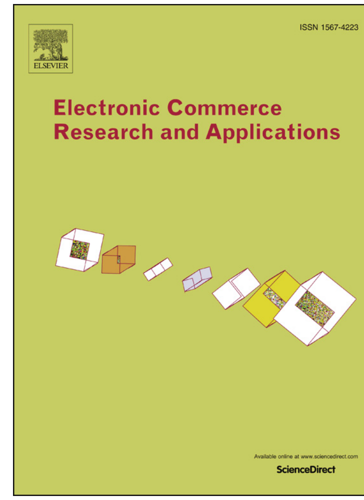

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THE EFFECTS OF INTERPLAY BETWEEN NEGOTIATION TACTICS AND TASK COMPLEXITY IN SOFTWARE AGENT TO HUMAN NEGOTIATIONS

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ABSTRACT

Modern networked business environment enables design of flexible and effective mechanisms of exchange between economic parties. Online negotiations allow geographically and temporally separated participants to engage in exchange of offers in search for acceptable agreements. The digital medium enables development of software agents, which can assist with negotiation tasks while saving time and human effort. The current paper investigates the prospects of utilizing software agents in negotiations with the human counterparts. It presents the findings from experiment where human subjects acted as buyers negotiating with software agent sellers over a mobile phone plan. An electronic negotiation system incorporating software agents was used in the experiment. The agents employed various concession-making schedules while engaging in negotiation tasks involving one of two complexity levels. Negotiation task complexity was manipulated using different number of issues involved in the negotiations. Subjects were recruited among university students. Negotiations between the subjects and agents took place during a two-day period in an asynchronous mode through the web. The findings suggest that interaction between negotiation task complexity and negotiation tactic has significant effects on negotiation outcomes and subjective assessments by the human participants. In particular, task complexity had a higher impact on the agreement rate when agents employed a competitive tactic vs. when they used a conceding one.

Keywords: Concession-making, electronic negotiations, experimental studies, mechanism design, multi-issue negotiations, negotiations, software agents.

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1. INTRODUCTION

Electronic negotiation systems (ENSs) allow parties to exchange offers over the Internet in an organized manner, thus facilitating online negotiations (Kersten and Noronha, 1999). Compared with generic communication tools, such as e-mail, these systems typically impose a certain structure on the process of interaction between the parties, as well as on the format of the offers. Additionally, they can provide analytical support for negotiators in the negotiation process. Such support can help ENS users formulate their objectives, preferences, reservation levels, and other pertinent aspects which may have impact on the negotiation process and outcomes. Nonetheless, negotiations are cognitively challenging for humans, as they have to deal with the complexity of the task, while assessing offers, constructing counter-offers, and considering acceptance or termination decisions.

Automating, or assisting the process of exchanging offers can be achieved with the use of *software agents* (SAs). Agents have been utilized in various roles to facilitate e-commerce processes (Yu et al., 2015). Automating commerce negotiations have long been targeted by the SA research community (Maes et al., 1998). Recently, the *Automated Negotiating Agents Competition* (ANAC) has been held (Baarslag et al., 2012). The distinguishing feature of employing agents in negotiations is that the outcome cannot be predicted in advance, though it can be restricted to a certain set by imposing constraints. While, for many tasks, objectives can be either achieved or not, in negotiations the final agreement partly depends on the other party's behavior. In view of this inherent uncertainty in agent-run negotiations, assessment of their performance while utilizing various negotiation tactics and strategies is an important research objective.

Despite the above uncertainty, agent-managed negotiations promise a number of important benefits (Lin and Kraus, 2010; Yang and Singhal, 2009). First, agent-led negotiation behavior is, in general, more consistent than that of the human negotiators. Agents can be designed and instructed to act according to specified plans. Provided with the preferences for various negotiation issues, the reservation levels, and the negotiation tactic, an agent will make decisions in accordance with these specifications (although some randomness may be present due to the nature of the decision-making algorithm, or it may be introduced intentionally to hide the agent's inner workings). Second, agents would alleviate human effort related to exchanging offers in the negotiation process. Third, they can help people with limited negotiation skills to negotiate better. Fourth, they can be active at any time, unlike human beings.

In accordance with a model for comparison of various types of ENSs (Kersten et al., 2006), successful use of agents in negotiations can be influenced by a number of factors. These include economic outcomes achieved by the agents, as well as the subjective assessments by human counterparts of the outcome and the process of negotiations. The current work aims at investigating performance of negotiating agents while being paired with human counterparts in experimental settings. SA negotiation style and negotiation task complexity have been used as experimental treatments. Their impacts on objective outcomes, including agreement rate and agreement utility have been measured. Additionally, the effects on subjective variables, including perceived usefulness and perceived ease of use are reported in the paper. An ENS incorporating software agents (Vahidov et al., 2012b) have been used in the experiment. The system enables creation of negotiation cases, pairing agent and human participants in negotiation dyads, setting up multiple negotiation issues and preference structures, defining negotiation tactics for agents, and other functions.

2. BACKGROUND

Concerning agent involvement in negotiations, there are two major aspects: agent's negotiation tactics/strategies and the role agents play in the negotiation process. In defining agent behavior the negotiation tactics and strategies play the key part. While the terms negotiation tactic and negotiation strategy have been used in the past somewhat loosely, in this work we will follow the definitions provided by Faratin et al. (1998). According to them a negotiation tactic is used to decide what kind of offer to make at a given point in the negotiation process. A negotiation strategy, on the other hand dictates the choice of tactics based on negotiation history, context, and other variables. Therefore, a strategy can employ multiple tactics.

Faratin et al. (1998) defined three categories of tactics: behavior-dependent, time-dependent, and resource-dependent. Behavior-dependent tactics base the choice of offer on the moves made by the parties. The most prominent tactic in this category is “tit-for-tat”, which states that the next concession to be made by a party should be proportional, or symmetrical to the one made by the counterpart. The second family of tactics employs models on concession-making as a function of time elapsed between the beginning of negotiation and the estimated or defined ending point. Curves showing small concessions in the beginning correspond to tougher competitive behavior, while those making large concessions early model conceding behavior. Resource-dependent tactics adjust concession levels based on the scarcity of the resources at any point in the negotiation process.

Experiments with Kasbah marketplace involving agent-to-agent single issue negotiations adopted three time-dependent negotiation tactics (Chavez et al., 1997; Chavez and Maes, 1996). They were defined by the shape of the curve dictating how quickly agent would be dropping the price. Tactics can also be adjusted in the negotiation process. For example, Cao et al. (2015) have proposed an approach where negotiation tactics (curves) can be adjusted as new offers arrive based on the opponent’s concession-making rate. Their simulation-based study revealed that adaptive agents outperformed the static-tactic agents.

Regarding agent role in conducting electronic negotiations three categories can be mentioned: (1) human-to-human negotiations with agent support; (2) agent-to-agent negotiations featuring full automation on both sides, and (3) human-to-agent negotiations, where SAs are paired up with human counterparts (Yang and Singhal, 2009). The first category includes use of agents as advisors for assisting human negotiators to cope with the complexity of negotiation tasks. These agents may help humans to stay in line with their defined preference structures and concession-making plans. Examples include Aspire agent (Kersten and Lo, 2003) and eAgora marketplace (Chen et al., 2005). The second category includes completely automated negotiations on both sides. The current work focuses on the third category, agent-to-human negotiations.

Designing agents that can negotiate with human counter-parts is not a trivial task (Lin and Kraus, 2010), with most pertinent challenges including bounded rationality and incomplete information. Yang and Singhal (Yang and Singhal, 2009) made several suggestions concerning agent tactics, including: making a tough initial offer; making simultaneous offers that are of equal value to the agent; making monotonously decreasing concessions – a suggestion initially made by Raiffa (1982) to signal "approaching the limit; making large concession in the final offer; and using strategic delays.

