The Politeness Effect: Pedagogical Agents and Learning Gains

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Abstract. Pedagogical agent research seeks to exploit Reeves and Nass's Media Equation, which holds that users respond to interactive media as if they were social actors. Investigations have tended to focus on the media used to realize the pedagogical agent, e.g., the use of animated talking heads and voices, and the results have been mixed. This paper focuses instead on the manner in which a pedagogical agent communicates with learners, on the extent to which it exhibits social intelligence. A model of socially intelligent tutorial dialog was developed based on politeness theory, and implemented in an agent interface. A series of Wizard-of-Oz studies were conducted in which subjects either received polite tutorial feedback that promotes learner face and mitigates face threat, or received direct feedback that disregarded learner face. The polite version yielded better learning outcomes, and the effect was amplified in learners who expressed a preference for indirect feedback. These results confirm the hypothesis that learners tend to respond to pedagogical agents as social actors, and suggest that research should perhaps focus less on the media in which agents are realized, and place more emphasis on the agents' social intelligence.

Introduction

Researchers have for several years been investigating the potential of pedagogical agents to promote learning. One of the most influential papers in this area was the study by Lester et al. [24] that demonstrated a Persona Effect: that learning was facilitated by an animated pedagogical agent that had a life-like persona and expressed affect. The rationale for this research has been the Media Equation of Reeves and Nass [30], which holds that people tend to respond to interactive media much as they do to human beings. That is, they respond as if the media were social actors.

A number of pedagogical agent investigations have since been conducted, seeking to understand the Persona Effect in more detail, and replicate it in a range of learning domains [17]. The results of these studies have been mixed. For example, the study by Andre et al. [3] showed that animated agents reduce the perceived difficulty of the material being learned, and the study of Bickmore [5] showed that subjects liked an animated agent that responded socially to them, but neither study reported significant learning gains. Moreover, studies by Moreno and Mayer [26] and by Graesser et al. [13] indicated that the agent's voice was the significant contributor to learning outcomes, not the animated persona. Thus the Persona Effect is at best unreliable, and may in fact be a misnomer if the animated persona is not the primary cause of the learning outcomes.

This paper examines a different approach to applying the Media Equation to intelligent tutoring. If as Reeves and Nass suggest learners respond to pedagogical agents as if they were social actors, then the agents' effectiveness should depend upon whether or not they *behave* like social actors. The agents should be socially intelligent, acting in a manner that is consistent with their social role, in accordance with social norms. In fact, human tutors make extensive use of social intelligence when they motivate and support learners [23]. Thus social intelligence in pedagogical agents may be important not just to gain user acceptance, but also to increase the effectiveness of the agent as a pedagogical intervention.

To test this hypothesis, a model of motivational tutorial tactics was developed, based upon politeness theory [18]. A series of Wizard-of-Oz studies were conducted in which subjects either received polite tutorial feedback that promotes learner face and mitigates face threat, or received direct feedback that disregards learner face. The polite version led to improvements in learning outcomes, and the effect was amplified in learners who expressed a preference for indirect feedback. We also observed effects on learner attitudes and motivation [32]. However, we will not describe effects on attitude and motivation in detail here in order to devote as much space as possible to an analysis of the learning outcomes achieved by the polite agent interface.

We term the effect demonstrated here the Politeness Effect. Our results suggest that pedagogical agent research should perhaps place less emphasis on the Persona Effect in animated pedagogical agents, and focus more on the Politeness Effect and related means by which pedagogical agents can exhibit social intelligence in their interactions with learners.

1. The Politeness Theory and Student Motivation

Brown and Levinson [6] have devised a cross-cultural theory of politeness, according to which everybody has a positive and negative "face". Negative face is the want to be unimpeded by others (autonomy), while positive face is the want to be desirable to others (approval). Some communicative acts, such as requests and offers, can threaten the hearer's negative face, positive face, or both, and therefore are referred to as Face Threatening Acts (FTAs). Consider a critique of the learner such as "You did not save your factory. Save it now." There are two types of face threat in this example: the criticism of the learner's action is a threat to positive face, and the instruction of what to do is a threat to negative face.

Speakers use various politeness strategies to mitigate face threats, according to the severity, or "weightiness", of the FTA. In the above case ("You did not save your factory. Save it now."), the tutor could omit the criticism of the learner and focus on the suggested action, i.e., to save the factory. Alternatively the tutor could perform the face-threatening act off record, i.e., so as to avoid assigning responsibility to the hearer. An example of this would be "The factory parameters need saving." The face threat of the instruction can be mitigated using negative politeness tactics, i.e., phrasing that gives the hearer the option of not following the advice, e.g., "Do you want to save the factory now?" Positive politeness strategies can also be employed that emphasizes common ground and cooperation between the tutor and learner, e.g., "How about if we save our factory now?" Other positive politeness strategies include overt expressions of approval, such as "That is very good".

