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Effect of Awareness of Other Side’s Gain on Negotiation Outcome, Emotion, Argument and Bidding Behavior

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Abstract

Designing agents aiming to negotiate with human counterparts requires additional factors. In this work, we analyze the main elements of human negotiations in a structured human experiment. Particularly, we focus on studying the effect of negotiators’ being aware of the other side’s gain on the bidding behavior and the negotiation outcome. We compare the negotiations in two settings where one allows human negotiators to see their opponent’s utility and the other does not. Furthermore, we study what kind of emotional state expressed and arguments sent in those setups. We rigorously discuss the findings from our experiments.

1 Introduction

In the broadest sense, negotiation resolves conflicts and finds mutually acceptable solutions among two or more parties with different preferences [Raiffa, 1982]. Negotiations are in human lives such as selling a house, arranging a travel plan, and so on. With the advancements in artificial intelligence, autonomous agents can alleviate the burden of negotiating if they can make rational decisions during negotiations [Jonker *et al.*, 2017]. Such agents may negotiate with each other or with a human. Especially, for agents which are capable of negotiating with human counterparts, it is of utmost importance to understand the human behavior [Mell *et al.*, 2018].

A deep analysis of human-human negotiations provide valuable insights into the design of such negotiating agents. For instance, the offers are the most prevalent “language” in negotiations and indicates how self-centered or cooperative the players are. As illustrated by Axelrod [1984], in iterative games (one can conceive negotiations as such games), players adapt their behavior according to opponents’ behaviour. Particularly, “Tit for Tat” [Faratin *et al.*, 1998], a negotiation strategy where the player imitates the behavior of the opponent in the last turn, has proven to improve cooperation among players. In this paper, we analyze the bidding behaviour of the human negotiators in different settings by particularly aiming to measure the effect of observing the other side’s gain on their bidding strategy.

Human negotiators do not only express their offers during the negotiation. Emotions also play a significant role in

their decision-making process. To illustrate, consider a scenario where Joe (human negotiator) believes that his bids (so far) should have given some signal to his opponent (Mary) and he expects a more empathetic offer from her. If Mary’s next offer doesn’t comply with this expectation, Joe may be upset, and this emotion could be reflected in his next offer. There are several studies investigating the effect of emotions in negotiation [Sinaceur and Tiedens, 2006; Pietroni *et al.*, 2008]. For instance, de Melo *et al.* [2011] share that people tend to concede more to a person showing anger than a person mostly expressing their happiness. Accordingly, our work investigates the effect of awareness of the other side’s gain on participant’s emotional state changes.

Furthermore, the role of argumentation in negotiations has been recognized and studied well [Amgoud and Prade, 2004; Carabelea, 2001]. Kraus *et al.* [1998] analyze different types of arguments based on their effects such as promise, reward, threat as well as supporting arguments. They also introduce a taxonomy of arguments for negotiation. However, this taxonomy is limited where we observe some of the arguments our human subjects used in our experiments cannot be classified. We have therefore revised and adapted the given taxonomy, and elaborated on the relationships between argument types and bidding behaviors.

In order to design more human likely negotiating agents, we perform a deep analysis of human-human negotiations in a structured experimental setup. Fundamentally, we incorporate the following dimensions into our work:

1. *Awareness of Opponent’s Gain:* In negotiation, participants mostly know their own gain in terms of the utility of the agreement for themselves. In order to investigate the effect of knowing your opponent’s utility on bidding behavior, we design two interfaces: one of them allows participants to see the other side’s utility while the other interface does not. We observed that 67% of negotiations reached higher or the same social welfare when participants know each other’s utilities compared to the case they do not. Moreover, some participants have a more tendency to competing behavior when they are aware of the other side’s gain. Some participants expressing a neutral emotional state in the case of knowing only their own utility, are inclined to express other emotional states such as frustration and pleasure.

2. *Emotion*: Expressed emotion towards an opponent’s previous offer may affect the whole negotiation process. In our analysis, we examine if we can see this effect on ultimate utility values. We observed that participants reaching a low utility expressed more frustration during their negotiation.
3. *Argument*: We introduce a classification of arguments particularly for human negotiation and our results indicated that participants who are aware of the other side’s utility are more likely to provide arguments that explain the motivation underlying the offer for both sides while a number of self-explanatory arguments are higher where they cannot see opponent’s utility. Moreover, the ones who do not know their opponent’s gain did not provide any rewarding argument. Also, the number of arguments that seem threatening is twofold in the ones who know/see the opponent’s gain.

