FAMILIARITY EFFECT ON HUMAN-AGENT NEGOTIATIONS

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by

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FAMILIARITY EFFECT ON HUMAN-AGENT NEGOTIATIONS

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To my family

ABSTRACT

Artificial Intelligence has changed our world in various ways. People have started to interact with a variety of intelligent systems on a daily basis. As the interaction between human and AI systems increases day by day, the factors influencing their communication have become more and more important especially in the field of human-agent negotiation. Therefore, it is necessary to study the factors affecting human-human negotiation while designing agents negotiating with their human counterparts. As familiarity is one of these factors, this work aims to investigate the effect of familiarity on human-agent negotiation so that we can design more effective negotiation systems.

Being familiar to other party may influence how we interact and hence the process and outcome of the negotiation. Our hypothesis is that negotiating with a familiar opponent would create a difference in terms of negotiation process and outcome. In order to study this effect in human-agent negotiations, we developed negotiation framework in which human participants negotiate with an avatar in a bilateral fashion. To measure the effect of the appearance familiarity in negotiation, two control variables are defined: negotiating with a celebrity avatar and negotiating with a non-celebrity avatar. In order to avoid the learning effect, we adopt a between-subject experiment design. We recruited 67 participants and analyzed their negotiation data elaborately as well as their subjective opinions specified in the questionnaires. Our experimental results showed that being familiar with the opponent affected both negotiation process and outcome. Particularly, human participants had a tendency to be more collaborative when their opponent is a celebrity avatar versus a non-celebrity avatar.

ÖZETÇE

Yapay zeka çalışmaları hayatımızı birçok yönden değiştirmektedir. İnsanlar günlük yaşantılarında akıllı sistemlerle çeşitli şekillerde etkileşime girmektedirler. İnsan ve yapay zeka sistemleri arasındaki etkileşim arttıkça bu etkileşimi etkileyen faktörler özellikle insan-etmen müzakereleri alanında çok daha fazla önem kazanmaktadır. Bu nedenle, insanlarla pazarlık yapabilen akıllı sistemler geliştirirken, insanlar arasındaki etkileşime etki eden faktörleri de göz önünde bulundurmak önemli hale gelmektedir. Bu tez çalışmasında daha etkili müzakere sistemleri tasarlayabilmek için insan etmen müzakerelerinde insanlardaki etkileşimi etkileyen faktörlerden görsel aşinalığın etkisi araştırılmıştır.

Karşı tarafı tanıyor olmak, karşı taraf ile etkileşime girme yollarımızı değiştirebilir ve bu yüzden müzakere sürecini ve sonucunu da etkileyebilir. Bizim hipotezimiz karşı tarafın tanıdık biri olup olmadığının müzakere sürecini ve sonucunu etkileyeceği yönündedir. Bu etkiyi test edebilmek için insanların sanal bir avatarla belirli bir konuda müzakere edebileceği bir sistem tasarladık. Bu sistemde katılımcıların yarısı ünlü görünümlü bir avatar ile pazarlık yaparken, katılımcıların diğer yarısı daha önce hiç görmedikleri ve ünlü görünümlü olmayan bir avatar ile pazarlık yaptılar. Öğrenme etkisini ortadan kaldırmak için 67 kişinin katıldığı ana deneyimizde gruplar arası tasarımı kullandık. Katılımcıların pazarlık verileri ve doldurdukları anket verileri detaylıca incelenmiştir. Deneysel sonuçlarımız, rakibe aşina olmanın hem müzakere sürecini hem de sonucunu etkilediğini gösterdi. Özellikle rakipleri ünlü görünümlü olan bir avatar ile pazarlık yapan katılımcıların rakipleri ünlü görünümlü olmayan avatar ile pazarlık yapanlara kıyasla daha çok işbirliği yapma eğiliminde oldukları gözlemlenmiştir.

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LIST OF SYMBOLS/ABBREVIATIONS

α_{next}	Prepared offer by agent to be sent
ΔU_o	Utility difference between previous and current offer for opponent
ΔU_s	Utility difference between previous and current offer for negotiator itself
γ	Reservation value
$\mathcal{D}$	Negotiation domain
$\mathcal{I}$	Negotiation issues
$\mathcal{O}$	Set of all possible offers
$\mathcal{U}(o)$	Utility of a given offer o
ρ_{beh}	Estimated opponent behaviour
τ	Kendall tau distance value
θ	Importance of update parameter
c	Concordant pair
d	Discordant pair
f_{exp}	Agent's facial expression
n	Number of total pairs
o	Representation of an offer
$o^A_{current}$	Agent's current offer
$o^H_{current}$	Human participant's current offer

o_i	The value for issue i in offer o
o^A_{prev}	Agent's previous offer
o^H_{prev}	Human participant's previous offer
s_c	Current negotiation time stage
t	Remaining normalized negotiation time
u_{next}	Utility of the next offer
$V_i(.)$	Valuation function for issue i
w_i	Importance coefficient of the negotiation issue i

CHAPTER I

INTRODUCTION

With the ongoing development in the field of Artificial Intelligence, use of intelligent agents in different parts of our lives has become more and more prevalent. In some cases, those agents may need to communicate and collaborate with each other in order to achieve a common goal. In the case of any conflict between them, negotiation – process of resolving conflicts may take a place to find an agreement [4]. Without doubt, this kind of interaction may be necessary with their human counterparts. AI agents, compared to humans, can be far more efficient at optimizing bids in negotiations. Combined with recent advances in human-computer interaction in automatic speech recognition and text-to-speech, these agents can have the ability to negotiate with a human via a natural dialogue. One can foresee a future where humans negotiate with AI agents or along with AI agents. Therefore, it is important to design and develop a human-agent negotiation framework, which involves different kinds of challenges [5].

Designing such interactive systems may require taking human factors into account and benefit from theories introduced by different fields such as psychology, economics, behavioral sciences and cognitive science. Especially, understanding psychological factors affecting human negotiators' behaviours and attitudes plays a key role in the development of human-agent negotiation systems. The best course of action to build up such systems may be studying human-human negotiations and derive the important factors influencing their decisions [2, 6, 7]. Another way is to develop a virtual human-agent negotiation framework that can allow researchers to study the effect of the chosen factor. While some works investigate the effect of facial expressions and emotions on negotiation outcome and process [8, 9], some focus on the effect of gender in different forms [10, 11, 12]. Accordingly, our work pursues the effect of familiarity to the opponent on negotiator's attitude and consequently on negotiation outcome.

As far as studies in the field of psychology are concerned, it has been shown that familiarity plays an important role on negotiation outcome in human-human negotiations [6, 7]. For instance, Druckman and Broome show that a decrease in familiarity to the opponent causes a decrease in human negotiator's willingness to act collaboratively and consequently reach an agreement. Moreland and Zajong investigate the effect of visual familiarity on the perceived similarity [7]. According to the experiments conducted in that study, participants believed that they shared similar preferences and values with the people whom they are more visually familiar than the people whom they saw first time. Those works encourage us to explore whether the effect of familiarity in human-human negotiations will transfer to human-agent negotiation in which agents present themselves as humanoid avatars. Our contributions are two-fold. Firstly, we introduce a human-agent negotiation framework in which the virtual avatar employing a novel negotiation strategy inspired from the existing strategies. The proposed strategy considers opponent's behavior and preferences as well as the remaining negotiation time. Secondly, we conduct a user experiment in which some participants negotiated with an agent that looks like a celebrity whereas others negotiated with an agent whose appearance is not familiar to them (non-celebrity). We compared the negotiation process and outcome of those groups to find out the effect of familiarity in negotiation. Our main finding is that participants had a tendency to collaborate more with the celebrity agent. To the best of our knowledge, our work is the first study pursuing this research question in human-agent negotiations.

The remainder of this thesis is organized as follows. First, we discuss related work (Section 2) and describe the general negotiation setting that we have considered (Section 3). Section 4 explains our human-agent negotiation framework while Section 4.2 introduces a novel negotiation strategy that is employed by our agent during the user experiments. Afterwards, Section 5 explains pilot studies and shows findings of these studies. Section 6 explains the user experiments that we conducted to study the effect of human negotiator's familiarity to their opponent and analyzes our findings. Finally, Section 7 concludes our work with future research directions.

CHAPTER II

RELATED WORK

Automated agent negotiation has been taken attention for several decades and a variety of research studies have been conducted in this field [13, 14, 15, 4, 16, 17, 18, 19, 20, 21, 22]. Moreover, the research community has been organizing international competition in the field of agent-based negotiation to facilitate the research and to provide benchmarks for the community [23]. The community has largely focused on agent-agent negotiations where one agent outperforms the other in one or many ways like monetary gain, user interactions, etc. Recently, new leagues in this competition regarding human-agent negotiation have been introduced [24, 25], which indicates that human-agent negotiation has become more and more interesting for the community in terms of the challenges required to build agents interacting with human negotiators. There are a number of challenges in human-agent negotiation [5, 26]. That is, the designers of the agents should concern the human factor [27, 28, 29]. In a limited number of interactions, agents should be able to reach a consensus with their human counterparts. One of the main research questions is how a negotiating agent effectively interacts with human negotiators, which is the focus of this work. In the literature, human-agent interaction aspects of negotiating agents are being explored currently from a variety of perspectives: finding a way to outperform people by considering culture differences of the opponents in negotiation [30]; the use of facial expressions and emotions to explore affect on outcomes [31, 8, 32]; exploring the effect of argument usage in negotiation [33, 2]; including the use of multiple modalities to explore human-agent negotiation dynamics [34, 27] and using agents to train people in the art of negotiation [35, 36, 37, 38].

