

Autonomous Agent that Provides Automated Feedback Improves Negotiation Skills

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Abstract. Research has found that individuals can improve their negotiation abilities by practicing with virtual agents [1, 2]. For these pedagogical agents to become more "intelligent," the system should be able to give feedback on negotiation performance [3, 4]. In this study, we examined the impact of providing such individualized feedback. Participants first engaged in a negotiation with a virtual agent. After this negotiation, participants were either given automated individualized feedback or not. Feedback was based on negotiation principles [4], which were quantified using a validated approach [5]. Participants then completed a second, parallel negotiation. Our results show that, compared to the control condition, participants who received such feedback after the first negotiation showed a significantly greater improvement in the strength of their first offer, concession curve, and thus their final outcome in the negotiation.

Keywords: Negotiation · Individualized feedback · Automated metrics

1 Introduction

Emerging research suggests that learning technology holds promise for assessing and teaching a range of interpersonal skills [6-8], including negotiation [1, 2]. Skills in negotiation are essential in many careers, especially politics [9], military [10], law [11, 12], and business [13]. However, Intelligent Tutoring Systems for negotiation training are not yet common practice. Typically, during negotiation training sessions, students practice against each other while the instructor walks around the room, observing and evaluating their use of negotiation principles. The issue with this approach is that instructors' attention is limited and they cannot evaluate all students' use of the negotiation principles, especially in large classes. This is problematic as receiving constructive individualized feedback is integral to skill development [14]. Virtual agents that allow users to practice negotiation and provide individualized feedback holds great potential for addressing these limitations. Previous research has shown that individuals can improve their negotiation abilities just by practicing with these agents even without receiving individualized feedback [1, 2]. Importantly, however, the systems could be more intelligent if they provided individualized feedback [14]. Accordingly, in the current work, we extend one of these previous systems [1] to automatically provide such

[©] Springer International Publishing AG, part of Springer Nature 2018 C. Penstein Rosé et al. (Eds.): AIED 2018, LNAI 10948, pp. 225–229, 2018. https://doi.org/10.1007/978-3-319-93846-2_41

feedback using negotiation principles established by Kelley [4]. Kelley identified a set of principles that have been correlated with good negotiation outcomes [4]. Importantly, these principles have been quantified through automated methods [5]. Here, we take the important next step: we empirically test the impact of providing students such automated feedback about their negotiation skills.

One "theme" in Kelley's principles is to avoid early commitment. Avoiding early commitment means negotiators should avoid conceding to their opponent early on. To do this Kelley suggests negotiators should (1) *make high initial offers*, (2) *use more of the available time* while (3) *maintaining strong offers* throughout. These practices may lead to more satisfactory solutions as they discourage naively accepting deals that are presented early in a negotiation. In this paper, we focus on teaching these three specific, established negotiation principles.

2 Current Work

Participants and Design. We recruited 63 participants (34 females) through Craigslist; and they were paid \$30. Technical failures resulted in unusable data for 3 participants, leaving 60 participants (30 per condition). They were also incentivized to perform well in the negotiation with entries into a \$100 lottery based on the items that they got in the negotiation. Participants were randomly assigned to either receive (or not) individualized feedback on their first negotiation performance prior to a second negotiation beginning. Feedback that the experimental group received is described below in the Task and Feedback section. Controls received their negotiation score following the first round and were told to just reflect on the negotiation for 5 min.

Agent. Participants completed two negotiations with a virtual agent (CRA [15]). CRA is a semi-automated system capable of carrying out a negotiation with a user. The virtual human toolkit [16] executed low-level dialogue functions automatically, while two wizards (WoZ) provide high-level guidance for the agent's behaviors. We tested the impact of automated individualized feedback (which would be equivalent when using WoZ) to see if this feature should be implemented in a fully-automated system.

Like the AI system's choices will be based on algorithms, wizards' selected actions were based on a script. First, the agent revealed its preferences if the participant revealed theirs. The agent waited for participants to make the first offer, and the script (see Fig. 1) used this offer as an anchor [4]. For example, if the participant's first offer gave the agent items worth 50–60 points, the agent's initial acceptance threshold would be 90 points, and the ultimate acceptance threshold would be 75 points. This means that the agent would reject the initial offer made by the participant and counter-offer with a claim of 90 points (e.g. offering the participant to take the painting and lamps while the agent keeps all the records), and the agent would never accept a deal affording it less than 75 points. If the participants' next offer was not above the current acceptance threshold, the agent would reject it. Then, the agent would attempt to make a triangulating offer (e.g. claiming both lamps and two records if the previous offer claimed all three records). If a triangulating offer had already been made or none was possible, the agent would lower its acceptance threshold by the minimum possible

difference in point value (e.g. from 90 to 80 points). This process would repeat until an agreement was reached or the ultimate threshold was reached, at which point the agent would continue to make the same offer at the ultimate threshold.

