Effects of Communicating Issue Priority for Preference Tradeoffs in Agent-human Negotiations

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Abstract
This study explores the consequences of a software agent volunteering one of its issue priorities and inviting its human counterpart to reciprocate in order to obtain preference tradeoffs in a multi-issue e-commerce negotiation scenario. Results indicated that while the agent followed the same negotiation strategy algorithm, agent-human dyads achieved better agreement rate and joint outcomes, and the human negotiators experienced more positive post-negotiation affect when the agent volunteered to communicate an issue priority than when it didn’t. The findings have implications for automated negotiation research and practice.

Keywords: Automated negotiation, preference tradeoff, multi-issue negotiation, agent-human negotiation, software agents, negotiation outcome, e-commerce
Extended Abstract

Negotiation that involves multiple issues is a pervasive phenomenon in the business and social world. A basic process in a multi-issue is information exchange (Fisher and Ury, 1981; Raiffa, 1982). By increasing the amount of information, the parties reduce their information asymmetry and so are more likely to identify opportunities for preference tradeoffs. One way to accomplish this is for the parties to communicate information about their issue priorities.

In the literature dealing with “automated negotiations” (Jennings et al., 2001), and in particular with multi-issue negotiations under incomplete information, preference tradeoffs are obtained by designing the agent to estimate or learn the counterpart’s issue ranking, or by assuming that issue order information is given a priori. For example, Faratin et al. (2002) introduce a “fuzzy similarity” based tradeoff method as a concession strategy, assuming the counterpart’s issue order is given. Coelho and Jennings (2004) propose a “kernel density estimation” method to estimate the counterpart’s issue weights, assuming that past negotiation history is given and that the counterpart has full knowledge about the agent. Ros and Sierra (2006) describe a technique based on a “variability” method to estimate the counterpart’s issue order assuming that the counterpart is more likely to concede on less important issues, and therefore less important issues have greater variability from the counterpart’s offer history. Noh et al. (2010) develop a “modified dynamic weighted majority (DWM)” learning algorithm for the negotiation agent to estimate the issue weights and issue ranks of the human counterpart, based on the assumption similar to the one in Ros and Sierra (2006) that a rational human counterpart is more likely to concede on less important issues. All the above machine learning approaches involve a process of estimating a counterpart’s preference structure for preference tradeoffs.

In contrast, this paper explores an “open communication” approach in designing automated negotiation agents wherein a negotiation agent voluntarily shares one of its priorities to initiate the exchange of issue priorities with its human counterpart and then invites the human counterpart to reciprocate in order to directly achieve preference tradeoffs. We hypothesize the following effects of this approach:

**Effects on agreement rate, individual and joint outcomes**
When the automated agent volunteers to communicate an issue priority (as opposed to not volunteering),

- **H1.** Agent-human dyads are more likely to obtain an agreement.
- **H2.** The individual outcomes for agent-human dyads (buyer utility and seller utility) are likely to be higher.
- **H3.** The joint outcomes of agent-human dyads (joint utility, the distance to Pareto-efficient frontier, and the distance to Nash solution) are likely to be better.

**Effects on post-negotiation satisfaction, perception and affect on human counterparts**
When the automated agent volunteers to communicate an issue priority (as opposed to not volunteering),

- **H4.** Human counterparts are more likely to be satisfied with the outcome.
- **H5.** Human counterparts are more likely to have positive perceptions of the agent.
- **H6.** Human counterparts are more/less likely to have positive/negative post-negotiation affect.

In a laboratory experiment setting to test these hypotheses, the software agent, employing a “simultaneous-equivalent offers (SIM)” and “delayed acceptance (DLY)” negotiation strategy algorithm described in detail in Yang et al. (2009), communicates that “purchase quantity” is its top priority and invites the counterpart to reciprocate. A control group is subjected to the same negotiation strategy algorithm, but the agent does not communicate its issue priority and does not invite the counterpart to do
so. All other negotiation attributes (e.g., utility functions, bargaining powers, and experiment environment) are identical for the treatment and control groups.

In a between-subject, one-factor randomized block design (Fig. 1), MBA students enrolled in a negotiation dynamics class at the INSEAD business school (Singapore campus) were recruited as subjects, 30 before the class was exposed to the win-win concept, and 24 after. The average age of the subjects was 29.0 with 64.8% males. All subjects had at least two years working experience and experience with group work. As an incentive for active participation in the experiment, subjects received tiered bonus course credit based on their negotiation performance in the experiment.

Subjects were tasked to play the buyer role negotiating a purchase with a seller over the seller’s website. Although subjects were not explicitly told that the seller was a software agent, questioning subjects after the experiment proper revealed that most subjects believed that it was. Most subjects in the treatment condition (21 out of 27 subjects) responded to the agent’s invitation and revealed (based on their task scenario) that the “unit price” issue was their top priority, while 3 revealed that the “purchase quantity” issue was their top priority, and 3 chose not to reveal their priority.

<table>
<thead>
<tr>
<th>Agent’s communication about issue priority</th>
<th>Control (No)</th>
<th>Treatment (Yes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human counterparts’ exposure to win-win concept</td>
<td>15 15</td>
<td>12 12</td>
</tr>
<tr>
<td>Block 1 (Before exposure)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Block 2 (After exposure)</td>
<td>12 12</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>27 27</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 1. The negotiation experiment design (n=54). The number in each cell indicates the number of agent-human dyadic negotiation cases, with each case being a negotiation between a buyer (the human subject) and a seller (the software agent) over a four-issue task.