Employing agents in negotiations could serve the purposes of simulation and training of human negotiators, as well as for the automation of negotiations per se. For example, Traum et al. (2003) developed agent-based system, which employed negotiations for simulation-based training with application to peace-keeping situations. Lin et al. (2014) designed two experiments to evaluate the effectiveness of negotiation training by agents. Their study tested three treatments: training of humans by other humans, training by automated agents, and letting humans to configure agents to negotiate on their behalf. The negotiation tasks involved job candidate negotiations and the coordination game. The findings indicate that use of agents leads to better development of negotiations skills as opposed to use of humans as trainers.

There have been past experimental studies involving human and agents in exchange settings focusing on objective as well as subjective aspects of negotiations. An early experimental work matching humans with agent counterparts was reported by Byde et al. (2003). A salesperson agent that employed persuasion and negotiation techniques while negotiating product price with a customer has been described in Huang and Lin (2007). Persuasion took place through customer-agent dialogue with the use of pre-defined arguments organized as a tree. Price was the single negotiated issue. The findings suggested that persuasion increased buyers' product valuation and willingness to pay.

Haim et al. (2012) have found that negotiating agents' performance could be improved when the opponent's cultural background was taken into account in designing agent's tactics. Their study involved subjects from the US and the Middle East. de Melo et al. (2011) examined the effects of agents' expression of emotions on the negotiator's concession behavior. In this study, human subjects were paired up with agents, which expressed anger, neutrality, or happiness during negotiations using both verbal and non-verbal expression mode. They found that "angry" agents were able to gain more concessions from the human opponents, than the "happy" ones.

Bosse and Jonker (2005) conducted an experiment to compare the performance of agents with that of humans in agent-human negotiations. Their findings indicated that humans achieved higher results in regards with the individual outcomes, while in agent-involved negotiations fairness of deals was higher. Vahidov et al. (2014) have investigated effects of using various agent negotiation tactics in experiments with human subjects. In these bilateral negotiation experiments involving sale of computers, five different concession-making styles were used: competing, linear, conceding, competing-then-conceding, and tit-for-tat. Agents acted as sellers while humans were assigned a buyer's role. A control group on the seller side included human subjects. The results revealed that most agent types outperformed human "colleagues" in terms of utility of the achieved agreement, and the agreement rate. Competing agents achieved the highest utility levels, while conceding agents had the highest number of agreements. In Vahidov et al. (2012a), agents were employed in multi-bilateral negotiation settings. Here, the negotiation task featured a procurement scenario with a single buyer and three sellers. Buyer were given a task of awarding a single contract to one of the sellers based on simultaneous negotiations with all three counterparts. While most of the participants were human subjects, agents were present in some of the seller groups. The results showed that conceding agents achieved higher agreement rates than humans, while competing ones failed to win any contract.

In order to get more thorough insights into agent-human negotiations, it is important to investigate possible impacts of negotiation task complexity. In particular, task complexity may influence negotiation outcomes, and user assessments of the system. From the general perspective of information systems, the *task-technology fit* (TTF) model posits that higher task complexity negatively affects the fit between the task at hand and the technology used to perform the task (Goodhue, 1995; Goodhue and Thompson, 1995). Furthermore, lower fit leads to lower individual performance. As applied to negotiations, this means that higher task complexity would hinder positive outcomes, such as agreement rates.

User assessments of the systems are critical for the intended usage of the system as posited by *technology acceptance model* (TAM). Perceived usefulness and perceived ease of use are the key variables influencing intention to use (Davis, 1989; Davis et al., 1989). In Dishaw and Strong (1999) a model unifying both TAM and TTF has been proposed. Therefore, the aforementioned assessment variables, together with task complexity are important factors that could influence the actual acceptance of the online negotiation systems. Hence, they have been included in the current study.

Past research on the effects of negotiation task complexity in agent-human negotiations is scarce. A study investigating the impacts of conflict-handling style and task complexity while using negotiation support systems had been reported in (Jain and Solomon, 2000). The authors hypothesized that face-to-face groups would experience greater satisfaction with the outcome and more favorable perceptions of the group process than NSS-supported groups in complex negotiation tasks. In another study, experiments with agent-supported negotiations revealed that human negotiators using agents as advisors performed better in complex (involving a higher number of issues) tasks than unassisted human negotiators (Vahidov et al., 2013).

The current study looks to evaluate the impacts of agent negotiation tactics and task complexity on the negotiation outcomes and assessments. The complexity of negotiation task is reflected in the effort and time spent by negotiators. These can be influenced by such factors as number and positions of the parties involved, and the number of issues included in the negotiation process. In this work the complexity is operationalized by manipulating number of issues, as it was done in Vahidov et al. (2013). Higher number of issues significantly increase the number of possible offers, leading to increased time and effort. Thus, on one hand, increasing number of issues leads to more room for maneuver, and potentially for higher propensity towards making an agreement. On the other hand, higher task complexity results in a higher cognitive effort, which might discourage human negotiators and push them towards terminating negotiations before the agreement could be reached.

In this work, we investigate the performance of agent and user negotiators, as well as users' perceptions of the system influenced by the agents' tactics and the complexity of the negotiation task. The key outcome variables include the agreement rate, and the utility of the agreements. The assessment variables include perceived usefulness and perceived ease of use of the system. Negotiation task complexity is manipulated by varying the number of issues involved in the negotiation process. We anticipate that there will be an interaction effect between task complexity and tactics, since in conceding tactics complexity may have a smaller impact on the outcomes than in competing tactics.

3. NEGOTIATION SYSTEM

In order to conduct the experiments, an ENS that facilitates the creation and deployment of negotiating agents was used. The system architecture is shown in Figure 1. Human negotiators can interact with the system and view and make offers. The offer exchange is managed by the negotiation engine, which can work in both synchronous and asynchronous mode. The engine runs one of the negotiation cases retrieved from the case library. These cases are prepared by the administrator and they feature negotiation tasks, including description of the issues involved. While making decisions human negotiators may be supported by the preference modeling module. The model calculates the utility of a given offer based on the specified preferences. In our case the preference structure for the human participants was pre-set by the experimenters in order to minimize the extraneous variation.

Agents can be created and equipped with a negotiation tactic (henceforth the terms "agent tactic" and "agent type" will be used interchangeably). The tactics toolbox contains both time- and behavior-dependent tactics, and it can be expanded to include new types of tactics. Time-dependent tactics used in the experiments allow the human principal to specify the shape of the curve defining the manner in which target utility changes with time. The curves used in the experiments will be described in the subsequent section. An agent uses given tactic in order to generate offers at any given time. It uses preference modeling module to calculate utility of the offers.

