The Role of Affect and Sociality in the Agent-based Collaborative Learning System

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Abstract. As computer systems are evolving and coming to be regarded as social actors, the importance of social intelligence that enables natural and socially appropriate interactions is gaining a growing interest among the human-computer interaction researchers. This article discusses the definition, importance, and benefits of social intelligence as agent technology. It then describes a collaborative learning system that incorporates agents that are equipped with a social intelligence model. We argue that socially appropriate affective behaviors provide a new dimension for collaborative learning systems. The system provides an environment in which learning takes place through interactions with a coaching computer agent and a co-learner, an autonomous agent that makes affective responses. The social intelligence model that handles affective responses is based on psychological theories of personality, emotion, and human-media interaction, such as appraisal theory and the Media Equation. Experiments conducted with this collaborative learning system to examine the effect of the social intelligence model suggested that users had more positive impressions about the usefulness, the application, and their learning experience when the co-learner agent displayed social responses with personality and emotions than when it did not express them. It should be noted here that the co-learner agent did not provide any explicit assistance for the learner, such as giving clues and showing answers, yet it influenced the user's evaluation on the usefulness of the learning system. Experimental data also suggest that the co-learner agent contributed to the effectiveness of the learning system.

Introduction

A recent new direction of research in human-computer interaction is to integrate sociality into human-computer interaction. As computer systems are becoming more and more ubiquitous, they are evolving from computing machines to communication machines. A speech-enabled automated system is an example of such machines. In this trend, computer systems are coming to be regarded as social actors rather than simply as tools. The ability involved with social aspects of interactions may be referred to as 'social intelligence', which makes contrast with 'rational intelligence' (Katagiri, 2003). 'Rational intelligence' refers to the kind of intelligence that artificial intelligence has traditionally dealt with. According to Katagiri (2003), it is goal-oriented intelligence that enables one to find an answer to a question, generate a solution to a problem, and so on. 'Social intelligence' is the type of intelligence that enables one to share information and feelings with others, and behave in such a way one is accepted as a member of a community.

Our research is concerned with the development and application of social intelligence for computer-assisted learning. Education, as traditionally interpreted through classroom-based school systems, is a social activity in many respects, particularly in that learning is mediated and influenced by the content and manner of social interactions between teachers and students, and among students. We argue that affective aspects of those social interactions can be utilized to make learning activities more effective and beneficial. In recent years, there has been a major shift in the paradigm of computer-supported learning. The research efforts on learning systems have traditionally been centered on individualized environments where a single user interacts with the computer system, which often serves as a teacher or a tutor. The new trend is an emphasis on collaborative learning environments (Goodman, Soller, Linton, & Gaimari, 1998; Kasai & Okamoto, 1999). There are two kinds of benefits for learning in the collaborative learning environment. One is what is often called 'learning by teaching,' in which one can learn given knowledge by explaining it to another learner. The other benefit is often called 'leaning by observation,' in which one can learn given knowledge by observing another learner working on problem solving, teaching other learners, and so on.

While in these approaches to collaborative learning, learning takes place in the interactions between the learners, the kind of intelligence these approaches are primarily concerned with is knowledge-based, goal-oriented, and rational, and thus social intelligence might only be utilized as a side effect. In contrast, our approach attempts to make use of affective and social intelligence in a more direct manner.

In this article, we discuss the theoretical model of social intelligence and our implementation of it in a collaborative learning system. We then present a report of an experiment conducted to examine the effects of the social intelligence model in the learning system.

Collaborative Learning System

We have developed an agent-based learning system incorporating social intelligence for human-machine interaction. We call it the *e-School* system. In addition to the social intelligence model, a distinguishing characteristic of our system is the introduction of an embodied co-learner agent. The co-learner, as its name indicates, is learning alongside the human student, has no additional knowledge on the subject nor explanations to provide, and is also lacking "ulterior" motives – such as eliciting nuanced explanations from the student – as is the case with some intelligent tutoring systems (for example, see Goodman, et al., 1998).

