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A politeness effect in learning with web-based intelligent tutors

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Abstract

College students learned to solve chemistry stoichiometry problems with a web-based intelligent tutor that provided hints and feedback, using either polite or direct language. There was a pattern in which students with low prior knowledge of chemistry performed better on subsequent problem-solving tests if they learned from the polite tutor rather than the direct tutor ($d = .78$ on an immediate test, $d = .51$ on a delayed test), whereas students with high prior knowledge showed the reverse trend ($d = -.47$ for an immediate test; $d = -.13$ for a delayed test). These results point to a boundary condition for the *politeness principle*—the idea that people learn more deeply when words are in polite style. At least for low-knowledge learners, the results are consistent with *social agency theory*—the idea that social cues, such as politeness, can prime learners to accept a web-based tutor as a social partner and therefore try harder to make sense of the tutor's messages.

Keywords: Intelligent tutoring system; Politeness; Learning

1. Introduction

Intelligent tutoring systems (ITSs) are computer-based instructional systems that seek to provide one-on-one tutoring to students based on the science of learning and artificial intelligence techniques (Anderson et al., 1995; Koedinger and Corbett, 2006; VanLehn, 2006; Mitrovic et al., 2008). Intelligent tutors work by placing students in a problem-solving situation and providing needed guidance based on their performance. Students can ask for hints when they need them and error messages are provided to indicate incorrect answers or problem-solving steps to students. With intelligent tutors, students engage in "learning by doing, an essential aspect of human tutoring" (Koedinger and Corbett, 2006, p. 62). ITSs have demonstrated impressive improvement in student learning in a range of domains and with different techniques (cf. Koedinger et al., 1997; VanLehn et al., 2005; Mostow and Beck, 2007). In addition, with the advancements of computer software and hardware, as well as widespread use of the world-wide web and the deployment of intelligent tutors on the web, we can now can provide many more students with economical one-on-one tutoring, something that was previously not possible (Koedinger and Corbett, 2006).

In light of advances in the development of intelligent tutors based on principles from the learning sciences, an important next step is to develop research-based instructional design principles that prescribe effective ways to promote deep learning with such software tutors. For example, the most widely used of intelligent tutors, cognitive tutors, are based on six instructional design principles, such as using immediate feedback and minimizing cognitive load (Anderson et al., 1995; Koedinger and Corbett, 2006). Yet these instructional design principles do not include how best to incorporate *social cues*, which may be an essential element in student–tutor interactions (Person et al., 1995).

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1.1. Objective

The goal of the present study is to determine how to improve the instructional effectiveness of a web-based intelligent tutor by focusing on the tutor's conversational style. In particular, our goal is to examine the cognitive consequences of incorporating potentially important social cues in the conversation provided by the tutor—using polite rather than direct wording of feedback and hints. This study is an example of the *value-added* approach to instructional design research, in which the goal is to determine whether a particular instructional feature—such as changing from direct to polite conversational style—affects learning outcomes. More generally, our goal is to determine which instructional features are helpful for which kinds of learners and on which kinds of instructional objectives when incorporated into an intelligent tutoring system.

For example, in the present study we began with an intelligent tutor for teaching students how to solve stoichiometry problems in chemistry, in which students learned by solving a series of 10 problems with feedback and hints from the tutor, with interspersed instructional videos. The software tutor was developed using authoring software specifically designed to build intelligent tutors; many software tutors have been developed with these tools (Aleven et al., 2009). Table 1 provides examples of direct and polite ways of wording the feedback and hints provided by the tutor from a corpus of over 4000 messages. We began with the direct wording of each hint or feedback message already being used by the tutor and created polite versions based on face-saving techniques (Brown and Levinson, 1987) described in the next section.

Much instructional design research on intelligent tutoring systems has focused on the cognitive issue of determining what software tutors should say to students (i.e., communication content) or when they should say it (i.e., communication pacing), whereas in this study we focus on the social issue of *how* they should say it (i.e., communication style), such as with polite or direct wording. In short, this work is based on the idea that intelligent tutors should not only exhibit *cognitive intelligence*—by knowing what to say and when to say it—but also should exhibit *social intelligence*—by knowing how to say it. In an influential paper, Lester et al. (1997) described a *persona effect*, in which learning was improved by a computer-based agent's social cues including having a life-like persona and expressing affect. Graesser et al. (2004) have shown how a web-based tutor can be designed in line with principles of human conversation, and Person et al. (1995) found evidence that politeness strategies are commonly used in one-on-one tutoring interactions between humans, although not always effectively.

1.2. Theoretical framework

The theoretical roots of this project rest in *politeness theory* (Brown and Levinson, 1987), *media equation theory* (Nass and Brave, 2005; Reeves and Nass, 1996), and *social agency theory* (Mayer, 2005, 2009), all of which focus on the role of social cues in human communication.

Politeness theory: Brown and Levinson (1987) argue that politeness reflects a universal aspect of human social interaction that goes far beyond the niceties of proper manners or etiquette. In particular, linguistic expressions of

Table 1
Examples of Direct and polite feedback and hints.

