Simulating Instructional Roles through Pedagogical Agents

Amy L. Baylor, *Center for Research of Innovative Technologies for Learning (RITL), Dept. Educational Psychology & Learning Systems, Florida State University*
baylor@coe.fsu.edu
http://ritl.fsu.edu

Yanghee Kim, *Dept. Instructional Technology, Utah State University*
yanghee.kim@usu.edu

Abstract. This paper describes the design and empirical validation of three distinct pedagogical agent roles (Expert, Motivator, and Mentor) for college students within the MIMIC (Multiple Intelligent Mentors Instructing Collaboratively) agent-based research environment. The pedagogical agent roles were operationalized by image, animation, affect, voice and script, and were developed in Poser 4 and implemented via Microsoft Agent. Two controlled experiments validated the instantiation of the three roles according to learner perception (N=78) and actual impact on motivation and learning (N=71). The results confirmed that the agent roles were not only perceived by the students to reflect their intended purposes but also led to significant changes in learning and motivation, as designed. Specifically, the Expert agent led to increased information acquisition, the Motivator led to increased self-efficacy, and the Mentor led to overall improved learning and motivation. The implications for intelligent tutoring and multi-agent system design and development is discussed.

Keywords. Pedagogical Agents, Instructional Design, Interface Design

INTRODUCTION

Advances in computer and communication technology have provided new opportunities to facilitate human learning through technologies such as pedagogical agents (Baylor, 1999a, 2002a; Johnson et al., 2000; Kearsley, 1993). Students interacting with animated pedagogical agents have been shown to demonstrate deeper learning and greater motivation (Atkinson, 2002; Baylor, 2002b; Driscoll et al., 2003; Moreno et al., 2001). A unique affordance of a pedagogical agent is its capacity to add a social component to the environment, thereby extending the horizon of intelligent tutoring systems, which tend to focus on the cognitive aspects of teaching and learning. Given the importance of social aspects of learning across learning platforms (e.g., Bull et al., 2003; Cooper, 2003; Palinscar & Brown, 1984; Soller, 2001; Vygotsky et al., 1978), the agent's persona and associated role within the environment is of importance.

In a traditional intelligent tutoring system, a pedagogical agent could serve as an expert tutor to "teach" knowledge to learners (e.g., Graesser et al., 2001; Koedinger & Anderson, 1997). Along this line, the Steve and Adele agents, developed by CARTE (Johnson et al., 2000), represent pedagogical agents as experts in the domains of military training and medicine. Similarly, the AutoTutor (Graesser et al., 2001) interface agent engages learners in a dialogue to highlight misconceptions in computer literacy and physics. Aside from the traditional role of "agent as expert tutor," others have suggested that agents could serve in instructional roles such as mentor (Baylor, 2000), learning companion (Chan & Chou, 1997; Goodman et al., 1997; Hietala & Niemirepo, 1998; Ur & VanLehn, 1995), collaborator (Dillenbourg & Self, 1992), competitor (Chan & Baskin, 1990), or even trouble maker (Aimeur & Frasson, 1996).

Three particularly salient roles for a pedagogical agent could be drawn from research on how students perceive good human teachers. Beishuizen and colleagues (2001) found that both students and teachers evaluated the characteristics of good human teachers in terms of expertise (knowledge and experience in a domain) and personality (e.g., friendliness, kindness and enthusiasm). This finding suggests three possible functional roles for pedagogical agents: agent as *expert* (knowledgeable), agent as *motivator* (supportive), and agent as *mentor* (both knowledgeable and supportive). A key characteristic of a human expert is advanced knowledge in a domain (Ericsson et al., 1993). A good motivator uses verbal encouragement to engage learners in the task (Bandura, 1997). A mentor, as an ideal instructor, provides motivational support and guidance as well as information (Beishuizen et al., 2001). Yet, given that a pedagogical agent is an anthropomorphic visual interface, it is also important that it is *perceived* by learners as representing its role and functionality. Thus, it is important for the learners to know the functionality of the agent - what and how well the agent will do - in order to build trust and form a social relationship with the agent (Norman, 1997). Given the potential of a pedagogical agent to represent a social role, it is critical that the agent is designed to best *represent* as well as *achieve* its intended functionality (Odell et al., 2003; Prendinger & Ishizuka, 2001a, 2001b).

The resulting question is can these human instructional roles (Expert, Motivator, Mentor) be effectively simulated through pedagogical agents? To address this question, we conducted two controlled studies that investigated the learner's *perceptions* of agent functionality as represented by its role, as well as the actual *impact* of the agent role on motivation and learning.

METHODS

Operationalization of Pedagogical Agent Roles

To operationalize the three agent roles, we focused on both the media features as well as functionality. Given that people tend to apply the same social rules and expectations from human-human interaction to computer-human interaction (Reeves & Nass, 1996), we referred to research with human instructors where necessary to support the agent role design. Each agent was designed to represent a viable persona that is human-like in representation, a defining feature of pedagogical agents (Baylor, 2002b; Erickson, 1997). The three agent role characteristics are summarized below in Table 1, and described in more detail in the next sub-sections.