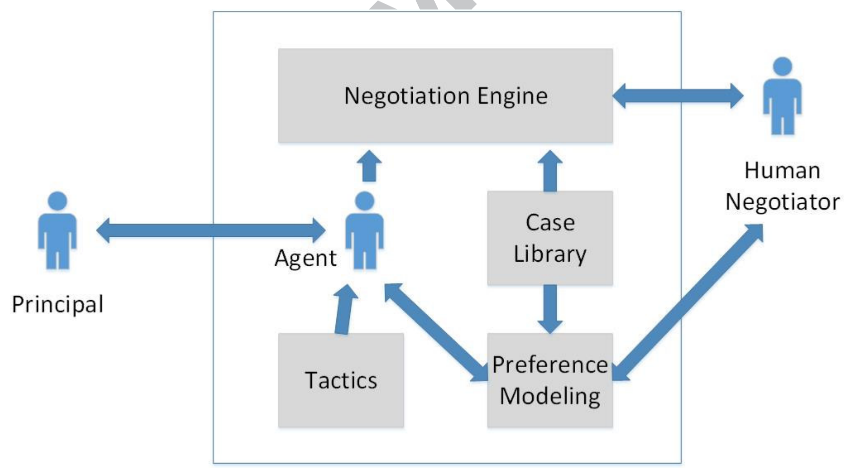

Figure 1. System architecture

The operation of the negotiation agent is shown in Figure 2. The agent becomes active at the specified day and time and sends out an initial offer that best suits its specified preferences. The issues in the offer may include both continuous (e.g., price), as well as categorical values (e.g., "call forwarding" option). Subsequently, the agent stays dormant for a time that has a specified period plus, optionally, a random component (the random part can be added to avoid being detected as a "machine" by the opponents), and then checks negotiation status. If the opponent has accepted the previously submitted offer, the negotiation terminates.

If the negotiation is in progress, the agent checks if there have been any new offers by the counterpart. In the absence of new offers, the agent becomes dormant again until the next check point in time. If an offer from the opponent has been submitted, the agent examines it and calculates its utility level. The utility is calculated using weighted sum of individual issue values and it varies from 0 (worst) to 100 (best):

$$U^o = \sum_{i=1}^{n} w_i u(v_i^o)$$

$$\sum_{i=1}^{n} w_i = 1$$

Here, U^o is the overall utility of a given offer o, $u(v_i^o)$ is the utility of the value v of issue i in offer o, and w_i is a weight for issue i in calculating the total utility of an offer. For each value of each negotiation issue, its utility level is specified. This could be done by using mapping for discrete (e.g., "data plan"), as well as continuous (e.g., "price") issues. The issue value utilities and weights are different for the buyers and the sellers. For instance, for sellers (agents in our study) higher price translates into higher utility, while for the buyers (humans) the opposite is true.

Agent uses tactics in order to set the target utility level. If the utility of the received offer exceeds the target value at a given time, the agent accepts the offer and the negotiation session terminates. Otherwise, the agent generates a new offer. In doing so the agent takes the opponent's latest offer and tries to modify it, so that the utility is brought to the desired level. Since the agent starts with the opponent's offer, there is a good chance that the new offer will be similar to that of the opponent. This is in line with the "smart" strategy proposed by Faratin et al. (2002) looking to minimize the distance between the newly generated offer and the opponent's last offer. The agent randomly picks issues and makes random changes to their values (in an iterative improvement, or "hill climbing" fashion) until the utility of the trial offer is within the allowed distance from the target utility level. When such an offer is found, the agent sends it to the negotiation engine for the opponent to view, and then becomes inactive.

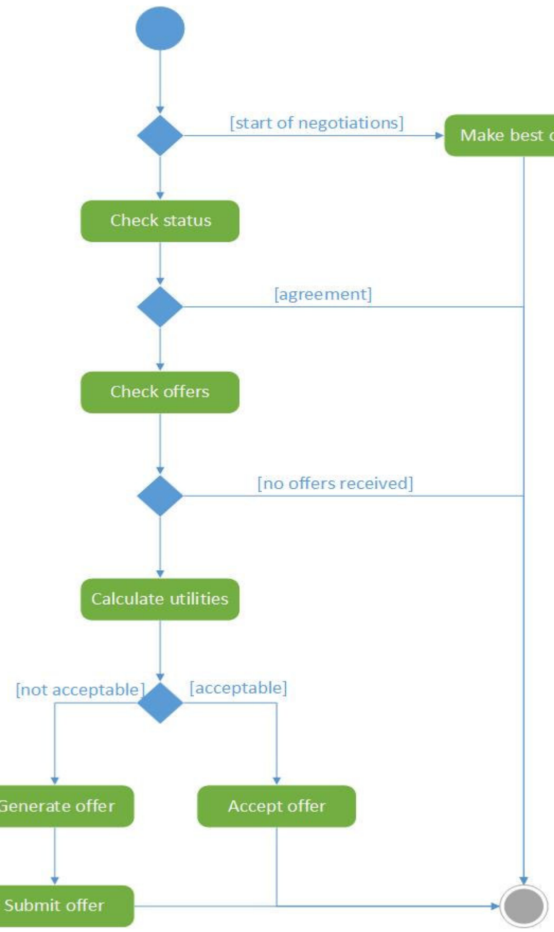

Figure 2. Agent's algorithm

4. NEGOTIATION SETUP

The subjects were recruited from university students enrolled in an online course. A negotiation case was developed with the consideration of the subject's familiarity level. The case featured a sale of a mobile phone plan. Most students are well aware of the issues involved in such plans. Two types of cases were included: a simple one and a complex one. The simple case involved the following issues: price, regular air time, extra air time, text messaging, and data. The buyers and sellers were given different weights for these issues according to their importance levels. Figure 3 shows the screenshot for the setup of the simple case.

In order to calculate the total utility of the offer, the issues were assigned different weights. These weights would be used in an additive utility function for calculating the degree of attractiveness of a given offer. Agents would use this information in order to generate offers and to decide on the acceptability of the received counter-offers. The complex case additionally included call display, voicemail, call waiting, conference call, and call forwarding. (See Figure 4.)

Issue	Type	Weight S↓ B↓	Initially Activated
Price	Numeric	40 % 60 %	Yes
Regular air time (7am to 7pm)	Categorical (single choice)	5 % 10 %	Yes
Extra air time (outside 7am to 7pm)	Categorical (single choice)	5 % 10 %	Yes
Text messaging	Categorical (single choice)	25 % 10 %	Yes
Data	Categorical (single choice)	25 % 10 %	Yes

Figure 3. Set-up of the simple case

Issue	Type	Weight S↓ B↓	Initially Activated
Price	Numeric	35 % 0 %	Yes
Regular air time (7am to 7pm)	Categorical (single choice)	20 % 0 %	Yes
Extra air time (outside 7am to 7pm)	Categorical (single choice)	10 % 0 %	Yes
Text messaging	Categorical (single choice)	7 % 0 %	Yes
Data	Categorical (single choice)	12 % 0 %	Yes
Call display	Boolean	4 % 0 %	Yes
Voicemail	Boolean	4 % 0 %	Yes
Call waiting	Boolean	3 % 0 %	Yes
Conference call	Boolean	2 % 0 %	Yes
Call forwarding	Boolean	3 % 0 %	Yes

Figure 4. Setup of the complex case

Four different time-depending tactics were used in the experiments. These included: competing, conceding, competing-then-conceding, and conceding-then-competing tactics. Figures 5 to 8 show the concession schedules for these tactics (the off-curve dots allow the user to set the shapes of the curves by dragging).