Direct version	Polite version
Hints:	
1. The tutor would like you to convert the units of the first item.	1. Let's convert the units of the first item
2. The unit conversion involved is from mg to g. The quantity provided here should be the number of g that corresponds to 1000 mg of COH_4.	2. What about converting mg to g? The quantity we provide here may be the number of g that corresponds to 1000 mg of COH_4.
3. Since 1 g is equivalent to 1000 mg of COH_4, type 1 as your answer here.	3. Since 1 g is equivalent to 1000 mg, maybe we should put 1 here.
4. The tutor wants you to calculate the result now.	4. Shall we calculate the result now?
5. Perform the arithmetic operations on the quantities that will remain after cancelling to obtain the result.	5. Let's work on the result by performing arithmetic operations on the quantities that remain after cancelling.
6. 10.6 and 1 remain in the numerators and 1000 in the denominator.	6. Did you get the values 10.6 and 1 remaining in the numerators and 1000 in the denominator?
7. Obtain the result by doing the following math: $(10.6 \times 1)/1000$.	7. So let's do the following math: $(10.6 \times 1)/1000$.
8. The result is .0106. Type .0106 in the highlighted field now.	8. Is the result you got .0106?
Error feedback:	
1. No. Molecular weight is not part of this problem. Select another reason for this term.	1. Are you sure molecular weight is part of this problem? Maybe there is another reason for this term?
2. No need to use this term for this problem. Work on the terms that are necessary, moving from left to right to solve the problem.	2. Are you sure we need to use this term for this problem? Perhaps we should work on the terms left to right, only using the terms that are necessary for this problem.
3. Wrong. Create a ratio of the target compound, i.e., put the target compound in both the numerator and denominator. $C_6H_{12}O_6$ is not the target compound.	3. Do we need to create a ratio of the target compound, i.e., put the target compound in both the numerator and denominator? If so, is $C_6H_{12}O_6$ the target compound?

politeness serve the universally important function of minimizing threats to face (i.e., the public self-image of participants in a conversation), thereby reducing tension in human interaction that could disrupt the social order. Brown and Levinson (1987, p. 61) document the ways in which people from diverse language groups and cultures use the same politeness tactics for making requests that minimize threats to negative face (i.e., "freedom of action and freedom from imposition") and to positive face (i.e., "desire to [be] appreciated and approved of").

For example, in the context of our research on intelligent tutors, direct wording of hints or feedback (such as "Convert the units of the first term now.") can threaten negative face by restricting the student's freedom of action and can threaten positive face by implying an unwillingness to work cooperatively with the student. Based on Brown and Levinson's research on universally used politeness tactics, certain forms of polite wording for web-based tutors can reduce the threat to negative face by allowing freedom of action (e.g., "Do you want to convert the units of the first term?" or "You may want to convert the units of the first term") or reduce the threat to positive face by offering a more co-operative stance (e.g., "Let's convert the units of the first term" or "Our goal here is to convert the units of the first term."). In short, the theoretical motivation for using polite tutors in the present study is to prime the learner's universal inclination for social cooperation.

Media equation theory: The media equation refers to the idea that people "respond socially and naturally to media" (Reeves and Nass, 1996, p. 1), thereby acting as if a computer equates to a real person. According to Reeves and Nass' media equation theory, people can easily accept a computer as a social partner, especially when appropriate social cues are present. Reeves and Nass (1996, p. 10) present evidence that people treat computers as real people, responding based on "rules that apply to social relationships" rather than "rules about how to use appliances." For example, when people worked on a computer to learn a lesson, people were polite to the computer, that is, the computers were seen as "social actors that people reacted to with the same polite treatment they would give to another human" (Reeves and Nass, 1996, p. 26). Overall, Reeves and Nass (1996) and Nass and Brave (2005) provide evidence that people need a minimal amount of priming to accept a computer as a social partner. Reeves and Nass's media equation theory suggests that "we should design [computer artifacts] with social interaction in mind—that is, design interfaces that make interacting with computers even more like interacting with other people" (Churchill et al., 2000, p. 64). In the current study, we seek to use polite conversational style as a way to encourage students to view a web-based tutor as a social partner.

Social agency theory: What is the role of social cues in learning with web-based tutors? In order to address this question, Mayer and colleagues (Mayer, 2005, 2009) have proposed social agency theory as an extension of the cognitive theory of multimedia learning. As shown in Fig. 1, social agency theory is based on the idea that instructional messages—including feedback and hints from web-based tutors—may be presented in a way that does or does not involve social cues (e.g., does or does not use polite conversational style). In the top row of the figure, when a tutor's message contains appropriate social cues (such as polite wording), the learner accepts the tutor as a conversational partner, which results in increased effort to engage in cognitive processing aimed at making sense of the tutor's message, thereby creating a higher quality learning outcome. In the bottom row, when the tutor's message does not contain social cues (such as direct wording), the learner is less likely to accept the tutor as a conversational partner, and therefore the learner is less likely to work hard to make sense of the tutor's message, resulting in a lower quality learning outcome. The cognitive processes that lead to better learning are spelled out in the cognitive theory of multimedia learning (Mayer, 2005, 2009), and include selecting relevant information, mentally organizing it into a coherent structure, and integrating it with other knowledge.