In several of these use cases involving human-agent negotiation interactions, agents are embodied in various forms that fit best. Some include humanoid animated avatars that can see and hear the human participant [35, 27] while some agents are accessed through a text-based chat window [39, 40, 41]. Divekar *et al.* uses an immersive room where agents appear as human-scale animated avatars in an extended reality environment [35]. Their goal is to make a user feel as if they are somewhere else, negotiating with street market shopkeepers in a foreign country. An important aspect of their work is making the agents believable in the sense that users engage with it as if they are believed to be human beings. Especially in such settings, the effect of familiarity could be important to the human interlocutors and this is the focus of this thesis. As research gears towards representations of agents where agents look and communicate like humans, we ask the question whether such a representation will also mean that some characteristics of human-human negotiations will translate into human-agent negotiations where the agent is humanoid. We focus on a specific aspect of human-agent negotiations, specifically the effect of familiarity on negotiation. Sid, Peter, and Donald have stated that familiarity plays an important role on negotiation outcome [42]. Accordingly, we aim to investigate the effect of familiarity to the opponent on negotiation process in human-agent negotiations.

Yuasa and Mukawa study facial expression and history effect on decision making process in a negotiation game, a variation of Prisoner's Dilemma [8]. In their study, participants are asked to negotiate a couple of times with software agents that can show different facial expressions (i.e., bow, avert, happy, angry and cool). In some cases, they negotiate with the same opponent to study the effect of the history. Their experimental results showed that happy agents made participants act more collaboratively. Furthermore, negotiation result of previous sessions with the same appearance agents affected participant's current decisions since familiarity to the current opponent builds up a certain level of trust. For example, participants have a tendency to cooperate more if their opponent acted collaboratively in the past. Although we investigated the effect of familiarity from a different perspective (i.e., negotiating with a celebrity versus negotiating with the same person repeatedly), our results support each other.

De Melo, Carnevale, and Gratch study the effect of agent's emotion, particularly anger and happiness, on negotiation [31]. Participants are asked to negotiate with virtual agents adopting different facial expressions. 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. During our experiment, we observed that participants took their opponent's facial expression into account while generating their bids. Therefore, it is very important to use the right facial expression while designing a virtual negotiating agent.

Mell, Gratch, and Lucas study how human counterparts can be affected by competitive or collaborative agent opponents [43]. Their results show that competitive strategies made the human participants concede more. On the other hand, a study [32] advocates that people are more willing to renegotiate with warm agents all though there is no significant difference found on negotiation outcome in their experiments. Another study exploring the effect of aggressive attitudes on human-agent negotiations [44] 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 the real one. Lin, Hu, and Lai measure the effect of gender in negotiation [10]. Their results show that negotiators change their strategy according to the opponent's gender.

On the other hand, familiarity effect has been studied in different context [45, 46]. Wauck *et al.* developed a search and rescue game in a virtual environment where the main characters look like participants or another avatar appearance [45]. Their experimental results show there is no significant effect of using self-similar characters on the performance for designed games. Another study [46] investigates the familiarity effect on negotiation in a task-based game environment. For this purpose, participants were divided into two groups: participants in the former group were not allowed to communicate with each other before the game begins whereas participants in the later group are allowed to communicate with each other.

During the game, the participants do not see each other but they know with whom they are playing. In this virtual environment, each player is demonstrated by a robot-like avatar. The results showed that the participants felt more comfortable working with a partner whom they had met face-to-face first although there is no significant performance difference between groups. No significant difference in their performance may stem from the simplicity of the rules in the game. In our work, we have two groups negotiating with a virtual avatar. Similarly, one group negotiated with an avatar who looks like a celebrity they know before while the other group negotiated with an avatar who is not familiar to the participants. Our results showed that participants collaborated more when they negotiated with the celebrity avatar.

Since there is an undeniable effect of humans' perception and their psychological tendencies on the human-human relations, it is worthy to take a look at the studies in the field of psychology. As far as the studies conducting experiments on the familiarity effect in the field of psychology are concerned, it can be seen that our findings are supported. Moreland and Zajong measure the influence of the mere exposure effect on the perceived similarity [7]. They divided participants into two groups where photos of different people were shown to the first group while the photos of the same people were shown to the second group each week. Afterwards, they studied participants' attitudes toward the people they saw in the photos and their beliefs about in which degree these persons are similar to them and share their values. They found a positive correlation between attraction, perceived similarity and familiarity. The results showed that the mere exposure to the same individual's photo each week increased their familiarity with this stranger and hence it increased attraction toward this person and participants' perceived similarity between their values and this individual's values. They considered this person's preferences more and more similar to their preferences. Furthermore, Reder and Ritter claim that the participants respond faster and put less efforts when they are familiar with the given problem [47].

In another study, Druckman and Broome aim to understand the effect of liking and familiarity on the negotiation outcome [6]. They design a game where the participants play a representative of a culture and negotiate with a representative of a totally different culture to reach an agreement on a variety of issues. They investigated three conditions: (1) high familiarity and high liking; (2) low familiarity, high liking and (3) high familiarity, low liking. Their experimental results showed that decrease in either of liking or familiarity followed by a decrease in the participants' willingness in reaching mutual agreement and being collaborative.

CHAPTER III

BACKGROUND

In this section, we introduce how the preferences of the negotiating parties are represented and elicited in our framework. Basically, we construct the preference profiles by using Analytic Hierarchy Process (Section 3.2) and model them in terms of additive utility function (Section 3.1). After that, we provide background knowledge about an opponent modeling called Frequency Model (Section 3.3).

3.1 Additive Utility Function

In our framework, negotiating parties negotiate over multiple issues particularly on their future holiday similar to the work [2]. According to the negotiation scenario, there are $\mathcal{I} = \{1, 2, \ldots, n\}$ negotiation issues whose possible values are defined in $\mathcal{D}$. The set of all possible offers according to the negotiation domain is represented by $\mathcal{O}$ and an offer from this set is represented by o. The representation of the agent's preferences is given by using additive utility function [48] as follows:

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

Regarding the equation, w_i represents the importance of the negotiation issue i for the agent, o_i stands for the value for issue i in offer o, and $V_i(.)$ represents the valuation function for issue i, which denotes to what extent that issue value is preferred by the agent. It is worth noting that the sum of weight values adds up to 1 represented by $\sum_{i \in \mathcal{I}} w_i = 1$ and the domain of $V_i(.)$ is [0,1] for any i.

To determine the values of w_i and V_i in the equation, we use the analytic hierarchy process. In the next subsection, we will be giving the details about how we use this approach to construct the preference profiles of the participants as well as the agent.

3.2 Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) is a technique to determine importance of a set of evaluation criteria and related possible alternatives in multi-criteria decision making [49]. To achieve an objective, a set of evaluation criteria and possible set of alternatives are defined. Afterwards, pairwise comparisons of evaluation criteria are elicited from the user to construct a pairwise comparison matrix. Eigenvalues of this matrix denote the relative ranking of priorities. Note that those relative rankings are normalized so that the sum of those weights is equal to 1. Similar operation is also performed on alternatives by taking each criterion into account separately. In our setting, w_i values are assigned from eigenvalues calculated from issue pairwise comparisons. Additionally, V_i values are assigned by eigenvalues, which is divided maximum possible value for the related issue.

3.3 Frequency Model

Frequency model is a basic but most widely-used opponent modeling technique in automated negotiation [50, 51]. This model assumes that the opponent's preferences are represented in terms of additive utility function and opponent employs a concession-based strategy. It is based on two heuristics: (1) If an issue value is often changed, then the issue gets a low weight and (2) a preferred value will appear more often in agent's offers than a less preferred value. Algorithm 1 shows how this model estimates opponent's preferences. The algorithm compares opponent's consecutive bids during the negotiation and update its model. In the bid sequences, if the value of an issue does not change, the importance of that issue is increased by adding a parameter θ (Lines 1-5). For evaluation values, the number of appearance of an issue value is updated over time (Lines 6-8). Afterwards, those values are normalized between zero and one (Line 9-10).

Algorithm 1: Basic Frequency Model

$o_{prev} \leftarrow$ Opponent previous offer
$o_{cur} \leftarrow$ Opponent current offer
θ denotes the importance update parameter

$\triangleright$ Updating issue importance

for each issue i in o_{cur} **do**
    if $_{cur}$[i].value == o_{prev}[i].value **then**
        importance[i] += θ
    end if
end for

$\triangleright$ Updating issue value importance

for each issue value v_i in o_{cur}[i] **do**
    evaluationValue[v_i] += 1
end for
normalize(importance);
normalize (evaluationValuation);

CHAPTER IV

VIRTUAL NEGOTIATING AVATAR FRAMEWORK

For examining human-agent negotiations experimentally, we have designed and developed a Web-based negotiation framework where a virtual avatar agent negotiates with a human counterpart in a bilateral fashion. The framework allows us to design and integrate negotiation strategies, and to change the avatar character interacting with the human. The framework adopts alternating offers protocol [52] where negotiating parties make offers iteratively in a turn-taking fashion until reaching a termination condition (i.e., reaching a predefined deadline or reaching an agreement). In our framework, human negotiator initiates the negotiation by making an offer and the framework counts down the timer after sending her/his first bid.

4.1 Framework Design

Our framework consists of five main components: *Virtual Avatar Character*, *Human Offer Generator*, *Conversation History*, *Time Remainder*, and *Preference Profile Chart*. Illustration of the framework is shown in Figure 1 including those components.

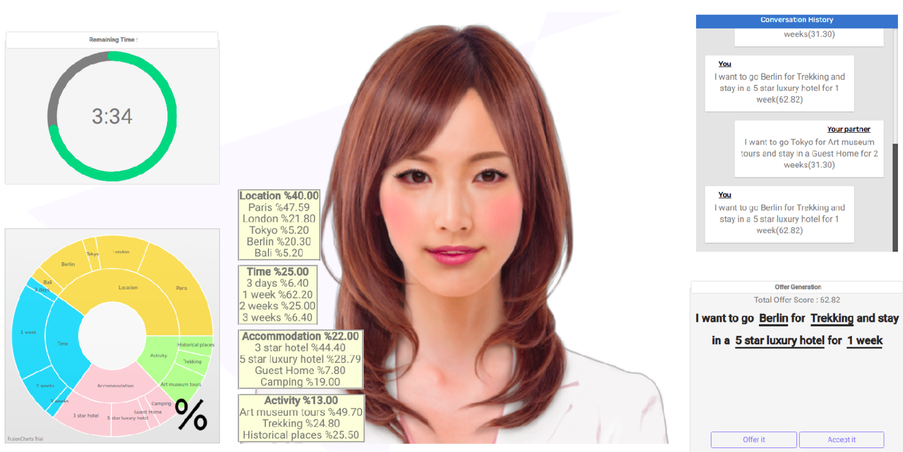

Figure 1: Human-Agent Negotiation Interface

In the next sections, we explain main components in a detailed way.

