn-taking fashion until reaching an agreement or a predefined deadline.

The underlying protocol is flexible enough for enabling agents to perform different types of bilateral negotiation. While they may negotiate on their holiday (e.g. location, duration, activities), they can also negotiate how to allocate a set of resources between them. The proposed speech-based protocol consists of four fundamental phases as follows:

- **Notification Phase (Turn 1–3):** Human negotiators may sometimes think out loud and what they said can be perceived as an offer by Jennifer. To avoid such misunderstanding, SHRNP ensures when exactly the human negotiator makes her/his offer by confirming when they are ready to make their offers so that Jennifer can process the right utterances to gather her opponent's offer.

- **Offering Phase for Human Agent (Turn 4):** Human negotiator makes his/her offer.

- **Robot-Response Phase (Turn 5)**: Jennifer evaluates her opponent's offer and either accepts it or makes a counter offer.

- **Human-Response Phase (Turn 6):** If Jennifer makes a counter offer, the human agent should inform whether she/he accepts/rejects the given offer.

One of the biggest challenges in this interaction is speech recognition errors. To get the content of the offers accurately, we calculate the similarity between the underlying recognized word and any similar word in our negotiation corpus. For this purpose, we use Levenshtein distance [55], which takes the number of modifications (deletions, insertions, or substitutions) account that are required to transform the former string to the latter string.

3.2 Negotiation Strategy

A negotiation strategy determines how an agent makes its decisions during the negotiation [14]. The decision mechanism involves bidding and acceptance strategy as well as opponent modeling. This component is the core element for determining the behavior of the agents during the negotiation. In this work, we introduce our negotiation strategy remarkably proposed for a negotiating robot with a human counterpart [2].

As human negotiators' mood changes overtime during the negotiation depending on their opponent's attitude and remaining time, we describe a number of behavior for Jennifer related to negotiation as follows: *Offended*, *Unpleasant*, *Neutral*, *Pleasant*, *Mild*, *Satisfied*, and *Stressed*. According to this work, an agent feels unpleasant when its opponent makes a non-collaborative offer (i.e., selfish move). According to the agent's preferences, the agent feels offended when the offer's utility is shallow, which is not an acceptable offer at all. When the opponent makes a slightly nice move, its feeling is mild, while it starts to get pleasant when its opponent makes a much nicer offer. When the opponent's offer is acceptable, it feels satisfied. Lastly, it feels stressed under time pressure when the deadline is approaching.

Algorithm 1 illustrates how Jennifer makes her decisions and how her mood changes during the negotiation. At the beginning of each round, Jennifer first checks whether the deadline is reached; if so, she ends the negotiation (Line 1–2). Otherwise, Jennifer generates her next offer according to her bidding tactic (Line 4). If the utility of the opponent's current bid is higher than or equal to the utility of Jennifer's incoming offer (i.e., satisfied mood), she accepts the given offer (Line 5–6). Otherwise, Jennifer makes her counteroffer (Line 8). Recall that her opponent first makes an offer, and Jennifer responds with an acceptance or a counter offer.

Afterward, Jennifer decides her attitude towards her opponent. Table 1 indicates the aforementioned predefined moods and what Jennifer says to her human opponent in each case. Those moods and their conditions are explained as follows:

- **Satisfied:** If the utility of the opponents is greater than or equal to Jennifer's next offer, Jennifer is satisfied and accepts her opponent's offer. Note that when the agent accepts the opponent's offer, the negotiation ends.

- **Stressed:** Jennifer hurries her opponent along as the deadline approaches. There is a predefined time, T_Θ to warn the opponent once. If the deadline is reached, Jennifer tells the opponent to hurry up.

- **Offended:** When the utility of the given offer is less than the reservation

Algorithm 1: Jennifer's Decision Module

```
Data: T_{deadline}: deadline, t_{cur}: the current time,
T_{\Theta}: warning time for deadline, tactic: Jennifer's tactic
O_h^{t_{cur}}: human opponent's current offer,
O_h^{t_{prev}}: human opponent's previous offer,
O_j^{t_{cur}}: Jennifer's counter offer, R: reservation utility,
U(O_h^t) human opponent's offer utility for Jennifer,
if t_{cur} >= T_{deadline} then
    Behavior ← End-Negotiation ;
else
    O_j^{t_{cur}} ← generateBid(tactic);
    if U(O_j^{t_{cur}}) ≤ U(O_h^{t_{cur}}) then
        Behavior ← Accept ;
    else
        Make O_j^{t_{cur}} ;
        if O_h^{t_{prev}} == null then
            isHurryUp ← false ;
        else
            if isHurryUp = false & T_{\Theta} <= t_{cur} then
                Behavior ← Hurry-up ;
                isHurryUp ← true ;
            else
                if U(O_h^{t_{cur}}) < R then
                    Behavior ← Offended ;
                else
                    ΔU ← U(O_h^{t_{cur}}) − U(O_h^{t_{prev}}) ;
                    Behavior ← getMood(ΔU,O_h^{t_{cur}}) ;
                end
            end
        end
    end
end
```

Figure 2: Jennifer's Decision Module

utility – the minimum acceptable utility, Jennifer feels "offended".

- **Mild:** A mild behavior is adopted by Jennifer if she thinks that they are slowly approaching a consensus. When Jennifer employs time-based bidding tactics, it adopts a mild behavior if the utility of her opponent's offer for Jennifer, $U(O_h^{t_{cur}})$ is higher than or equal to the estimated lower threshold, LT. In the case of behavior-based bidding tactics, the condition for a mild behavior is that the utility of the opponent's offer is equal to or higher than a proportion of Jennifer's target utility ($\beta = U(O_j^{t_{cur}}) * \Theta$).

- **Neutral:** When the opponent does not change the utility of its offer, it corresponds to a neutral behavior.

- **Pleasant:** If the opponent concedes ($\Delta U > 0$), Jennifer feels pleasant. This mood is only triggered if the opponent's offer is below the acceptance threshold.

- **Unpleasant:** If the opponent makes a selfish move (e.g., decreasing Jennifer's utility), she shows her dissatisfaction by saying that she did not like her opponent's offer.

Table 1: Mood and Argument Decision Matrix

Case	**Mood**	**Arguments**
$T_\Theta <= t_{cur}$	Stressed	Hurry up! We need to find an agreement soon
$U(O_h^{t_{cur}}) < R$	Offended	It is not acceptable!
$\Delta U > 0$	Pleasant	It is getting better but not enough.
$\Delta U = 0$	Neutral	Hmm...
$U(O_h^{t_{cur}}) >= \beta$ $U(O_h^{t_{cur}}) >= LT$	Mild	I like your offer but you can increase a little bit.
$\Delta U < 0$	Unpleasant	I don't like your offer. You should revise it.
$U(O_h^{t_{cur}}) >= U(O_j^{t_{cur}})$	Satisfied	Yes, I accept your offer!
$t_{cur} >= T_{deadline}$	Unsatisfied	Let's stop ! We cannot reach an agreement.

To determine the target utility, the agent adopts a bidding tactic. In this study, we consider two well-known bidding tactics families: *time-based concession* (Section 3.2.1) and *behavior-based concession*(Section 3.2.2) and present variants of those bidding tactics as follows.

3.2.1 Time-dependent Stochastic Bidding Tactic

Time-dependent concession strategies have been widely used in automated negotiation [56]. When a negotiating agent employs such a concession strategy, its behavior changes concerning the remaining time. That is, the agent calculates its concession by estimating a target utility concerning the remaining time. This function produces higher utility values at the beginning of the negotiation, and the target utility value decays over time. The agent employing this tactic makes an offer having a utility close to the estimated target utility.

In this work, we used our time-dependent stochastic bidding tactic (TSBT) [2]. This tactic defines time-dependent lower and upper bounds and randomly generates a bid between them. To estimate their values, the tactic uses a time-dependent concession function proposed by [57]. Equation 1 represents the adopted concession function where t denotes the scaled time $t \in [0, 1]$ and P_0, P_1, P_2 are the maximum value, the curvature, and minimum value of the curve respectively. Note that for the lower bound, P_0, P_1, P_2 are 0.94, 0.5, 0.4 respectively and for the upper bound they are 1, 0.9, and 0.7 respectively in our human-robot experiments as seen in Figure 1. Those values are empirically determined in line with the *Conceder* and *Boulware* as seen in Figure 3.

$$TU(t) = (1-t)^2 \times P_0 + 2 \times (1-t) \times t \times P_1 + t^2 \times P_2 \tag{1}$$

It is worth noting that the adaptive lower and upper bounds correspond to *Conceder* and *Boulware* behaviors, respectively. Recall that the Conceder agent concedes fast during the negotiation while the Boulware agent hardly concedes until the deadline. Our agent may switch its strategy between these tactics stochastically. Consequently, the human opponent may not easily guess our agent's behavior. Furthermore, this twist allows the agent to concede over time and make selfish moves so that agent may end up with a better outcome.