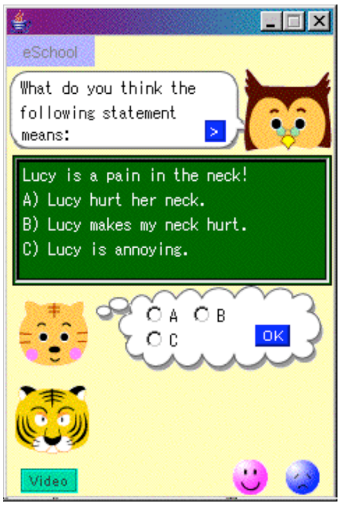

Fig. 1. Interface of e-School System.

Embodied, interactive computer characters have been shown to be effective teachers by increasing interest and transfer of knowledge (Moreno, et al., 2001), yet these studies have often focused the nature of interaction in a one-to-one interaction between the teacher agent, assuming roles such as tutor or coach, and the human learner. We argue that the presence of an embodied co-learner character provides increased richness in the social interaction space, which leads to increased learning.

As shown in Figure 1, our learning system employs a classroom metaphor, with the traditional chalkboard. There are three cartoon characters in the classroom: a teacher agent, a student agent, and an avatar for the human learner. In Figure 1, the teacher agent is represented by an owl, shown to possess wisdom attributes across cultures, the co-learner agent is represented by a tiger, and the human learner has chosen the representation of a cat. Interactions occur between the teacher and each learner, as well as between the learners. Furthermore, one type of interactions may influence the other type of interactions. For example, when the teacher gives the co-learner feedback to its answer, the human learner may want to comment on it.

The agents are equipped with the social intelligence model that controls their behaviors, including emotional expressions. The avatar's behavior is partially autonomous and can also be directly manipulated by the human learner. Each agent has its own profile that defines the attributes of its personality and the role it plays (e.g., teacher, co-learner). The social intelligence model uses the profile information to generate the agents' behaviors. Although the user may only click on appropriate answers and emotions, the agents and the avatar use facial expressions (see Figure 2) as well as text output to communicate with each other. A chalkboard is available for the teacher agent and the students to present learning materials. The current version (version 1) of the *e-School* system has the functionality that meets the minimum requirements for demonstration and the experiment reported below. The social intelligence model implemented in this version is still simple, but is complex enough to study some affective factors such as liking, emotion, and personality. Though not yet implemented yet in the current system, in terms of the architecture, it is possible to place more agents and avatars in the environment.

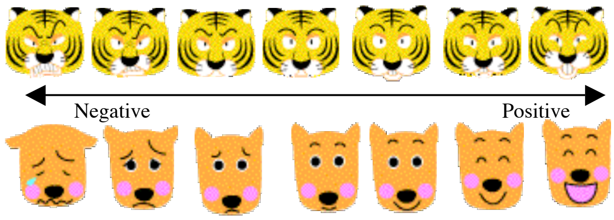

Fig. 2. Examples of the Agents' Facial Expressions

Theoretical Model of Social Intelligence

In this section, we discuss the theoretical bases for the social intelligence model implemented in the *e-School* characters. Unlike some intelligent tutoring systems, *e-School* uses the character's emotional models to engage the human learner, and motivate him or her to learn the content, rather than modeling his/her affective states and understandings. Appraisal theories of emotion and most emotion theorists in general agree that emotion is essentially a reaction to events deemed relevant to the needs and goals of an individual (Brave & Nass, 2003). At the most basic level, the achievement of goals leads to happiness, and the failure to achieve goals leads to sadness: this is the current level employed in our system.

Various versions of appraisal theory exist which specify in greater detail the critical properties of a goal-relevant event that lead to specific emotions (e.g., frustration, anger, hope, etc.). Goals can take many forms, but Maslow's Hierarchy provides a useful way of categorizing these goals. In his later work, Maslow (1968) grouped an individual's basic needs into eight categories:

Physiological: hunger, thirst, bodily comforts, etc.
Safety/security: being out of danger

Social: affiliate with others, be accepted
Esteem: to achieve, be competent, gain approval and recognition
Cognitive: to know, to understand, and explore
Aesthetic: symmetry, order, and beauty
Self-actualization: to find self-fulfillment and realize one's potential
Transcendence: to help others find self-fulfillment and realize their potential.