4.1.1 Virtual Avatar Character

A virtual embodied avatar character interacts with the user through his/her facial expression as well as speech. We can use different facial expressions for the avatar in order to express its feelings. During the negotiation, this character can change its facial expression in line with the designed strategy. We have used five facial expressions for the virtual avatar character: *neutral*, *happy*, *frustrated*, *sad*, and *excited*. Figure 2 shows those facial expressions that we used during the study.

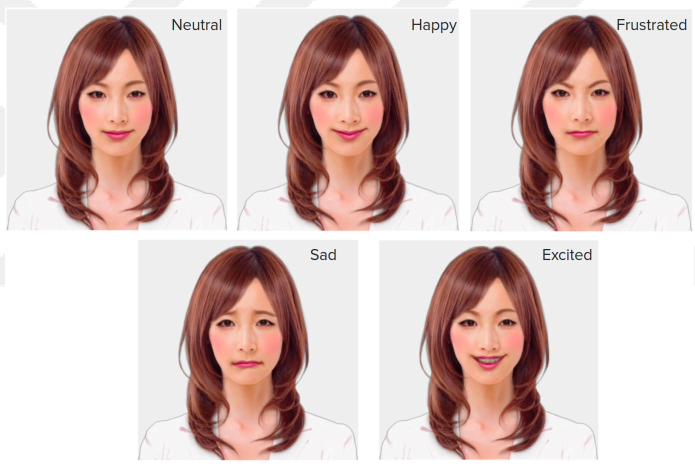

Figure 2: Facial Expressions Used in Our Study [3]

In addition to the textual offer information, this character provides the content of its offers via speech. Since our research focus is on analyzing the effect of the familiarity of the opponent in negotiation, this component plays a key role in our setting. Virtual avatar is located in the center and its size is bigger than the other user interface components so that human participants can focus on avatar's facial expression straightforwardly. Figure 1 shows the avatar that we used in training session. It is worth noting that celebrity and real human face appearances are used during the real negotiation sessions. To give the real human effects periodically such as blinking effect and minor head movements as well as speaking effect and emotional facial expression such as sadness or happiness, a software toolkit has been used [3]. When participants negotiate with the chosen celebrity, the voice of the avatar should be inline with that celebrity's own voice. To achieve this, we use a web service, which generates celebrity's voice from predefined sentences [53]. Note that there are limited number of celebrity options for this tool, which restricts the set of celebrity options we used in our experiments.

4.1.2 Human Offer Generator

In our framework, human negotiators specify their offers through a textual interface. This interface provides a predefined offer sentence form, which allows users to alter the content of the offers by using drop-down in a user-friendly way. If the human negotiator wants to modify the content of the offer, s/he can click the related issue (e.g, location, accommodation, etc. in our holiday domain) value, which is underlined in the interface. It is worth noting that when the human negotiator enters a complete offer, a score box above the offer sentence appears and shows the utility score of that offer for human negotiator. A utility score of an offer can take a real number between 0 and 100. Note that each negotiating party knows only their own preferences and does not have access to other side's preferences. On one hand, this utility score bar enables human negotiators to see their score without making any calculations; consequently, human participants can act according to their given roles during the experiments. On the other hand, being aware of received score while making offers may influence their negotiation attitude. In order to send his/her offer to the avatar, the human negotiator should click the "Offer" button while s/he should click the "Accept" button to accept the given counter offer by the avatar.

4.1.3 Conversation History

To enable the keep track of bidding history, the framework provides a conversation history showing the exchanged offers with the utility scores for the human participants. This component is designed in a way that it gives the impression of chat-based communication.

4.1.4 Time Remainder

As mentioned above, the negotiating parties have a deadline in term of minutes (e.g. 5 or 10 minutes) to come up with an agreement. For a fair negotiation, the framework provides a time reminder denoting the remaining minutes and seconds. The indicator is in green color at the beginning of the negotiation while it becomes yellow after a while and finally turns into red color when it reaches a critical time point (e.g., last minute). Note that if time is up and no agreement occurs, then negotiation ends with a failure and both sides will take a utility of zero points.

4.1.5 Preference Profile Chart

In experiments, human participants are given a particular preference profile and are asked to act according to the given preferences. Before their negotiation, they have enough time to study their profiles. However, due to the nature of humans, they may forget some details regarding these preferences, which may influence their negotiation significantly. Therefore, for our experiments, a user friendly multi-level pie chart graph is created to show the preference profile visually, which is modelled in terms of a additive utility function. The inner part of this graph represents the importance levels of negotiation issues while the outer part denotes preferences on issue values accordingly. The larger the segment associated with the issue becomes, the more important that the issue is. Similarly, larger segments for issue values mean “more preferred”. For instance, if Paris is more preferred over Tokyo for location, it is expected to have a larger segment than Tokyo as seen in Figure 3. For the sake of simplicity, every issue and related issue values have the same color to distinguish categories easily. When the user hovering the issue values in the chart, they can see the exact utility score of that issue. In addition to this, they can see the utility distribution of each issue by hovering the percentage sign located next to the graph.

During the design stage of this framework, we did some pilot studies and got feedback regarding the design and location of those components. We finalized the design and location

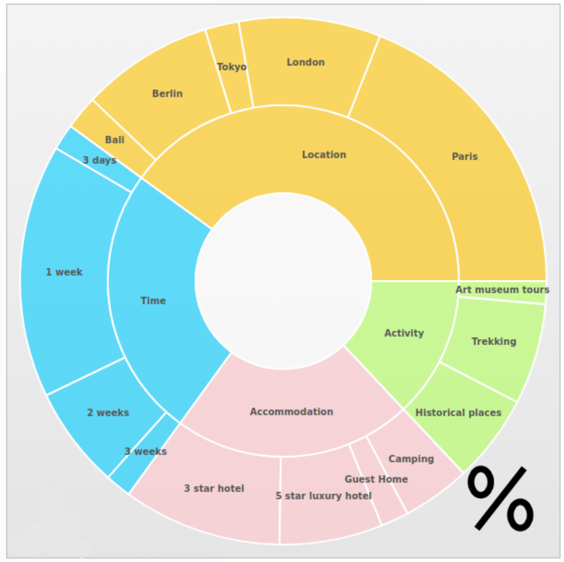

Figure 3: Holiday Preference Graph - Multi-Level Pie Chart

of those components based on those feedback accordingly.

4.2 Agent Design

Human-agent negotiations are fundamentally different from the agent-agent negotiations [25, 27, 54]. To investigate the effect of opponent's familiarity in human-agent negotiation, we design a basic negotiating agent, which takes human factors into account.

4.2.1 Negotiation Strategy

One of the concerns regarding human-agent interaction is the time limitation and human patience. As our agent negotiates with its human counterparts, it does not have enough time to make random or same offers again and again to observe its opponent behaviour change. Moreover, repeating the same offer many times may bother the human partner and make them walk away. Therefore, our agent avoids falling repetition as much as possible.

On the other hand, it is required to consider opponent's behaviour during the negotiation while generating the counter offer. In [55, 2], a negotiating party's behavior is classified into five categories: *competing*, *avoiding*, *compromising*, *accommodating*, *collaborating*. In our study, our agent also adopts this classification and tries to predict its opponent's attitude based on exchanged bids during the negotiation. Behaviour classification is determined by considering assertiveness and cooperativeness categorization of the opponent as it is defined in [2]. To achieve this, we first calculate each participant's sensitivity to their opponent's preferences according to Equation 2 proposed by [1].

$$Sensitivity_a(t) = \frac{\%_{Fortunate} + \%_{Nice} + \%_{Concession}}{\%_{Selfish} + \%_{Unfortunate} + \%_{Silent}} \tag{2}$$

Here, sensitivity is calculated by taking into account the percentages of negotiator's different moves. A move is determined based on the utility difference of 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. 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.

Table 1: 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	$\Delta U_s > 0$	$\Delta U_o < 0$

Since cooperativeness level is determined by using sensitivity value, assertiveness level of the opponent is determined according to the agent's own utility function as follows:

- High assertive : The utility of the bid is between [68-100],
- Moderate assertive : The utility of the bid is between [34-67], and
- Low assertive : The utility of the bid is between [0-34].

Finally, the classification of the opponent behaviour is determined by the rules defined in Table 2. Accordingly, our agent adapts its bidding and communication way (e.g., facial expressions). To sum up, our agent follows a hybrid bidding strategy considering both remaining time and behavior of the opponent.

Table 2: Behaviour Classification [2]

Assertiveness	**Cooperativeness**	**Behaviour**
High	Cooperative	Collaborating
High	Neutral	Competing
High	Uncooperative	Competing
Moderate	Cooperative	Accommodating
Moderate	Neutral	Compromising
Moderate	Uncooperative	Avoiding
Low	Cooperative	Accommodating
Low	Neutral	Avoiding
Low	Uncooperative	Avoiding

As mentioned above, our agent's bidding behavior changes according to the remaining time. It considers three stages during the negotiation according to the normalized current time as follows and adopts a different strategy accordingly:

$$stage = \begin{cases} initial, & \text{if } t < 0.1 \\ main, & \text{if } 0.1 \leq t \leq 0.9 \\ final, & \text{if } t > 0.9 \end{cases} \tag{3}$$

Our agent's negotiation strategy is illustrated in Algorithm 2. When the agent gets an offer from the opponent, it first checks if the offer is acceptable. Our agent adopts AC_{next} [56] approach for this purpose. It accepts the opponent's offer if the utility of that offer is higher than or equal to the utility of our agent's coming offer, $o^{A}_{current}$ (Lines 1-2). Otherwise, it generates its counter offer as explained below. Note that the first offer of our agent is always the most preferred offer according to its own preferences.