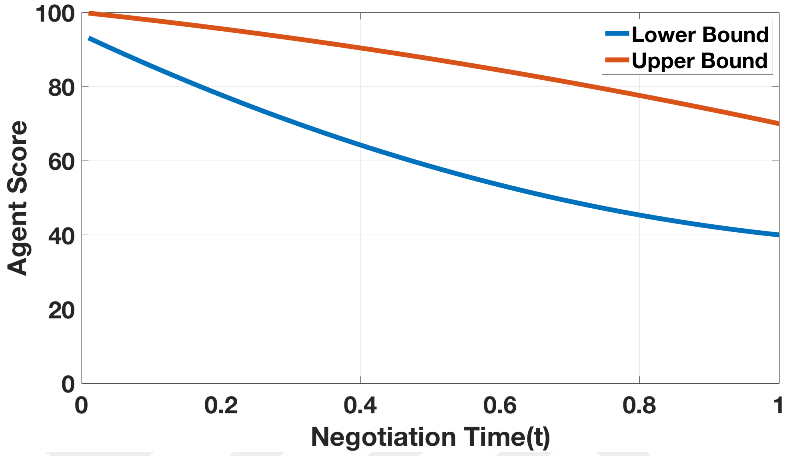


Figure 3: Time-dependent Lower and Upper Bounds [2]

3.2.2 Behavior-dependent Adaptive Bidding Tactic

When a negotiating agent does not take their opponent's moves into account, the negotiation may end up with an unfortunate agreement for itself. For example, the agent may concede over time while its opponent may not make any compromising moves at all. The opponent may gain much more than the agent. Therefore, it is essential to consider the opponent's attitude during the negotiation and act accordingly. Faratin *et al.* propose behavior-dependent bidding tactics, mimicking the opponent's behavior to some extent [56].

The Behavior-dependent Adaptive Bidding Tactic (BABT) proposed in this work is a variant of the relative Tit-For-Tat (TFT) strategy, which mimics the opponent's behavior percentage-wise. The main difference between them is that *our tactic dynamically changes according to what extent the agent mimics the opponent's behavior*. According to this tactic, the agent starts with its best offer and makes the following bids. It calculates the utility changes in its opponent's subsequent offers regarding its utility as seen in Equation 2, where $U(O_h^{t_{cur}})$ and $U(O_h^{t_{prev}})$ denote the utility of the human opponent's current and previous offers for our agent, Jennifer, respectively. Note that each agent knows only their preferences in negotiation, and utility value denotes the degree of satisfaction. The higher the utility an offer is, the more preferred it is.

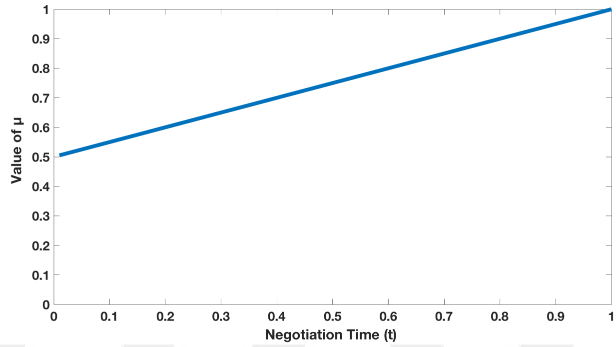


Figure 4: Determining Percentage of Mimicking Opponent

$$\Delta U = (U(O_h^{t_{cur-i}}) - U(O_h^{t_{prev-i}})) \tag{2}$$

$$TU = U(O_j^{t_{prev}}) - \Delta U \times \mu \tag{3}$$

$$\mu = P_3 + t \times P_3 \tag{4}$$

A time parameter scales the utility change, μ to estimate a target utility TU as seen in Equation 3 where $U(O_j^{t_{prev}})$ denotes the utility of the agent's previous offer. The agent subtracts the scaled utility changes to mimic its opponent. The positive changes mean that the opponent concedes; hence, the agent should concede as well. It generates an offer whose utility is closest to the estimated target utility. In Equation 4, the value of coefficient μ is determined by the current time and P_3, controlling the percentage of mimic. It initially tends to decrease/increase the target utility less than its opponent does, and afterward, the degree of mimic increases over time. The value of μ is initially set to 0.5 and increased gradually till reaching to 1.0. That is, our agent is more sensitive to its opponent's moves, towards to end of negotiation.

Figure 4 shows how the value of μ changes over time when μ approaches 1, the agent's offer reflects the absolute value of increase or decrease performed by her opponent.

3.3 Gesture for Negotiation

Body language plays an essential role in human negotiations [58]. Using "gesture" would make communication more natural, and it might profoundly influence the negotiation process. Therefore, we develop some fundamental gestures to show Jennifer's reaction to her opponent's behavior inspired by the gestures used during the actual negotiations. We cover gestures reflecting the essential moods available in negotiation, such as pleasant, unpleasant, offended, mild, stressed. Accordingly, nine different gestures have been designed and developed to capture the aforementioned emotional moods for Jennifer in line with the decisions in Table 1. Figure 5 illustrates Jennifer's gestures in her ongoing negotiation with her human counterpart.

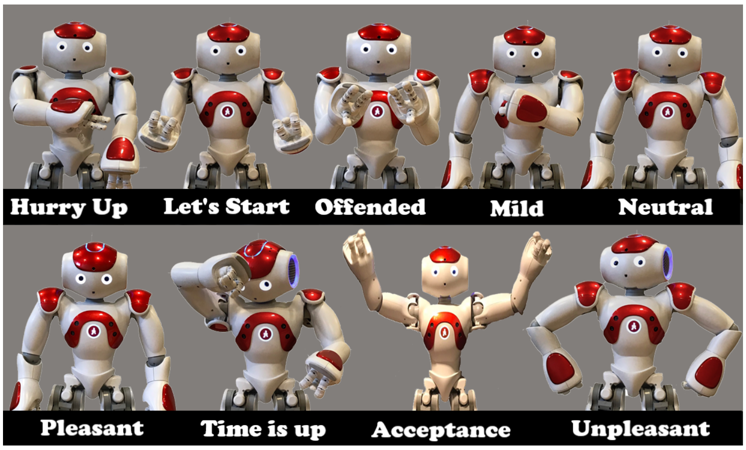


Figure 5: Corresponding Gestures for Jennifer's Moods

The important gestures are listed as follows:

- **"Hurry up"** gesture: Jennifer aims to notify the opponent that the deadline is approaching to be in a hurry to find a consensus. To create a time pressure on the opponent, Jennifer points at her 'imaginary watch" on the right wrist.

This gesture reflects the mood of stressed.

- **“Offended”** gesture: Jennifer moves her arms forward, denoting a direct refusal as well as negatively nodding her head.
- **“Mild”** gesture: Jennifer moves her arm and nods her head slightly so that she shows her appreciation for the improvements in the offer.
- **“Neutral”** gesture: Jennifer stands in its default position and makes a thinking sound (i.e.,“‘Hmm”) to denote that there is no difference between subsequent offers for herself.
- **“Pleasant”** gesture: Jennifer moves its head up and down ambitiously as approving that opponent’s moves are much better than the previous ones.
- **“Unpleasant”** gesture: Jennifer puts her arms to her waist in an angry mood and nods her head negatively to notify her opponent that she does not like the offer.
- **“Acceptance”** gesture: Jennifer raises her arms to show her joy due to finding an agreement. It reflects the mood of satisfaction.
- **“Time is up”** gesture: Jennifer expresses her sadness by hitting her forehead when the negotiation fails (i.e., unsatisfied mood).

3.4 Evaluation

In our experiments, we study the effect of using gestures on well-known negotiation tactics in terms of negotiation outcomes. Considering the complexity of human-robot negotiation (e.g., learning effect and individual differences), we follow a split-plot design, a mixture of between-subject design and within-subject design. Each condition is examined by different participants in a between-subject design, whereas each subject is asked to experience all possible conditions in a within-subject design. In our setup, “gesture” is tested by within-subject design while “negotiation tactic” is tested by between-subject design to deal with these issues.

Our experimental design involves two groups where Jennifer employs *TSBT* in the former group while she employs *BABT* in the latter group. Each participant is asked to negotiate with Jennifer two times (i.e., Jennifer with gesture and without gesture). To minimize the effect of the learning effect, we use the randomization technique. Some participants first negotiate with Jennifer using gestures and then negotiate with Jennifer without any gestures, while other participants negotiate in reverse order. Furthermore, each participant has a 15-minute break between their negotiation sessions. During their break, some tasks such as playing a mind game and watching entertaining videos are given to the participants to make them forget the details of their former negotiation (i.e., reducing the learning effect).

In the experiment, a negotiation scenario is given to each participant. As a role-playing game, they are asked to study their preference profiles and the interaction protocol elaborately before their negotiation. First, an easy negotiation scenario consisting of only three issues has been created for a training session. Participants watch a demonstration video and perform a five-minute negotiation on the given training scenario. After the training session, the participant's preference profile for the first negotiation session is studied, and then s/he negotiates with Jennifer for up to 10 minutes. If there is no agreement within 10 minutes, both parties receive zero points. Note that the goal of the participants is to receive at least 30 points out of 100. The participants are encouraged to maximize their score by pointing out that the participants with the highest score will win a gift card from a well-known coffee brand. Thus, we provide an incentive for participants to take their negotiations seriously.

As explained above, each participant has a 15-minute break before starting their second negotiation. Adopting an entirely different negotiation scenario and preference profile in the second negotiation may prevent us from accurately comparing negotiation outcomes. Recall that we aim to study the effect of the gesture, and if we change the negotiation scenario in the second session, the performance difference between the two negotiations may stem from the negotiation scenario or use of gestures. The actual cause could be unclear. On the other hand, using the same preference profile would cause a significant learning effect. Therefore, we keep the utility function structure the same as the first negotiation (i.e., same score distribution) but change their assignments (i.e., assigning each score to different items/issues) as explained below.

According to our scenario, our participants are asked to negotiate with Jennifer on resource allocation to survive on a deserted island similar to the scenario in [59]. There are eight indivisible items: some of them will be given to the participant, and Jennifer will take the rest of them. Note that human participants ask for what they would like to get, and Jennifer offers what items to be given to the participants to avoid misunderstanding. In other words, the negotiation is on what items would be given to the participant. Table 2 shows these items and their score for Jennifer and her human counterpart. Figure 6 shows the utilities of each possible bid in the given scenario as well as the agreement zone. It can be seen that the bargaining power of the two parties is almost the same. It is worth noting that the participants only know their scores and are informed that Jennifer does not know their scores. In the second negotiation session, it is told that their preferences are completely different, although only the order of the scores is changed, and the value distribution of the scores remains the same. Since the value distribution of the scores is the same in both negotiations (See Table 2), agents have the same negotiation power in both sessions. Note that the participants can only see the relevant preference profile in each negotiation session.