In the *e-School* system, we focus on *social* and *esteem goals*. We also arguably take *cognitive goals* into account, but we do not distinguish these from *esteem goals*. A strong argument can be made that social, esteem, and cognitive goals are the most appropriate for artificial agents given that computer agents do not have true physical form (so do not need to worry about food or safety issues) and do not have enough intelligence to be concerned with aesthetics or higher level goals.

Unlike appraisal theory, current 2-factor theories of emotion (e.g., Lang, 1995) do not focus on what causes emotion, but instead argue that all emotions can be fully described using two dimensions: valence (positive/negative) and arousal (low/high). The *e-School* social intelligence can be seen to employ 2-factor theory, in addition to appraisal theory, since our current emotion model includes valence (as a dichotomous variable) and arousal (as a continuous variable).

Brave (2003) extends appraisal theories of emotion to develop a new theoretical framework for empathy. The basic idea is that when we care about another person (i.e., value their welfare), we may take on some of their goals as if they were our own. Such "adopted" goals may now lead to emotion just as any of our own personal goals. When we react emotionally to adopted goals, it is called "empathy."

To illustrate, let us assume that student #1 self-formulates the goal of answering a question correctly. Based on appraisal theory, this student will become happy if successful and sad if not. If a second student (student #2) is a good friend of student #1, then student #2 will also want student #1 to get the answer correct; in other words, student #2 will "adopt" student#1's goal because he/she cares about student #1. Now student #2 may also become happy or sad depending on whether student #1 answers correctly or incorrectly, an empathic response. Although not discussed in the literature, it is reasonable to imagine that the intensity (arousal) of the emotion empathically experienced as such is related to the degree of caring or friendship for the target of empathy. In the *e-School* environment, we can have the co-learner agent behave as if it had empathy toward the human learner, displaying that it cares about him/her. Then, it would follow that if these behaviors are done appropriately, they could impact the human learner to achieve their goals.

Interpersonal attraction (including liking and affiliation) is considered to be a fundamental component of social psychology. The two employed in the *e-School* social intelligence are the *reinforcement-affect model* (Clore, & Byrne, 1974) and *balance theory* (Heider 1958). According to the reinforcement-affect model, likes and dislikes are based on whether positive or negative feelings are aroused. We like any rewarding stimulus because of our positive feelings, and we dislike any punishing stimulus because of our negative feelings. When a stranger (or any other neutral stimulus) is present at the same time, that person becomes associated with the positive or negative feelings. This conditioning results in liking for any stranger associated with positive feelings and dislike for any stranger associated with negative feelings.

This reinforcement-affect model is strongly related to the "don't kill the messenger" phenomenon (Reeves & Nass, 1996) that says that the receiver of a message often orients emotionally toward the most proximal source of a message (i.e., the message deliverer) rather than the true source of the message, who may be at a distance.

Combined with emotion appraisal theory, the reinforcement-affect model can also be used to explain the phenomenon of *liking reciprocity* (Berscheid & Walster, 1978; Curtis & Miller, 1986), which says that we tend to like people who like us. Being liked meets our social goals, which according to appraisal theory makes us happy. The reinforcement-affect model then says that we will like the person that made us happy, and so we get reciprocal liking.

Balance theory of Heider (1958) extends this notion of liking reciprocity to groups of three (triadic reciprocity). If person #1 likes person #2, then person #1 tends to like those things (or people) that person #2 likes. If, on the other hand, person #1 *dislikes* person #2, then person #1 tends *not* to like those things (or people) that person #2 likes. Effects can also occur in the reverse direction: if two people like the same thing (or person), they tend to like each other. If, on the other hand, they disagree about some thing (or person) they tend to *dislike* each other.