In the initial stage, the agent tries to recognize its opponent's attitude in terms of cooperativeness. To achieve this, it simply compares the utility of the bids coming from its

Algorithm 2: Next Offer Decision

o^A_{prev} and o^H_{prev} represents agent's and human's previous offer respectively while $o^A_{current}$ and $o^H_{current}$ denote their current offers. γ is the minimum acceptable value for the agent, also called as reservation value. s_c and ρ_{beh} denote current state and estimated opponent behaviour respectively.

```
if U(o^H_current >= U(o^A_current) then
    acceptOffer()
else
    switch s_c do
        case initial
            if isCooperative(o^H_prev, o^H_current) then
                u_next = max(U(o^A_prev) - u_dif, γ)
                f_exp = happy
            else
                u_next = min(U(o^A_prev) + u_dif, 1)
                f_exp = frustrated
            end if
        case main
            switch ρ_beh do
                case competing
                    u_next = max(U(o^A_prev), γ)
                    f_exp = frustrated
                case avoiding
                    u_next = getNextBestOffer(U(o^A_prev))
                    f_exp = sad
                case compromising
                    u_next = nearest(U(o^A_prev))
                    f_exp = neutral
                case accommodating
                    u_next = max(U(o^A_prev) - u_dif, γ)
                    f_exp = happy
                case collaborating
                    α_next = selectBestForBothFromEstimatedPareto()
                    f_exp = excited
        case final
            α_next = selectBestForBothFromEstimatedPareto()
            f_exp = frustrated
    if α_next is not assigned then
        α_next = pickOfferWithUtility(u_next)
    end if
    sendOffer(α_next, f_exp)
end if
```

opponent according to its own preferences. If the utility of the opponent's offer is greater than that of its previous offer, our agent considers its opponent as cooperative; otherwise, it is considered as uncooperative (Line 6). If the opponent is cooperative, then the agent also concedes and reduces its target utility value (Line 7); otherwise, it increases its target utility accordingly (Line 10). If the human opponent acts cooperatively, the agent demonstrates a happy facial expression (Line 8). Otherwise, it shows a frustrated facial expression (Line 11).

In the main stage, our main focus is to detect our opponent's attitude in terms of the aforementioned classification and act accordingly. If its opponent's behaviour is determined as *competing*, our agent adopts a frustrated facial expression and makes an offer whose utility is the same with its previous one (Lines 15-17). For the *avoiding* opponent, it selects next best offer according to the utility of its previous bid and shows a sad facial expression (Line 18-20). *Compromising* opponent makes a silent move so our agent does too by making an offer whose utility approximately the same with its previous offer and adopts a neutral facial expression (Line 21-23). For the *accommodating* opponent, happy face is adopted to express appreciation and the agent concedes with the same concession value (Line 24-26). When the opponent's attitude is detected as *collaborating*, the agent tries to make an offer, which is good for both sides. To do this, the agent estimates Pareto optimal offers and makes the best offer from these candidates with an excited facial expression (Line 27-29). The best offer is determined by ordering multiplication of both sides' utility (Nash product) in the Pareto optimal offers.

In the final stage of the negotiation (i.e, approaching the deadline), our agent orders the estimated Pareto optimal offers according to the Nash product and stores them in a list. Then, the agent asks offers in descending order from top of the list in this stage. To create a pressure on its opponent, it shows frustrated facial expression in this stage.

4.2.2 Opponent Modelling Strategy

Understanding opponent's preferences in agent-based negotiation mostly means to get insight about the importance of negotiation issues (i.e., the most/least important issue and which issue is more important than others etc.) and preference ordering of alternative values for each issue (e.g., Tokyo is more preferred over Rome three times, the estimated utility of Tokyo and Rome are 0.8 and 0.5 respectively). In this work, we assume that opponent' preferences are represented by means of an additive utility function (See Equation 1) and we aim to estimate this function by analyzing the bid exchanges during the negotiation. In automated negotiation, a variety of opponent modeling models have been proposed [50]. Among those models, it is seen that Frequency Model [51] has been widely-used due to its simplicity and relatively good performance over other models. Our model is also based on the heuristics proposed by this model. Similarly, our main intuition is that most frequently values appeared in opponent's offers during the negotiation are directly proportional with their actual utility values of these options, and if the value of an issue does not change for a long time, it also means that importance value of this issue is higher than the others whose issue value is changed frequently.

Algorithm 3 illustrates how we estimate the opponent's utility function by comparing opponent's consecutive bids during the negotiation. Similar to the Frequency Model, we update the importance values of each issue. In the bid sequences, if the value of an issue does not change, we increase the importance of that issue by adding a parameter θ (Lines 1-5). Likewise, we update the number of appearance of an issue value (Lines 6-8). To estimate the final importance and evaluation values, we apply AHP to those vectors (Line 9) as explained in Algorithm 4.

In order to apply the AHP, pairwise comparison matrix is needed. We calculate these matrices from the importance (Lines 1-5) and evaluation value vectors (Lines 7-12). The Eigen values of those matrices are taken as updated importance (Line 6) and evaluation values (Line 13).

Algorithm 3: Proposed AHP-Frequency Model

$o_{prev} \leftarrow$ Opponent previous offer
$o_{cur} \leftarrow$ Opponent current offer
θ denotes the importance update parameter

▷ Updating issue importance

for each issue i in o_{cur} **do**
    if $_{cur}$[i].value == o_{prev}[i].value **then**
        importance[i] += θ
    end if
end for

▷ Updating issue value importance

for each issue value v_i in o_{cur}[i] **do**
    evaluationValue[v_i] += 1
end for

▷ After that, AHP modelling is applied

$applyAHP(importance, evalautionValue)$

Algorithm 4: Applying AHP

▷ Creating issue matrix first by using pairwise comparisons

for $j = 1 \ldots n$ **do**
    for $k = 1 \ldots n$ **do**
        issueMatrix[j][k] = importance[issueList[j]] / importance[issueList[k]]
    end for
end for
$importance$ ←calculateEigenValue(issueMatrix)

▷ Creating issue value matrix for every issue with same way

for each issue i from issueList **do**
    for $j = 1 \ldots IssueValueList[j].size$ **do**
        for $k = 1 \ldots IssueValueList[j].size$ **do**
            issueValueMatrix[j][k] = $\frac{evaluationValue[issueValueList[i][j]]}{evaluationValue[issueValueList[i][k]]}$
        end for
    end for
    $evaluationValue$ ←calculateEigenValue(issueValueMatrix)
end for

In automated negotiation, frequency model is one of the most widely used model [51]. Despite of the simplicity of the model, the model performs well in compared to more complex models such as Bayesian model because more sophisticated models tend to overfit [55] in this field. In order to evaluate the performance of the proposed AHP extension of frequency modeling namely AHP-Frequency, we asked 43 human participants to specify their first 10 offers irrespective of their opponent's behavior. Note that each participant studied the given preference profile and specify their offers by considering those given preferences. Figure 4 shows how we elicited those offer sequences from the user.

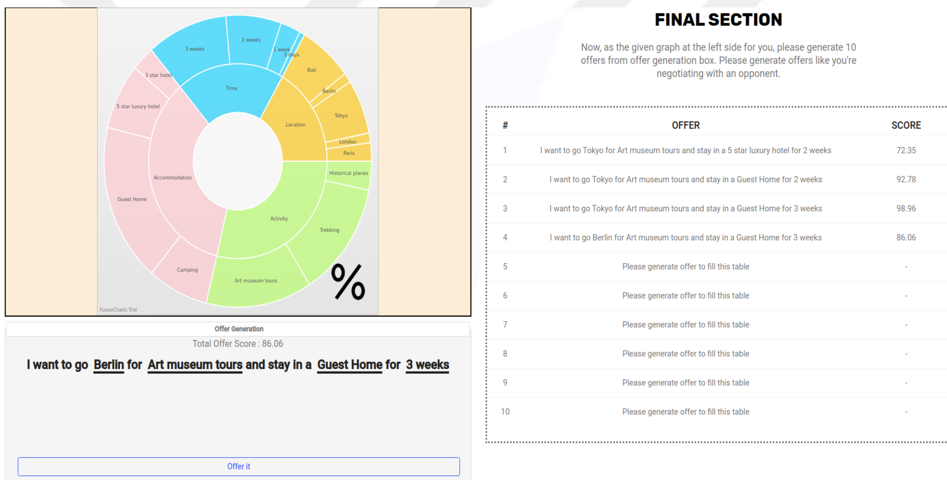

Figure 4: Eliciting Opponent's Offers to Evaluate Opponent Modelling

By using those bid sequences, we trained our model and classical frequency model separately and compared the performance of the estimated models. As a performance metric, we consider Kendall Tau Distance to the ranking of the offers according to the ground truth preferences. Kendall Tau distance metric is a well-known metric for comparing two rankings [57]. The rankings are compared by counting the number of pairwise disagreements between those rankings. To do this, for every pair from the first ranking, if the order of the pair is the same as in the second ranking, it is considered as **concordant** pairs denoted as c. Likewise, if there is a conflict of order between them, it is considered as **discordant** pairs denoted as d. Kendall tau coefficient is found by the Equation 4 where n is the number of total pairs, $|c|$ and $|d|$ are the number of c and d respectively. The value of the Kendall Tau distance is between zero and one where 1 means given two lists' order are completely different while 0 means they have same order.

$$\tau = \frac{|c| - |d|}{\frac{n\times(n-1)}{2}} \tag{4}$$

Table 3 shows the distance between estimated ranking and true ranking for both opponent models for each participant. Every row in the table corresponds to a participant. The average Kendall Tau Distance between the true ranking and estimated ranking by Frequency Model is 0.18 while the mean value of this distance for AHP-Frequency is 0.21. The standard deviations for AHP-Frequency and Frequency, 0.07 and 0.09 respectively. Our extension did not perform better than the classic model, but the average distance to the actual ranking shows that the performance of the model is reasonably good enough.