The rest of the paper is organized as follows: Section 2 lists the relevant studies in comparison to our work and outlines the differences between them. Section 3 discusses the main elements influencing human negotiation. Section 4 explains how we identify the bidding behavior of participants in our analysis. Section 5 describes the negotiation tool we designed that is used in our experiments. Section 6 first presents our experimental setup and then provides a detailed analysis of the experiments from different perspectives. Section 7 concludes the paper with future work directions.

2 Related Work

Bosse and Jonker [2005] develop the current benchmark of artificial negotiators. They analyze human and computer behavior in multi-issue negotiation by conducting two different sets of experiments. They evaluate the results of the experiments based on predetermined performance (e.g. fairness of deals) as well as step properties (e.g. the number of concession steps taken) using the SAMIN negotiation environment introduced in Bosse *et al.* [2004]. In the first experimental setup, they compare human-human negotiations with computer-computer ones while in the second setup they compare human-computer negotiations with computer-computer negotiations. Results of their work demonstrate three facts: 1) the computer-computer negotiations have the fairest outcome, 2) computers make more unfortunate moves (i.e. making an offer decreasing both sides’ utility), and 3) humans act more diversely. This indicates a need for a better understanding of human-human negotiations in order to develop more human-likely negotiating agents. Our work paves the way for a deeper understanding of human-human negotiations.

Malhotra and Bazerman [2008] make a connection between psychological influence and negotiation by presenting psychological principles for a negotiation environment. They propose 13 different psychological tactics including punishment, giving something in return, providing a reason, etc. to influence the opponent. In our work, we investigate what kind of arguments are used for these purposes. de Melo *et al.* [2011] study the effect of emotions in human-computer negotiations. They found that people concede more to an agent

that expresses anger than to one that expresses happiness and the way of (non-verbal vs. verbal) expressing an emotion.

Haim *et al.* [2010] analyze negotiation behavior across cultures. They predict negotiation behaviors using machine learning methods. Their ultimate aim is to build an agent that is capable of learning to negotiate with people from different cultures. Accordingly, they conduct human-computer negotiation experiments in three different countries namely the United States, Lebanon, and Israel. They conclude that cultural differences have a significant effect in predicting negotiation behavior. Although it is an important aspect, we do not focus on the effect of the culture in this work.

Lin and Kraus [2010] question whether an automated agent is capable of negotiating with humans. They identify the main challenges and review current approaches for automated agents that can learn human related factors (e.g. bounded rationality, incomplete information) and the opponent’s model. By studying seven different agents designed for negotiating with their human counterparts, they identify common features to be used in designing a new agent. Similarly, Oshrat *et al.* [2009] present an automated agent which can negotiate with humans efficiently. They focus on modeling human opponents from past negotiations. The proposed agent is compared with QOAgent (Lin *et al.* [2006]) and it achieves higher utility values. This provides us further motivation for analyzing human-human negotiations.

Mell and Gratch [2016] develop human-agent negotiation tool (namely IAGO). This tool enables emotion exchange using emoji and arguments. It is designed for human-agent negotiation where an agent negotiates with a human counterpart. While our negotiation tool is particularly used for a deep analysis of human-human negotiations in order to design agents negotiating with humans effectively. In that sense, they are complementary to each other.

3 Human-Human Negotiation

The process of human negotiation is steered by several factors such as awareness of the opponent’s gain and emotion, personality, arguments exchanged during the negotiation, and so on. We briefly discuss those elements in the following parts.

3.1 Awareness of Opponent’s Gain

Being aware of the opponent’s gain may affect the human negotiator’s decisions during the negotiation. On one hand, this can impact negotiation process positively. For instance, it may cause better judgment for the offers made in terms of fairness, hence the likelihood of the acceptance by the opponent. That is, the negotiator can better anticipate opponent’s responses to the offers which can be adapted accordingly. On the other hand, it may also have a negative impact on the negotiator’s behavior in some cases. For example, if a negotiator is preoccupied with fairness and observes that the opponent’s bid is not fair at all, then the negotiator may have a tendency to be less cooperative which may create a challenge for reaching an agreement. In our experiments, we study this effect by testing two environments in which one of the environments allows the negotiators to observe the utility of their opponent while the other environment does not.

