Would You Imagine Yourself Negotiating With a Robot, Jennifer? Why Not?

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***Abstract*—With the improvement of intelligent systems and robotics, social robots are becoming part of our society. To accomplish complex tasks, robots and humans may need to collaborate, and when necessary, they need to negotiate with each other. While designing such socially interacting robots, it is crucial to consider human factors such as facial expression, emotions, and body language. Since gestures play a crucial role in interaction, this article studies the effect of gestures in human–robot negotiation experiments. Additionally, it compares the performance of variants of the well-known negotiation tactics (i.e., time-based and behavior-based) in automated negotiation literature in the context of human–robot negotiations. Our experimental results support the finding in automated negotiation. That is, the robot gained higher utility when it imitates its opponent's bidding strategy than employing a time-based negotiation strategy. When adopting a behavior-based technique, there is a statistically significant effect of gestures on the underlying negotiation process, and, therefore, on negotiation outcome.**

***Index Terms*—Effect of gestures in negotiation, human–agent negotiation, human–robot negotiation.**

I. Introduction

DAY by day, our society benefits from more sophisticated intelligent systems solving complex social problems analytically and interacting with humans effectively [1]. 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 life [2], [3]. As robots become more human-like, they will be integrated into society in a more prevalent way. For instance, we can recently observe that socially interactive robots have been used to assist children with autism [4]. It can foresee that eldercare robots will play a key role in lonely older people's lives [5]. With the emergence of Industry 4.0, we expect to work together with robots to carry out some tasks [6]. Some decisions will presumably require to be decided jointly in such a collaborative environment where conflicts between humans and robots may occur. To resolve such conflicts, humans and robots would interact with each other and seek mutually acceptable decisions. We may need to negotiate with robots on task allocations or other daily conflicts to find common ground. For this reason, there is an immediate need for designing negotiating agents that are specialized in interaction with humans [7], [8]. Although human–agent negotiation has been studied in the literature, most of the 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 [9]. Moreover, underlying interaction with the human may end up with a different outcome depending on whether the physical or virtual embodiment is adopted [10]. It would be 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 [11]. 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 [11], there are relatively fewer works in the field of human–agent negotiation, which requires considering different dynamics such as bounded rationality, interaction medium, emotions [12], and gestures [13]. While human factors such as facial expressions, emotions, or gestures do not take place in automated negotiation in which smart software agents negotiate with each other, these factors play a key role in human–human and human–agent negotiations. There are various approaches to design negotiation frameworks for human–agent negotiations considering those factors [14]–[18]. 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) [8], [19], [20], others investigate negotiating strategies resulting in efficient outcomes while establishing a good relationship with human counterparts [21], [22]. 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. Our study aims to fill this gap by studying gestures in human–robot negotiations (HRNs).

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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, it is vital to select the best communication channel while designing a negotiation protocol for 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 [23], 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 [24], [25]. 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 [26], [27]. In addition to that, using "gesture" would make the communication more natural as it might influence the negotiation process profoundly [28].

Accordingly, this work extends our work [29] significantly by introducing a variant of a behavior-based bidding tactic while mainly focusing on the effect of gestures in HRNs where a humanoid robot and its human counterpart negotiate about resource allocation (i.e., multi-issue negotiation) through speech. Our experimental results showed that the robot gains higher utility when it employs the proposed behavior-based tactic as expected. These results support the common findings in automated negotiation—behavior-based negotiation tactics outperform time-based tactics in most cases. Moreover, the agreement rate is slightly higher when our humanoid robot uses the gestures we developed. It can be concluded that the effect of gestures may differ depending on which negotiation tactics the robot adopts. On the other hand, in our experiments, the observed effect was on the negative side of the robot's score. The robot slightly gained less utility when it uses gestures while mimicking its opponent's bidding strategy. That may stem from the intuition that humans may better model the robot's behavior due to the feedback given by a combination of gestures and arguments. Alternatively, they may have perceived the robot as tougher and smarter, and thus, acted more deliberately, causing them to gain more utility.

The rest of the article is organized as follows. Section III mentions the negotiation protocol used to govern the negotiation between our humanoid robot and its human counterpart, while Section V shows the developed gestures. Section IV explains the negotiation and interaction decisions employed by the robot. Our experimental design and empirical evaluations of our findings are presented in Section VI. Finally, we summarize our contributions and discuss future work in Section VII after touching on related work in Section II.