Grice (1975) argues that participants in a conversation are subject to an implied social contract in which the speaker agrees to generate a message that is intended to make sense to the listener (i.e., the speaker agrees to be clear, relevant, concise, and truthful) and the listener agrees to exert effort to make sense of the message. Taking the perspective of one's conversational partner is at the heart of Grice's conversational theory, and thus a conversation is

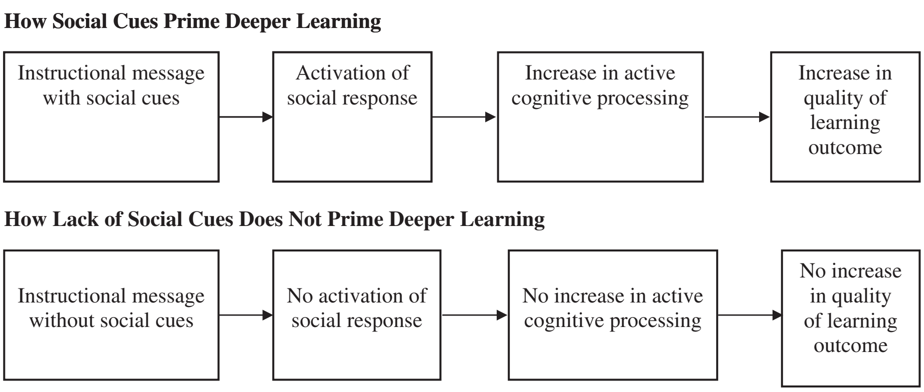

Fig. 1. Social agency theory.

an inherent social activity. When a learner accepts a computer tutor as a social partner, the learner views a tutor's message as part of a conversation, which is subject to the rules of conversation—including a commitment by the learner to try to make sense of what the tutor is saying. In our study, we seek to prime the conversational stance in learners by having tutors communicate in a polite style.

Based on the social agency theory, we predict that students who learn with polite tutors will perform better on subsequent transfer tests than will students who learn with direct tutors, and that this politeness effect will be strongest for students who have low rather than high prior knowledge. Students with high prior knowledge are more likely to engage in deep cognitive processing during learning because they can easily relate the incoming material to their existing knowledge. However, students with low prior knowledge are more likely to need some inducement to engage in deeper processing, such as trying to make sense of messages from a social partner.

1.3. Literature review

Research on politeness: Empirical research on the instructional effectiveness of polite conversional style in computer-based tutors is in its infancy, but provides some preliminary evidence to encourage using polite tutors, particularly for inexperienced learners. In a preliminary study, Mayer et al. (2006) asked college students to rate a set of printed sentences—identified as hints from a computer tutor—in terms of negative politeness (e.g., how much the tutor ''allows me freedom to make my own decisions'') and positive politeness (e.g., how much the tutor was ''working with me''). Statements that were constructed to be polite based on Brown and Levinson's (1987) theory of politeness (e.g., ''You may want to press the ENTER key'') were rated as more polite than were statements that were constructed to be direct (e.g., ''Press the ENTER key''); importantly, this politeness effect was stronger for students with low experience in using computers than for students with high experience. This research encourages the idea that students are sensitive to the level of politeness in the computer tutors' statements, especially when the students do not have extensive experience in working with computers. In this case, computing experience is a proxy for the student's domain knowledge because the sentences involved entering data on a computer or using an equation.

Having determined that learners can be sensitive to the politeness level of computer tutors' comments, the next step was to determine whether students learn better with tutors that use polite conversational style than with tutors that use direct conversational style. Wang et al. (2008) asked college students to learn to play an industrial engineering game called Virtual Factory that tutored on how to design efficient assembly line processes by giving students practical assembly line problems. In the direct version of the game, the onscreen tutor provided feedback and hints using direct conversational style (e.g., ''Save the factory now'') whereas in the polite version of the game the onscreen tutor provided feedback and hints using polite conversational style (e.g., ''Do you want to save the factory now?''). Students performed better on a subsequent 25-item posttest covering the content of the game (i.e., how to construct efficient assembly lines) if they had learned with a polite tutor rather than a direct tutor; importantly, this politeness effect was obtained for non-engineering students but not for engineering students. This research provides evidence that polite computer tutors can be more effective than direct computer tutors, especially when the learners lack domain knowledge. Wang and Johnson (2008) also found a politeness effect in a web-based tutoring system for teaching foreign language, with adults who were unfamiliar with the cultural context of the language.