Although caring (as discussed above in relation to empathy) can be considered a social-psychological construct distinct from liking, the two are often very highly correlated. As such, a modeling approximation used in the *e-School* intelligence is to consider them the same dimension.

Experiment

This section presents the experiment that we conducted to examine the effect of the social intelligence model in the collaborative learning system described above. For this initial testbed, our domain was English idioms for intermediate learners of the language, in particular, Japanese students. The lesson consisted of fifteen questions across three levels of difficulty. Questions were of the single-correct or multiple-choice format, drawn from standard English idiom teaching materials, such as "choose all the answers that apply," "choose the correct answer," and "choose the incorrect interpretation." Instructions for answering each kind of question were clearly presented before each section.

The entire lesson format followed a sequence where the teacher agent presents a question, the learners' choose a response from available choices, the teacher provides feedback on the response and concludes with further explanations on the question. For example, a sample question within the "easy" category in this format was presented as:

> [Instructions:] Teacher Agent Says:
>
> "What do you think the following statement means:"
>
> [Statement:] "Lucy is a pain in the neck!"
>
> [Chalkboard displays answer choices]:
>
> Possible Interpretations:
>
> a) "Lucy hurt her neck."

b) "Lucy makes my neck hurt."
c) "Lucy is annoying."
d) I don't know.

[Learners choose their answer]
Correct Answer: (c)
[Teacher grades the answer:] Teacher Agent Says:
"That is correct/incorrect"
[Follow up Explanation:] Teacher Agent Says:
"Calling someone a pain in the neck is not very nice – and something people tend to say only when the "pain in the neck" person is not present. It means they are annoying or troublesome to you, perhaps because they ask too many questions or put too many demands on your time."

Method

Participants:
A total of seventy-seven (77) undergraduate students at International Christian University (ICU) participated in the experiment. All participants were native speakers of Japanese learning English.

Design:
Three versions of the application were prepared for the experiment:

a) No co-learner agent (No Agent Condition)
On the interface, there were only the teacher agent and the avatar.
b) Co-learner agent without social intelligence model (No Social Model Condition)
On the interface, there were the teacher agent, the co-learner agent, and the avatar. The co-learner agent did not have social intelligence and as such it did not display any emotional or social responses, having what is often referred to as a neutral or 'poker face.'
c) Co-learner agent with social intelligence model (Social Model Condition)
On the interface, there were the teacher agent, the co-learner agent, and the avatar. The co-learner agent was controlled by the social intelligence model. It had friendly and mildly dominant or confident personality, and graphically displayed emotional and social responses depending on the human learner's performance in class.

Procedure:
The experiment was conducted in ICU's language lab, where all the participants participated in the experimental session together. Each participant was randomly assigned to one of the conditions. The participants first received the instructions on how to work with the application verbally and in writing. Following the self-

enrollment procedure, the participants had the experimental session of learning English idiomatic expression using the application. The session was conducted in the following way. For each problem, the teacher agent presented a question, showing it on the blackboard. Then the human learner made a response, by choosing one of the alternatives. In this case, the response was not disclosed to the teacher or the co-learner. In other words, the learner simply thought of an answer in her mind. The teacher either called on the human learner's avatar or the co-learner agent to answer. The teacher agent then gave feedback (positive or negative). If the human learner had answered, the co-learner agent made a reaction to the situation. If the co-learner agent had answered, the human learner was given a few possible reactions to choose from. Then, the teacher agent gave a brief explanation about the expression independent of the student choice; that is, whether the student answered correctly or incorrectly, s/he will hear and see the idiom explanation. Thus, every participant is privy to the same amount of information, presented in the same order, independent of the rightness of his or her answers.

The relationship between the human learner and the character co-learner is one of peer-to-peer, without the hierarchical relationships that additional knowledge or mastery of the language that other language learning character-based systems use in practice coaches (see for example, Extempo's FLOW system in Maldonado & Hayes-Roth, 2004).