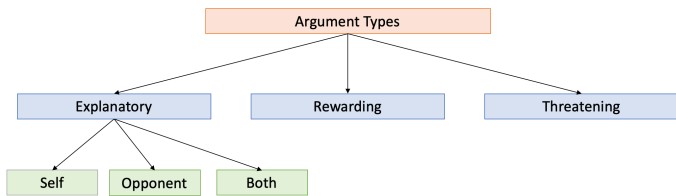


Figure 1: Argument Types Framework

3.2 Emotions in Negotiation

Human decision making can be highly influenced by people’s moods. In any negotiation context, this effect can be observed. The bidding behavior of a negotiating party may cause a change in the other side’s emotions. To illustrate, if you receive a humiliating offer, then you may become upset or frustrated. Consequently, this will change your bidding behavior which is triggered by your emotion. That may cause you to give a less flattering offer. In our work, we consider five different emotions: positive (*pleasant, very pleasant*), *neutral*, and negative (*unpleasant, frustrated*). Furthermore, observing the opponent’s emotions may help the negotiator to guess the opponent’s next moves and it can be considered as feedback to revise your offers towards finding a consensus.

3.3 Argumentation in Negotiation

Types of arguments exchanged during the negotiation can give some clues about the behavior of the human negotiator; therefore, in this section, we focus on how to classify given arguments. There are many related works in the literature that specifically work on finding argument types. Kraus *et al.* [1998] proposes the idea of using argumentation for achieving cooperation and agreements. They present six distinctive argument types (i.e. categories) from weakest to strongest: appeal to prevailing practice, counterexample, appeal to past promise, appeal to self-interest, the promise of future reward, and threat. Amgoud and Prade [2004] introduce another classification which consists of three main categories: threats, rewards and explanatory. In threats, a negotiator forces the opponent to behave in a certain way; in rewards, a negotiator proposes a reward in order to make the offer accepted; and in explanatory arguments, a negotiator gives some reasons to make the opponent believe the offer. Furthermore, Sierra *et al.* [1997] accumulate argument types under three categories similar to Amgoud and Prade [2004]. They classify arguments as threatening, rewarding, or appealing. Note that the explanatory arguments in those studies are intended for only opponents (i.e., stating the benefits for the opponent); however, they can also explain from their own perspective as well as from a mutual benefit perspective.

We observe that *self explanatory* and *both explanatory* arguments are not mentioned in those works after a detailed analysis of our experiments. Specifically, we add those categories in order to cover all arguments provided in our experiments as depicted in Figure 1. In our argument framework there are three main types of arguments:

Explanatory: These arguments provide reason why the given offer is acceptable. Explanatory arguments should be analyzed from three different perspectives:

1. **Self:** Here, arguments are provided considering player’s own perspective solely. It is more likely for player to provide arguments using a self centered approach. **E.g.** “I have been there before and I did not like it”.
2. **Opponent:** Arguments are based on opponent actions, and they try to modify the behavior of the opponent. Giving counter example is a good tactic where a player tells the opponent that current actions contradicts with opponent’s past action(s). **E.g.** “Museums are not suitable for us, you did not like museums the last time”.
3. **Both:** These are the arguments which consider both sides of the negotiation. It can be thought as a way to increase the social welfare. They can be categorized as:
 - (a) **Promoting:** It aims to glorify the offer. **E.g.** “Festival is very nice, we will be having so much fun”.
 - (b) **Demoting:** The player shows the infeasibility of the current offer. **E.g.** “It is not possible to make holiday in Stockholm given 300 euros and 7 days”.

Rewarding: Rewarding arguments aim for convincing opponent to do something by offering a reward. **E.g.** “If you accept Stockholm, I will increase the budget”.

Threatening: These are the arguments which force an agent to behave in a certain way. They can be in different forms. For instance you should do α ; otherwise, I will do β is one type of threatening arguments. **E.g.** “This is your Last chance to accept I’m NOT gonna concede, ever again”.