In contrast, McLaren et al. (2007) did not find a politeness effect for a web-based intelligent tutor that taught high school students in a classroom setting how to solve stoichiometry problems as an extra credit assignment within a college prep chemistry class. Students solved 10 practice problems in which they received hints and feedback from a tutor that used direct wording (e.g., ''Put 1 mole in the numerator'') or polite wording (e.g., ''Do you want to put 1 mole in the numerator?''). Although the polite group performed slightly better than the direct group on a posttest, the difference was not statistically significant. Why did the McLaren et al. experiment not obtain a politeness effect whereas previous experiments did? One potentially important difference is that the learners in this experiment were predominantly high-performing students who were familiar with the material (i.e., students taking a college prep chemistry course), whereas the learners who produced a politeness effect in the previous experiments were unfamiliar with the material. In the present experiment, we explore the idea that the prior domain knowledge of the learner may be an important boundary condition for the politeness effect in which low knowledge learners are most likely to display a politeness effect.

Research on personalization: Politeness is one type of social cue that can be exhibited in a web-based tutor's communications to a learner, and a related social cue concerning the tutor's communication style is personalization (Mayer, 2005, 2009). Personalization refers to communicating with the learner by using conversational style (such as using first and second person constructions or self-revealing comments) rather than formal style (such as using third person constructions and no self-revealing comments). Based on social agency theory, Mayer and colleagues (Mayer, 2005, 2009) proposed the *personalization principle*: People learn better when the instructor's words are in conversational style rather than formal style. Mayer and colleagues (Mayer, 2005, 2009) found consistent evidence for the personalization principle in 10 out of 10 experimental comparisons, including a multimedia lesson on lightning (Moreno and Mayer, 2000, Experiments 1 and 2), a multimedia lesson on how the human respiratory system works (Mayer et al., 2004, Experiments 1, 2, and 3), and an interactive simulation game on environmental science (Moreno and Mayer, 2000, Experiments 3, 4, and 5; Moreno and Mayer, 2004, Experiments 1a and 1b), yielding a median effect size of $d = 1.11$.

In contrast McLaren et al. (2006) did not find that personalization helped university chemistry students learn to solve stoichiometry problems from a web-based intelligent tutor. McLaren et al. reported that some of the students in their study were chemistry majors whereas in the previous 10 experiments all of the learners were low in prior knowledge of the domain. It is possible that personalization effects may be stronger for low knowledge learners than for high knowledge learners. We also note that many of McLaren et al.'s subjects may have been non-native English speakers, while all of the personalization language was in English, so it is also possible the personalization principle simply had less effect in this case due to subtleties in language. Overall, there is a small but growing research base that encourages intelligent tutoring system (ITS) designers to consider not only the content of tutors' messages but also the social cues in the tutor's communication style.

2. Method

2.1. Participants and design

Ninety college students (54 women and 36 men) participated in two sessions for which they were paid a total of 30 US dollars. The experiment was based on a 2×2 between-subjects factorial design with the factors being conversational style for the feedback and hints (direct versus polite) and presentation format for the feedback and hints (text versus audio-and-text).[1] Twenty-three students were in the direct/text group, 23 in the direct/audio group, 22 in the polite/text group, and 22 in the polite/audio group. Within each group some students scored above the mean on a self-evaluation of prior knowledge in chemistry (high knowledge) and some students scored at or below the mean (low knowledge): within the direct/text group there were 11 low knowledge students and 12 high knowledge students; within the direct/audio group there were 8 low knowledge and 15 high knowledge students; within the polite/text group there were 14 low knowledge students and 8 high knowledge students; and within the polite/audio group there were 7 low knowledge students and 15 high knowledge students.

[1]The original design of the study included an additional independent variable—whether the feedback hints were provided with a human voice and printed text or with printed text alone. We also had intended to examine the cognitive consequences of providing feedback and hints with human voice and printed text rather than text alone, but later determined that voice was incorporated in a way that created redundancy thereby diminishing its effectiveness as a social cue. Therefore, we focus only on the effects of politeness in this study.

2.2. Materials, apparatus, and procedure

Participants were randomly assigned to a treatment group. They participated in two sessions—the first session lasted 2 h, and the second session lasted 1 h and occurred one week later. There were up to 10 participants in each session. Each participant sat in a cubicle facing a Mac or Dell computer with a 21-in screen and Cyber-Acoustics headphones. The cubicles were arranged so that participants could not see one another.

When participants arrived at the lab for the first session, the experimenter first explained that they would be learning about stoichiometry from a web-based computer program that consisted of training videos, practice problems, and a test. The experimenter told them that during the practice problems there would be a web-based tutor to help them and that the tutor would tell them whether their work was correct or incorrect and that they could ask for hints from the tutor if they got stuck.