II. Related Work

Agent-based negotiation has been widely studied for several decades, and a variety of negotiation frameworks have been proposed so far [30]–[37]. 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.* [17] developed a situated multiagent game environment named Colored Trails where players can be humans, agents, or both. It is a configurable and extensible system used by the research community that investigates multiagent decision-making. As Lin and Kraus [13] denoted in their vision paper, 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 Rosenfeld *et al.* [14], where a negotiating agent and a human negotiator can negotiate by exchanging their bids in English. 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 [15]. 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 [19]. As a communication medium plays a significant role in human interactions, Divekar *et al.* [38] introduced a framework where a virtual agent communicates with human negotiators through speech. Complementary to those works, our work focuses on the effect of physical embodiment 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 [39]. For instance, Xu *et al.* [40] investigate the effects of a humanoid robot's body language to express the underlying mood where the robot plays a teacher role. 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 coverbal 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) [41]. 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 [42]. 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 and Chao [23] propose a model of turn-taking for a humanoid robot to interact with people. 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.

Bevan and Fraser [26] studied the effect of handshaking on negotiation from different perspectives, such as negotiation outcome and trustworthiness. Like our study, they also use a Nao humanoid robot negotiating with a human participant, but it is remotely controlled, whereas our robot is negotiating autonomously. Remarkably, they have three different settings. In the first setup, the robot does not handshake with its partner, while in the second setup, the robot handshakes autonomously before its negotiation. In the third setup, handshaking is supported by a human party via haptic systems; therefore, it is more human-likely. They conducted human experiments in between design, where each condition is tested separately. Note that they have 120 participants in total, and that is, 60 participants for each role (i.e., buyer and seller), which means 20 participants per condition. The seller robot gains more profit when it shakes its partner's hand before the negotiation compared to the case, with no handshaking. Furthermore, its performance is better when a haptic system supports handshake. This study supports the importance of gesture in negotiation. In this case, it was handshaking. Similarly, our work investigates the effect of other types of gestures during the negotiation. While their robot does not have its decision function, our robot negotiates with its human counterpart autonomously. To the best of our knowledge, it is the first humanoid robot using some gestures and negotiating with human participants autonomously.

Other than gestures, the effect of facial expression has been studied in the context of human–agent negotiation. For instance, De Melo *et al.* [19] study the effect of the agent's emotion, particularly anger and happiness, on negotiation. Participants are asked to negotiate with virtual agents adopting a different facial expression. The results showed that when participants negotiated with the virtual agent expressing anger, it was observed that they conceded more than the case of negotiating with a neutral or happy opponent. In our work, the robot tried to express its feelings with its gestures and arguments. Furthermore, Mell *et al.* [43] study how human counterparts can be affected by competitive or collaborative opponents. Their results show that competitive strategies made the human participants concede more. On the other hand, a study [44] showed that people are more willing to renegotiate with warm agents, although there is no significant difference found on negotiation outcome in their experiments. Another study exploring the effect of aggressive attitudes on human–agent negotiations [45] shows that aggressive attitudes in virtual environments affect participants' emotional states similar to the real environment. Note that the degree of this impact is lower in the virtual environment than in the real one.

Finally, we would like to mention another study that investigates the effect of a robot's disagreement attitude and its source of voice on the negotiation process with a human counterpart [46]. Although our work addresses a similar resource allocation problem, their negotiation setting is entirely different from ours. First, they do not define utility functions per party. Second, the robot does not generate counteroffers in their work; instead, the robot can take two actions: either to accept the human party's request or to reject it by specifying a reason. That is repeated until reaching an agreement. Note that their robot does not have any sophisticated decision mechanism. Their negotiation is formed in an agenda-based negotiation in which negotiation items are negotiated one by one. Two types of robot behaviors are defined: agreement and disagreement attitude (i.e., rejecting human request in the first turn). They conducted human experiments ($N = 40$), and their results showed that participants changed their decisions when the robot disagrees with them in the first turn. Furthermore, they found out that the disagreement agent is perceived as more human-like, and they tested the effect of the source of the robot's voice (i.e., sounds come from the robot itself or a control box outside of the robot in the same environment). Here, they could not find any significant differences. Complementary to this work, we studied the effect of the robot's gestures on the negotiation outcome and process.