To investigate the role that politeness plays in learner-tutor interaction, in a previous study [16] we videotaped interactions between learners and an expert human tutor while the students were working with the Virtual Factory Teaching System (VFTS) [12], a web-based learning environment for factory modelling and simulation. The expert tutor's comments tended to be phrased in such a way as to have an indirect effect on motivational factors, e.g., phrasing a hint as a question reinforces the learner's sense of control, since the learner can choose whether or not to answer the question affirmatively. Also, the tutor's comments often reinforced the learner's sense of being an active participant in the problem solving process, e.g., by phrasing suggestions as activities to be performed jointly by the tutor and the learner. We are led to think that tutors may use politeness strategies not only for minimizing the weightiness of face threatening acts, but also for indirectly supporting the student's motivation. For instance, the tutor may use positive politeness for promoting the student positive face (e.g. his desire for successful learning), and negative politeness for supporting the student negative face (e.g. his desire for autonomous learning).

2. Related work

In recent years, the recognition of the importance of affect and motivation on learning has led increasingly to the development of socially-aware pedagogical agents as reflected in the work of del Soldato et al. [11] and de Vicente [10]. Heylen et al. [14] highlight the importance of these factors in tutors, and examine the interpersonal factors that should be taken into account when creating socially intelligent computer tutors. Cooper [9] has shown that profound empathy in teaching relationships is important because it stimulates positive emotions and interactions that favour learning. Baylor [4] has conducted experiments in which learners interact with multiple pedagogical agents, one of which seeks to motivate the learner. Other researchers such as Kort et al. [1, 21], and Zhou and Conati [33] have been addressing the problem of detecting learner affect and motivation, and influencing it. User interface and agent researchers are also beginning to apply the Brown & Levinson model to human-computer interaction in other contexts [8, 25]; see also André's work in this area [2].

Porayska-Pomsta [27] has also been using the Brown & Levinson model to analyse teacher communications in classroom settings. Although there are similarities between her approach and the approach described here, her model makes relatively less use of face threat mitigating strategies. This may be due to the differences in the social contexts being modelled.

3. A Wizard-Of-Oz Experiment For Generating And Evaluating Polite Tutor Interventions

In order to apply the theory by Brown and Levinson to the context of interactions in ITSs, we have realized a computational model of politeness in tutorial dialog [18]. In this model, positive and negative politeness values are assigned beforehand to each natural language template that may be used by the tutor. Such values measure the degree to which a template redresses the student's face. We also assign positive and negative politeness values to the tutor, i.e. the degree to which we want the tutor to address the student's positive and negative face. During each communicative act, the template with the politeness values that is closest to the tutor politeness values is selected and used to produce an utterance. For example, a suggestion to save the current factory description, can be stated either bald on record (e.g., "Save the factory now"), as a hint, ("Do you want to save the factory now?"), as a suggestion of what the tutor would do ("I would save the factory now"), or as a suggestion of a joint action ("Why do not we save our factory now?").

To evaluate the intervention tactics, we created a Wizard-of-Oz experiment system aimed at teaching students how to use the VFTS. The student's and experimenter's interfaces are described in detail in [32, 29]; the Plan Recognition and Focus of Attention modules, that help the experimenter analyze student behavior, are described in [28]. The Wizard-of-Oz interface enables a human tutor to use the politeness model to generate the tutorial dialog for those tactics. To communicate with the student, the tutor selects an item in the student activity window (e.g., "copy_factory") then chooses from among a set of communicative acts associated with the current pedagogical goal (e.g., "indicate action & explain reason" or "tell how to perform action") and generates an intervention. The intervention is sent to the agent window on the student interface. An animation engine [31] produces the gestures and a text-to-speech synthesizer synthesizes speech from the text.

3.1. Method

Fifty-one students participated in the study, including 17 students from USC and 34 students from UCSB. The subjects from USC were either engineering graduate or undergraduate students, and all were male. Subjects from UCSB were mostly undergraduate students from introductory psychology classes. Five students from USC participated in a pilot study, which allowed us to test the experiment set-up. Subjects were randomly assigned to either a Polite treatment or a Direct treatment. In the Polite treatment, positive and negative politeness values varied randomly in a moderate to high range, causing the tutor to use politeness in a variety of ways both in giving hints and in providing feedback. In the Direct treatment, positive and negative politeness values were fixed at minimum values, forcing the tutor to communicate directly and not allowing for mitigation of face threat. In all other respects the two treatments were identical.