The participants' first task was to read a web-based consent form and click "I agree" if they agreed to participate. Next, they created a login and password. Then, they answered a web-based demographics questionnaire that included items about their knowledge of chemistry. The first knowledge item was "Please rate your overall knowledge of chemistry" along with five response options: "highly above average," "above average," "average," "below average," and "far below average." The second knowledge item was "Please indicate the items that apply to you" followed by a checklist containing "I plan to major in chemistry," "I know what the 2 stands for in H2O," "I know what a mol is," "I have heard of Avogadro's number," "I know what NA stands for," "I know what mL stands for," "I know how many significant figures are in .0310," "I know how many grams are in a kg," "I know what stoichometry is," "I know the difference between an atom and a molecule," and "None of the above are true." For the first item a score of 1 ("Far below average") to 5 ("Highly above average") was given to each student. For the second question, if the student selected "None of the above are true" he or she was assigned a score of 0; otherwise, the student received a score between 1 and 10, based on the total number of items selected. The scores of the two questions were then added together, with a highest possible value of 15. All students who scored below the mean on the two questions (which was 9.32 for our data) were classified as low prior knowledge learners, while all students who scored above the mean were classified as high prior knowledge learners.

Once the questionnaire was completed, participants were shown a series of five short web-based videos, which corresponded to each condition (i.e., students in the polite condition saw a video with polite language, and students in the direct condition saw a video with direct language). The first video introduced the topic of stoichiometry, the second video explained the user interface of the stoichiometry problems within the lesson, and the following three videos explained the concepts behind and how to solve various kinds of stoichiometry problems.

After viewing these videos, participants began work on the first of 10 practice problems presented by the stoichiometry tutor based on the participant's treatment condition. The top of Fig. 2 shows an example of a practice problem with direct feedback and hints whereas the bottom of Fig. 2 shows an example of a practice problem with polite feedback and hints. If the participant was in the audio-and-text treatment, in addition to seeing the printed text, the participant also heard an audio recording of a human voice saying the same words as in the printed text (via headphones that they were instructed to put on). Table 1 provides examples of the wording of direct and polite comments made by the web-based tutor. As exemplified in Fig. 2, each practice problem contained the text of a stoichiometry problem to solve, text boxes for participants to type in the relevant numbers for each step, and pull-down menus for participants to select the correct units, substance, and reason for each step of the problem. If the number typed (or the unit, substance, or reason selected) was correct, the typed (or selected) information appeared in a green font and occasionally positive feedback was given by the tutor in the polite condition, following Brown and Levinson's (1987) "overt expressions of approval" form of politeness. If the information was incorrect, it appeared in a red font and occasionally an error message appeared below the practice problem, if the subject took a step that matched an error or misconception known by the intelligent tutor. At the top right-hand corner of the problem there was a "hint" button where participants could click to see a hint from the tutor. The hints gave progressively more information for solving the problem, with the last hint on each step giving the final answer for that step (the "bottom-out hint"). During the practice problems, participants had the opportunity to review any of the videos (which they could select from a pull-down menu). The first two practice problems dealt with scale conversion.

After the first two practice problems, participants viewed another video that explained molecular weight, and then completed two practice problems dealing with this sub-topic. Next, they watched a video on composition stoichiometry, followed by two more problems. A final