III. 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 [3]. 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 [47]. Accordingly, this work studies the effect of the gestures in HRNs governed by the speech-based human–robot negotiation protocol (SHRNP) [29] depicted in Fig. 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

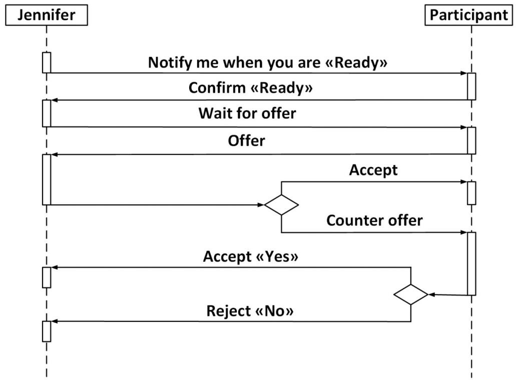


Fig. 1. FIPA representation of speech-based protocol [29].

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 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 counteroffer 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.

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 [48], which takes the number of modifications (deletions, insertions, or substitutions) account that are required to transform the former string to the latter string.

IV. Negotiation Strategy

A negotiation strategy determines how an agent makes its decisions during the negotiation [11]. 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 [29].

As human negotiators' mood changes over time 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 noncollaborative 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. Finally, it feels stressed under time pressure when the deadline is approaching.

Algorithm 1: Jennifer's Decision Module

Data: $T_{deadline}$: deadline, t_{cur}: the current time,
T_{Θ}: 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,

1 **if** $t_{cur} >= T_{deadline}$ **then**
2   Behavior $\leftarrow$ End-Negotiation ;
3 **else**
4     $O_j^{t_{cur}} \leftarrow$ generateBid($tactic$);
5   **if** $U(O_j^{t_{cur}}) \leq U(O_h^{t_{cur}})$ **then**
6   Behavior $\leftarrow$ Accept ;
7   **else**
8   Make $O_j^{t_{cur}}$;
9   **if** $O_h^{t_{prev}} == null$ **then**
10   isHurryUp $\leftarrow$ false ;
11   **else**
12   **if** $isHurryUp = false \;\&\; T_{\Theta} <= t_{cur}$ **then**
13   Behavior $\leftarrow$ Hurry-up ;
14   isHurryUp $\leftarrow$ true ;
15   **else**
16   **if** $U(O_h^{t_{cur}}) < R$ **then**
17   Behavior $\leftarrow$ Offended ;
18   **else**
19                     $\Delta U \leftarrow U(O_h^{t_{cur}}) - U(O_h^{t_{prev}})$;
20   Behavior $\leftarrow$ getMood(ΔU,$O_h^{t_{cur}}$) ;
21   **end**
22   **end**
23   **end**
24   **end**
25 **end**

Fig. 2. Jennifer's decision module.

As seen in Fig. 2, 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 (Lines 1 and 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 (Lines 5 and 6). Otherwise, Jennifer makes her counteroffer (Line 8). Recall that her opponent first makes an offer, and Jennifer responds with an acceptance or a counteroffer.

Afterward, Jennifer decides her attitude toward her opponent. Table I 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.

TABLE I
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.

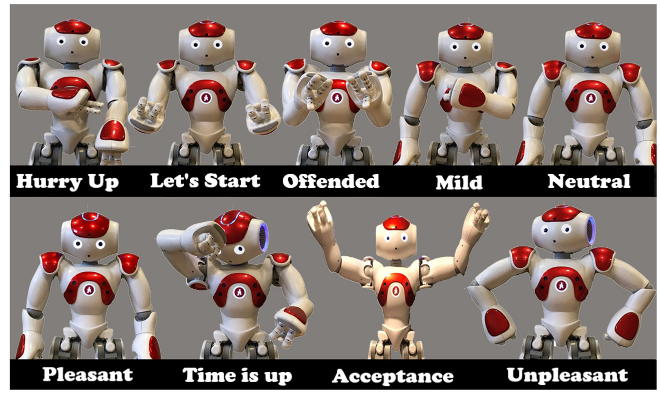


Fig. 3. Corresponding gestures for Jennifer's moods.

- **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 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, $U(O_h^{t_{\mathrm{cur}}})$, 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.

V. GESTURE FOR NEGOTIATION

Body language plays an essential role in human negotiations [49]. 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, and 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 I. Fig. 3 illustrates Jennifer's gestures in her ongoing negotiation with her human counterpart.

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 her 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 her 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).

VI. EVALUATION

To study the effect of using gestures in our negotiation setup, we developed the interaction and negotiation strategy with two different well-known bidding tactic families in the literature. These are time-based stochastic bidding tactic (TSBT) and behavior-based adaptive bidding tactic (BABT). The evaluation is based on comparing the negotiation result when the robot uses gesture versus when it does not use it. In the following part, we first explain our experimental setup and then report our findings.