4 Bidding Behavior

In this section, we present how we classify the bidding behaviors of a human negotiator in a systematic way. In the literature, Thomas [2008] proposes Thomas-Kilmann Conflict Mode Instrument which has five different behavior modes in order to cope up with conflict situations. These modes are determined based on the degree of assertiveness (i.e. satisfying own concerns) and cooperativeness (i.e. satisfying other person’s concerns) of humans. The offered modes are: competing (high assertiveness & low cooperativeness), collaborating (high assertiveness & high cooperativeness), compromising (mediocre assertiveness & mediocre cooperativeness), avoiding (low assertiveness & low cooperativeness), and accommodating (low assertiveness & high cooperativeness).

Based on the aforementioned model, Baarslag *et al.* [2011] introduce another classification, which is based on the player’s concession rate against particular opponents. Those are inverter (i.e. inverts opponent behavior), concenter, competitor, and matcher (i.e. matches opponent behavior). This model requires agents negotiating with the same type of agents - which is not possible in our case. Therefore, we need to come up with a mathematical model to classify the bidding behavior based on Thomas-Kilmann Model by taking two dimensions into account:

1. **Assertiveness:** It measures the individual attempts to satisfy own concerns/preferences. Specific to our experiments, we calculate assertiveness by considering players’ own utility values while making their own offers. We measure and categorize assertiveness into three categories: high, mediocre, and low. High class corresponds

to utility of the bid is between 68-100, mediocre class corresponds to utility between 34-67, low class corresponds to utility between 0-33. By applying a majority voting on the classification of each offer made by the human negotiator, we decide the level of assertiveness. For example, if there are 5 High, 2 Mediocre, and 1 Low, then the assertiveness is considered as High.

2. **Cooperativeness:** Cooperativeness is the measurement of the individual attempts to find a mutual agreement. In our work, we consider that the cooperativeness of the negotiators can be determined based on their sensitivity to their opponent's preferences. Therefore, we adopt the sensitivity calculation in Equation 1 proposed by Hindriks *et al.* [2011].

$$Sensitivity_a(t) = \frac{\%_{Fortunate} + \%_{Nice} + \%_{Concession}}{\%_{Selfish} + \%_{Unfortunate} + \%_{Silent}} \quad (1)$$

Sensitivity is calculated by taking into account the percentages of the negotiator's different moves. A move is determined based on the utility difference of the negotiator's subsequent offers for both sides. There are six different move types (fortunate, nice, concession, selfish, unfortunate, and silent). Table 1 demonstrates the calculation of move types of a player where ΔU_s and ΔU_o represent the utility difference for negotiator itself and that for opponent respectively.

	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	$\Delta U_s > 0$	$\Delta U_o < 0$

Table 1: Move Specification of a Negotiator [Hindriks *et al.*, 2011]

If sensitivity > 1 , we consider player as cooperative (C), if sensitivity < 1 we classify player as uncooperative (U). Otherwise, the player is considered as neutral (N) to opponent's preferences. In order to decide on bidding behavior of each player, we need to combine the assertiveness and cooperativeness results according to our classification depicted in Figure 2. Note that according to Thomas-Kilmann Conflict Mode Instrument model, it is hard to differentiate some behaviors formally (e.g. which behavior to be assigned for neutral assertiveness level and uncooperative behavior). Therefore, we extend this model as seen in Table 2.

5 Structured Human Negotiations

Observing and analyzing human-human negotiations can give valuable insights for designing human-likely negotiating agents. In this work, we develop a negotiation tool, which allows human negotiators to negotiate with each other in a more structured way, particularly by following the alternating offers protocol proposed by Aydogan *et al.* [2017]. Human negotiators can exchange offers in a turn-taking fashion and

Assertiveness	Cooperativeness	Behavior
H	C	Collaborating
H	N	Competing
H	U	Competing
M	C	Accommodating
M	N	Compromising
M	U	Avoiding
L	C	Accommodating
L	N	Avoiding
L	U	Avoiding