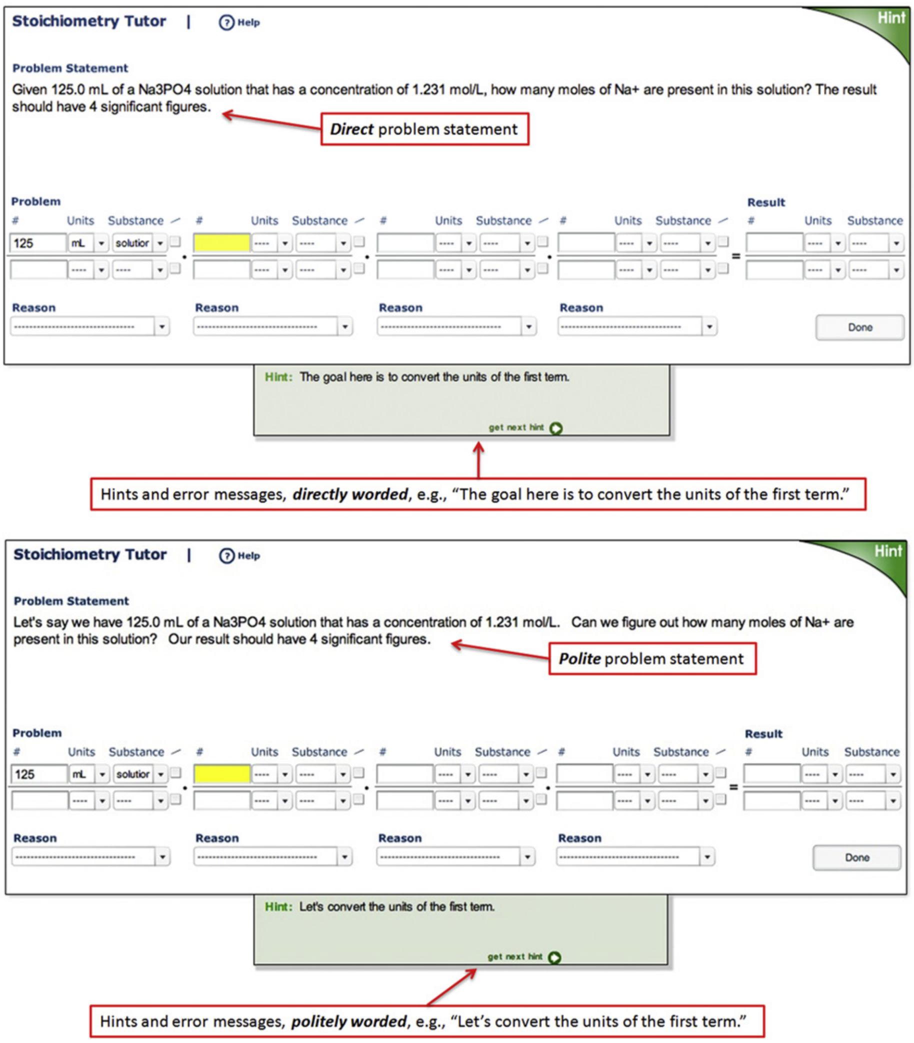

Fig. 2. Screen shot of direct and polite versions of a practice problem.

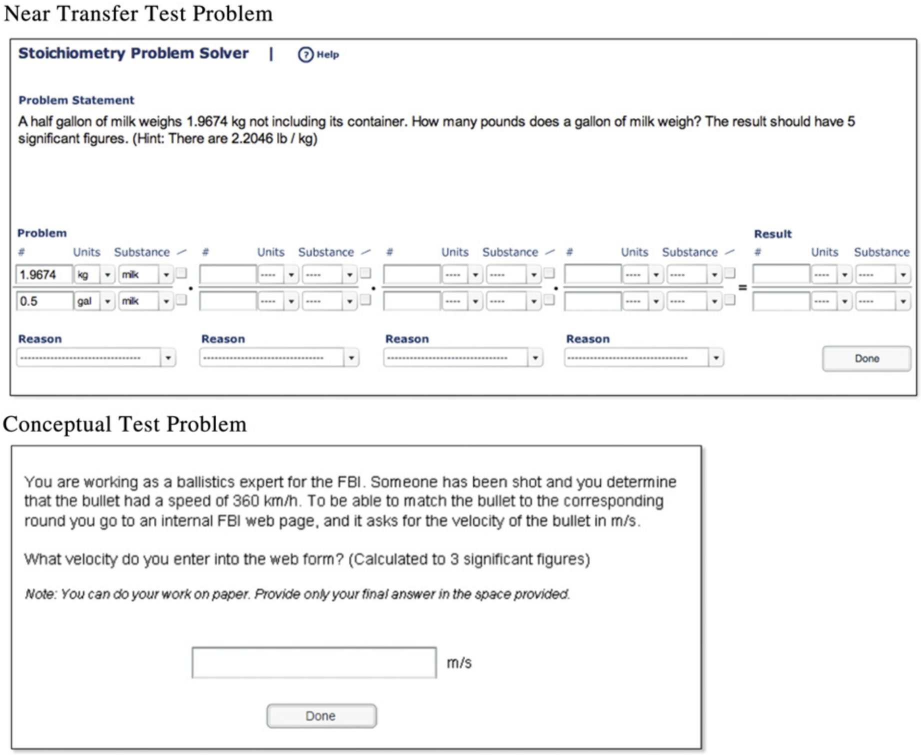

Fig. 3. Examples of test problems.

instructional video explained solution concentration, followed by the final four practice problems.[2]

Participants next completed the first test (the immediate test). This test contained eight problems, four of which were of the same type and had the same user interface as the practice problems (*near transfer*) and four of which were more conceptual questions for which participants provided a final result in one or two boxes (*conceptual questions*). The near transfer problems dealt with weight unit conversions, molecular weight conversions, composition stoichiometry, and solution concentration conversions and the far transfer problems dealt with velocity unit conversions, general knowledge of the mole, general knowledge of chemical formulas, and proportional reasoning. Fig. 3 shows an example of both a near transfer problem and a conceptual question. The tests were scored by calculating an average per problem (i.e., by dividing the number of correct steps the student took on a single problem by the total number of correct steps for that problem).

Exactly one week later, participants returned to the lab for the second (delayed) test. This test also contained eight problems—four near transfer questions and four conceptual questions—that were analogous to but different from the immediate test. The order of the two tests was counterbalanced across participants (i.e., half of the participants received test A as the immediate test and test B as the delayed test, and vice versa). Upon completion of the delayed test, participants were debriefed, thanked, and given their payment.