Two pre-tests were administered: A Background Questionnaire was used to collect information about gender, major and learning style and a Personality Questionnaire was used to measure self-esteem, need for cognition, extroversion and optimism. Personality questions came from the International Personality Item Pool [15]. Two post-test questionnaires were administered as well: A Tutor and Motivation questionnaire was used to evaluate the learner's motivation and perception of the Wizard-of-Oz tutor, and a Learning Outcome questionnaire was used to assess the learner's ability to solve problems on the VFTS.

4. Results

Since the experiment materials and the procedures were identical, we combined the data collected from the experiments carried out in Summer 2004 at USC and in Fall 2004 at UCSB. A two-way analysis of variance (ANOVA) using condition (polite vs. direct) and experiment location (USC vs. UCSB) as between-subject factors showed that there was no significant interaction between condition and experiment location ($F(1, 33)=0.003$, $p=0.957$). Therefore, we focused on comparing the polite and direct conditions using two-tailed t-tests on the combined data (with alpha at $p < .05$).

We excluded a few problematic and extreme cases, due to technical difficulties during the experiment, very extreme personality profiles, and high student ability to complete the task independently. We then grouped the remaining 37 students into two groups: 20 students in Polite and 17 in Direct group, based on the treatment they received. For each group, we calculated the average score of the Learning Outcomes questionnaires and applied Student's t-test to analyze the variance. In this paper, we will only include the analysis on learning gains. The influence on affective factors is not the focus for this paper and will not be included here.

4.1 Overall Polite vs. Direct

Overall, students who received the Polite treatment scored better ($M_{polite}=19.450$, $SD_{polite}=5.6052$) than students who received the Direct treatment ($M_{direct}=15.647$, $SD_{direct}=5.1471$). This is consistent with what we found in our previous study [32]. In the t-test for variance, the difference shows statistical significence ($t(35)= 2.135$, $p=0.040$).

Even though the politeness strategy made an impact on students' learning performance across all students, we're still interested in what group of students is most likely to be influenced by politeness strategies. We grouped students based on their report on the Background and Personality questionnaire, then compared the means between polite and direct groups within students of similar background or personality. The results are presented below.

4.2 Computer skills

From students' self-ratings of their computer skills, we found that almost all students rated their computer skills either average or above average. We then grouped students into 2 groups, 19 with average computer skills and 17 above average (one student with below average computer skill was not included). Overall, students with above average computer skills performed better than students with average computer skills. This may because our test-bed, VFTS, is a relatively complicated computer based teaching system. Better computer skills help students understand the basic concepts of operations in VFTS. But for students with average computer skills, those who received polite treatment (M_{polite}=18.417, SD_{polite}=5.0174) performed better than those who received direct treatment (M_{direct}=14.143, SD_{direct}=3.3877, $t(17)$= 1.993, p=0.063). We did not observe this difference within students with above average computer skills. In this case the tutor, either polite or direct, has less impact on students learning performance. On the other hand, students with poorer computer skills relied more on tutor to help them through the learning task.

4.3 Engineering background

We asked the students whether they work or study in an engineering discipline. Within the students with no engineering background (28 students), we found a major difference between the polite (M_{polite}=18.800, SD_{polite}=5.7966) and direct groups (M_{direct}=14.077, SD_{direct}=4.3677, $t(26)$=2.403, p=0.024). We did not find much difference within engineering students (9 students). VFTS is a system built for Industrial Engineering students. For students who do not work/study in a engineering discipline, such as psychology students, performing tasks in the VFTS could be much more challenging. This is consistent with our hypothesis that students with better ability to perform the task relied less on the tutor.

4.4 Preference for direct help

Direct help are tutor feedbacks that are devoid of any politeness strategy, while Indirect help are the ones that are phrased using politeness strategies. Based on students' preference of direct or indirect help, we grouped them into 3 groups: 15 prefered direct help, 13 prefered indirect and 9 had no preference. For students that prefered direct help or do not have any preference, we did not observe any difference made by the Polite tutor. But for students that specifically reported their preference for indirect help, the Polite tutor made a big difference on their learning performance (M_{polite}=20.429, SD_{polite}=5.7404, M_{direct}=13.000, SD_{direct}=4.5607, $t(11)$= 2.550, p=0.027).

4.5 Frequency of tutor intervention

Tutor attentiveness could be a factor that affected students' learning outcomes. During the experiment, tutor attentiveness was balanced under both experimental conditions. However, how many times of tutor gave feedback to the students depended on the students' need. We grouped students into two groups based on the amount of tutor feedback: 11 students in low and 26 students in average-to-high groups. On average students spent 36 minutes on the VFTS. We considered a low interaction as less than 20 feedbacks during the experiments, while average to high is 20 or more feedbacks. Our hypothesis is that when the number of tutor interventions is low, politeness would have less effect on students' learning. The result confirmed our hypothesis. We found that when the tutor's interventions were low, the Polite tutor did not affect students learning as much. But when the tutor's interventions were average to high, the Polite tutor made a big difference (M_{polite}=18.214, SD_{polite}=5.6046, M_{direct}=13.833, SD_{direct}=3.3530, $t(24)$= 2.365, p=0.026).