A. Negotiation Tactics

1) Time-Dependent Stochastic Bidding Tactic: Time-dependent concession strategies have been widely used in automated negotiation [50]. When a negotiating agent employs such a concession strategy, its behavior changes concerning the

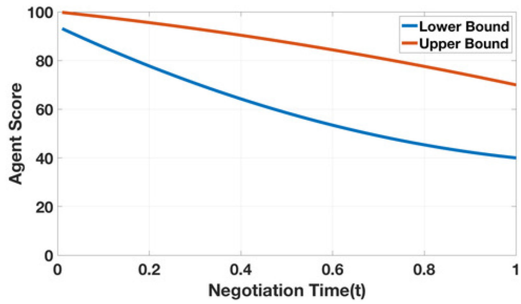


Fig. 4. Time-dependent lower and upper bounds [29].

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 TSBT [29]. 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 [51]. Equation (1) represents the adopted concession function where t denotes the scaled time $t \in [0, 1]$ and P_0, P_1, and 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 Fig. 1. Those values are empirically determined in line with the *Conceder* and *Boulware* as seen in Fig. 4.

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

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.

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.* [50] propose behavior-dependent bidding tactics, mimicking the opponent's behavior to some extent.

The BABT proposed in this work is a variant of the relative tit-for-tat 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 (2), where $U(O_h^{t_{\text{cur}}})$ and $U(O_h^{t_{\text{prev}}})$ 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.

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

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

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

A time parameter scales the utility change, μ, to estimate a target utility TU as seen in (3), where $U(O_j^{t_{\text{prev}}})$ 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 (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, toward to end of negotiation.

B. Experimental Setup

In our experiments, we study the effect of using gestures on well-known negotiation tactics in terms of negotiation outcomes. Considering the complexity of HRN (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-min 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, participants are asked to study their preference profiles and the interaction protocol elaborately before their negotiation. First, an easy negotiation scenario

TABLE II
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

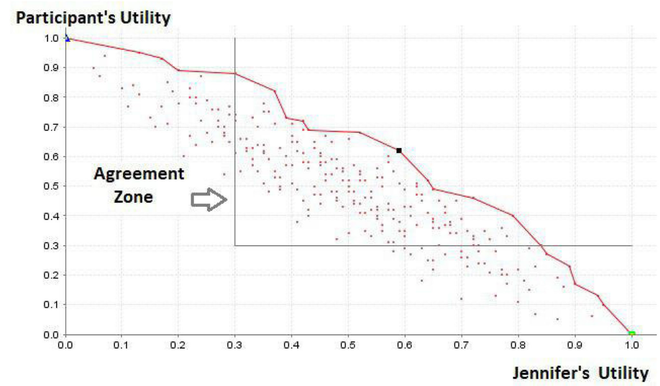


Fig. 5. Outcome space for negotiating parties.

Fig. 6. Experiment setup.

consisting of only three issues has been created for a training session. Participants watch a demonstration video and perform a 5-min negotiation on the given training scenario. After the training session, the participant's preference profile for the first negotiation session is studied, and then she/he negotiates with Jennifer for up to 10 min. If there is no agreement within 10 min, 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-min 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., the 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 Ref. [46]. 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 II shows these items and their score for Jennifer and her human counterpart. Fig. 5 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 II), 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 Fig. 6, 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.

C. 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 negotiation strategy). Since each participant negotiates two times, it makes 120 negotiations in total.

D. Experimental Result

We first examine the negotiation success rates for each setting. Table III shows the number of negotiation sessions where the participants could not find an agreement. When Jennifer employs

TABLE III
NUMBER OF UNSUCCESSFUL NEGOTIATIONS

Type	With Gesture	Without Gesture
TSBT	3	4
BABT	5	6

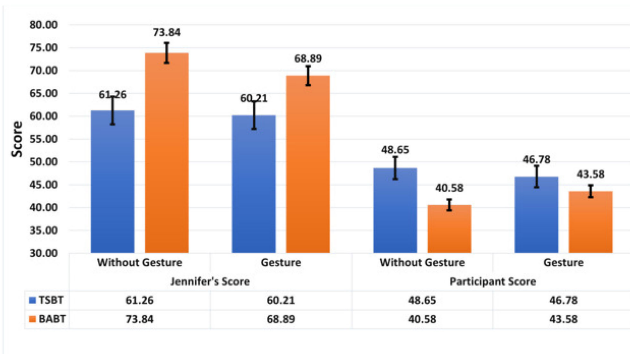


Fig. 7. Average scores of successful negotiation outcomes.