Table 3: Kendall Tau Distance to Actual Ranking

#	AHP-Frequency	Frequency
1	0.168	0.113
2	0.231	0.171
3	0.189	0.147
4	0.240	0.249
5	0.209	0.186
6	0.257	0.188
7	0.126	0.103
8	0.205	0.157
9	0.279	0.291
10	0.165	0.105
11	0.575	0.606
12	0.136	0.113
13	0.244	0.232
14	0.226	0.170
15	0.239	0.217
16	0.214	0.192
17	0.252	0.237
18	0.185	0.122
19	0.175	0.145
20	0.141	0.119
21	0.174	0.139
22	0.276	0.220
23	0.211	0.164
24	0.213	0.177
25	0.188	0.145
26	0.107	0.076
27	0.194	0.165
28	0.126	0.078
29	0.234	0.224
30	0.230	0.183
31	0.185	0.151
32	0.199	0.159
33	0.183	0.138
34	0.165	0.104
35	0.185	0.110
36	0.328	0.298
37	0.203	0.178
38	0.265	0.255
39	0.185	0.154
40	0.133	0.118
41	0.201	0.172
42	0.167	0.123
43	0.229	0.224

CHAPTER V

PILOT STUDIES

Before our main user experiment regarding the studying the effect of opponent familiarity, two pilot studies were conducted. It is worth noting the adjustments we made after these pilot studies shows the importance of the pilot studies before conducting the actual experiments.

During the first pilot study in which the framework is designed as shown in Figure 5, we had the opportunity to have a debriefing session with the participants to understand the usability of the framework and the applicability of the experiment. They informed us that they had a difficulty in grasping the utilities from the preference graph; therefore, a percentage icon was added at the right bottom of the graph to display the respective importance percentages for each value and issues. Secondly, they suggested us to change the flow of the conversation history. Initially, last offer was shown at the top of conversation history frame while their first offer was shown at the bottom. We reverse the ordering in the second pilot study as shown in Figure 6.

Furthermore, we made more critical changes in the design of the framework after the second pilot study. For instance, avatar was displayed on the right side of the screen in

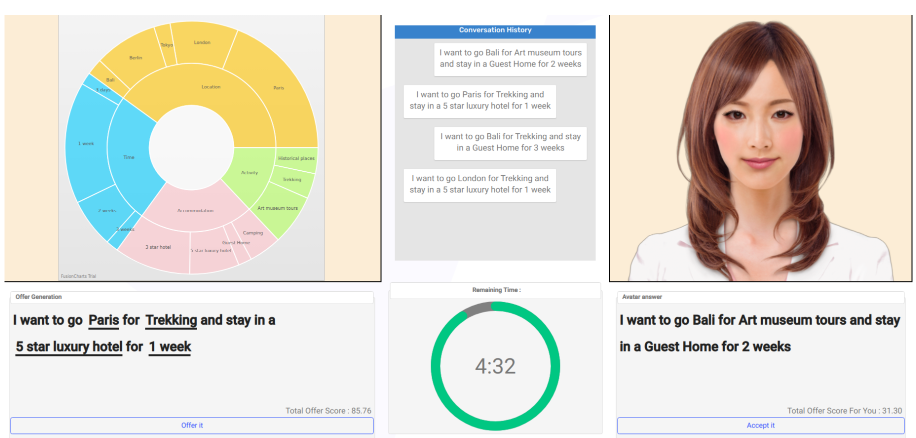

Figure 5: User Interface Used in the First Pilot Study

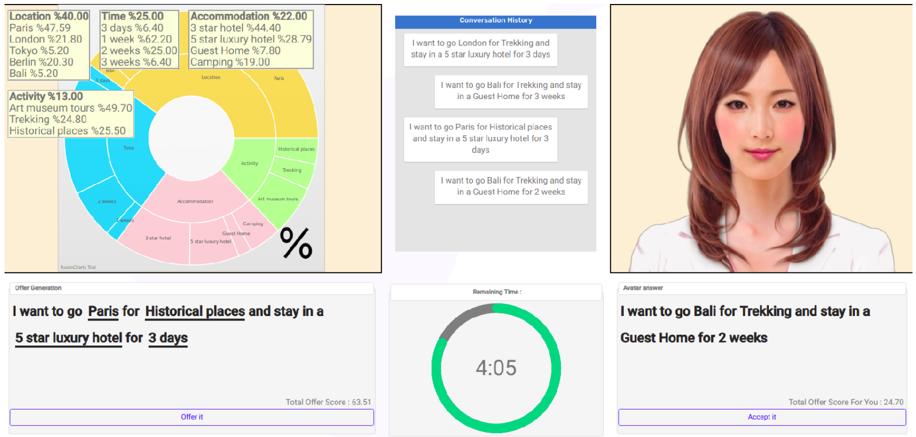

Figure 6: User Interface Used in the Second Pilot Study

pilot studies. However, we noticed that they did not look at the avatar directly. Since we study the opponent familiarity, the appearance of the avatar plays a key role; therefore, the participants should focus on the avatar's face. Consequently, we moved the avatar into center of the screen and increased its size as shown in Figure 1. We also made some changes in the agent's negotiation strategy after analyzing the feedback given by some participants. Furthermore, we had an offer generation box for the avatar as well as the participant. We removed that box to have a more compact interface.

Finally, our experimental design was within-subject design in the pilot studies. We found out that some participants changed their negotiation behavior in order to beat the agent irrespective of the negotiation setting. This would prevent us to understand whether or not their behavior change was due to their familiarity to their opponent. Therefore, we had to change our experimental design and adopted a between-subject design for the actual experiment. Accordingly, we adopted the questionnaires.

All participants in the pilot studies were Engineering students or graduates. For the analysis of the collected data, we first apply some normality tests (Kolmogorov-Smirnov and Shapiro-Wilk Tests) in order to decide which statistical test (parametric or non-parametric) should be applied. Since the data was not normally distributed, the Wilcoxon signed-rank test was used to analyze them in our pilot studies. In the following part, we discuss those results and mention the experimental changes we made for the main experiments.

5.1 *Results of the First Pilot Study*

In the first pilot study, there were 14 participants (11 males and 3 females): 11 Computer Science graduate students and 3 Electronic Engineering graduate students. Each participant negotiates with the avatar in both settings: celebrity and non-celebrity. Note that 7 of the participants negotiated with the non-celebrity avatar and the rest of the participants negotiated with the celebrity avatar in their first sessions. The average scores of the user utilities, agent utilities, total negotiation time, social welfare and utility product for this group were listed in Table 4 and illustrated in Figure 7.

Table 4: Statistical Results of the First Pilot Study

	N	Mean	Standard Deviation	Variance	Min	Max
User Utility (Non-C.)	14	.8164	.0751	.006	.69	1.00
User Utility (C.)	14	.7586	.1248	.016	.40	.88
Agent Utility (Non-C.)	14	.8207	.0755	.006	.61	.88
Agent Utility (C.)	14	.8736	.0683	.005	.80	1.00
Total Time (Non-C.)	14	.3936	.1626	.026	.16	.67
Total Time (C.)	14	.4493	.2618	.069	.19	.99
Social Welfare (Non-C)	14	1.6371	.0645	.004	1.48	1.68
Social Welfare (C.)	14	1.6321	.0725	.005	1.40	1.68
Utility Product (Non-C.)	14	.6667	.0541	.003	.55	.70
Utility Product (C.)	14	.6557	.0794	.006	.40	.70

Although the average individual utilities gained by human participants are higher in non-celebrity setting than those ones in celebrity setting, there is no statistically significantly differences between those means. Result of the Wilcoxon signed-rank test shows that there is no significant difference between the user utilities in two paired sessions (z=-1.481, p=.139). Also, there is no significant difference between the agent utilities (z=-1.890, p=.059) and between the negotiation time averages (z=-.440, p=.660). The agent and user utilities were added and multiplied to observe whether there is a difference between them from the social welfare perspective and between their Nash products. There is found no significant difference in terms of social welfare (z=.000, p=1.000) and Nash product (z=-313, p=754).

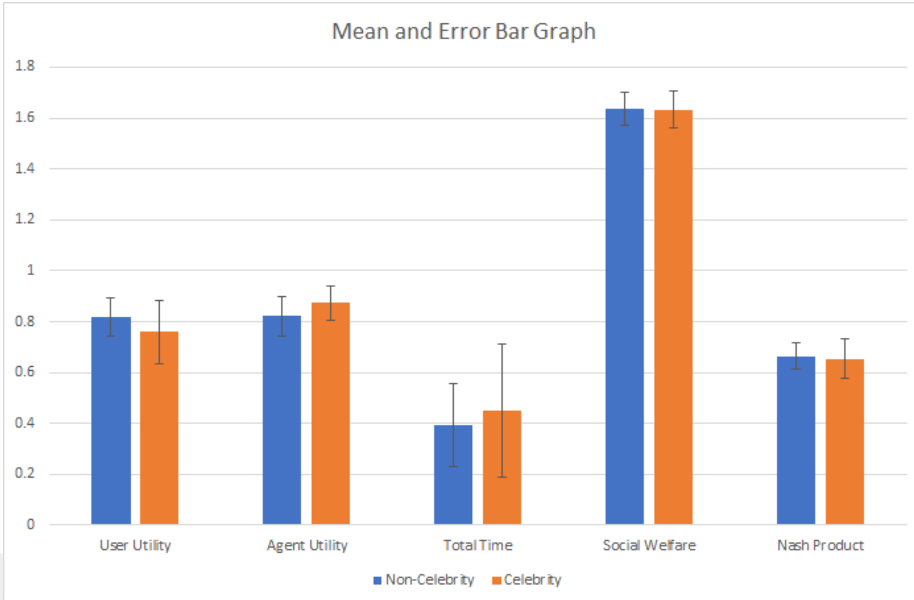

Figure 7: Analysis of Negotiation Results for the First Pilot Study

There is no significant difference between the mean values in terms of user utility, agent utility, total time, social welfare and utility product. Therefore, we cannot make any claims regarding those metrics.