4.6 Personality

We measured 4 personality traits: self-esteem, optimism, need for cognition and extroversion. On self-esteem and optimism, we found our sample distribution is skewed – most subjects have a high self-esteem and are pretty optimistic. We grouped students based on their level of need for cognition and extroversion. On overall learning results, we did not find interaction between these two personality traits and politeness strategy. However, on students' performance on learning difficult concepts, there are some interesting differences between the polite and direct groups.

For the 20 students scored high on extroversion, we found out that polite tutor helped students to learn difficult concepts more than direct tutor (M_{polite}=10.455, SD_{polite}=2.0671, M_{direct}=8.556, SD_{direct}=1.5899, $t(18)$= 2.259, p=0.037). Same difference found for 22 students scored high on need for cognition (M_{polite}=10.000, SD_{polite}=1.4832, M_{direct}=8.182, SD_{direct}=2.5226, $t(20)$= 2.061, p=0.053). Students with high need for cognition are probably more motivated to learn difficult concepts. Students with high extroversion are more open to discuss their problems with the tutor when trying to understand difficult concepts. This leads us to believe that, when learning materials are relatively challenging, students with either high extroversion or need for cognition are more likely to be influenced by politeness strategies.

4.7 Liking the tutor

On the post-questionnaire, students were asked whether or not they liked the tutor. We grouped students into 2 groups based on their answers: 20 students liked the tutor and 17 did not or had no preference. We did not find statistical significance between polite and direct group within students did not like the tutor or did not have a preference. But within students that reported that they liked the tutor, we found that students who worked with polite tutor performed better than students worked with direct tutor (M_{polite}=20.333, SD_{polite}=5.2628, M_{direct}=15.500, SD_{direct}=4.9570, $t(18)$=2.058, p=0.054), especially on learning difficult concepts (M_{polite}=11.083, SD_{polite}=2.6097, M_{direct}=8.375, SD_{direct}=1.7678, $t(18)$=2.559, p=0.020). However, whether students like the tutor or not is not as accurate a predictor of learning performance as preference for direct help.

4.8 Desire to work again with the tutor

We also asked students in the post-questionnaire whether or not they would like to work with the tutor again. We grouped students into 2 groups based on their answers: 22 students would like to work with tutor again and 15 did not or had no preference. We did not find statistical significance between polite and direct group within students who would not like to work with the tutor again or did not have a preference. But within students who reported a desire to work with the tutor again, we found that students who worked with the polite tutor performed better on learning difficult concepts than students worked with the direct tutor (M_{polite}=10.917, SD_{polite}=2.7455, M_{direct}=8.500, SD_{direct}=1.5092, $t(20)$= 2.482, p=0.022).

5. Discussion and Conclusion

In this paper, we presented the effect of politeness strategies on students' learning performance, which we call the Politeness Effect. Across all students, a polite agent, compared to a direct agent, had a positive impact on students' learning gains. Richer interaction amplified this effect. And for students with need for indirect help or who had lower ability for the task, the polite agent was much more effective than the direct agent. For students with high extroversion or who were more open to communication with the agent, the polite agent helped them better understand difficult concepts. Making students like the agent appeared to help students learn. But it was not the appearance of the agent, but rather the helpfulness and feedback manner adopted by the agent that created the effect.

Tutorial dialogue is certainly not the only place to apply politeness strategies. In our study, we artificially restricted the use of politeness in tutorial interaction to ensure that the polite condition and the direct condition were as similar as possible. In real human-human interaction, people employ a range of additional strategies to build rapport and react empathetically. These strategies have been modelled in other learning domains [5, 19], and could complement the strategies studied here. We did not include them in this particular study because it would have increased the frequency of tutorial interaction, making it harder to tell whether the Politeness Effect was really a consequence of the frequency of interaction rather than the politeness strategies themselves.

The politeness effect goes beyond the engineering training system we demonstrated here. Other studies we have conducted shown that politeness strategies do occur pervasively in other domains such as second language learning [20]. However, more research will have to be done to study their effects on learning outcomes in other domains.

We recommend that developers of intelligent tutors and pedagogical agents examine the tutorial messages that their tutors are generating from a politeness perspective, as politeness may have an impact on the tutors' effectiveness. Meanwhile, more research needs to be done to study how the Politeness Effect applies in other learning contexts, and investigate other aspects of social actor modelling that go beyond the tactics studied here.

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