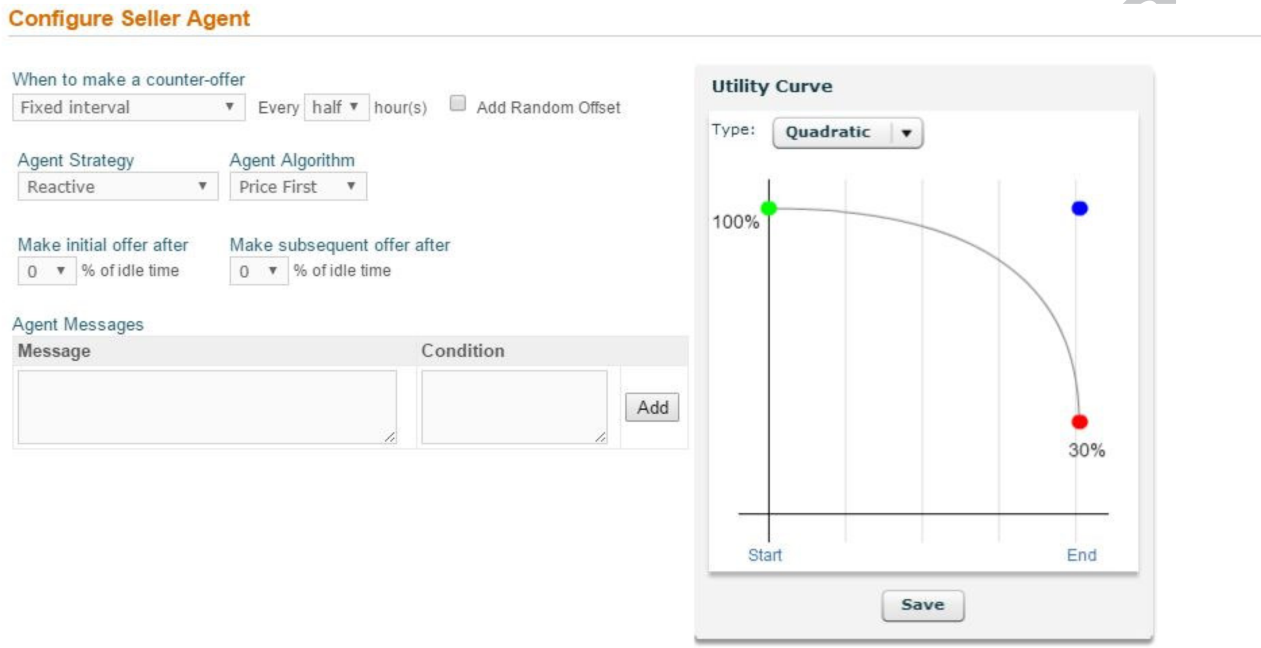

Figure 5. Competing schedule

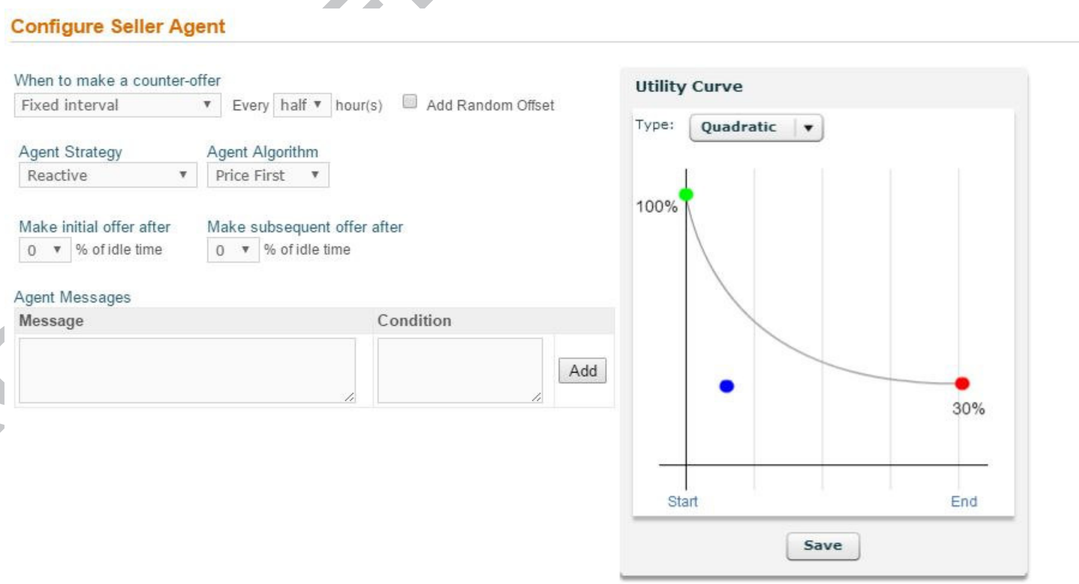

Figure 6. Conceding schedule

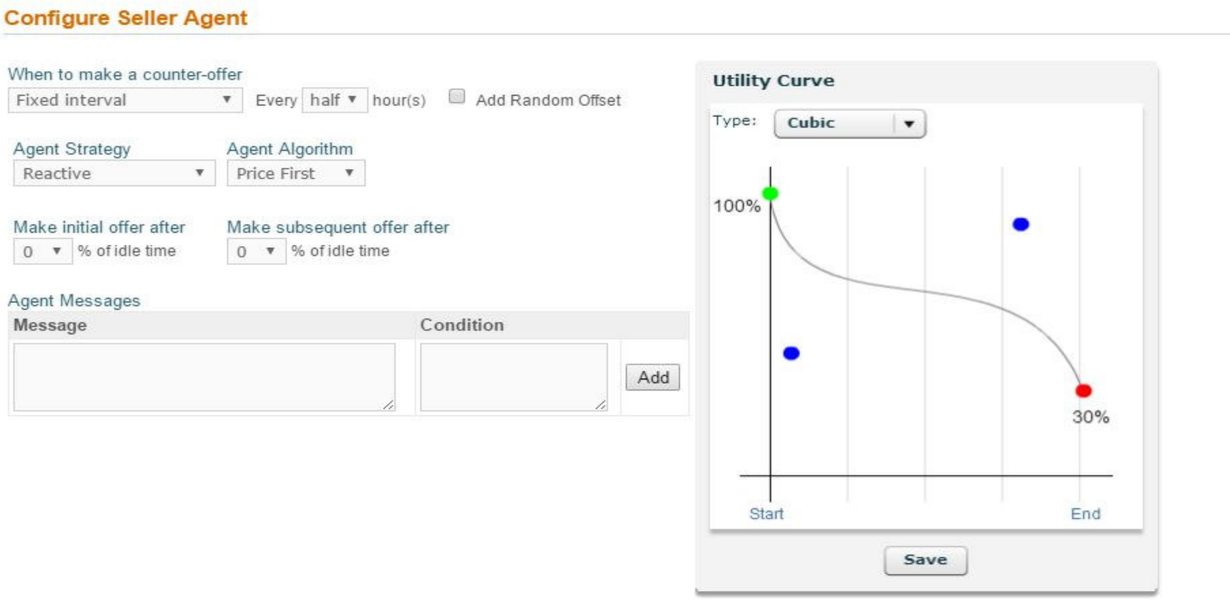

Figure 7. Conceding-then-competing schedule

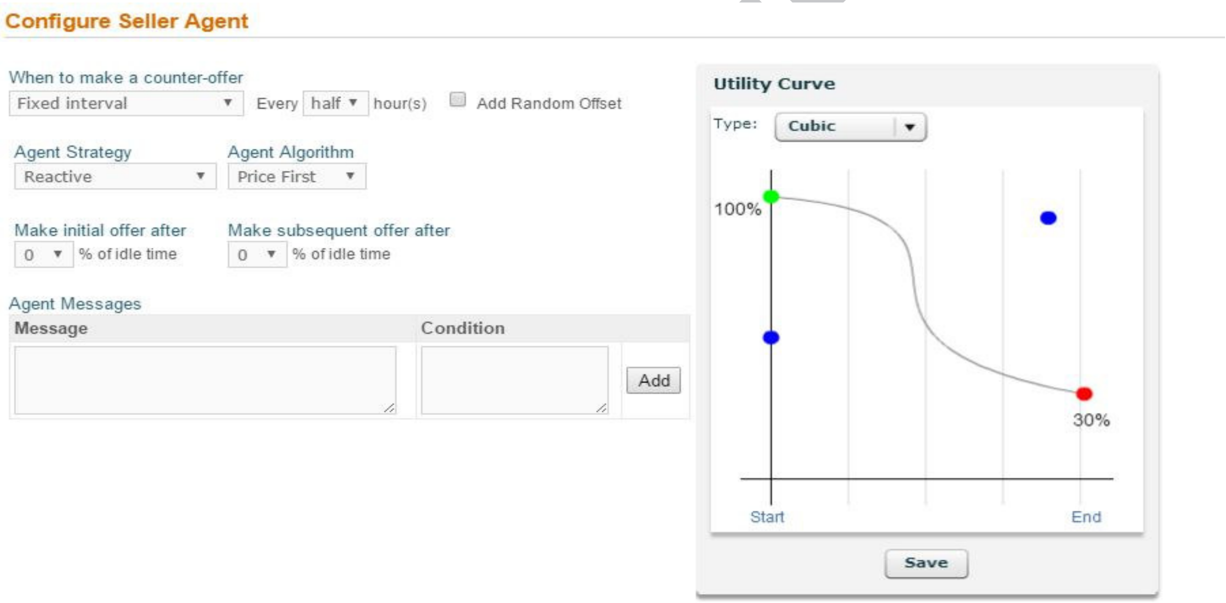

Figure 8. Competing-then-conceding schedule

Competing agents tend to make smaller concessions in terms of utility of generated offers in the beginning of the negotiation period. However, as they approach the end of the period, they start making larger concessions in search of an agreement. Conceding agents tend to make large concessions in the very beginning of the negotiation period in search of a quick agreement. This represents the case where a seller is anxious to sell the plan. Conceding agents are not expected to have high utility deals, although they are expected to make more agreements than competing agents.

Two remaining tactics represent the mix of the above two schedules. The guidelines for agent tactic design mentioned earlier (Yang and Singhal, 2009) suggested making a tough initial offer, followed by making monotonously decreasing concessions, and making a large concession in the final offer. The conceding-competing schedule mimics this sort of behavior. It starts with the tough offer, then makes monotonously decreasing concessions to signal to the opponent the vicinity of its reservation level. If the deal is still not made midway through the negotiation period, the agent starts making large concessions in order to grab the deal.

The competing-conceding tactic starts out tough in the hopes of grabbing high-value deals. However, if agreement is not made in the initial phases, the agent switches to the conceding mode. In this way, the agent could combine the benefits of both competing and competing tactics. The tactics for the agents are modeled using Bezier curves.

Treatments involved randomly pairing up the subjects with various types of agents in a simple or complex task as described above. The experiment was conducted on the web, whereby subjects could perform their tasks from any location in an asynchronous mode during a two-day period. The subjects were invited to join the negotiations via email containing the link to the system. They could choose to terminate the negotiation at any time without reaching an agreement.

5. RESULTS

A total of 754 subjects registered for the experiment and completed the experimental task. A data cleaning procedure was conducted to select only those subjects who made more than one offer in order to filter out the cases where subjects did not take the experimental task seriously. After filtering the number of subjects dropped to 368. Based on these retained observations, 262 negotiations (71%) ended up in an agreement, while 106 (29%) dyads did not make an agreement.

The agreement rate for the simple negotiation task setting was 75.5%, while for the complex task it was 65.4%. Thus, in the simple task, the agreements were more frequent. On one hand, a larger number of issues should have given negotiators more space for "maneuvering" in negotiations, therefore leading to a higher likelihood of making an agreement. On the other hand, the complexity of the task has taxed the cognitive capabilities of the human participants and required higher cognitive effort. In our setup, the simple task included five issues, while the complex one featured ten. The fairly large number of issues probably resulted in the burden of cognitive effort outweighing the benefits of a larger search space for the potential agreements. This seems to have been the reason why fewer agreements were made in the complex task. Table 1 displays the agreement rates for the four tactics overall, and for simple vs. complex tasks separately.

Task		**Simple**			**Complex**		