In Figure 7, participants are allowed to use a paper to take their notes and their phones to check the remaining time. They keep the current preference profile and interaction flowchart with them during their negotiation. Their negotiation session is recorded to check the quality of speech recognition with our detailed log files. Furthermore, participants are asked to fill out a questionnaire form at the end of the experiment.

Table 2: Preference Profiles for Negotiation Sessions

	First Negotiation		Second Negotiation	
Items	Jennifer's Profile	Human's Profile	Jennifer's Profile	Human's Profile
Compass	13	5	6	13
Container	22	20	13	5
Food	17	7	20	22
Hammer	6	13	5	10
Knife	5	10	10	17
Match	20	22	7	6
Medicine	7	6	17	7
Rope	10	17	22	20

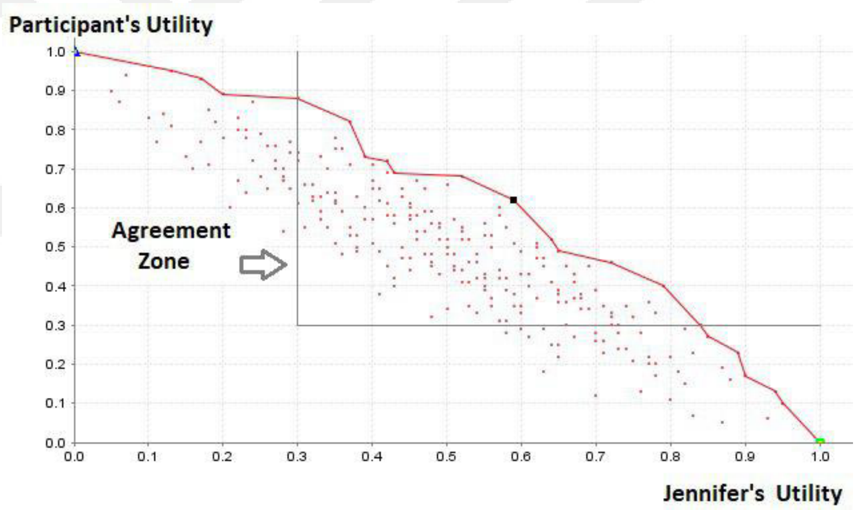


Figure 6: Outcome Space for Negotiating Parties

Figure 7: Experiment Setup

3.4.1 Participants

We have recruited 84 participants (i.e., university students and faculty members; 62 males, 22 females; median age: 23) for conducting our human-robot experiments. To obtain reliable results, we compared all offers made by each participant during their negotiation (i.e., checking recorded videos) with the bid history saved in the log files. We discarded the negotiations in which we found some bids misinterpreted by Jennifer due to the failure of the speech recognition tool. Therefore, we consider the negotiations that belong to 60 participants out of 84 in our analysis (i.e., 30 participants per each negotiation strategy). Since each participant negotiates two times, it makes 120 negotiations in total.

3.4.2 Experimental Result

We first examine the negotiation success rates for each setting. Table 3 shows the number of negotiation sessions where the participants could not find an agreement. When Jennifer employs *TSBT* without any gestures, 86.67 % of the negotiations end up with an agreement, while the agreement rate becomes 90 % when she employs the same negotiation strategy with gestures. In the case of *BABT* without any gestures, 80 % of the negotiations end up with an agreement, while the rate is for the same strategy with the gestures is 83.33 %. Somehow the percentage of a successful negotiation is higher when the agent uses its gestures. Some participants might find the robot with gestures more empathetic and tend to reach an agreement. As expected, when the agent employs a time-based concession strategy in contrast to a behavior-based concession strategy, the percentage of agreements is higher. That stems from the fact that the agent concedes more against a formidable opponent and ends up with an agreement even though it gains a relatively lower score.

In further analysis, we only consider negotiation results when the participants have an agreement in both negotiations (with/without gesture) to compare the

Table 3: Number of unsuccessful negotiations

Type	With Gesture	Without Gesture
TSBT	3	4
BABT	5	6

average utilities of the agreements in a fairway. Therefore, we only use the negotiation results of 42 participants out of 60 participants. As evaluation metrics, we consider the score gained by the participant and Jennifer. Figure 8 illustrates the average score for both human participants and Jennifer when the user completes both negotiations (i.e., gesture/without gesture) successfully. Those negotiation results belong to 19 participants negotiating against to *BABT* and 23 participants negotiating against to *TSBT*.

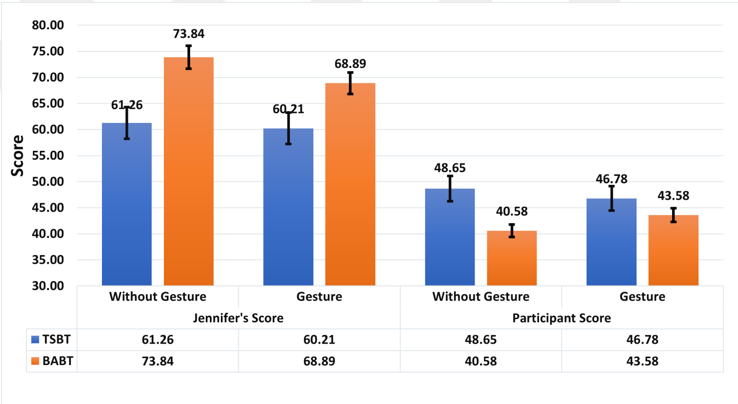


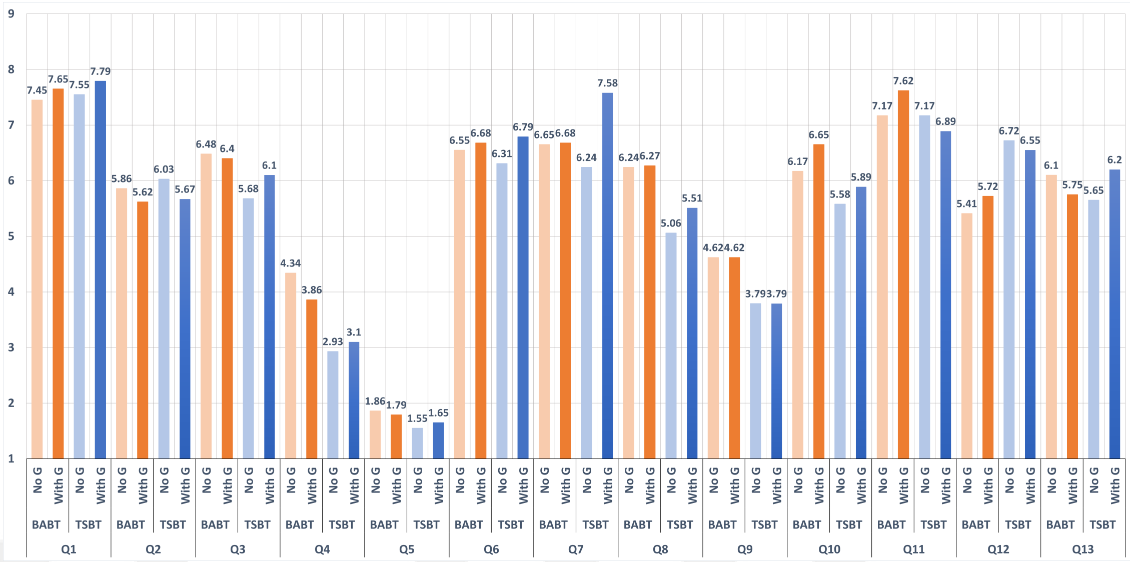
Figure 8: Average Scores Of Successful Negotiation Outcomes

It can be easily seen that Jennifer received a higher score on average when she mimics her opponent to some extent (68.89 versus 60.21 with gestures; 73.84 versus 61.26 without gesture). To study the impact of the negotiation strategy and the effect of gesture, we applied ANOVA split-plot test due to our experiment design [60]. We found out that there is a significant difference in terms of agent score between when Jennifer employs *TSBT* and when she employs *BABT* ($F = 21.11$, $p < 0.01$) as far as the agent score is concerned. Furthermore, we performed an additional analysis by considering only the participants' first negotiation session to eliminate the learning effect. Therefore, a two-tailed Mann Whitney U Test was applied to the results, while Jennifer using gestures, the strategy has a statistically significant difference in agent scores ($p < 0.01$, z=-2.62). Similarly, the same test on the results, while Jennifer does not use any gestures, shows the statistically significant difference in agent score ($p < 0.01$, z=-3.82). Those results align with each other and support that the average agent scores are significantly different for each negotiation strategy. It can be concluded that the agent gains a higher score when it employs *BABT* compared to *TSBT*.

Surprisingly when she employs a behavior-based bidding strategy (*BABT*), using gestures affects Jennifer's score negatively, as seen in Figure 8 (68.89 versus 73.84, with gesture and without gesture, respectively). When we applied a two-tailed Wilcoxon signed-rank test on the participants' results who negotiate against *BABT*, we found out that gesture has a statistically significant effect on agent score ($p = 0.018 < 0.05$, z=-2.35). When Jennifer makes her offers in line with her opponent's behavior (e.g., selfish) and uses suitable gestures, Jennifer's body language may frustrate the participants (i.e., giving an impression of a pushy/tough negotiator) so that powerful negotiators may not tend to concede. However, there are no significant results for the cases when human participants negotiate with the agent employing *TSBT* ($p > 0.05$, z=-0.21). When Jennifer employs *BABT*, Jennifer exposes her opponent's selfish moves and makes an offer accordingly. Nevertheless, in the case of *TSBT*, her actions are not inclined with the recognized opponent's behavior (i.e., continue conceding despite her opponent's selfish moves). Therefore, human participants may find Jennifer neutral so that their attitude may not be negatively affected.