In addition to mean values, the frequencies of acceptance were also analyzed and given as a pie-chart. Considering the sessions with celebrity avatar, from 14 negotiation sessions, 4 of them were accepted by the agent and the other 10 were accepted by the user and for the sessions with non-celebrity avatar, again from 14 negotiation sessions, 9 of them were accepted by the user and 5 of them were accepted by the agent (Figure 8).

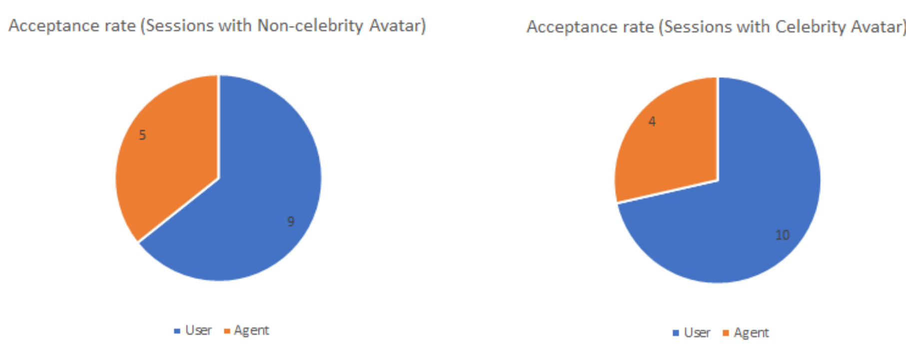

Figure 8: Acceptance Rates for the First Pilot Study

After each negotiation session, participants filled out a questionnaire involving some questions about the fairness of the avatars, whether participants perceive their negotiation partner collaborative or competitive, whether the avatar were human-like or not, participant's frustration levels during their negotiation sessions and their deadline considerations were asked after each session. For the surveys, 9 point likert scale was used in the questions (1-strongly disagree, 9-strongly agree). Finally the questionnaires were also analyzed to understand whether there happened significant changes in the perception of the participants.

The results of the first pilot study showed that there is no significant difference between the participants' perceptions about the celebrity and non-celebrity avatar. Only the question by which we asked participants' frustration level when their negotiated with the celebrity avatar or non-celebrity avatar in their first sessions shows a significant difference between the two groups ($U=5.000$, $p<.05$). Participants who negotiated with non-celebrity avatar showed significantly higher level of frustration than the group who negotiate with celebrity avatar in their first sessions regarding results coming from their responses to the aforementioned question. Figure 9 shows the mean score of each question in the post-survey involving questions comparing their negotiations with celebrity and with non-celebrity avatar.

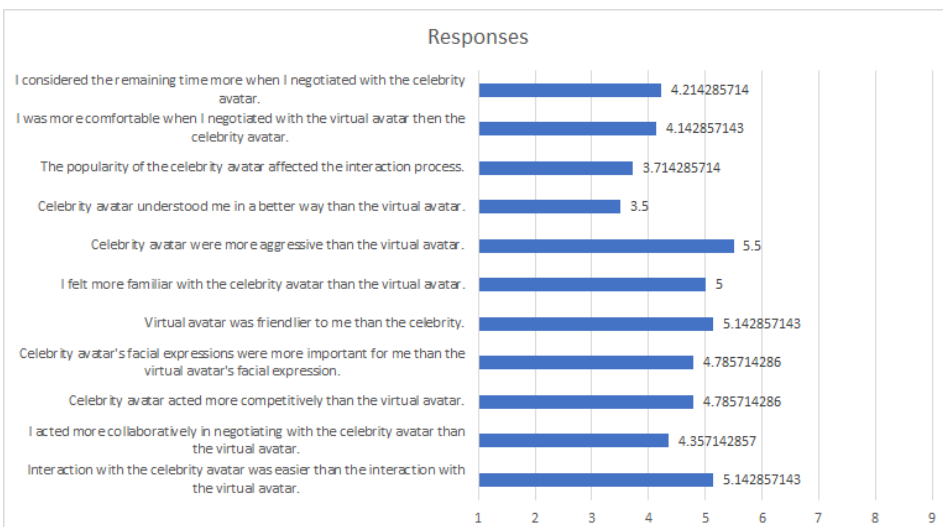

Figure 9: Questionnaire Responses in the First Pilot Study

5.2 *Results of the Second Pilot Study*

In the second pilot study, there were 29 bachelor and graduate engineering students (23 males and 6 females) at Ozyegin University. The age of participant ranges from 21 to 37. We adopted the same experimental design with the first pilot study. 15 participants negotiated with the celebrity avatar and 14 participants negotiated with the non-celebrity avatar in their first negotiation sessions. The average scores of the user utilities, agent utilities, total negotiation time, social welfare and utility product for this group were listed in Table 5 and illustrated in Figure 10.

Table 5: Statistical Results of the Second Pilot Study

	N	Mean	Standard Deviation	Variance	Min	Max
User Utility (Non-C.)	29	.7628	.0810	.007	.61	.88
User Utility (C.)	29	.7628	.0924	.009	.61	.88
Agent Utility (Non-C.)	29	.8690	.0812	.007	.60	1.00
Agent Utility (C.)	29	.8697	.0751	.006	.73	1.00
Total Time (Non-C.)	29	.4074	.2261	.051	.09	.98
Total Time (C.)	29	.4047	.2489	.062	.02	.97
Social Welfare (Non-C.)	29	1.6317	.0775	.006	1.29	1.68
Social Welfare (C.)	29	1.6324	.0481	.002	1.51	1.68
Utility Product (Non-C.)	29	.6594	.0618	.004	.41	.70
Utility Product (C.)	29	.6576	.0459	.002	.57	.70

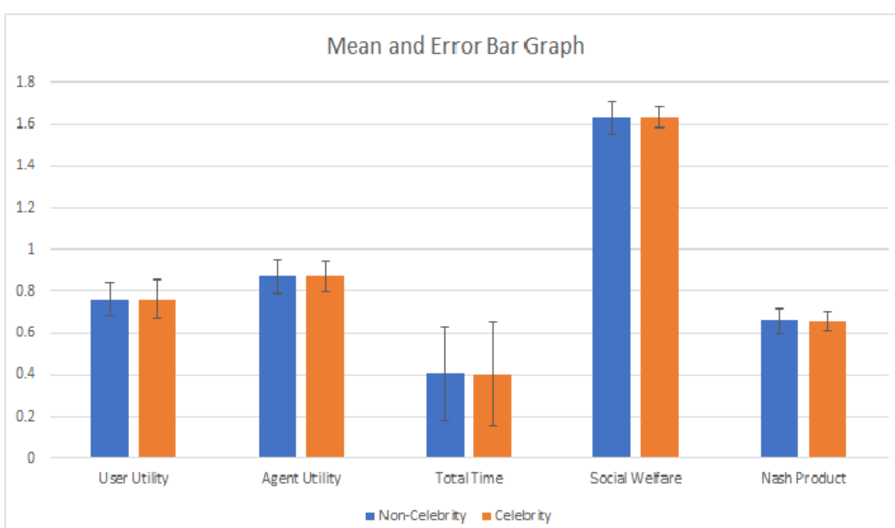

Figure 10: Analysis of Negotiation Results for the Second Pilot Study

It can be seen that the average values are really close and the result of the Wilcoxon signed-rank test shows that there is no significant difference between the user utilities in two paired sessions (z=-.011, p=.991). Also, there is no significant difference between the agent utilities (z=-.160, p=.873) and between the negotiation time averages (z=-.324, p=.746). Also, there is no significant difference between the two groups in terms of social welfare (z=-.613, p=.540) and utility product (z=-.602, p=547). To sum up, there is no significant difference between the mean values in terms of user utility, agent utility, total time, social welfare and utility product. Therefore, we cannot make any claims regarding those metrics.

Regarding the acceptance rates shown in Figure 11, our agent accepted the participants' offers in 14 out of 29 negotiations while 15 human participants accepted our agent's offer. For the sessions with celebrity avatar, our agent's offers were accepted by 18 participants while 11 human participants' offers were accepted by our agent.

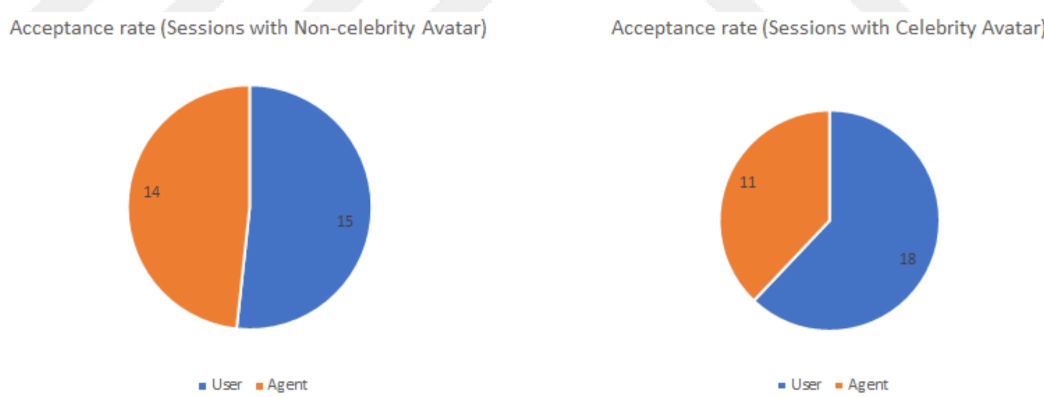

Figure 11: Acceptance Rates for the Second Pilot Study

Analysis of the questionnaire also showed that there is no significant difference between the participants' perceptions about the celebrity and non-celebrity avatar in general. For the second pilot study, questionnaire results show that there is a significant difference between the two groups for the question stated that "My partner's reactions during negotiation pushed me away." (U=56.000, $p<.05$). Participants negotiated with non-celebrity avatar had higher mean for this question than the other group according to the results. Also, the group negotiated with the celebrity avatar in their first sessions found their partner more collaborative. Result shows that there is a significant difference between the two groups in accepting their partner as collaborative (U=50.000, p<.05). Figure 12 shows the mean score of each question in the post-survey involving questions comparing their negotiations with celebrity and with non-celebrity avatar.