Agreement		*No*	*Yes*	*Rate*	*No*	*Yes*	*Rate*
Tactic	*Competing*	27	36	57.1%	24	23	48.9%
	Competing-Conceding	9	22	71.0%	10	15	60.0%
	Conceding-Competing	6	31	83.8%	15	35	70.0%
	Conceding	10	71	87.7%	5	29	85.3%
Total		52	160	75.5%	54	102	65.4%

Table 1. Agreement rates for different agent tactics

The chi-square test for independence based on the number of agreements has yielded the value of 9.707 (p-value = 0.021). Therefore, there is a significant difference between various complexity-tactic combinations in terms of agreement rates. As one can see from the table, the highest agreement rate was achieved by the conceding agents, and the lowest one by the competing agents. This is not surprising given the concession schedules of these agents. The other two agent tactics fell in between the extremes in terms of agreement rate. Conceding-competing agents have made more agreements than the competing-conceding ones. Thus, apparently the guideline mentioned earlier, that is "signaling approaching the limit" seems to have had a positive impact in terms of the likelihood of an agreement.

Task complexity does not seem to have a large effect on the agreement rate for the conceding agents. This makes sense, as the agents using this tactic would concede so quickly that agreements were reached early regardless of the complexity of the task. It does seem to have had a larger impact when an agent was of the competing type. The implication here is that competing agents are more likely to make an agreement in simpler tasks.

Table 2 shows the average utilities achieved by sellers (agents) and buyers (humans). For the simple task, the average utility per one seller is the highest for the competing tactic followed by the conceding-competing tactic. For the complex task, interestingly, agents employing the conceding tactic have achieved highest utility values. Overall, these three strategies yielded much higher utility, compared to the competing-conceding tactic. Therefore, in terms of expected utility of agreements our findings suggest that competing agents should be employed in simple negotiation tasks, while conceding agents better suit complex tasks. Nonetheless, conceding-competing agents perform fairly well regardless of the task complexity. On the buyer side, agent's conceding tactic generated highest average utilities in both simple and complex tasks. Competing tactic resulted in the lowest average utilities in both tasks.

Average Utility		**Seller**			**Buyer**		
Task		*Simple*	*Complex*	*Total*	*Simple*	*Complex*	Total
Tactic	*Competing*	46.52	30.12	38.32	4.90	9.15	7.03
	Competing-Conceding	37.80	27.80	32.80	13.42	18.48	15.95
	Conceding-Competing	45.38	34.90	40.14	25.46	13.31	19.38
	Conceding	41.24	39.20	40.22	32.69	34.09	33.39
Overall		42.74	33.01	37.87	19.12	18.76	18.94

Table 2. Average utility per seller and buyer

Next, we analyze the agent performance in terms of the agent sellers' and human buyers' utilities of the achieved agreements. For this analysis only the instances where the agreement was achieved were included in the calculation of the utilities. First, we examined the agreement utilities on both the seller and the buyer sides. The results, reported in Table 3 show that, overall, agent sellers achieved higher final utility (58.97) in simple task settings than in complex settings (50.93). Conversely, human buyers achieved higher utility in more complex tasks. Also, all types of agent sellers received higher utilities than human buyers. Overall, competing agents achieved highest utility agreements, followed by the conceding-competing, competing-conceding, and lastly, conceding agents. Task complexity has the largest impact for competing agents, medium impact for the conceding-competing and competing-conceding agents, and virtually no impact for the conceding agents.