After the teaching session was over, the participants responded to a questionnaire that presented as a web page and displayed on the computer's internet browser. It included questions concerning impressions on the application, the co-learner agent, and user experience. A short quiz - also online - followed to measure the participants' performance on recall and recognition of the idiomatic expressions presented in the lesson, selecting from thirty true/false and eleven fill in the blank questions. The experiment took approximately an hour for each participant.

Results and Discussion

Quiz Results and Self-assessment of Learning

The effectiveness of the application was first examined based on the results of the content quiz, which are shown on Table 1. The participants in the two co-learner conditions (Social Model and No Social Model) attained higher scores of correct answers in the forty-one content questions than those in the no-agent condition. Furthermore, students in the Social Model Condition left a fewer number of questions blank than students in the other two conditions. These results seem to indicate that the co-learner produced greater retention of the lesson, and that participants were more motivated to answer the questions, even guessing their response, when they worked with the co-learner agent with social intelligence model.

In addition to the content quiz, the post-experience questionnaire assessed how much (in a 10-point scale) the participants felt they had learned the materials. The results are shown on Table 2. The statistical analysis showed that the participants' self-assessment of their learning was significantly higher for the co-learner conditions (Social Model and No Social Model) than for the No Co-learner Condition [$F(1, 76)$ =

5.32, p < .05]. This pattern of results indicates that the participants had more positive impressions about their experience and the content of learning when they worked with a co-learner agent.

Condition	Percentage of Correct Responses	Percentage of Responses left blank
No Co-learner	51%	27%
Co-learner without Social Intelligence Model	60%	22%
Co-learner with Social Intelligence Model	69%	07%

Table 1. Quiz Results (Ratio to the total number of responses)

However, the difference between the two co-learner agent conditions (Social Model and No Social Model) did not turn out to be significant [F(1, 76) = .26, n.s.]. Does this mean that the social intelligence model had no effect on the students' learning experiences? To examine this question, further analyses were performed on other aspects of the participants' learning experiences and impressions.

	No Agent	Agent (No Social Intelligence Model)	Agent (Social Intelligence Model)
Mean	3.86	4.96	5.28
SD	2.08	2.34	2.31

Table 2. Self-assessment of Idiom Learning

Evaluation of Co-learner Agent

We first tested whether the participant's impression of the co-learner's characteristics (evaluation in a 10-point scale) varied depending on the presence or absence of social responses. The analysis showed that the Social Model Condition marked significantly higher scores than the No Social Model Condition in the following evaluation items:

(1) Cooperativeness [F(1, 51) = 13.82, p < .01]

(2) Trustworthiness [F(1, 51) = 8.56, p < .01]

(3) Feels warm [F(1, 51) = 6.6.5, p < .02]

These results showed that the social intelligence model and behaviors generated by it had more positive influence on the impressions of the co-learner agent.

Evaluation of Leaning System

As stated above, the purpose of this study was to investigate the effect that the affective aspects of social intelligence may have on the usefulness and impression of the learning system. The question we should ask is how those impressions and evaluations that the participants had about the agents influenced the evaluation of the application as a whole. In other words, how could the social intelligence model affect the evaluations of the characters, and in turn have an effect on the evaluation of the learning system itself?

Before broaching into this question, there is one factor that we should take into consideration. The analysis indicated that under both of the Social Model Condition and the No Social Model Condition, the impressions on the application was dependent on how the participant was attracted by the agent [$F(1, 51) = 12.16$, $p < .01$]. This means that regardless of the presence of social intelligence, liking varied from person to person. That is, some individuals liked the agent without social responses more than others and some liked the agent with social responses less than others, depending on their personal preferences. Similar results have been observed with characters based on personality similarities and differences, indicating the possibility that this preference may be generalizable based on each participant's personality characteristics (see Reeves and Nass, 1996). To control for this personal preference effect in the analysis of the effect of the social intelligence model, an analysis of covariance was performed with personal preference on the agent as a covariate. The result revealed that the main effect of the social model on the evaluation of the application was found in the following items:

(1) Ease of use [$F(1, 51) = 6.11$, $p < .02$]
(2) Satisfaction (Would recommend it to others) [$F(1, 51) = 4.82$, $p < .04$]
(3) Pleasantness in learning (Not frustrated) [$F(1, 51) = 6.62$, $p < .02$]
(4) Supportivenss [$F(1, 51) = 3.28$, $.05 < p < .08$]

For these evaluation items, the Social Model condition marked higher scores than the No Social Model condition.