Furthermore, we examined the effect of gesture on agreement time and the number of bids exchange. On average, participants reached an agreement around 6-8 rounds in both setups (i.e., 6-7 minutes out of 10 minutes). When we applied a two-tailed Wilcoxon signed-rank test on the results of the participants, we found out that gesture does not have a statistically significant effect on agreement time

($p > 0.05$, z=-0.10) and on the number of rounds ($p > 0.05$, z=-0.69).



Q1 It was easy to communicate with Jennifer.
Q2 Jennifer negotiated with me in a fair way.
Q3 Jennifer negotiated with me like a human negotiator and adapted her next offer.
Q4 Jennifer had difficulty in understanding me during the negotiation; thus, we could not have a fluent interaction.
Q5 I had difficulty in understanding Jennifer's speech; thus, I misunderstood some offers.
Q6 Since our communication channel was speech, I found the interaction is as human likely.
Q7 Jennifer's gestures were mostly consistent with the situation.
Q8 Jennifer's reaction made me concede more.
Q9 I was frustrated with Jennifer's attitude during the negotiation.
Q10 Jennifer often made very unfair offers.
Q11 It was easy for me to keep track of what Jennifer offered me.
Q12 My performance in this negotiation was good.
Q13 I felt that Jennifer considered my preferences/interests/attitude as well as hers while generating her bids.

Figure 9: Average Ratings of Questionnaire Responses

In addition to the objective performance metrics such as agent score and agreement time, subjective evaluation of the system has been done through the questionnaire survey filled in by the participants at the end of the experiment. The likert questions are formed on a 9-point scale (1 for strong disagreement, 5 is for neutral, and 9 for strong agreement). The questionnaire consists of three sections: the first section including questions about the experimental setup in general, the second and third sections including identical questions about their first and second negotiation sessions, respectively. The reader may wonder why we did not ask the survey questions related to the first session after their first negotiation session. If we asked them before their second negotiation, those questions might influence their attitude in their second negotiation. Therefore, we had to ask them at the end of both negotiation sessions.

In the first part of the questionnaire, participants are asked about the experimental setup in general. The means and standard deviations of their responses to those questions are given below. It can be seen that the instructions and interaction protocol were clear for the participants.

- "The instructions provided to me for the experimental negotiation were clear." (on average 8.63 ± 0.61)
- "Before starting the real experiment, I had a training session in which I negotiated with Jennifer for 5 minutes. It was sufficient for me to understand how to interact with Jennifer during a negotiation session." (on average 8.55 ± 1.22)
- "It was not clear to me how I should interact with Jennifer to give my offer during the negotiation session." (on average 2.11 ± 2.26)

Figure 9 shows the negotiation and gesture related survey questions and the average rating of the participants' responses where **NoG** denotes their negotiation session where Jennifer did not use her gestures, and **WithG** stands for their negotiation where Jennifer uses her gestures. Recall that some participants negotiated with the *BABT* agent strategy while others negotiated with TSBT. The responses are grouped according to which strategy they negotiate against. The resulting average ratings of the more positively structured statements are above 5 points (i.e., neutral), where the responses to the negative-structured statements such as Q4, Q5, and Q9, are below 5 points.

We observed that human participants negotiate more comfortably and smoothly against *TSBT* since the robot constantly concedes over time. On the other hand, when Jennifer employs *BABT*, it mimics its opponents; therefore, the human participants put more effort. Irrespective of using or not using gestures, there is a statistically significant difference in the participant's response to "Jennifer's reaction made me concede more" (Q8) and "My performance in this negotiation was good." (Q12) between when Jennifer employs *TSBT* and when she employs *BABT* according to the Mann-Whitney U test – a non-parametric independent test ($p=.0394 <0.05$ and $z=2.0617$ for Q8; $p=0.0007 <0.05$ and $z=-3.39401$ for Q12). That shows the participants who negotiate with *TSBT* were more satisfied with their negotiation. The average ratings for Q12 in without and with gesture settings are 5.41 versus 6.72 and 5.72 versus 6.55 (*BABT* versus *TSBT*), respectively. Moreover, the group negotiating against *BABT* felt that they concede more due to Jennifer's reaction. The average ratings for Q8 in without and with gesture settings are 6.24 versus 5.06 and 6.27 versus 5.51 (*BABT* versus *TSBT*), respectively. Those results are in line with the gained utilities by the participants.

Furthermore, when we analyze the participants' responses to the Q7 for their session with and without gestures when Jennifer employs a time-based concession strategy, we observe a statistically significant difference ($p = 0.004 <0.05$ and $z=-2.857$) according to the Wilcoxon signed-rank test – a non-parametric test for two related samples. It shows that participants noticed differences between the two sessions concerning the consistency of the gestures with the situation. The overall average rating of the responses to Q7 is higher when Jennifer employs her gestures than without gestures (6.24 versus 7.58). Surprisingly, we do not observe such a significant difference when Jennifer employs a behavior-based strategy. This may stem from that they may focus on the exchanged offers or Jennifer's attitude more than her gestures since *BABT* is tougher than *TSBT*. Lastly, it is worth mentioning that during our unstructured interview at the end of the experiment, some participants specified that they perceived Jennifer as more human-like when it uses developed gestures, and they could get some insights about whether or not Jennifer liked their offer through Jennifer's gestures. Some positive comments are

"*Jennifer's gestures are actually simple but understandable. If she does not like the offer, you can understand easily with her gestures.*", "*Her gestures were in line with her answers and also made me think that my offer is really getting worse or better for her.*", "*Her gestures made me feel more like I am talking with something more than just a robot.*", and "*The gestures were clear for me to understand.*". We received a few negative comments such as "*It was overwhelming.*" and "*They were not so bad but they are not as good as human*".

CHAPTER IV

STUDYING THE EFFECT OF EMBODIMENT

This chapter examines whether the physical embodiment influences the human negotiator's decisions or attitudes during the negotiation. Therefore, we build a digital replica of the negotiation environment, including the robot. In this virtual environment, the robot acts the same way as it does in the physical environment. Afterward, we conduct an experiment where each participant negotiates with the robot on equivalent negotiation scenarios in both environments. We compare their negotiation results regarding the received utility by human participants and our agent, negotiation time, and round number. Then, we analyze the participants ' responses to the survey questions related to embodiment, gestures, and negotiation strategy. In the following sections, we first explain our negotiation setting, including the description of the negotiation protocol, strategy, and gestured employed by the robot (Section 4.4) and describe our experimental setting (Section 4.5). Finally, we report our findings.

4.1 Negotiation Protocol

In the previous experiments, the participants followed the SHRNP protocol we described in Section 3.1. Recall that the protocol includes a notification phase where participants should confirm that they are ready to make their offer so that our robot can process the right utterances as the content of the offer and avoid misunderstanding due to the possibility that human negotiators may sometimes think out loud out and that could be perceived as an offer by the robot. Based on the feedback given by the participants about the interaction, we observed that this additional notification phase might end up with a tedious interaction from a human point of view. Therefore, we decided to remove this step and follow the Alternating Offers Protocol [61, 45] to make the communication channel more natural.

Figure 10 illustrates how a human participant and our robot interact during the negotiation. 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 counter-offer. This process continues in a turn-taking fashion until a termination condition is reached (i.e., reaching a deadline or agreement). It is worth noting that we allow only complete offers during the negotiation. In our case study, agents are negotiating to allocate limited resources among themselves. As a result, they must explicitly specify what resources they want for themselves and their amount. We aim to let them express their offers differently instead of enforcing them to one particular structure. For example, a human negotiator can specify his offer as "I want three apples, and the rest is yours", "you can take two apples and all oranges; that is all," or "I want all of them except two apples.". Similarly, they can use different keywords such as "deal", "yes", and "agree" when accepting a given offer.

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.

4.2 Hybrid Strategy

The way an agent makes decisions during a negotiation is determined by their negotiation strategy [14]. The bidding strategy determines what to offer during the negotiation, while the acceptance strategy determines when and what offer is acceptable for the agent. We empirically compared the performances of the time-dependent concession strategy and behavior-dependent strategy in human-robot negotiations [62]. It was observed that the robot usually gained higher utility

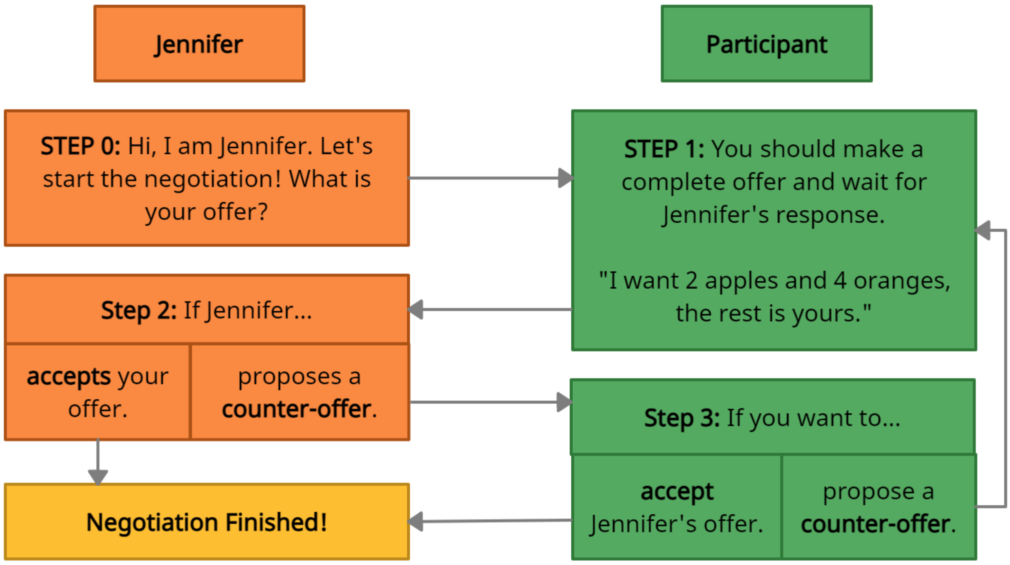


Figure 10: Improved Speech-based Protocol

when it mimics its opponent to a certain degree, while human participants found it easier to find an agreement with a robot employing the time-based concession strategy. Therefore, we prefer to adopt the "Hybrid" Strategy [15], which combines well-known time-dependent and behavior-dependent strategies in our setting to examine the effect of physical embodiment.