We have developed a general linear model incorporating agent tactic and task complexity level for predicting the obtained utilities of agent sellers and human buyers. Number of offers was included as a co-variate as it reflected negotiators' effort. The results of the multivariate tests of the general linear model are shown in Table 4, and the between-subject effects are provided in Table 5. The findings suggest that task complexity (Wilks' Lambda = 0.011), agent tactic (Wilks' Lambda = 0.000), and number of offers (Wilks' Lambda = 0.000), were all significant. Furthermore, the interaction of task complexity and agent tactic, as expected, was also significant (Wilks' Lambda = 0.004). The decomposed effect of the independent variables was further checked. Number of offers had a significant effect only on human buyers' utilities (p = 0.000). Agent tactic had significant effects on both human buyers' and agent sellers' utilities (p = 0.000). Similarly, task complexity had significant effects on both human buyers' (p = 0.011) and agent sellers' utilities (p = 0.013). The interaction of task complexity and agent type had a significant effect only on human buyers' utilities (p = 0.002).

Table 3. Average utilities when agreements were reached

Average Agreement Utility		**Seller**			**Buyer**		
Task		*Simple*	*Complex*	*Total*	*Simple*	*Complex*	Total
Tactic	*Competing*	81.42	61.55	71.49	8.57	18.70	13.64
	Competing-Conceding	53.26	46.33	49.80	18.91	30.81	24.86
	Conceding-Competing	54.16	49.86	52.01	30.39	19.01	24.70
	Conceding	47.05	45.96	46.51	37.29	39.96	38.63
Overall		58.97	50.93	54.95	23.79	27.12	24.46

Table 4. The results of multivariate tests of the general linear model

Effect	**Wilks' Lambda**	**F**	**Hypothesis df**	**Error df**	**Sig.**
Intercept	0.199	508.46	2	252	0.000
Number of offers	0.914	11.85	2	252	0.000
Agent tactic	0.714	15.44	6	504	0.000
Case complexity	0.965	4.56	2	252	0.011
Agent tactic * Case complexity	0.078	3.27	6	502	0.004

In order to develop a deeper understanding of the effects of agent tactic and task complexity a set of pair-wise comparisons have been conducted. The groups included in the comparisons and the testing results are reported in Table 6. This analysis includes those negotiation instances where agreements were reached. The instances are divided into 8 groups formed by four agent tactics and two levels of task complexity. Each group is assigned a number. The comparisons of paired groups focused on either sellers' or buyers' utilities using Mann-Whitney U tests. Pairs of mean ranks for each comparison along with the corresponding p-values are shown in the table cells. The significant results are highlighted in bold.

Table 5. The results of between-subject effects of the general linear model

Source	Dependent Variable	Type III Sum of Squares	df	F	Sig.
Corrected model	*Seller Final Utility*	36,017.3	8	7.04	0.000
	Buyer Final Utility	37,130.5	8	16.06	0.000
Intercept	*Seller Final Utility*	32,775.1	1	512.28	0.000
	Buyer Final Utility	37,809.1	1	130.81	0.000
Number of offers	*Seller Final Utility*	952.7	1	1.49	0.224
	Buyer Final Utility	6,691.1	1	23.2	0.000
Agent tactic	*Seller Final Utility*	23,598.9	3	12.3	0.000
	Buyer Final Utility	25,321.7	3	29.2	0.000
Case complexity	*Seller Final Utility*	4,216.2	1	6.6	0.011
	Buyer Final Utility	1,812.7	1	6.3	0.013
Agent tactic * Case complexity	*Seller Final Utility*	3,187.4	3	1.7	0.176
	Buyer Final Utility	4,395.5	3	5.1	0.002
Error	*Seller Final Utility*	161,868.2	253	-	-
	Buyer Final Utility	73,124.8	253	-	-
Total	*Seller Final Utility*	979,616.8	262	-	-
	Buyer Final Utility	298,917.0	262	-	-
Corrected total	*Seller Final Utility*	197,885.5	261	-	-
	Buyer Final Utility	110,255.4	261	-	-

The results suggest that agent tactic plays a more significant role in influencing sellers' utilities in simple, rather than in complex settings. There are four pair comparisons of sellers' average utilities (1 vs. 2, 1 vs. 3, 1 vs. 4, and 3 vs. 4) that are significant in simple settings. In contrast, there is only one pair (5 vs. 6), which is significant in complex settings. Particularly, seller agents with the competing tactic were likely to achieve significantly higher utilities. The competing tactic featuring in four pair comparisons (1 vs. 2, 1 vs. 3, 1 vs. 4, and 5 vs. 6) in both simple and complex settings led to significantly higher utilities than other tactics did.

The findings also suggest that competing and competing-conceding tactics resulted in lower buyers' utilities in simple settings as opposed to the complex ones. The results of five pair comparisons of buyers' utilities (1 vs. 2, 1 vs. 3, 1 vs. 4, 2 vs. 3, and 2 vs. 4) turned out to be significant. At the same time, the effects of competing and conceding-competing tactics on buyers' utility are less significant under the complex settings.

Task complexity had a stronger influence on both buyers' and sellers' utilities when agent sellers used the competing tactic. The comparisons of the pair 1 vs. 5 on both sellers' and buyers' utilities shows a significant result. Additionally, task complexity had a significant influence on buyers' utilities when agent sellers adopted competing-conceding and conceding-competing tactics. The comparisons 2 vs. 6 and 3 vs. 7 on buyers' utilities also show significant effects.

Table 6. Pair-wise comparisons of buyers' and seller's utilities

Groups for comparisons		***Task Complexity***	
		Simple	*Complex*
Agent Tactic	*Competing*	1	5
	Competing-Conceding	2	6
	Conceding-Competing	3	7
	Conceding	4	8

In Simple Task		**Seller Utility**				**Buyer Utility**		
		2	3	4		2	3	4
	1	**35.53/19.64 (.000)**	**41.99/27.73 (.000)**	**76.43/42.63 (.000)**	1	**24.10/38.34 (.001)**	**22.5/47.35 (.000)**	**27.58/67.39 (.000)**
	2		25.89/27.27 (.658)	50.45/45.93 (.491)	2		**21.09/31.19 (.019)**	**29.57/52.40 (.001)**
	3			**60.81/47.44 (0.036)**	3			45.65/54.06 (.186)
In Complex Task		6	7	8		6	7	8
	5	**22.54/14.83 (.035)**	34.61/26.14 (.061)	30.15/23.60 (.121)	5	**16.39/24.27 (.028)**	31.48/28.20 (.467)	**16.52/34.41 (.000)**
	6		23.57/26.33 (.539)	21.90/22.81 (.824)	6		**33.93/21.89 (.007)**	19.33.24.14 (.239)
	7			34.33/30.29 (.388)	7			**23.77/43.03 (.000)**
Between Task	1 vs. 5	**36.32/20.11 (.000)**			1 vs. 5	**21.00/44.09 (.000)**		
	2 vs. 6	19.89/17.70 (.551)			2 vs. 6	**15.34/24.37 (.011)**		
	3 vs. 7	34.98/32.19 (.554)			3 vs. 7	**39.73/27.99 (.013)**		
	4 vs. 8	51.05/49.16 (.767)			4 vs. 8	49.98/51.78 (.779)		

As mentioned earlier, the current study is largely exploratory as little prior work has been done on the assessment of agent-human negotiations with different levels of task complexity. The interactions between agent tactics, task complexity, and system features make it difficult to develop strong hypotheses. For example, larger number of issues, while allowing more space for potential agreements can be counterweighed by the effort involved. We have conducted a survey among the participants to obtain insights into the user assessments that could serve as a basis for future research. Survey questions were asked about two aspects of user experience including *perceived ease of use* (PEU) and *perceived usefulness* (PU), using a seven-point Likert scale. (See Table 7.) In total, we have obtained 229 complete responses from the participants. Most of the participants were between 19 and 21 old. Other demographic statistics of the participants are shown in Tables 8 and 9. The total number of respondents is smaller than the number of the participants, because some subjects completed the experimental task, but chose not to fill out the survey questionnaire.