The data were analyzed using logistic regression and multi-attribute analysis of variance (MANOVA) tests. The results confirmed that more agreement cases were obtained when the agent communicated its issue priority than when it did not (22/27=81.5% vs. 14/27=51.9%; \( B=1.407, SE=0.628, \) Wald =5.031, \( p=.03^* \)). There was no interaction between the independent variable and the block variable on the dependent measures, confirming that subjects’ exposure to win-win concept was a valid block variable. As can be seen in Table 1, main effects for agent’s issue priority communication were found for buyer utility, joint utility, the distance to Pareto-efficient frontier, the distance to Nash solution, subjects’ perceptions of the agent (being considerate), and their post-negotiation affect (feeling frustrated, content, and lucky).
The results of this study indicated that more positive negotiation outcomes including higher agreement rate and better joint utilities were achieved when the agent volunteered information about an issue priority than when it didn’t. Furthermore, subjects rated the agent as more considerate and reported less negative affect after the negotiation. It is worth noting that in both the treatment and control conditions, the agent followed the same negotiation strategy algorithm. These findings suggest that merely the simple gesture of offering cooperative information exchange can have beneficial economic as well as affective consequences—a conclusion which, in the present case, appeared to hold even though most subjects assumed that they were negotiating with a mechanistic agent. It makes sense for the agent to initiate cooperative win-win moves to instill positive reciprocation. In comparison with sophisticated machine learning approaches to estimating a counterpart’s preference, the present findings support a direct agent design approach to exploring issue tradeoffs for win-win solutions.

An interesting extension to this study would be to explore whether this kind of initial move generates any liability for the agent negotiator in the value claiming (or distributive) phase of a negotiation. Meanwhile, as both negotiation theory and practice (such as in our study) suggest, most negotiators engaged in business multi-issue negotiations are willing (or do not find it disadvantageous) to share information about their issue priorities, perhaps more research attention should be devoted to how issue priority information exchange can enhance the design of more effective and efficient learning algorithm for complex negotiation scenarios.

### Table 1. Descriptive statistics and MANOVA results (n=54).

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Mean (Std. deviation)</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Individual outcome</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Buyer Utility</td>
<td>56.95 (13.41)</td>
<td>5.15</td>
<td>.03*</td>
</tr>
<tr>
<td>Seller Utility</td>
<td>49.33 (7.10)</td>
<td>3.18</td>
<td>.08</td>
</tr>
<tr>
<td><strong>Dyadic outcome</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Joint Utility</td>
<td>106.30 (18.96)</td>
<td>5.69</td>
<td>.02*</td>
</tr>
<tr>
<td>Distance to Pareto Frontier</td>
<td>16.84 (13.55)</td>
<td>3.68</td>
<td>.06*</td>
</tr>
<tr>
<td>Distance to Nash Solution</td>
<td>21.47 (11.53)</td>
<td>5.82</td>
<td>.02*</td>
</tr>
<tr>
<td><strong>Counterparts’ outcome satisfaction</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>How satisfied are you with the utility score you earned?*</td>
<td>3.22 (2.06)</td>
<td>2.97</td>
<td>.09</td>
</tr>
<tr>
<td>What do you think of the relative ranking of your utility score among all other buyers?*^</td>
<td>2.85 (1.88)</td>
<td>3.51</td>
<td>.07</td>
</tr>
<tr>
<td><strong>Counterparts’ perceptions of the agent</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Do you think your counterpart was considerate about your interests and concerns?*#</td>
<td>3.52 (0.98)</td>
<td>5.78</td>
<td>.02*</td>
</tr>
<tr>
<td>Do you think your counterpart was flexible in making offers?*#</td>
<td>3.78 (1.45)</td>
<td>0.61</td>
<td>.44</td>
</tr>
<tr>
<td><strong>Counterparts’ post-negotiation affect</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Having finished the negotiation, to what extent did you feel*:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Content</td>
<td>2.15 (1.23)</td>
<td>8.01</td>
<td>.01**</td>
</tr>
<tr>
<td>Grateful</td>
<td>1.67 (0.92)</td>
<td>2.72</td>
<td>.11</td>
</tr>
<tr>
<td>Lucky</td>
<td>1.67 (1.24)</td>
<td>3.59</td>
<td>.06*</td>
</tr>
<tr>
<td>Frustrated</td>
<td>3.04 (1.40)</td>
<td>4.25</td>
<td>.05*</td>
</tr>
<tr>
<td>Angry</td>
<td>1.81 (1.00)</td>
<td>0.14</td>
<td>.71</td>
</tr>
<tr>
<td>Disappointed</td>
<td>2.81 (1.52)</td>
<td>0.38</td>
<td>.54</td>
</tr>
</tbody>
</table>

* (1—Extremely Dissatisfied, 4—Indifferent, 7—Extremely Satisfied)
^ (1—I’m much lower than average, 4—I’m average, 7—I’m much higher than average)
# (1—Extremely inconsiderate/unfriendly/rigid/, 4—Moderately, 7—Extremely considerate/friendly/flexible)
+ (1—Not at all, 4—Moderately, 7—Extremely); the order of the six affects was randomized in the questionnaire.
* including marginal significance
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