According to the "Hybrid" Strategy, the strategy takes its opponent's bidding behavior into account more than the remaining time in the beginning. However, as the negotiation progresses and the deadline approaches, it pays more attention to the remaining time. Accordingly, the target utility at each turn is calculated as shown in Equation 5, and the agent makes an offer with the calculated target utility. If there is no such offer, the agent makes an offer whose utility is the closest to the target utility.

$$TU_{Hybrid} = (t^2) \times TU_{Times} + (1 - t^2) \times TU_{Behavior} \tag{5}$$

The strategy uses a time dependent concession function provided by Vahidov [57] to calculate time-based target utility (TU_{Times}). The concession function is represented by Equation 6, where t is the scaled time $t \in [0, 1]$ and P_0, P_1, P_2 are the curve's maximum value, curvature, and minimum value, respectively. [1]

$$TU_{Times} = (1 - t)^2 \times P_0 + [2 \times (1 - t) \times t \times P_1] + t^2 \times P_2 \tag{6}$$

The "Hybrid" strategy uses an extension of Tit-For-Tat Strategy [56] to calculate the behavior-based target utility ($TU_{Behavior}$), which replicates the opponent's moves to some extent. One of the primary differences between the two strategies is that the "Hybrid" strategy uses a dynamically changing ratio rather than a set ratio. Furthermore, Tit-For-Tat Strategy only evaluates the opponent's latest two offers and ignores all previous offers. The employed technique considers a window of opponents' bids and evaluates the utility changes of the opponents' bids inside that window by prioritizing the most recent ones to capture the opponent's general bidding pattern.

The "Hybrid" strategy scales the overall utility change by a time-dependent parameter, μ, to calculate a target utility, as shown in Equation 7, where $U(O_a^{t-1})$ denotes the utility of the agent's prior offer. The positive changes indicate that the opponent has conceded; as a result, the agent should also concede. The "Hybrid" approach determines overall utility changes by considering the opponent's latest n consecutive bids, where W_i specifies the weights of each utility difference, as shown in Equation 8. The value of coefficient μ is determined by the current time and P_3, which controls the proportion of mimic, as shown in Equation 9. Initially, the agent decreases/increases the target utility less than its opponent, and then the degree of mimic increases over time.

$$TU_{Behavior} = U(O_a^{t-1}) - \mu \times \Delta U \tag{7}$$

$$\Delta U = \sum_{i=1}^{n} [W_i \times (U(O_h^{t-i}) - U(O_h^{t-i-1}))] \tag{8}$$

$$\mu = P_3 + t \times P_3 \tag{9}$$

[1]In our experiment, P_0, P_1, P_2 values are 0.9, 0.7, 0.4 respectively.

4.3 Gestures and Arguments

Based on the feedback received from our previous work [62], this work enriches the gestures and arguments used during the negotiation. In total, 14 gestures and 31 different arguments are designed for our robot as shown in Table 4 and Figure 11. Accordingly, we revise the set of possible moods and associated gestures according to [63]. The final set of moods consists of *Happy*, *Pleased*, *Hopeful*, *Neutral*, *Dissatisfied*, *Annoyed*, *Frustrated*, and *Worried*. The robot adapts its moods and gestures in line with the opponent's offer and the remaining negotiation time during the negotiation. Table 4 indicates what mood is adopted by the robot under which circumstances.

Table 4: Case and Mood Decision Matrix

Case	Mood	Arguments
$U(O_h^{t_{cur}}) >= U(O_a^{t_{cur}})$	Happy	Great! I accept your offer!
$\Delta U > \alpha$ & $U(O_h^{t_{cur}}) < U(O_a^{t_{cur}})$	Pleased	It is getting better but not enough. That sounds good but you can give me a little bit more.
$\alpha => \Delta U > 0$ & $U(O_h^{t_{cur}}) < U(O_a^{t_{cur}})$	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 little bit more. If I'm going to consider your offer, it would be great if you concede little bit more. Hmm.. Sounds good, we are almost there.
$\Delta U = 0$	Neutral	Hmm... Let's talk about other options.
$\alpha <= \Delta U < 0$	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 to your offer. Your offer is not fair enough. Sorry, your offer doesn't go far enough. I don't consider that fair.
$\Delta U <$ -α $U(O_h^{t_{cur}}) == U(O_h^{t_{cur-1}})$	Annoyed	No, It is not acceptable! I wish you did not make this offer. That's so disappointing! How am I supposed to accept this offer? Are you serious? I don't like your offer. You should revise it. I hope we can find a deal today!
$t_{cur} > 0.7$ & $U(O_h^{t_{cur}}) <= 0.5$ $U(O_h^{t_{cur}}) == U(O_h^{t_{cur-1}}) == U(O_h^{t_{cur-2}})$ $U(O_h^{t_{cur}}) < R$	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 on my shoes. We cannot reach an agreement. Let's try to be more collaborative.
6 min $<= t_{cur}$ 4 min $<= t_{cur}$ 2 min $<= t_{cur}$	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.

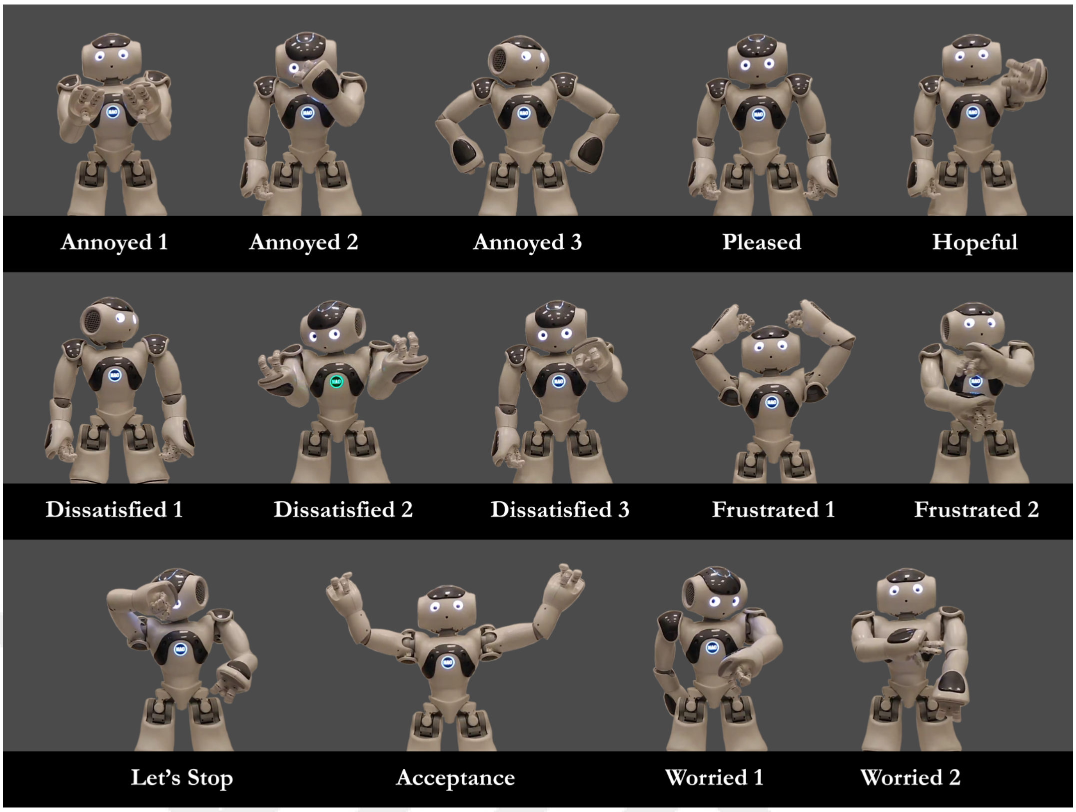


Figure 11: Enriched Gesture Set

Those moods and their conditions are explained in detail as follows:

- **Happy:** Our humanoid robot is satisfied with its opponent's offer and accepts it if the opponents' utility is greater than or equal to the robot's next offer. The negotiation is over when the agent accepts the opponent's offer.

- **Pleased:** If the opponent concedes and the humanoid robot's utility has increased significantly ($\Delta U > 0.25$), but her/his offer is not still acceptable for the robot (i.e., the opponent's offer utility is less than the acceptance threshold), it feels pleased.

- **Hopeful:** The robot adopts the hopeful mood if its opponent concedes, although its utility is not considerably changed ($\Delta U <= 0.25$). This mood is only 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 then the robot's utility is not changed ($\Delta U = 0$), its mood becomes neutral.