These results seem to suggest that the social intelligence model and the social responses (i.e., friendly and confident) generated by the model had positive impact on the impressions on the learning system as a whole.

Finally, some may argue that it was not the model-based affective responses that impacted on the participants. In other words, as long as they are friendly, random and superficial responses could do as well as the model-controlled social responses. To this question, the present experiment does not offer a definitive answer since the study compared the agent with the social intelligence model and the one without. However, a closer analysis on the No Social Model Condition revealed the potential mismatch between the anthropomorphism suggested by the animated appearance of the co-learner and the lack of socially appropriate responses. This mismatch in the No Social Model Condition could violate the participant's expectations and lead to negative impressions. The analysis of covariance with the system impression as a covariate showed that the participants felt it was significantly less enjoyable to work with the system in the No Social Model Condition, when compared both with the Social Model Condition and the No Agent Condition [$F(1, 76) = 5.25$, $p < .03$]. This result seems to indicate that the lack of appropriate affective responses of an embodied agent is worse than the absence of an agent. In light of this finding, we would argue that participants may not respond to the superficial level of affective responses of an agent (i.e., randomly generated affective response) rather showing greater sensitivity to the naturalness of such response patterns. In that regard, the social intelligence model plays an important role in the interaction.

In summary, the results of the experiment provided support for the following assertions:

(1) The co-learner agent contributed to the effectiveness of the learning system.

(2) The users had more positive impressions about the usefulness and the application and learning experience when the co-learner agent displayed social responses indicating personality, emotions, and awareness of the human learner's emotions (empathy).

It should be noted here that the co-learner agent in the current system did not provide any explicit assistance for the learner such as giving clues and showing answers. It only made some limited social responses such as praise, encouragement, and comfort (typical responses include "that was a hard question!"). Yet, the participant's evaluation on the usefulness of the learning system was influenced by such an agent. These results are consistent with the claims that Media Equation theory (Reeves & Nass, 1996) makes. That is, even if the co-learner is an artificial entity like a software agent with simple animation, a social relationship will be inferred by the human user, and social-psychological behaviors of the user can be influenced according to the nature of interactions that takes place on that relationship.

Conclusion

In this article, we discussed the social intelligence that renders affective behaviors of software agents and its application to a collaborative learning system. We argued that socially appropriate affective behaviors would provide a new dimension for collaborative learning systems. We presented the experiment that tested our hypothesis using our implementation of the collaborative learning system. The experimental data seem to agree that social and affective agents have a great potential to enhance learning.

As noted above, our system is on the initial stage and the social intelligence model is still rather simple and limited. It is encouraging that even such a simple model could generate significant effects on certain aspects of the user experience and achievement of the goal (i.e., English idiom learning). Needless to say, there are more challenges and issues with the development of and research on social intelligence. Obviously, the social intelligence model should be further enhanced. In order for that, a better understanding of social intelligence, especially in terms of modeling, must be gained. Second, further studies are needed to substantiate our claims on the social and affective aspects of collaborative learning in education. There are probably some universal characteristics about the nature of interactions and collaborations across different educational domains beyond foreign language learning, but there must also be differences depending on the educational domain and on the educational goals of the application. Different pedagogies may result in applications as widely varying within the same domain as those across domains. The better we understand the dynamics of social interactions, the better the social model can be. In that regard, collaborations among researchers in the related fields such as human-computer interaction, artificial intelligence, psychology, and education should be sought out. Our team is certainly growing in that direction, and we expect to make more progress in the near future.

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