Participant initial offer strength (claimed points)	Initial acceptance threshold	Ultimate acceptance threshold
0-50	75	None*
60-65	95	80
75-80	95	65
90-95	80	50
105-110	65	35
120-125	120	None**

^{*}If the participant claimed 50 or less points with the initial offer, the agent accepted immediately

Fig. 1. Negotiation rules for agent.

Task and Feedback. Figure 2 depicts the payoff matrices for the two negotiation tasks. Prior to each negotiation, participants were given the relative value of each item. In the feedback condition, we provided feedback using Johnson et al.'s [5] metrics. Participants were shown a graphical display of negotiation metrics automatically collected from the participant's first negotiation (Fig. 3), accompanied by an automatically generated script explaining the feedback (for user comprehension). Although the script will be read by the VH in future iterations, here it was read by an experimenter.

Participant Payoff									
Records		Lamps		Painting					
Level	Value	Level	Value	Level	Value				
	(points)		(points)		(points)				
0	0	0	0	0	0				
1	30	1	15	1	5				
2	60	2	30						
3	90								

Agent Payoff										
Re	Records		Lamps		Painting					
Level	Value (points)	Level	Value (points)	Level	Value (points)					
0	0	0	0	0	0					
1	30	1	15	1	0					
2	60	2	30							
3	90									

Fig. 2. Payoff matrix for participant and agent in negotiation task.

3 Results and Discussion

The metrics described above based on Johnson et al. [5] were also used to measure the extent to which participants adhered to the negotiation principles. Using 2 (feedback: feedback vs. no) x 2 (time: 1 vs. 2) mixed ANOVAs, we analyzed strength of initial offer, use of available time, and value claimed. Analysis of initial offer revealed a significant main effect of time (F(1,47) = 9.10, p = .004), which was qualified by feedback condition (F(1,47) = 8.26, p = .006). Participants who received feedback made stronger initial offers in the second negotiation (M = 95.42, SE = 2.91) than the first (M = 78.96, SE = 2.97; F(1,23) = 15.07, p = .001), but there was no difference in the control condition (M = 80.60, SE = 2.91 vs. M = 80.20, SE = 2.91; F(1,24) = 0.01, p = .91).

^{**}If the participant claimed 120 or more points with the initial offer, the agent retaliated by counter-offering with a claim of 120 points. However, the agent would adjust the initial and ultimate acceptance thresholds based on the next offer the participant made.

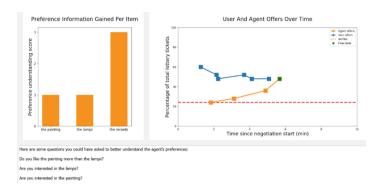


Fig. 3. Feedback interface.

In contrast, for use of available time, there was only a main effect of time (F(1,47) = 4.48, p = .04), and no interaction (F(1,47) = 0.25, p = .62). Participants spent longer negotiating in the first negotiation (M = 599618.76 ms, SE = 36913.79) than the second (M = 506452.28 ms, SE = 28345.94).

Analysis of average value claimed revealed a main effect of time (F(1,47) = 24.79, p < .001), which was qualified by feedback condition (F(1,47) = 7.14, p = .01). While the control group only claimed marginally more value in the second negotiation (M = 73.37, SE = 2.00) than the first (M = 69.90, SE = 1.65; F(1,24) = 3.38, p = .08), those who received feedback made higher claims in the second negotiation (M = 82.42, SE = 2.05) than the first (M = 70.88, SE = 1.68; F(1,23) = 23.81, p < .001).

Also, we measured the final outcome (score) in the negotiation (based on Fig. 2). A main effect of time (F(1.58) = 45.28, p < .001) was qualified by feedback condition (F(1,58) = 13.47, p = .001). While the control group obtained only marginally better outcomes in the second negotiation (M = 58.50, SE = 1.92) than the first (M = 54.33, SE = 2.19; F(1,29) = 3.92, p = .06), those who received feedback improved in the second negotiation (M = 67.33, SE = 1.92) compared to the first (M = 53.17, SE = 2.19; F(1,29) = 67.05, p < .001). Compared to those who did not receive feedback, providing automated individualized feedback about negotiation principles improved use of those principles. In addition to participants in the feedback condition showing greater improvement over time in their initial offer and value claimed, they also improved more at achieving good outcomes for themselves in the negotiation. As such, all but one of the metrics based on the principle of avoiding early commitment were impacted by feedback condition: extending negotiation time was only affected by practice (i.e. negotiation 1 vs. negotiation 2). However, these observed shorter durations in the second negotiation could simply be a consequence of the participants becoming more familiar with the virtual negotiator system. Here we establish that individualized feedback is superior to no feedback. While individualized feedback is theorized to be important in learning negotiation skills [14], it should be explicitly compared to a generic lesson about negotiation principles. Nevertheless, the current research establishes that pedagogical systems that provide automated individualized feedback on negotiations have potential to improve upon current approaches.

Acknowledgments. This research was supported by the US Army and the National Science Foundation. The content does not necessarily reflect the position or the policy of any Government, and no official endorsement should be inferred.

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