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

- **Annoyed:** If the opponent makes a selfish move that reduces the robot's utility significantly ($\Delta U < -0.25$) or makes the same offer twice, its mood becomes annoyed and expresses its annoyance by using arguments.

- **Frustrated:** When one of the three conditions is met, the robot becomes frustrated: when (1) the utility of its opponent's offer is less than the reservation utility, (2) the current negotiation time is greater than 0.7 ($t_{cur} > 0.7$) and the opponent's offer utility for the robot is less than 0.5 (i.e., $U(O_h^{t_{cur}}) < 0.5$), or (3) its opponent makes the same offer thrice or more.

- **Worried:** As the deadline approaches, the robot hurries its opponent. The robot advises the opponent to hurry up three times (i.e., $T1_\Theta$, $T2_\Theta$, $T3_\Theta$).

4.4 Settings

Figure 12 and Figure 13 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 the robot. It is worth noting that virtual and physical setups are almost identical. Furthermore, the virtual environment is displayed on the same screen shown in Figure 12 during the experiments. The details of the experimental setting are explained elaborately in the following section.

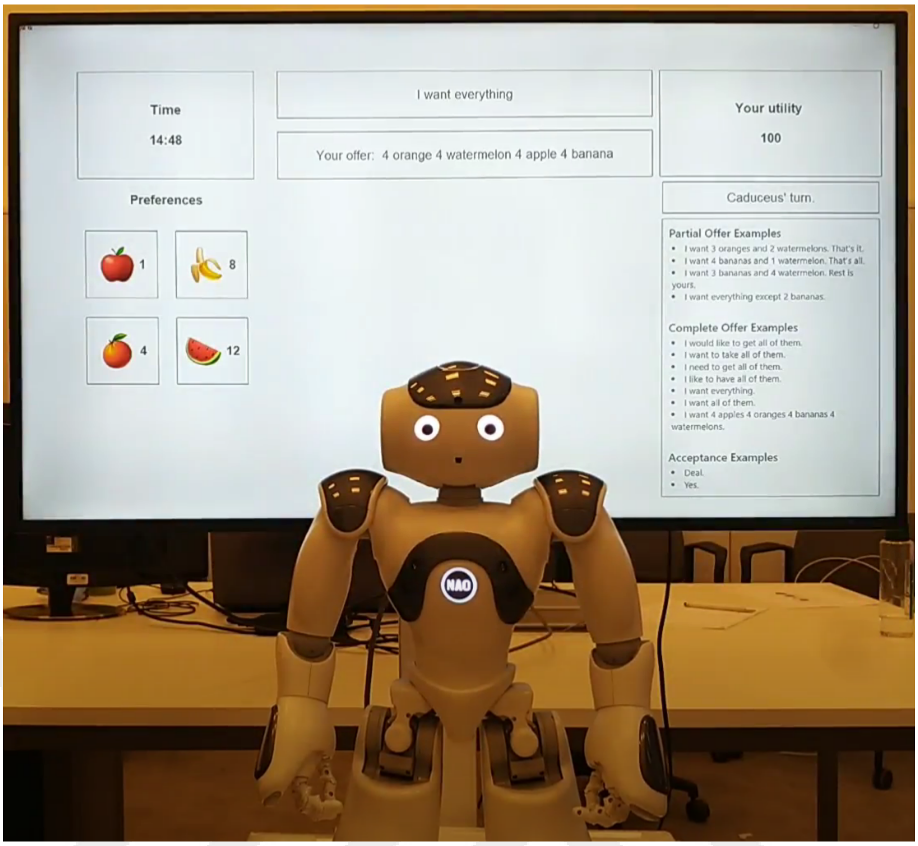


Figure 12: Physical Experiment Setup

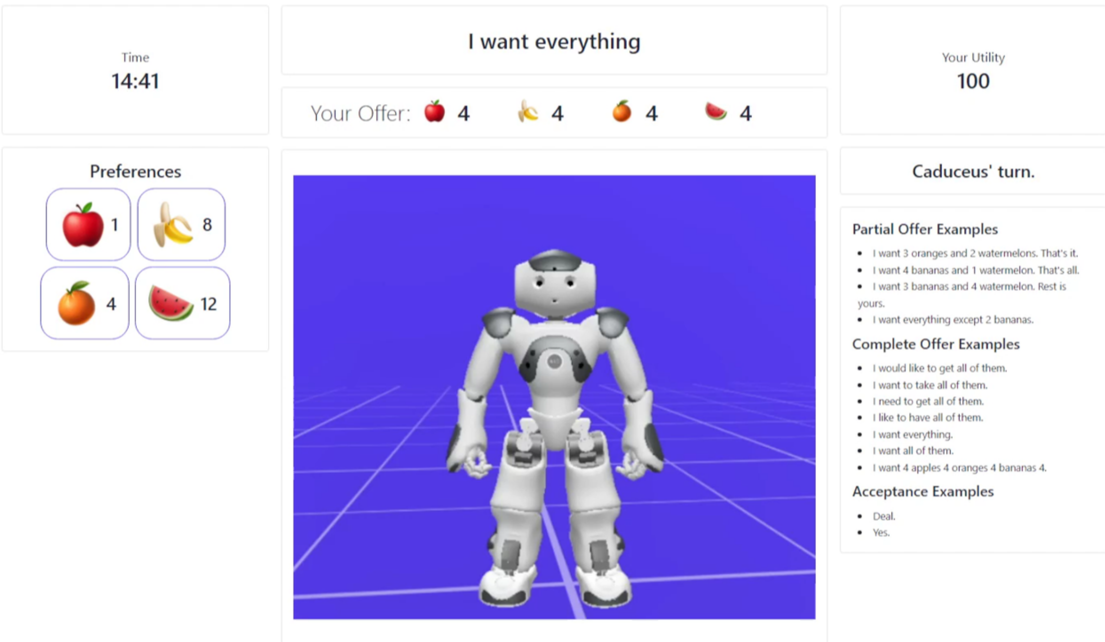


Figure 13: Virtual Experiment Setup

4.5 Evaluation

As explained in Section 4.4, we created a digital replica of our negotiating robot so that we can investigate whether there is any difference between its physical and virtual presence in terms of the negotiation outcome, process, or perception of the robot's behavior by the human opponents. In our experiments, human participants are asked to negotiate with the "Nao" humanoid robot named *Caduceus* in both physical and virtual environments. To minimize the learning effect, we randomize the negotiation order. Meaning that half of the participants negotiate with the physically embodied *Caduceus* and then negotiate with the virtually embodied *Caduceus* while the other half of the participants negotiate in reverse order. Note that there is a 5-minute break between two negotiation sessions.

Participants are asked to negotiate according to a given resource allocation scenario as a role-playing game. According to the given scenario, participants and *Caduceus* are lucky customers in a supermarket, and they will receive free fruits as a gift. All they need is to find an agreement on how they will share fruits between them. There are four types of fruits where there are four for each. 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 gift card from a well-known supermarket brand if they negotiate well and encourage them to maximize their score.

Table 5 shows preference profiles of *Caduceus* and its human counterpart for both sessions. It is worth noting that the participants know only their scores, and they are informed that *Caduceus* does not know their scores too. 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 in a more straightforward problem for 5 minutes to get familiar with the negotiation process.

Table 5: Preference Profiles for Negotiation Sessions

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

During their negotiation, participants communicate with *Caduceus* via speech in both virtual and physical environments. In addition, we prepared an interface displaying some necessary information that makes a human participant's life easier. As seen in Figure 12, 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*. Figure 14 shows the environment we conducted the experiments. As seen, the participant sits across *Caduceus* so that she 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. When they complete both sessions, they fill out two questionnaire forms regarding their first and second negotiation session.

4.5.1 Participants

We have recruited 52 participants (i.e., university students; 40 males, 12 females; age 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 of participants' English level is 5.65.

Figure 14: Experiment Setup

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 [15], 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, age between 18 and 36) participants' negotiation sessions.

To understand participants' negotiation style, we asked participants to rate four criteria influencing their negotiation pattern concerning their priorities, where the highest and lowest priority is denoted by 1 and 4 points, respectively. Those criteria are decreasing the opponent's utility, decreasing agreement time, increasing their utility, and getting the best deal for both sides. Figure 15 shows the histogram for participants' priority ratings for those criteria. It can be seen that one-third of the participants prioritize decreasing their opponent's points and the second or third prioritized criteria is to increase their points. According to their statements before their negotiations, only 6 of 30 participants aim to find the best deal for both sides. It seems that we have highly competitive participants and several collaborative participants.