3. Results and discussion

Does politeness affect learning outcomes as measured by the immediate posttest? The top row of Table 1 shows the mean score (and standard deviation) on the immediate posttest for low and high knowledge students who learned with a polite or direct tutor. An analysis of variance[3] performed on these data revealed a significant interaction between knowledge level and politeness, in which politeness helped the low knowledge learners but not the high knowledge learners, $F(1, 81) = 6.50$, $MSE = .03$, $p = .01$. A separate analysis of variance for low knowledge students revealed a

[2]After all of the instructional videos and practice problems, participants responded to a web-based questionnaire that asked about the effectiveness, helpfulness, and the likeability of the tutor. We do not include these results in this report because we were not satisfied with the wording of the questionnaire and the results were inconclusive.

[3]We examined the distribution of scores on individual questions before undertaking further analyses and there were no significant differences at the question level; therefore, all ANOVAs reported in the results section are based on the total score across all 8 test questions. The ANOVAs reported in the results section also included audio (text versus text-plus-audio) as a between subjects factor and total number of hints requested as a covariate. The audio treatment yielded no significant main effects or interactions except on the delayed posttest where there was a significant interaction between audio and knowledge in which adding speech to text hurt the performance of high knowledge learners ($M = .82$, $SD = .21$ for direct; $M = .72$, $SD = .24$ for polite) but helped the performance of low knowledge learners ($M = .54$, $SD = .19$ for direct, $M = .56$, $SD = .17$ for polite), $F(1, 89) = 4.09$, $MSE = .04$, $p = .046$.

Table 2
Proportion correct on immediate and delayed posttests for four groups.

Test	Group									
	Low knowledge					High knowledge				
	Direct		Polite			Direct		Polite		
	M	*SD*	*M*	*SD*	*d*	*M*	*SD*	*M*	*SD*	*d*
Immediate	.48	.18	.59	.19	.64*	.83	.21	.72	.19	−.58
Delayed	.50	.17	.58	.17	.50*	.81	.21	.76	.25	−.21

*Indicates $p<.05$.

Table 3
Mean number of hints and error messages during learning for four groups.

Test	Group									
	Low knowledge					High knowledge				
	Direct		Polite			Direct		Polite		
	M	*SD*	*M*	*SD*	*d*	*M*	*SD*	*M*	*SD*	*d*
Hints	46.23	28.78	54.48	44.18	.23	10.92	15.60	21.10	20.89	.57*
Errors	64.95	20.66	65.00	32.34	.00	29.29	19.73	38.33	16.74	.50
Total	111.18	38.94	119.48	71.41	.15	40.21	27.90	59.43	27.47	.71*

*Indicates $p<.05$.

politeness effect, in which students who learned with a polite tutor performed better on an immediate posttest than did students who learned with a direct tutor, $F(1, 40)=6.27$, $MSE=.15$, $p=.02$. The effect size favoring the polite tutor was $d=.64$, which is considered a medium-to-large effect (Cohen, 1988). This effect seems to be driven by near transfer problems, $F(1, 40)=6.32$, $MSE=.17$, $p=.02$, rather than conceptual problems, $F(1, 40)=1.26$, $MSE=.02$, $p=.27$, indicating that the polite tutor helped students better understand the procedural knowledge required for solving these problems. In contrast, a separate analysis of variance for high knowledge students revealed a non-significant trend in the opposite direction, in which students who learned with a polite tutor performed worse on an immediate posttest than did students who learned with a direct tutor, $F(1, 40)=.28$, $MSE=.01$, $p=.60$. The effect size favoring the direct tutor was $d=-.58$, which is near the medium range. Overall, students' performance on the immediate posttest reflects an expertise reversal effect (Kalyuga, 2005)—that is a pattern in which politeness improves learning for low knowledge learners but not for high knowledge learners. This pattern is consistent with the predictions of social agency theory.

Does politeness affect learning outcomes as measured by the delayed posttest? The second row of Table 2 shows the mean score (and SD) on the delayed posttest for low and high knowledge students who learned with a polite or direct tutor. Although the pattern is similar to that obtained on the immediate posttest, the politeness × knowledge interaction did not reach significance, $F(1, 81)=1.44, MSE=.03$, $p=.23$. However in separate analyses, for low knowledge students, the polite group performed significantly better than the direct group, $F(1, 40)=4.46$, $MSE=.10$, $p=.04$, $d=.50$, whereas for high knowledge students the polite and direct groups did not differ significantly, $F(1, 49)=.30$, $MSE=.01$, $p=.59$, $d=-.21$. Overall, the pattern of performance on the delayed posttest is similar to that obtained for the immediate posttest, but the interaction was not significant.