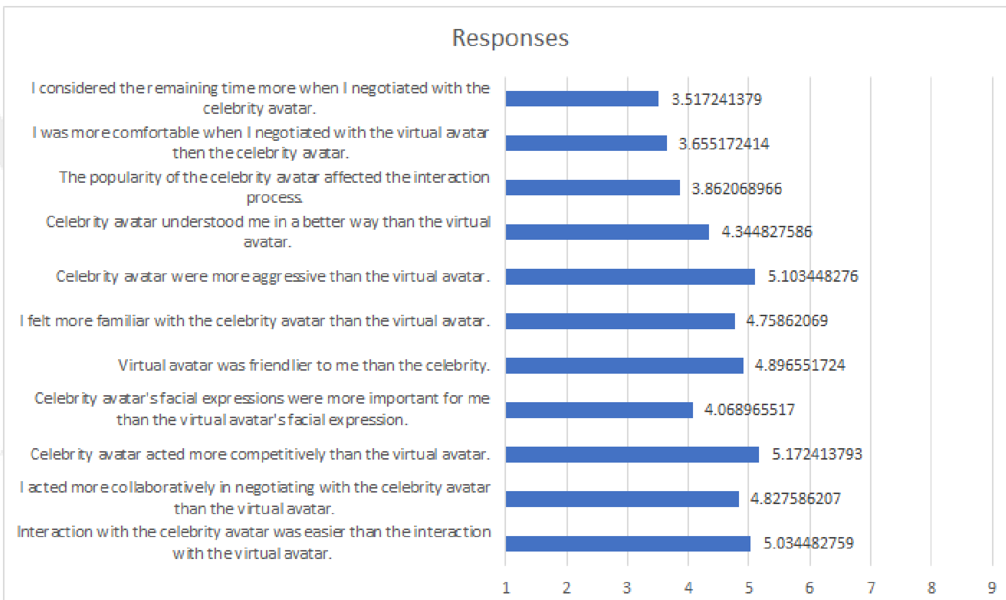

Figure 12: Questionnaire Responses in the Second Pilot Study

After analyzing these results and the discussion the debriefing sessions we made following the experiment, we decided to change the experimental design from within subject to between subject because participants stated that they applied different strategies in the second session in order to beat our agent. This shows us the influence of the learning effect on negotiation. To avoid this effect, by increasing our anticipated sample size, we chose to change our design to between subject. Within subject design was more preferable because a smaller sample size is feasible for the within subject design, nevertheless for the between subject design it is vital to increase the number of the participant for making the evaluation appropriately.

CHAPTER VI

STUDYING THE EFFECT OF FAMILIARITY

In order to study the effect of familiarity of the opponent in human-agent negotiation, we conducted a user experiment based on the results and feedback coming from the previous pilot studies. In the following section, we first explain our final experimental setup and report our main findings.

6.1 Experimental Setup

In our experiments, we aim to investigate the effect of negotiating with a celebrity virtual agent versus negotiating with a non-celebrity virtual agent on both negotiation process and outcome. In our first attempt, we adopted a within-subject design where each subject is asked to experience all possible conditions because a between-subject design requires relatively larger number of subjects to get significant results [58]. In our pilot studies in which each participant negotiated with the virtual agent in both conditions, we observed that participants had a tendency to change their strategy deliberately to beat the virtual agent in their second negotiations. This trial-error method of human participants prevents us to study the effect of the independent variable named "familarity" accurately. Therefore, we had to switch to between-subject design.

We have recruited 67 participants (i.e., some acquaintances and university students; 39 males, 28 females; median age: 25) for conducting our human-virtual agent experiments. 49 participants had an engineering background while the rest have different backgrounds such as social sciences, business management and law. We divided the participants into groups: A (the control group) and B (experimental group) where the participants in *Group* A negotiate with a non-celebrity agent while *Group* B negotiates with a celebrity agent. Note that there were 33 and 34 participants in *Group* A and *Group* B respectively.

In the experiment, a negotiation profile is given to each participant. As a role-playing game, they are asked to study their preference profiles elaborately before their negotiation. After studying their profiles, they are asked to answer three questions regarding their preferences in order to understand whether they grasp their preferences accurately. These questions are specifying the best and worst offer and deciding which offer is better for a given offer pair.

At the beginning, all participants are informed about the experiment and asked to fill out a short survey form in which demographics of the participants were collected. At this stage, consents of the participants were taken. In order to protect their privacy, the system generates a unique number, which will be used by the participants during their interaction with the system. That is, our system logs do not involve any personal information of the participants. Each participant is represented by the given unique number in the log files.

Before starting their real negotiation session, there was a training session for participants to experience the negotiation process and the framework. For the training session, a different profile from the real experiment was given to participants. Same process with the real experiment is used. Participants first watched a demonstration video and performed a five-minute negotiation on the given training scenario. During the training session, participants negotiated with a computerized virtual agent (Figure 1) employing a simple time-based negotiating strategy. It is worth noting that the virtual character and agent strategy are different from the ones that we used in the real experiment.

After the training session, the participants were asked to study the preference profile for the real negotiation session. Regardless of the group, all participants are asked to choose a celebrity that they would like to negotiate with, among six celebrities provided by the framework. While the participants negotiate with the chosen celebrity in *Group B*, the participants negotiate with a non-celebrity agent in *Group A*, which has the same gender of their choice. The deadline for this negotiation is set to 10 minutes. The time is initiated after human participant's first offer. If participants cannot reach an agreement within 10 minutes, both parties receive zero points. Note that the goal of the participants is to maximize their individual utility scores and participants could see their preference profiles at any time during the negotiation. It is also worth noting that participants were advised to look at the facial expression of the avatar agent during their negotiation.

According to our scenario, our participants are asked to negotiate with the virtual agent on their joint holiday plan similar to the one [2]. There are four negotiation issues: *Location* (Tokyo, Bali, London, Paris, Berlin), *Accommodation* (3-star hotel, guest home, 5-star luxury hotel and camping), *Duration* (3 days, 1 week, 2 weeks, and 3 weeks) and *Activities* (Museum tours, trekking and historical places). That is, there are 240 possible outcomes. Figure 13 shows the utilities of each possible bid in the given scenario. It can be seen that the bargaining power of the two parties is almost the same.

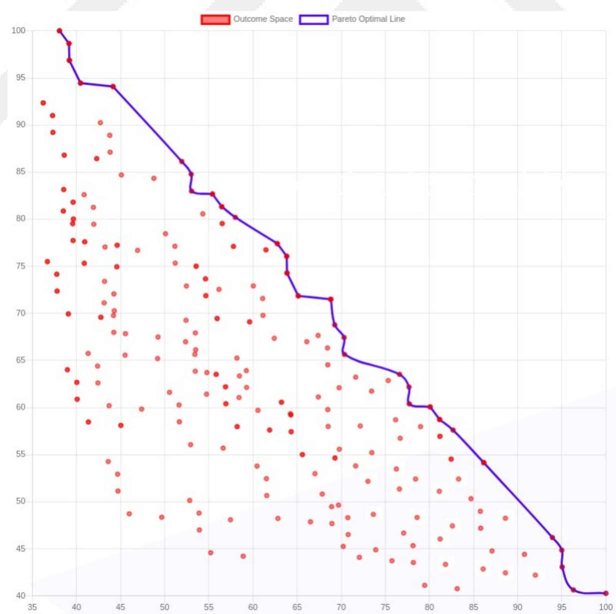

Figure 13: Utility Distribution of Outcome Space for the Given Scenario

After their negotiation session, the participants are asked to fill out a post-survey form consisting of general questions regarding their current negotiation and opinion questions about their negotiating partner.

6.2 *Experiment Results: Negotiation Outcome*

We first investigate the success rate (i.e., the percentage of reaching an agreement). Recall that 33 participants and 34 participants negotiated with the non-celebrity avatar and with the celebrity avatar respectively. Figure 14 shows the acceptance rate of each setting by specifying the number of negotiation sessions by whom the agreement is reached. It can be seen that 2 of 33 sessions with non-celebrity avatar resulted in failure to find a consensus while all sessions ended with an agreement for celebrity sessions. As seen from the charts, the percentage of sessions in which avatar's offer was accepted by the participants is higher in the celebrity setting than in the non-celebrity setting (% 61.8 versus % 48.5).