Table 2: Behavior Classification

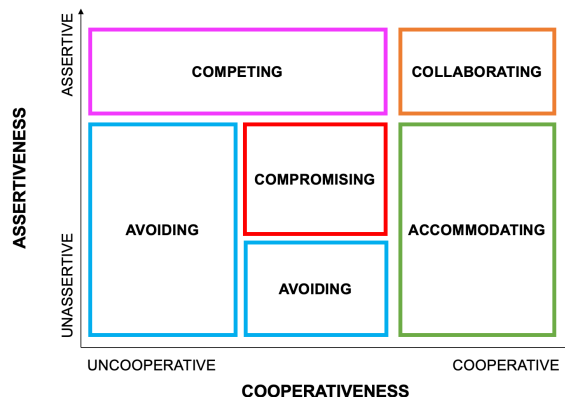



Figure 2: Bidding Behavior Classification


they can also send arguments to persuade their opponents and share their current emotional state. Note that the tool supports only bilateral negotiations.

Since one of our aims is to find out whether being aware of the other side's gain has an influence on human negotiator's bidding behavior, we design two interfaces that are almost identical to each other except one of the interfaces enables negotiators to observe their opponent's current gain (in terms of utility) while other interface hides this information. Figure 3 shows the bidding interface showing both sides' utilities for the chosen offer. The human participants can choose the values for each issue by using the drop boxes while making their offers. They can express their emotions and provide an argument about their opponent's previous offer or related to their current offer to convince their opponent. Negotiation is governed by alternating offer protocol in which bid exchanges continue in a turn-taking fashion until players reach an agreement or the given deadline. The time limit for each negotiation is set to 20 minutes. Additionally, players are informed about how many minutes left for the negotiation at specific time intervals (10 minutes, 5 minutes, 2 minutes, 1 minute).


In our negotiation tool, participants can choose one of the five emotional states: positive (**pleasant, very pleasant**), **neutral** and negative (**unpleasant, frustrated**). Players can provide any type of argument to their opponents. Participants in their turn can see their opponent's offer as well as their emotional state and arguments at that time. Consequently, they can assess whether their opponent is pleasant or unhappy about their previous offer. The given arguments may help

Issue:	Player 1's Offer:	Player 2's Offer:
Destination	Rome	Paris
Duration	7 days	5 days
Budget	1000 EURO	300 EURO
Amusement	Excursion	Excursion
Player 1's Utility	85	70
Player 2's Utility	45	80
Emotion	Neutral	Unpleasant
Argument	I want to visit Rome!	I prefer Paris!





Accept Offer



Make Offer

Figure 3: Bidding Screen

to convince the current player or help them understand each other's preferences.

6 Experimental Evaluation

In this section, we present our experimental setup, and we analyze the experiments by considering different dimensions.

6.1 Experimental Setup

In order to set up well-structured negotiation experiments, we prepare two negotiation scenarios on a travel domain. There are four issues: destination, duration, budget, and amusement type. All possible values for each issue are specified and the total number of possible outcome is equal to 320. The preferences of the participants are represented by a simple additive utility function. That is, the utility for each value of an issue is given between 0 and 100, and the overall utility of a given offer is calculated by the sum of the utility of issue values specified in the given bid.

For our human-human negotiation experiments, we recruit 24 students at Özyeğin University (%29.1 female, %70.8 male. %54 MSc., % 38 bachelor, %0.8 PhD. %63 between 21 and 25, % 29 between 26 and 30, % 4 between 18 and 20, % 4 between 31 and 35). As an incentive mechanism, we provide coffee gift cards to the most successful participants. Each participant is asked to negotiate in both scenarios where in the first scenario they can only see their own utilities while in the second scenario they can also see the utility of the opponents. Note that the utility function given to participants are different in both scenarios in order to decrease the learning effect. Besides, the utility functions are generated from the same utility distribution so that we can compare the utility of agreements fairly. Furthermore, in order to decrease the learning effect, we use the randomization technique. That is,

half of the participants start with the first scenario (Group1) while the other half starts with the second scenario (Group 2).

Before the experiment, we gave a live demo illustrating how to use the negotiation tool. For each negotiation session, participants are given 20 minutes, if participants cannot make an agreement within the specified time, both sides did obtain a score of 0 (100 being maximum). For all negotiation sessions, we log all negotiation related information (e.g. offer made at each round, elapsed time while making this offer) to be used for our further analysis. After a group is done with their negotiations, they are asked to fill out the questionnaire form to get feedback about their negotiation.