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 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 average utilities of the agreements in a fair way. 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. Fig. 7 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 BABT and 23 participants negotiating against TSBT.

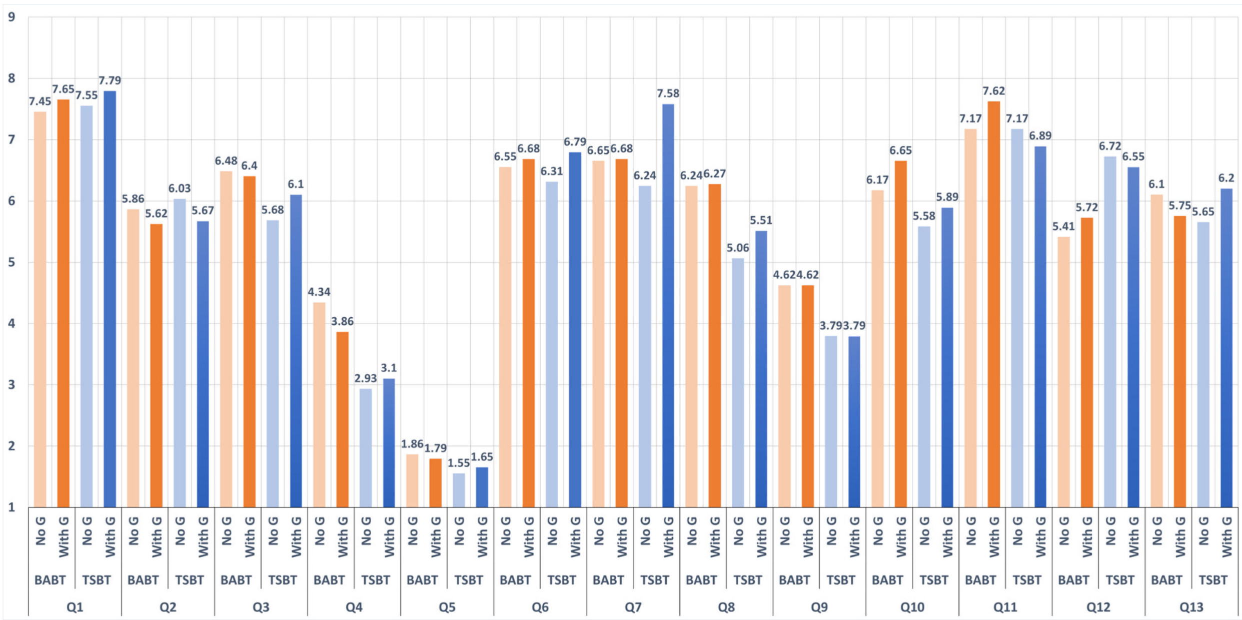
It can be easily seen that Jennifer received a higher score on average when she mimics her opponent to some extent (68.89 versus 60.21 with gestures; 73.84 versus 61.26 without gesture). To study the impact of the negotiation strategy and the effect of gesture, we applied ANOVA split-plot test due to our experiment design [52]. 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 agent scores when Jennifer used her gestures. There is a statistically significant difference between TSBT and BABT strategies ($p < 0.01$, $z = -2.62$). 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 Fig. 7 (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 six to eight rounds in both setups (i.e., 6–7 min out of 10 min). 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 ($p > 0.05$, $z = -0.69$).

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 nine-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, and 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.



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.

Fig. 8. Average ratings of questionnaire responses.

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 min. 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).

Fig. 8 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 five points (i.e., neutral), where the responses to the negative-structured statements such as Q4, Q5, and Q9 are below five 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 nonparametric independent test ($p = 0.0394 < 0.05$ 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 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 nonparametric 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. Finally, 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*."

VII. Discussion and Future Work

This study not only focuses on enabling humanoid robots to negotiate with their human counterparts effectively but also studies the effect of gestures in HRNs empirically. To the best of our knowledge, there is no other work investigating this effect on HRN in which a humanoid robot negotiates autonomously with its human partner. 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. Furthermore, this study 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 nongesture 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.

In future work, we plan to design more sophisticated gestures, which enable our humanoid robot to gain a higher score when it uses gestures. 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. Moreover, it would be interesting to design learning mechanisms for deciding the most appropriate gestures in the underlying interaction. Additionally, we are planning to examine how physical embodiment influences the negotiation.

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