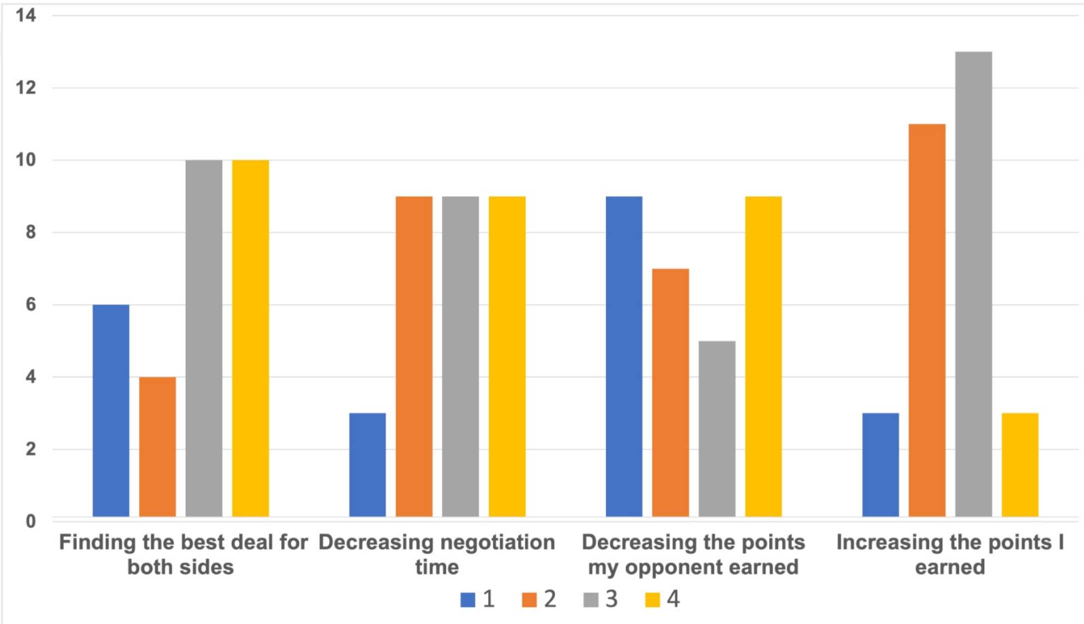


Figure 15: Pre-Negotiation Survey: Participants' Priority Orders

4.5.2 Experimental Results

We first compare the negotiation performance of the participants in both settings. First of all, all negotiation sessions end with an agreement. Figure 16 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). 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 is investigated, we observed that their averages are close to each other in both environments (0.80 vs. 0.81). Since these utilities are not normally distributed according to the Kolmogorov-Smirnov test, 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].

Moreover, normalized utility product 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. Although the averages of the utility products in physical and virtual environments 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 two-tailed dependent sample t-test. That means that the agreements were better for both parties when the negotiation was held in the virtual environment. According to our observations, participants' tendencies towards cooperation and negotiability increase as gamification increases. Interactions become more severe, and competitiveness increases during physically embodied negotiations.

Figure 17a demonstrates the average agreement time (i.e., negotiation time). As far as the normalized agreement time is concerned, 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). We have applied the two-tailed dependent sample t-test to see a statistically significant difference in the negotiation agreement time. 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

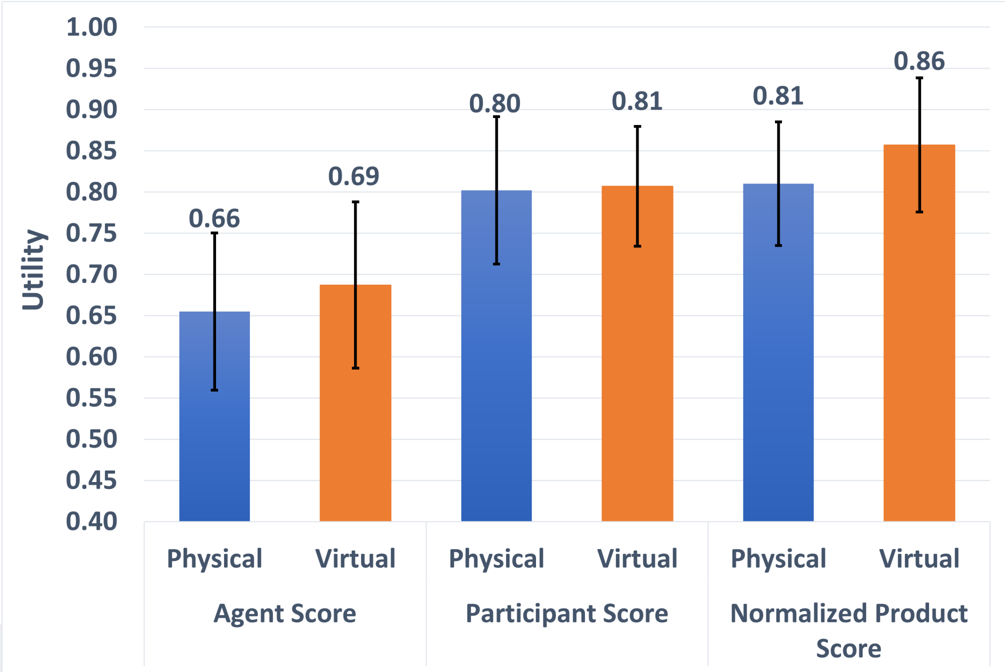
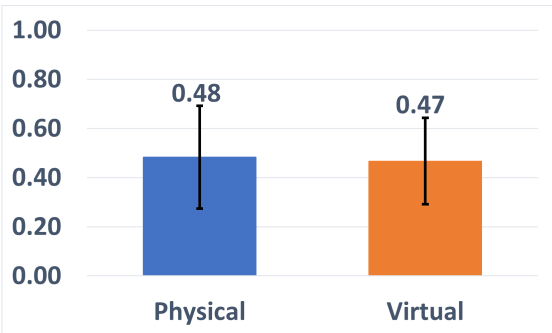
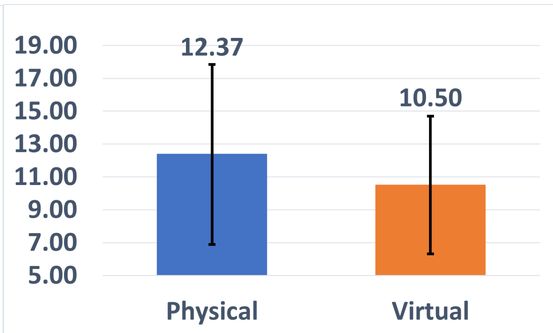


Figure 16: Average of Individual And Normalized Product Scores

number of rounds to reach an agreement [t=-1.64, p=0.11]. However, the participants reached an agreement in slightly lower rounds (on average 10.2 versus 12.13) as seen in Figure 17b.



(a) Average Negotiation Time



(b) Average Negotiation Rounds

Figure 17: Average Negotiation Time and Rounds

In addition to the outcome analysis, 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 [64]. Accordingly, we study the assertiveness and cooperativeness of the participants.

Since assertiveness measures the individual attempts to satisfy their preferences, we group the offers made by each participant and take their averages separately for both settings. Figure 18 shows their average offer utility with standard deviations. As seen, there is no statistically significant difference in the assertiveness of the participants on average in virtual and physical settings (respectively 0.83 and 0.84) 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' assertiveness levels changed drastically concerning physical presence. On the one hand, participants 1, 2, 6, 12, and 17 tended to offer higher utilities for themselves in the virtual environment compared to the physical environment. On the other hand, participants 5, 13, 15, and 24 assertiveness level is higher in the physical environment. Without a doubt, there are individual differences.

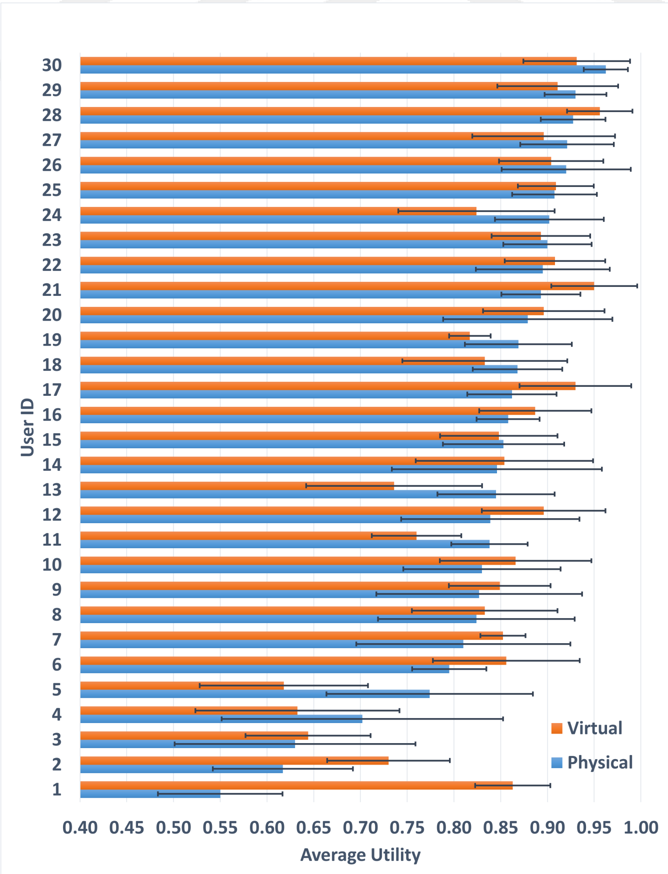


Figure 18: Average Utility of Human Participants' Offers

Cooperativeness is the measurement of the individual attempts to find a mutual agreement. In our work, we consider the percentages of cooperative moves made by the human participants in order to estimate their cooperativeness level as seen in Equation 10. Those moves are *fortunate*, *nice* and *concession* moves. For clarity, we refer to "move" definitions made by Hindriks *et. al.* where there are six different move types, namely fortunate, nice, concession, selfish, unfortunate, and silent [1]. Table 6 demonstrates the calculation of move types of a player where ΔU_s and ΔU_o represent the utility difference for the negotiator itself and that for the opponent, respectively. When we apply 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 virtually embodied robot.

Table 6: Move Specification of a Negotiator [1]

	Self Difference	**Opponent Difference**
Silent	$\Delta U_s = 0$	$\Delta U_o = 0$
Nice	$\Delta U_s = 0$	$\Delta U_o > 0$
Fortunate	$\Delta U_s > 0$	$\Delta U_o > 0$
Unfortunate	$\Delta U_s < 0$	$\Delta U_o < 0$
Concession	$\Delta U_s < 0$	$\Delta U_o > 0$
Selfish	$\Delta U_s > 0$	$\Delta U_o < 0$

$$Cooperativeness = \%_{Fortunate} + \%_{Nice} + \%_{Concession} \tag{10}$$

Lastly, we group the negotiation sessions of the participants according to participants' most prioritized criterion while negotiating with their opponents. Table 7 shows the average utility of all offers made by the participants per each group with respect to preferences of the Caduceus and its human counterpart separately.