6.2 Analysis of Negotiation Outcome

As our first main result, we observe that 23 out of 24 negotiation sessions are ended up with an agreement. Figure 4 shows the utilities that players received in both scenarios. On the x-axis, we have the player number, and on the y-axis we have corresponding utility values. Here, blue bars denote the results of the first scenario in which players cannot see each other's utility [non-observable scenario (NOS)] and orange bars depict the result of the second scenario where an opponent is able to see other's utility [observable scenario (OS)]. We discover that 33% of the players received higher utility in OS while 46% of the players received higher utility in NOS. Overall, 21% of the players received the same score.

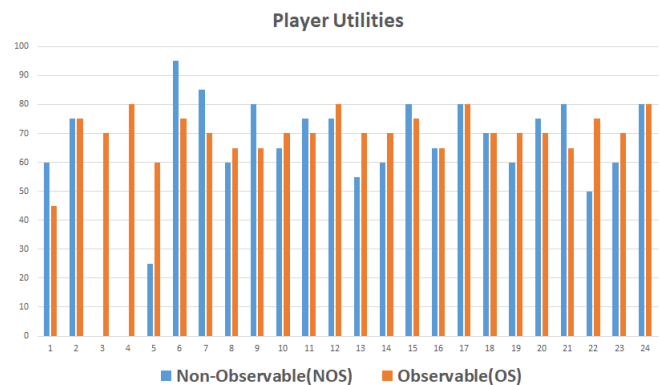


Figure 4: Player Scores of Both Negotiations

We apply mixed-ANOVA statistical test to see if there is a significant difference in gained utilities between two scenarios. We have not observed a significant effect of scenario (OS and NOS) on the received player utilities [$F(1, 22) = 0.48, p = 0.16$]. In addition to that, we observe that there is no significant difference between player's starting with OS or NOS [$F(1, 22) = 1.54, p = 0.23$].

We also measure the social welfare. When we compare the social welfare (i.e, the sum of both players' utilities) in both settings, we observe that participants obtained higher social welfare in OS in %50 of negotiations while in NOS %33 of negotiations they reached higher social welfare.

6.3 Analysis of Arguments

By using our proposed framework explained in Section 3.3, we make a detailed analysis of arguments provided in our ex-

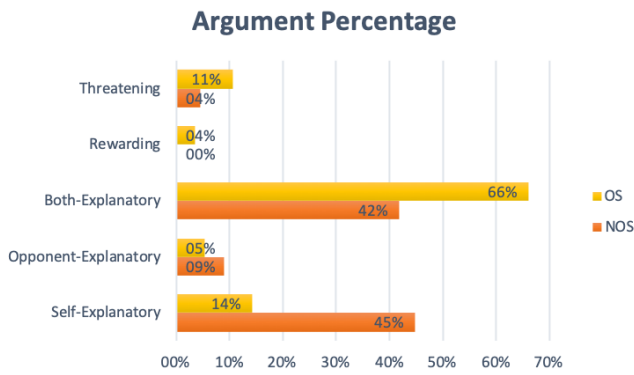


Figure 5: Argument Analysis

periments. We analyze the arguments one by one based on three main argument types and subcategories combined. The results can be seen in *Figure 5*. This figure demonstrates the percentages of different argument types with respect to each scenario. In total, in *NOS* 67 different arguments are provided by participants, while this number is 56 in *OS*. It is remarkable that both-explanatory arguments are seen more in *OS* while self-explanatory arguments are observed more in *NOS*. This implies that when players are aware of the other side’s gain, it is more likely for them to provide arguments which concern both sides of the negotiation. Moreover, players did not provide any rewarding argument in *NOS* while this number is 2 in *OS*. The number of threatening arguments is twofold in *OS* (6 vs 3). Other than these results, it is important to share the fact that threatening arguments are provided towards the end of the negotiation as expected.