Table 7. Questionnaire items

Aspect	Survey questions
PEU	I think that I was skillful at using THE SYSTEM.
	Learning to use THE SYSTEM was easy for me.
	I found it easy to get THE SYSTEM to do what I want it to do.
PU	I found THE SYSTEM useful to configure my mobile plan.
	Using THE SYSTEM would enable me to accomplish purchasing a mobile plan more quickly.
	Using THE SYSTEM would increase the effective use of my time in purchasing a mobile plan.

("THE SYSTEM" is used to replace the actual system name.)

Table 8. Demographic allocation given task complexity levels

		Task		**Sum**
		Simple	Complex	
Gender	Female	86	34	120
	Male	73	36	109
Ethnic Background	African	6	5	11
	Asian	31	10	41
	European (East/Russian)	10	8	18
	European (West)	19	11	30
	Latin American	10	3	13
	Middle Eastern	16	6	22
	North American	54	25	79
	Oceanian	1	0	1
	Other	12	2	14

Table 9. Demographic allocation given agent tactics

		Agent Tactics				Sum
		Competing	Competing-Conceding	Conceding-Competing	Conceding	
Gender	Female	42	14	24	40	120
	Male	35	20	18	36	109
Ethnic Background	African	4	2	3	2	11
	Asian	11	5	9	16	41
	European (East/Russian)	9	0	3	6	18
	European (West)	9	4	6	11	30
	Latin American	2	2	2	7	13
	Middle Eastern	8	5	4	5	22
	North American	29	12	13	25	79
	Oceanian	0	0	0	1	1
	Other	5	4	2	3	14

The results of the exploratory factor analysis using PEU and PU items showed that the items loaded on two factors. The reliability of these two factors have been checked using Cronbach's alpha, which had values of 0.91 for PU and 0.806 for PEU. The sum scores of the items measuring PU and PEU were used in further analysis.

Three tests using general linear model have been conducted. The overall effects of the test results (Wilks' Lambda) are reported in Table 10. Test 1 was conducted on the dataset including all instances. The scores of the two constructs were used as dependent variables. Task complexity and agent tactic were the independent variables, while number of offers was used as a covariate. Overall, the effects of number of offers (Wilks' Lambda = 0.004) was significant (at 0.05 significance level). Agent tactic and task complexity by themselves did not exhibit significant effects on the constructs. However, they had a significant interaction effect (Wilks' Lambda = 0.033). Test 2 was conducted using only the instances that featured an agreement. As one can see, here only the interaction of agent type and task complexity was significant (Wilks' Lambda = 0.009). Test 3 was conducted using the instances that had an agreement, however, it used utility achieved by the buyers as a covariate instead of the number of offers. The results of the three tests show that task complexity and agent tactic had a significant interaction effect (Wilk's Lambda = 0.033, 0.009, and 0.018).

Table 10. Overall effects on subjective assessments

	Agent Tactic	*Task Complexity*	*Achieved Utility*	*# Offers*	*Task Complexity * Agent Tactic*
Test 1 (all instances)	0.393	0.145		**0.004**	**0.033**
Test 2 (with agreement)	0.316	0.415		0.080	**0.009**
Test 3 (with agreement)	0.230	0.252	0.062		**0.018**

The decomposed effects of the independent variables on each of the subjective assessment variables are reported in Table 11. Task complexity and agent tactics had a significant interaction effect on PEU in the three tests (p = 0.003, 0.001, 0.002). The number of offers had significant direct effect on PU (p = 0.002 and 0.027) in its relevant tests (Test 1 and 2). Achieved utility had a significant direct effect on PEU in Test 3.

Table 11. Decomposed effects on subjective assessment

Decomposed effect		*Agent Tactic*	*Task Complexity*	*Number of Offers*	*Achieved Utility*	*Task Complexity * Agent Tactic*
PEU	Test 1	0.840	0.182	0.918		**0.003**
	Test 2	0.775	0.484	0.525		**0.001**
	Test 3	0.315	0.552		**0.019**	**0.002**
PU	Test 1	0.188	0.441	**0.002**		0.453
	Test 2	0.298	0.186	**0.027**		0.415
	Test 3	0.609	0.097		0.220	0.412

The above results suggest that agent tactic by itself does not have a significant effect on any of the dependent variables. This finding is compatible with a previous study (Vahidov et al., 2014) that included the subjective variables used in the current work as a subset.

As our primary interest is on the interaction between task complexity and agent tactic, this effect is further examined. The interaction effect on PEU is significant in all three tests. The means of the score of PEU are reported in Table 12. These results look surprising at the first glance. When negotiating with a conceding agent, users perceived system easier to use in simple settings as compared with the complex ones. However, paired with competing agents, subjects felt the system was *easier to use* in the *complex* negotiation setting. This finding sounds counter-intuitive and requires explanation. We believe, that this is due to the fact that concessions made by a competing agents on ten issues are less visible than those made by the same type of agent in simpler tasks. Therefore, subjects may be perceiving competing/complex setting more as a fixed-offer (take it or leave it) mechanism, rather than negotiation. The former is perceived as easier to use rather than latter, since negotiations involve more cognitive effort.

Table 12. Effects on perceived ease of use

Agent tactic	Test 1		Test 2		Test 3	
	Simple	*Complex*	*Simple*	*Complex*	*Simple*	*Complex*
Competing	9.57	10.87	9.07	11.85	8.92	11.36
Competing-Conceding	10.22	10.36	10.06	11.80	9.65	11.06
Conceding-Competing	11.42	9.88	11.41	10.36	10.69	9.93
Conceding	11.22	9.15	11.16	9.42	10.18	8.27

6. CONCLUSIONS

The purpose of the current work was to explore the effects of agent negotiation tactics and negotiation task complexity on agent performance and human assessments in electronic negotiations. As suspected, the agent negotiation tactic's interaction with negotiation task complexity has significant effects on both objective, as well as some subjective variables, although the actual direction of these effects were not trivial. The results suggest that competing agents made fewer agreements and had considerably lower agreement utilities in complex tasks compared to their performance in simple tasks. For the conceding agents there was not much difference between the complex and simple tasks. This is because these agents conceded fairly fast and many agreements were made at lower utility levels regardless of the task complexity.

Interesting insights were obtained while analyzing subjective assessments of the human participants. While agent tactic by itself did not have much impact on the subjective variables, its interaction with task complexity did prove to be significant for perceived ease of use. Interestingly, subjects negotiating with competing agents in complex settings found the system easier to use, than those paired up with the same kind of agents in simple settings. In other words, subjects facing "tougher" agents in more "difficult" circumstances reported higher ease of use. In our view, this is due to the fact that concessions made by competing agents on a multitude of issues are less noticeable by the subjects, and they perceive the interaction more as a fixed-offer mechanism. The fixed offer mechanism is perceived as easier to use than true negotiation exchange as more cognitive effort is required in the latter case.

The primary contribution of this paper is in the finding that the negotiation task complexity (represented by the number of issues) does impact the outcomes. Furthermore, the choice of the agent tactic has an impact on the extent of the influence of complexity on the agreement rates, as well as on the agreement utilities. To our knowledge, this is the first study of software agent – human negotiations investigating the interaction between agent tactics and task complexity.

The paper has important practical implications for websites that allow customers to make their own offers. While we have used the case involving smartphone plans, other example possible applications are selling vacation packages, or used cars featuring on dealership sites. Our findings indicate that overall, making offers overly complex (i.e., including the multitude of issues) does not lead to improved agreement rate. In tougher economic conditions and under increased competition more conceding tactics should be followed as they lead to a larger number of agreements. When competitive pressures are lower and the conditions are milder, competing tactics can be employed as they lead to higher agreement utilities. In this case, however, simpler offers (including fewer issues) are more likely to lead to more agreements. Also, conceding-then-competing strategy showed a good overall performance as it can be utilized when conditions are not overly favorable or unfavorable.