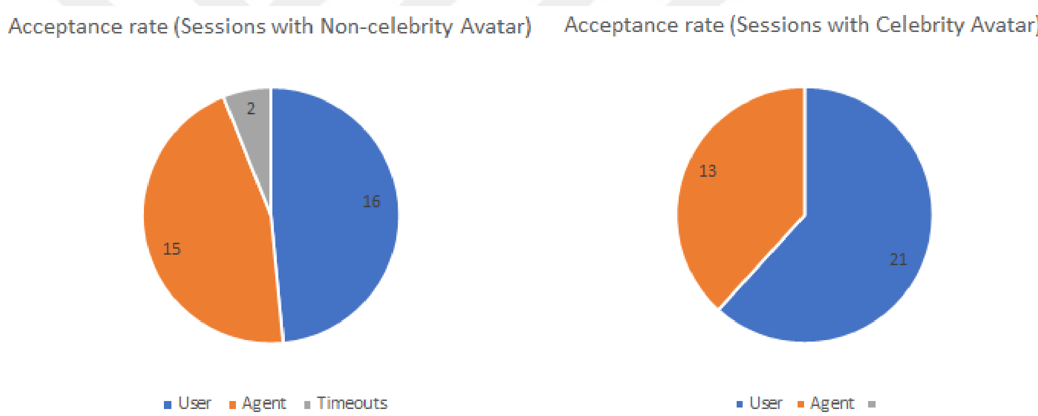

Figure 14: Acceptance Rates for the Main Experiment

After analyzing the acceptance rates, we study the negotiation results of the sessions ended successfully in terms of a variety of performance metrics: utility received by user (i.e, user utility), utility received by agent (i.e., agent utility), negotiation time to reach an agreement, the sum of user and agent utilities (i.e., social welfare) and the product of user and agent utilities (i.e., utility product). Note that when time out occurs and no agreement is reached, both party receives zero utility. Considering unsuccessful negotiations would act like outliers. Therefore, we filtered them out in our analysis. To apply the right statistical test, we first used a normality test to see whether or not the data is normally distributed. To achieve this, we applied Kolmogorov-Smirnov and Shapiro-Wilk normality tests on the data distribution regarding user and agent utility of the agreements, negotiation time, social welfare and utility product. As Table 6 shows, data is not normally distributed for all metrics except negotiation time. Therefore, we applied a non-parametric statistical test, namely Mann-Whitney U test.

Table 6: Results of Normality Tests

	Kolmogorov-Smirnov		Shapiro-Wilk	
	Statistics	P-value	Statistics	P-value
User Utility (Non-C.)	.289	.000	.868	.001
User Utility (C.)	.281	.000	.858	.000
Agent Utility (Non-C.)	.253	.000	.868	.001
Agent Utility (C.)	.258	.000	.919	.015
Total Time (Non-C.)	.139	.135	.945	.112
Total Time (C.)	.143	.074	.925	.022
Social Welfare (Non-C.)	.263	.000	.729	.000
Social Welfare (C.)	.261	.000	.871	.001
Utility Product (Non-C.)	.249	.000	.810	.000
Utility Product (C.)	.296	.000	.813	.000

At the same time, Table 7 shows the statistics such as mean values, standard deviations, variances, minimum and maximum values for each performance metric on both non-celebrity and celebrity settings.

Table 7: Statistical Results of the Main Experiment

	N	Mean	Std. Deviation	Variance	Min	Max
User Utility (Non-C.)	31	.5881	.1360	.018	.29	.75
User Utility (C.)	34	.4950	.1514	.023	.25	.94
Agent Utility (Non-C.)	31	.7526	.0826	.007	.62	.90
Agent Utility (C.)	34	.8144	.1002	.010	.54	1.00
Total Time (Non-C.)	31	.5748	.2388	.057	.19	.99
Total Time (C.)	34	.5874	.2878	.083	.08	.99
Social Welfare (Non-C.)	31	1.3406	.0979	.010	1.04	1.42
Social Welfare (C.)	34	1.3094	.0766	.006	1.08	1.48
Utility Product (Non-C.)	31	.4350	.0760	.006	.22	.50
Utility Product (C.)	34	.3900	.0760	.006	.24	.51

An error bar chart graph was also provided based on the mean and standard deviation values in Figure 15. In terms of user utility and agent utility, the results are statistically

Figure 15: Analysis of Negotiation Results for the Main Experiment

significantly different according to Mann-Whitney U test (p= 0.018 and 0.014 $<$.05 and U = 350.5 and 342 respectively). As expected, average agent utility received in celebrity setting is higher than that in non-celebrity setting. In line with those results, the average user utility is higher when the participants negotiate with a non-celebrity. We may draw a conclusion that participants conceded more against a celebrity opponent than a non-celebrity opponent. For negotiation time, there is no significant result (p=0.773 and U=505).

In terms of social welfare, the difference between the two settings is statistically significant (p=0.08 and U=328.5). It showed that the setting with non-celebrity resulted in higher social welfare on average (1.34 versus 1.30). Similarly, the higher product utilities are received when people negotiate with non-celebrity opponent (0.43 versus 0.39). It seems that more fair or socially balanced results are gained against to a non-celebrity opponent. Since participants had a tendency to concede more against a celebrity opponent, they may not consider fairness of the negotiation outcome much.

6.3 Experiment Results: Negotiation Process

In addition to the analysis of the negotiation outcome, we also analyze the negotiation process in terms of the participant's cooperativeness level as described in Section 4.2. According to this process analysis, out of 33 participants who negotiated with the non-celebrity avatar, 16 of them approached our agent collaboratively, 15 of them preferred a more competitive approach, and the rest were more neutral, neither collaborative nor competitive. For the participants who negotiated with the celebrity avatar, out of 34 participants, 23 of them were more collaborative and 8 of them acted competitively and again the 3 of them approached in a more neutral way. The percentage wise, 48.5 % and 69.7 % of the participants negotiated collaboratively when they negotiated with non-celebrity agent and celebrity agent respectively. These results are inline with our findings on the negotiation outcome. That is, the participants acted more collaboratively when they negotiated with the celebrity avatar.

6.4 Experiment Results: Questionnaires

We asked the participants their perceptions on their performances, their perceptions on the avatar's strategy, about the framework and the experimental setup. Results coming from the questionnaires show that the participants' perception who negotiated with the celebrity and the non-celebrity avatar didn't differ in significant level as seen Figure 16 where *Group A* and *Group B* negotiated with the non-celebrity and celebrity avatar respectively. We noticed that most of the participants found the virtual agent competitive in general. Regarding the responses to the experimental setup questions showed that participants understood the given profile and they took into account the avatar's facial expressions during their negotiation.

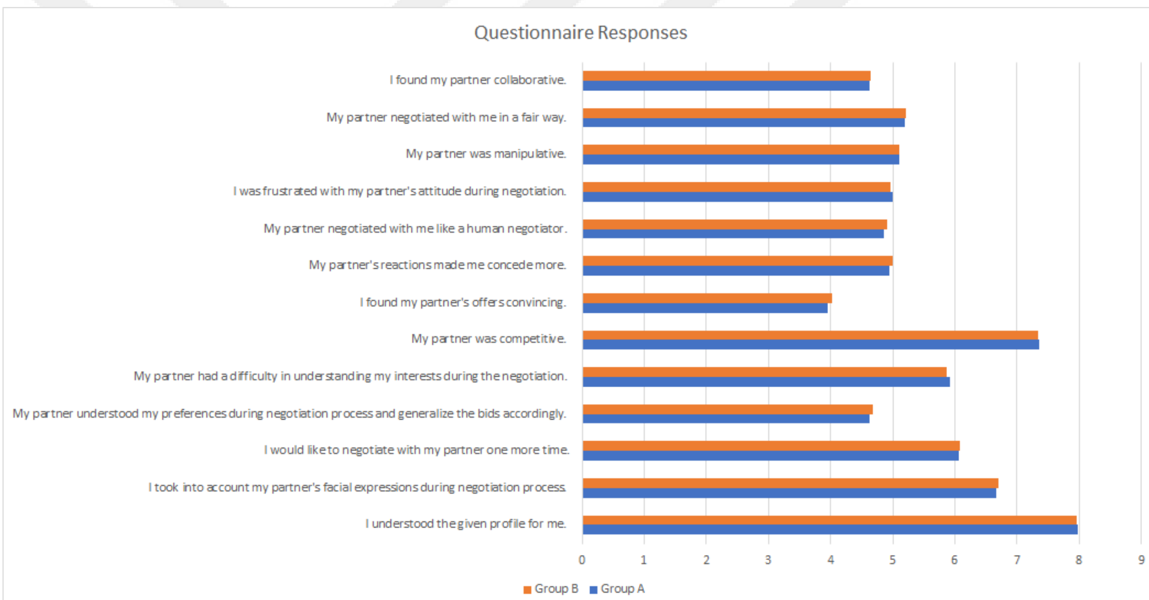

Figure 16: Questionnaire Responses in the Main Experiment

CHAPTER VII

CONCLUSION AND DISCUSSION

This work introduces a human-agent negotiation framework where a human negotiator can negotiate with a virtual avatar so that researchers can investigate the effect of the avatar's appearance on their human opponent's negotiation behavior. The main aim of this work is to study the effect of human negotiator's familiarity to their opponent in their negotiation attitude and also outcome. To achieve this, a user experiment was conducted where some participants negotiated with an avatar looks like a celebrity they preferred while others negotiated with a non-celebrity avatar. The experimental results showed that human participants had a tendency to concede more against their celebrity opponent than a non-celebrity opponent. That is, the participants acted more collaboratively when they negotiated with the celebrity avatar. While designing a virtual agent negotiating with a human, it might be beneficial to build a virtual avatar, which looks like a celebrity that the user likes.

The paradigm of conversationally negotiating with agents that appear like humans brings a naturalness to the interaction. In this new paradigm, many phenomena seen in human-human interactions could be translated to human-agent interactions. For example, in addition to visual similarity, rapport has shown to play a big effect on the process and outcome of negotiations between two parties [59]. It would be of interest to see how an AI agent is able to create such a rapport. Especially in a multi-modal paradigm where users also see the embodiment of the AI agent as well as converse with it, it would be of interest to explore how AI agents can express themselves using voice, emotion, facial expressions, gestures, etc. to develop rapport and come-off as a fair, trustworthy negotiation partner; an important prerequisite to successful negotiations. Further, the result of negotiations can be analyzed according to other metrics such as satisfaction level (i.e., is the human party more satisfied/comfortable with AI agents than fellow humans?), convincing power (i.e., can the AI agent convince a human to take a second-best deal compared to a human?), and so on. We are planning to investigate those kind of questions as a future work.

Furthermore, it would be interesting to study the effect of their opponent's gender on the negotiation outcome in the proposed negotiation framework as the work [10] did.

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