6.4 Analysis of Bidding Behavior

We calculate the assertiveness and cooperativeness of each participant in both settings. We observe that while 79% of the participants are highly assertive in *NOS*, 96% of them are highly assertive in *OS*. Both in *NOS* and *OS* 50% of the participants are sensitive to their opponent’s preferences. Additionally, 25% of the participants are insensitive in *NOS* while 12.5% of them are insensitive in *OS*. This shows that some of the participants increase their sensitivity while they can see their opponent’s utility. Based on *Table 2*, we classify each participant’s behavior demonstrated at *Table 3*. Remarkably, we do not have any compromising behavior. The percentage of participants who demonstrate competing behavior is increased by 12% when they negotiate in *OS*. There is a slight increase in the percentage of participants who are collaborating in their *OS*. Avoiding behavior can only be observed in *NOS*. When we compare *NOS* and *OS*, accommodating behavior is almost disappeared in *OS*.

6.5 Analysis of Emotion

We calculate percentages of all emotional states for each player. *Table 5* shows corresponding percentages of each emotional state for both *NOS* and *OS* scenarios. Although there is no significant effect of the scenario on the emotional states, we observe there are more unpleasant emotional state exchanged on average in *NOS* than *OS* (%24 versus %18)

Player	NOS	OS	Group
1	Avoiding	Competing	1
2	Competing	Collaborating	1
3	Competing	Competing	1
4	Collaborating	Competing	1
5	Avoiding	Accommodating	1
6	Competing	Collaborating	1
7	Competing	Competing	1
8	Collaborating	Competing	1
9	Collaborating	Competing	1
10	Collaborating	Collaborating	1
11	Collaborating	Collaborating	1
12	Competing	Collaborating	1
13	Competing	Competing	2
14	Competing	Competing	2
15	Collaborating	Collaborating	2
16	Avoiding	Collaborating	2
17	Collaborating	Competing	2
18	Collaborating	Competing	2
19	Collaborating	Collaborating	2
20	Competing	Collaborating	2
21	Competing	Collaborating	2
22	Accommodating	Collaborating	2
23	Accommodating	Competing	2
24	Competing	Competing	2

Table 3: Behavior Analysis

while more frustrated emotional states are observed on average in *OS* (%11 versus %4). In addition, we also compare participant’s each emotional state percentages in both scenarios and compute the number of participants whose emotional state percentage is higher in *NOS* than the percentage in *OS* and vice versa. *Table 4* shows, for each emotional state, how many participants expresses higher percentage of that particular emotional state in their *NOS* than *OS*. For example, the percentage of frustration emotion is higher for 4 participants in their *NOS* negotiation compared to *OS* ones while that of 7 participants is higher in their *OS* negotiations.

Players were more neutral in emotion in *NOS* than when in *OS* (11 versus 8). Being aware of the opponent’s gain may change the negotiator’s emotional state. Besides, players show a tendency to express stronger emotional states when they observe their opponents’ utility. To exemplify, players were more frustrated in *OS* than when in *NOS* (7 versus 4). In the questionnaire taken after their negotiation, some participants reported that they get frustrated more when they receive unfair offers. Note that players can detect unfairness only in *OS*. On the other hand, it is observed that more players have a higher percentage of unpleasant emotions in their *NOS* compared to their *OS* (11 versus 8). These unpleasant emotions may stem from getting a utility under their expectation irrespective of what their opponent’s gains.

Regarding the correlation between particular emotions and received agreement utilities, we observe a weak positive relation between neutral emotion and utilities in *NOS* ($R = 0.23$) and a weak negative correlation between neutral emotion and utilities in *OS* ($R = -0.2544$). Furthermore, there is a moder-

Frustrated		Unpleasant		Neutral		Pleasant		Very Pleasant	
NOS	OS	NOS	OS	NOS	OS	NOS	OS	NOS	OS
4	7	11	8	11	8	6	8	1	1