One limitation of the current research is that experiment was performed online. This reduced the potential control over the subject behavior in the experiments. Furthermore, the time span allocated for the experiment (two days) might have affected the results. Future in-lab studies can be performed to re-asses the key findings of the study. Furthermore, future research could be directed to study effects with varying levels of complexity. For example, treatments could include single issue, three issues, five issues, and ten issues. Additionally, consideration of human subject characteristics, such as conflict management style, may shed more light on the negotiation outcomes and the subjective assessments.

REFERENCES

Baarslag, T., Hindriks, K., Jonker, C., Kraus, S., Lin, R., 2012. The First Automated Negotiating Agents Competition (ANAC 2010), in: Ito, T., Zhang, M., Robu, V., Fatima, S., Matsuo, T. (eds.), New Trends in Agent-Based Complex Automated Negotiations. Springer, Berlin/ Heidelberg, pp. 113-135.

Bosse, T., Jonker, C.M., 2005. Human vs. computer behavior in multi-issue negotiation. In Proceedings of the 2005 Conference on Rational, Robust, and Secure Negotiation Mechanisms in Multi-Agent Systems, pp. 11-24.

Byde, A., Yearworth, M., Chen, K.-Y., Bartolini, C., 2003. Autona: A system for automated multiple 1-1 negotiation. In Proceedings of the IEEE International Conference on E-Commerce, IEEE Comp. Soc. Press, pp. 59-67.

Cao, M., Luo, X., Luo, X., Dai, X., 2015. Automated negotiation for e-commerce decision making: A goal deliberated agent architecture for multi-strategy selection. Decision Support Systems 73, 1-14.

Chavez, A., Dreilinger, D., Guttman, R., Maes, P., 1997. A real-life experiment in creating an agent marketplace. In: Nwana, H., Azarmi, N. (eds.), Software Agents and Soft Computing Towards Enhancing Machine Intelligence. Springer, Berlin / Heidelberg, pp. 160-179.

Chavez, A., Maes, P., 1996. Kasbah: An agent marketplace for buying and selling goods. First International Conference on the Practical Application of Intelligent Agents and Multi-Agent Technology. Practical Application Company, London, pp. 75-90.

Chen, E., Vahidov, R., Kersten, G.E., 2005. Agent-supported negotiations in the e-marketplace. International Journal of Electronic Business 3, 28-49.

Davis, F.D., 1989. Perceived usefulness, perceived ease of use and user acceptance of information technology. MIS Quarterly 13, 3, 319-340.

Davis, F.D., Bagozzi, R.P., Warshaw, P.R., 1989. User acceptance of information technology: A comparison of two theoretical models. Management Science 35, 982-1003.

de Melo, C.M., Carnevale, P., Gratch, J., 2011. The effect of expression of anger and happiness in computer agents on negotiations with humans. Autonomous Agents and Multi-Agent Systems, Taipei, Taiwan, pp. 937-944.

Dishaw, M.T., Strong, D.M., 1999. Extending the technology acceptance model with task–technology fit constructs. Information & Management 36, 9-21.

Faratin, P., Sierra, C., Jennings, N.R., 1998. Negotiation decision functions for autonomous agents. Robotics and Autonomous Systems 24, 159-182.

Faratin, P., Sierra, C., Jennings, N.R., 2002. Using similarity criteria to make issue trade-offs in automated negotiations. Artificial Intelligence 142, 205-237.

Goodhue, D.L., 1995. Understanding user evaluation of information systems. Management Science 41, 12, 1827-1844.

Goodhue, D.L., Thompson, R.L., 1995. Task-technology fit and individual performance. MIS Quarterly 19, 2, 213-236.

Haim, G., Gal, Y.a., Gelfand, M., Kraus, S., 2012. A cultural sensitive agent for human-computer negotiation. In Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems, 1, Valencia, Spain, pp. 451-458.

Huang, S.-L., Lin, F.R., 2007. The design and evaluation of an intelligent sales agent for online persuasion and negotiation. Electronic Commerce Research and Applications 6, 285-296.

Jain, B.A., Solomon, J.S., 2000. The effect of task complexity and conflict handling styles on computer-supported negotiations. Information & Management 37, 161-168.

Kersten, G., Chen, E., Neumann, D., Vahidov, R., Weinhardt, C., 2006. On comparison of mechanisms of economic and social exchanges: The times model. In Negotiation and Market Engineering. Dagstuhl Seminar, Dagstuhl, Germany.

Kersten, G., Noronha, S.J., 1999. WWW-based negotiation upport: Design, implementation, and use. Decision Support Systems 25, 135-154.

Kersten, G.E., Lo, G., 2003. Aspire: An integrated negotiation support system and software agents for e-business negotiation. International Journal of Internet and Enterprise Management 1, 293-315.

Lin, R., Gal, Y.a., Kraus, S., Mazliah, Y., 2014. Training with automated agents improves people's behavior in negotiation and coordination tasks. Decision Support Systems 60, 1-9.

Lin, R., Kraus, S., 2010. Can automated agents proficiently negotiate with humans? Comm. ACM 53, 78-88.

Maes, P., Guttman, R., Moukas, A., 1998. Agents that buy and sell. Comm. ACM 42, 81-91.

Raiffa, H., 1982. The Art and Science of Negotiation. Harvard University Press, Cambridge, MA.

Traum, D., Rickel, J., Gratch, J., Marsella, S., 2003. Negotiation over tasks in hybrid human-agent teams for simulation-based training, Proceedings of the Second International Joint Conference on Autonomous Agents and Multiagent Systems. ACM Press, Melbourne, Australia, pp. 441-448.

Vahidov, R., Chen, E., Kersten, G., 2013. Experimental assessment of agent-supported electronic negotiations. International Journal of Human-Computer Interaction 29, 764-774.

Vahidov, R., Kersten, G., Saade, R., 2014. An experimental study of software agent negotiations with humans. Decision Support Systems 66, 135-145.

Vahidov, R., Kersten, G.E., Gimon, D., 2012a. Interaction between software agent-enabled system with invite ENS users: Multi-bilateral negotiations. In Proceedings of the 2012 Conference Group Decision & Negotiation, Recife, Brazil.

Vahidov, R., Kersten, G.E., Saade, R., 2012b. Human–software agent negotiations: An experimental study. In: Shaw, M.J., Zhang, D., Yue, W.T. (eds.), E-Life: Web-Enabled Convergence of Commerce, Work, and Social Life. Lecture Notes in Business Information Processing (108). Springer, Berlin / Heidelberg, Germany, pp. 356-367.

Yang, Y., Singhal, S., 2009. Designing an intelligent agent that negotiates tactfully with human counterparts: A conceptual analysis and modeling framework. In Proceedings of the 42nd Hawaii International Conference on System Sciences, ACM Press, New York, NY, 2009, pp. 1-10.

Yu, B., Vahidov, R., Saade, R., 2015. Agents and e-commerce: Beyond automation. In Proceedings of the 2015 Americas Conference on Information Systems, Puerto Rico, Assoc. for Info, Sys. Atlanta, GA.

- Experiments involving negotiations between human subjects and software agents have been conducted.
- Agents used various concession-making tactics.
- Negotiation case featured purchase of a mobile phone plan.
- Simple case involved five issues, while complex case had ten issues to negotiate over.
- Results suggest significant effects of case complexity and concession-making tactic interaction on objective outcomes, as well as subjective assessments of negotiations.