We can see that the participants who first aimed to decrease their opponent's utility gained utility of 0.78, and their opponent received around 0.66 on average in the physical environment. It seems like participants sacrificed their utility while lowering their opponent's utility. In contrast, the participants who aim to increase their utility gain higher on average - which also yielded lower utility for their opponents. For participants who try to maximize the social welfare (i.e., finding the best deal for both sides), the average utilities for the opponent are higher than that of the other groups in the physical environment. To sum up, those average utilities received by the participants in the physical environment align with the participant's prioritized criterion, which is stated before their negotiation. Somehow, the results in the virtual environment do not show the same pattern. For instance, the participants who prioritized to increase their utility received lower utility (i.e., 0.79) on average in the virtual environment. Similarly, the participants who aim to maximize the social welfare almost gained the same utility as those who try to decrease their opponent's utility on average (0.82). However, the latter group's offers yield more utility for their opponent than the former group. (0.67 > 0.66). These results partially support that human participants' negotiation attitude is more close to their real attitudes when they negotiate with the physically embodied *Caduceus*.

Table 7: Average Utility of Participants' Offers

	Physical		**Virtual**	
Priority	**Human**	**Agent**	**Human**	**Agent**
Both sides	0.80 ± 0.08	0.69 ± 0.08	0.82 ± 0.07	0.66 ± 0.10
Negotiation time	0.83 ± 0.03	0.62 ± 0.06	0.86 ± 0.02	0.59 ± 0.02
Opponent's utility	0.78 ± 0.12	0.66 ± 0.12	0.82 ± 0.05	0.67 ± 0.09
Own utility	0.85 ± 0.01	0.57 ± 0.05	0.79 ± 0.10	0.73 ± 0.10

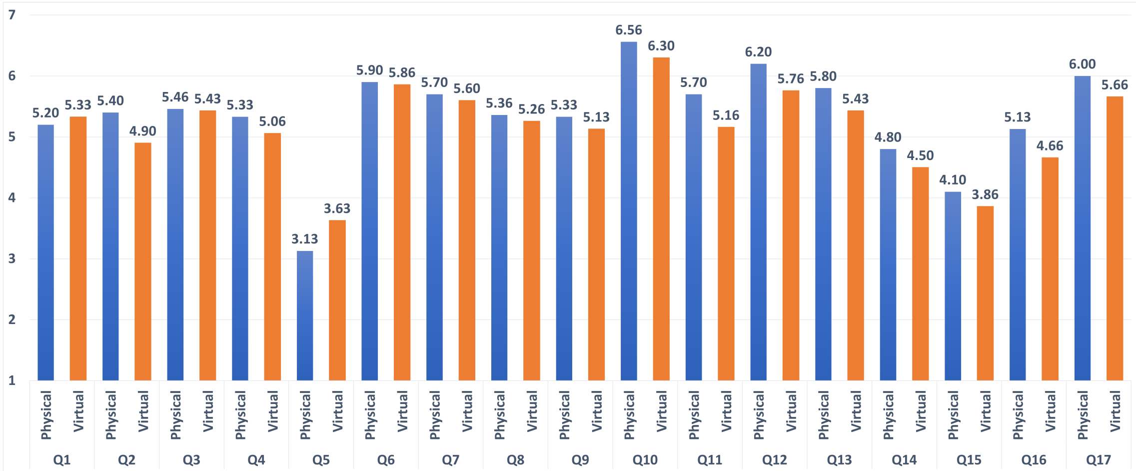
4.5.3 Analysis of Questionnaire

In addition to the objective performance metrics such as agent score and agreement time, subjective evaluation of the system has been done through the questionnaire survey filled in by the participants at the end of the experiment. The Likert questions are formed on a 7-point scale (1 for strong disagreement, four is for neutral, and 7 for strong agreement). The questionnaire consists of three sections: the first section includes questions about the experimental setup and practice session in general, the second and third sections include identical questions about their first and second negotiation sessions, respectively. The reader may wonder why we did not ask the survey questions related to the first session after their first negotiation session. If we asked them before their second negotiation, those questions might influence their attitude in their second negotiation. Therefore, we had to ask them at the end of both negotiation sessions.

In the first part of the questionnaire, participants are asked about the experimental setup in general. The means and standard deviations of their responses to those questions are given below. It can be seen that the instructions and interaction protocol were clear for the participants.

- "I understand the experimental instructions. They were clear." (on average 6.86 ± 0.36).
- "The demo session shown before the experiment was instructive." (on average 6.86 ± 0.36).

Figure 19 shows the negotiation and embodiment-related survey questions and the average rating of the participants' 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), where the responses to the negative-structured statements such as Q5 are below 4 points.



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 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, I observed that it consider my negotiation behavior (Selfish, Collaborative).
Q-9 While Caduceus was making its offers, I observed that 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 19: Average Ratings of Questionnaire Responses

When 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). Moreover, it also has a statistically significant effect in responses to "Caduceus' gestures were mostly consistent with the situation" (Q12), when dependent t-test is applied (t=-2.107, p=0.048). As a result, participants perceived Caduceus as more human-like (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.

According to the question, "I was frustrated with Caduceus' attitude during the negotiation." (Q5), it can be observed that the robot's attitude does not frustrate the participants for both physical and virtual versions (on average 3.13 versus 3.63). Moreover, regarding the question, "Caduceus paid attention to my gestures during the negotiation." Q(15), it can be seen that participants do not think that their gestures are considered by the robot (on average 4.1 versus 3.86). Indeed, *Caduceus* did not take their gestures into account during the negotiation.

Lastly, it is worth mentioning that 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 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 not to Caduceus to maximize my utility.*".

CHAPTER V

CONCLUSION

With the careful design of such negotiating robots, we expect to see a significant impact on society's productivity and well-being by human-robot collaboration. This thesis studies the effect of gestures and embodiment in human-robot negotiations empirically. Furthermore, it presents variants of the time-dependent and behavior-dependent negotiation tactics and conducts experiments to compare their negotiation performance.

One of the main results confirms that our humanoid robot, Jennifer, gained more beneficial outcomes for itself when it mimics its opponent to some extent than when it constantly concedes according to the remaining time. User survey responses also supported this result. People found the agent easy to negotiate with when it employs a time-based strategy. Moreover, our findings support our hypothesis that the gesture affects the negotiation process, consequently on the negotiation outcome. Notably, its effect is also related to the adopted negotiation strategy. When Jennifer employs a behavior-based negotiation strategy, a significant difference has been observed, but this effect was not seen in the time-based strategy.

Another important lesson we learned is that an agent designer should be careful while designing the gestures compatible with the agent's behavior. The gestures may affect the negotiation result negatively. In our case, when the agent negotiates with its partner by mimicking its bidding strategy, it gained lower utility on average in the case of using its gestures compared to the non-gesture setting. That may stem from the fact that Jennifer may irritate them or encourage them to play more challenging since it looks more smart and tough. Another reason may be that Jennifer's gesture helps human participants model Jennifer's preferences or strategy better. They can understand what bids are (not) good for Jennifer due to her response through both its gestures and arguments. As expected, using gestures may end up in a more human-like perception of a humanoid robot. The participants mostly found Jennifer more human-like when it uses developed gestures during the negotiation. A combination of gestures and arguments may give human participants more fluent interaction. Without any doubt, there is still some room for improving the gestures and make Jennifer more human-like and natural to negotiate.

Our vision is human-robot collaboration to considerably impact society's productivity and well-being if the underlying infrastructure for such collaboration is carefully designed. Accordingly, this work investigates the effect of physical embodiment on human-robot negotiations through human-agent negotiation experiments. Experimental results showed that the social welfare was higher when the negotiation was held with a virtual robot rather than a physical robot. According to our observations, people are more inclined to collaborate and reach an agreement as gamification increases (i.e., virtual environment). While negotiating with the physically embodied robot, interactions grew tenser, and competitiveness increased. When we analyze the negotiation traces, this observation is also supported. Human participants made more collaborative moves during the negotiation in the virtual setting compared to the physical environment. According to the pre-negotiation form, we group the negotiation sessions of the participants according to participants' most prioritized criterion while negotiating with their opponents. We observe that when humans negotiate with a physically embodied robot, their negotiating attitudes are closer to their actual attitudes. Lastly, when we analyzed the questionnaire results, we found that participants perceived our robot as more human-like in the physical setup as we expected. It is also seen that participants found the robot's gesture more appropriate when used in the physical setup.

As future work,it would be interesting to design learning mechanisms for deciding the most appropriate gestures in the underlying interaction. Since human understanding and human-like behavior play an essential role in human-agent interaction, it would be an excellent research direction to develop agents who can understand their human counterparts' preferences from a small set of bid exchanges and perceive their opponents' emotions negotiation to adjust its strategy accordingly.

Furthermore, it would be interesting to make human negotiators act more collaboratively towards the physically embodied robots. Moreover, we might consider studying 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 different humanoid robots varies concerning their appearance. Lastly, we plan to design negotiating agents that can perceive their human counterparts' gestures and adapt their gestures/bidding behaviors accordingly.

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VITA

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- R. Aydoğan, O. Keskin, and U. Çakan, 2021, "Would you imagine yourself negotiating with a robot, Jennifer? Why not?", in IEEE Transactions on Human-Machine Systems.

- O. Güngör, U. Çakan, R. Aydoğan, and P. Özturk, 2021, "Effect of Awareness of Other Side's Gain on Negotiation Outcome, Emotion, Argument, and Bidding Behavior". Recent Advances in Agent-based Negotiation - Formal Models and Human Aspects, pp. 3-20.

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