Table 4: Comparison of emotional state expressions for individuals

Player	Neutral		Pleasant		Unpleasant		Very Pleasant		Frustrated	
	NOS	OS	NOS	OS	NOS	OS	NOS	OS	NOS	OS
1	67	100	0	0	17	0	0	0	17	0
2	17	0	17	0	67	100	0	0	0	0
3	38	40	0	0	38	60	0	0	25	0
4	43	60	14	0	14	0	0	0	29	40
5	33	50	33	50	33	0	0	0	0	0
6	0	0	33	0	67	0	0	0	0	100
7	80	80	0	20	20	0	0	0	0	0
8	60	50	0	0	40	0	0	0	0	50
9	100	100	0	0	0	0	0	0	0	0
10	75	67	0	33	25	0	0	0	0	0
11	50	100	25	0	0	0	0	0	25	0
12	33	100	33	0	33	0	0	0	0	0
13	67	33	0	0	33	67	0	0	0	0
14	50	25	0	0	50	75	0	0	0	0
15	100	50	0	0	0	17	0	0	0	33
16	50	60	50	0	0	20	0	0	0	0
17	78	50	11	33	0	17	11	0	0	0
18	88	20	0	40	13	20	0	0	0	20
19	75	33	0	33	25	0	0	33	0	0
20	67	67	0	0	33	33	0	0	0	0
21	100	100	0	0	0	0	0	0	0	0
22	67	100	0	0	33	0	0	0	0	0
23	100	80	0	20	0	0	0	0	0	0
24	67	60	0	20	33	20	0	0	0	0
Average	63	59	9	10	24	18	1	1	4	11
STDEV	26	30	14	15	20	28	2	6	9	23

Table 5: Emotion percentages for each player

ate negative relation between frustrated emotion and utilities in NOS ($R = -0.61$) as expected. Also, there is a weak positive relation between positive emotion and utilities OS ($R = 0.245$). We can obtain more reliable results if we increase the number of participants.

6.6 Analysis of Questionnaire

Figure 6 shows the number of participants who take into consideration the underlying elements during their negotiation, according to their response to our questionnaire. 23 out of 24 players considered their own utility. It is seen that most of the players consider the notion of fairness, their own utilities, opponent's offers in their negotiation. A few people consider the opponent's gesture and emotions while 71% of the participants consider arguments.

7 Conclusion and future work

In this work, we conduct a structured human negotiation experiment and analyze the results from different perspectives. We mainly investigate how knowing the opponent's utility for the past and current offers affect the bidding behavior of players in the sequel, the negotiation outcome, and emotional state and arguments. Furthermore, we provide a classification for the arguments exchanged during the negotiation as well as bidding behaviors and use them in our experimental setup.

The analysis of the experiment results indicates that observing the opponents' utility (i.e., OS scenarios) for the given offers has a positive effect on social welfare. In particular, in 62% of OS negotiations, participants obtained higher

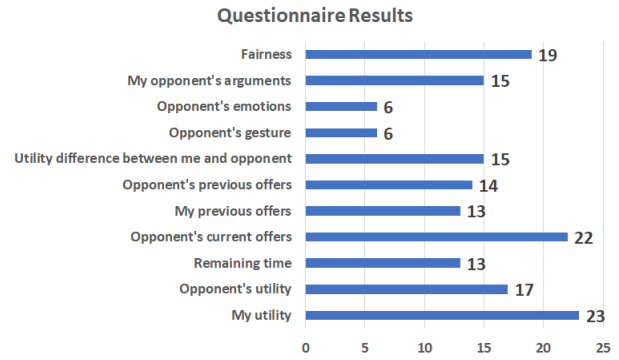


Figure 6: Negotiation Behavior Questionnaire Results

social welfare values than what is obtained in NOS experiments. Observing opponents' utilities affected the results in several other ways as well. For example, some participants exhibit more competing behavior when they are aware of the other side's gains.

Some participants expressing a neutral emotional state in the NOS cases are inclined to express other emotional states such as frustration and pleasant on observable cases. We observed also that participants reaching a low utility in the deal, expressed more frustration during their negotiation.

Regarding the arguments used in the experiments, we find that in OS cases where both could see each other's utilities for a given offer, players provide reasons involving both parties (i.e., from a fairness perspective) while in the NOS cases arguments are of a more self-explanatory nature, i.e., justification of themselves. Moreover, the ones who do not know their opponent's gain did not provide any rewarding argument. Also, the number of arguments that seem threatening is twofold in the ones who know the opponent's gain. It is worth noting that if we had more participants, more trustworthy results could be obtained.

Structured human-human experiments have provided interesting findings. However, because of the relatively small number of participants, the results were not conclusive enough. Further investigation with the participation of more subjects needs to be conducted to obtain more conclusive results. In future experiments, we can also investigate additional factors such as remaining time in negotiation, power differences between players.

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