Does politeness affect learning processes as measured by error messages and hints? Table 3 shows the mean number of error messages seen and hints requested (and SD) during learning for low and high knowledge students who learned with a polite or direct tutor. An analysis of variance performed on these data did not reveal a significant interaction between knowledge level and politeness, $F(1,82)=.28$, $MSE=2047.67$, $p=.60$, although high knowledge learners requested fewer hints and received fewer error messages than low knowledge learners, $F(1,82)=46.28$, $MSE=2047.67, p<.001$. A separate analysis of variance for low knowledge students revealed no significant difference between students who learned with a polite tutor versus the direct tutor, $F(1, 41)=.38$, $MSE=1254.83$, $p=.54$, $d=.15$. This was also the case when hints and error messages were analyzed separately for low knowledge students, $F(1, 41)=.003$, $MSE=769.09$, $p=.95$ for errors and $F(1, 41)=.84$, $MSE=1364.71$, $p=.37$ for hints. In contrast, a separate analysis of variance for high knowledge students revealed that students received more error messages and asked for more hints with the polite tutor than the direct tutor, $F(1, 41)=6.16$, $MSE=4726.10$, $p=.02$, $d=.71$. When analyzed separately, this effect held for the number of hints requested, $F(1, 41)=5.66$, $MSE=1686.97$, $p=.02$, $d=.57$ but not for the number of error messages seen, $F(1, 41)=2.19$, $MSE=765.85$, $p=.15$, $d=.50$ (but note that although not significant, there is still a medium effect size). In other words, high knowledge students requested more hints when the tutor was polite rather than direct. These results suggest that for high knowledge students, problem solving was more difficult with a polite tutor. Overall, students' performance during learning shows that politeness was disruptive to high knowledge students but not low knowledge students. This pattern is consistent with the predictions of social agency theory.

4. Conclusion

4.1. Empirical contributions

A politeness effect occurs when students learn better with a web-based tutor that communicates in polite style rather than direct style. The main finding in this study is a pattern showing a politeness effect for low knowledge learners but not for high knowledge learners. The discovery that the politeness effect works for low rather than high knowledge learners helps to bring coherence to the research base on polite tutors. Wang et al. (2008) found a politeness effect in an industrial engineering simulation game for a group of non-engineering students at one university but not for a group of engineering students from another university. In a subsequent study, Wang and Johnson (2008) reported a politeness effect in a foreign language learning game for adult learners who were unfamiliar with the cultural context of the language. In contrast, McLaren et al. (2007) did not find a significant politeness effect in an interactive chemistry problem-solving lesson for high school students who were taking a college prep chemistry class and thus might be considered to be more knowledgeable about chemistry than average. The present study is the first to directly compare the learning effects of polite and direct tutors for high and low knowledge learners within the same experiment. The results help to establish an important boundary condition for the politeness effect, in which the politeness effect occurs for low knowledge learners but not for high knowledge learners.

4.2. Theoretical contributions

The results for low knowledge learners are consistent with the social agency principle (as well as relevant aspects of politeness theory and media equation theory), which posit that learners will try harder to make sense out of the tutor's comments when they feel that the tutor is a social partner. According to these theories, when the tutor uses polite conversational style, the learner is more likely to accept the tutor as a social partner and therefore try harder to understand the tutor's hints and feedback. Thus, politeness fosters generative processing—organizing the material into a coherent structure and integrating it with other relevant knowledge.

Why does politeness not help high knowledge learners but help low knowledge learners? High knowledge learners are more likely to naturally engage in generative cognitive processing during learning by virtue of having access to relevant prior knowledge that can be used for integrating and organizing the incoming information. Thus, the added politeness features may not be needed, and in some cases high knowledge learners may even find the polite wording to be condescending or otherwise annoying. In contrast, low knowledge learners are more likely to respond to the tutor's social engagement approach (i.e., the polite wording) and therefore engage more deeply in low-level processing of the incoming material. This interpretation is consistent with the significant results on the immediate test but is limited by the fact that the same pattern of results did not reach significance on the delayed test.

4.3. Practical contributions

The results provide partial support for an important instructional design principle that can be called the *politeness principle*, in that students who are inexperienced learn better from a web-based tutor when the tutor's feedback and hints are presented in polite style rather than direct style. In short, this study suggests that politeness may be most useful when learners are not familiar with the material and the learning environment. Overall, when the learners are novices, instructional designers should consider the social intelligence of web-based tutors, focusing not only on what tutors say but also on *how* they say it. More specifically for intelligent tutoring systems, which can adapt their instruction to student knowledge levels, the implication is that such systems should monitor changes to student knowledge and switch from polite to direct language at an appropriate time during instruction.

4.4. Limitations and future directions

The present study is limited in that it took place in a laboratory rather than a classroom setting and lasted a short time. Thus, further research is needed to determine whether the politeness effect extends to more authentic learning environments. The content focused on a somewhat lock-step procedure for solving equations, so future research is needed to determine whether the politeness effect extends to other kinds of learning objectives with more conceptual material. Future research is needed that includes effective assessments of the amount of effort learners devote in trying to make sense of the tutor's comments during learning. Finally, research is needed on how best to fade a web-based tutor's politeness, that is, to determine how long it is necessary for a tutor to be polite before it becomes a hindrance to the learner. This type of adaptation is an important focus of ITS research; the key is in determining the optimal moment and manner to fade from polite to direct language based on an ITS's model of student knowledge. Overall, a useful theoretical and practical goal for the instructional design of intelligent tutoring systems is to contribute to our understanding of how and when a web-based tutor's politeness can improve a student's learning.

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