In terms of media features, researchers argue for the importance of agent image, animation, affect, and voice in impacting perceived agent persona. Image is a key factor in affecting the learners' perception of the computer-based agent as credible (Baylor & Ryu, 2003) and motivating (Baylor & Kim, 2003; Baylor et al., 2003b; Kim et al., 2003).

Animation includes body movements such as hand gestures, facial expression, and head nods, which can convey information and draw students' attention (Cassell, 1998; Johnson et al., 2000; McNeill, 1992; Roth, 2001). Affect, or emotion, is also an integral part of human intellectual and cognitive functioning (Kort et al., 2001; Picard, 1997) and thus was deemed as critical for facilitating the social relationship with learners and affecting their emotional development (Saarni, 2001). Finally, voice is a powerful indicator of social presence (Nass & Steuer, 1993), so the voices of the three agents were cast consistently with the behaviours, attitudes, and language of each agent (Nass & Brave, in press). The agent-student dialogue was pre-defined to control for agent functionality across students. The agent scripts were developed according to research on human experts, motivators and mentors, and reflected the given perspective in the content domain of instructional planning (the focus for this study).

Table 1
Agent Role Characteristics

	Expert	**Motivator**	**Mentor**
Image			
Animation	*Deictic*	*Emotional*	*Deictic & Emotional*
Voice	Authoritative & Monotone	Effusive & Enthusiastic	Confident & Calm
Affect	None	▪ Acknowledgment ▪ Confusion ▪ Disapproval ▪ Excitement ▪ Pleasure ▪ Surprise	▪ Acknowledgment ▪ Confusion ▪ Disapproval ▪ Excitement ▪ Pleasure ▪ Surprise
Script	Information	Encouragement	Information & Encouragement

It was important to design *overall* agent personas based on the role characteristics and corresponding media features. While the individual components, such as the script, may seem to obviously represent the intended role by themselves, each must function effectively together with all other agent media features. For example, just as a human expert with a non-expert-like appearance may not be readily perceived to be an expert, the agent role characteristics work together to function holistically. This relevancy of each media component of agent persona was indicated in other related research, where an extroverted, attractive agent engineer functioned as a more effective role model than a homely, introverted agent engineer (who had identical scripts) to influence college females to consider taking a class in engineering (Baylor & Plant, 2004).

Agent as Expert

The design of the Expert was based on research that shows that the development of expertise in humans requires years of deliberate practice in a domain (Ericsson et al., 1993), and experts exhibit mastery or extensive knowledge and perform better than the average within a domain (Ericsson, 1996; Gonzales et al., 2001). Also, experts will be confident and stable in performance and not swayed emotionally by internal or external stimulation. Based on this, we operationalized the expert agent through the image of a professor in his forties. His animation was limited to deictic gestures, and he spoke in a formal and professional manner, with authoritative speech. Being emotionally detached from the learners, his function was to provide accurate information in a succinct way (see sample script in Table 2).

Agent as Motivator

The design of the Motivator was based on social modelling research dealing with learners' efficacy beliefs, a critical component of learner motivation. According to Bandura (1997), attribute similarity between the learner and social model significantly affects the learners' self-efficacy belief. In other words, learning and motivation are enhanced when learners observed a social model of the same age (Schunk, 1989). Further, verbal encouragement in support of the learner performing a task facilitates learners' self-efficacy beliefs. Thus, we operationalized a motivator agent with a peer-like image of a casually-dressed student in his twenties, considering that our target population was college students. Given that expressive gestures of pedagogical agents may have a strong motivating effect (Johnson et al., 2000), the agent gestures were expressive and highly-animated. The Motivator Agent spoke enthusiastically and energetically, while sometimes using colloquial expressions, e.g., "What's your gut feeling?" He was not presented as particularly knowledgeable but as an eager participant who suggested his own ideas, verbally encouraged the learner to sustain at the tasks, and, by asking questions, stimulated the learners to reflect on their thinking (see sample script in Table 2). He expressed emotion that commonly occurs in learning, such as frustration, confusion, and enjoyment (Kort et al., 2001); thus, he was not always positive and supportive, but at times demonstrated his difficulty with the content to model coping strategies.

Agent as Mentor

An ideal human mentor does not simply give out information; rather, provides guidance for the learner to bridge the gap between the current and desired skill levels (Driscoll, 2000). Thus, a mentor should not be an authoritarian figure, but rather a guide or coach with advanced experience and knowledge that can work collaboratively with the learners to achieve goals. Thus, the agent as mentor should demonstrate competence to the learner while simultaneously developing a social relationship to motivate the learner (Baylor, 2000). Consequently, the design of the Mentor included an image that was less formal than the

Expert, yet older than the peer-like Motivator. The Mentor's gestures were designed to be identical to the Motivator, incorporating both deictic and emotional expressions. His voice was friendly and approachable, yet more professional and confident than the Motivator. We operationalized the Mentor's functionality to incorporate the characteristics of *both* the Expert and Motivator, (i.e., to provide information *and* motivation); thus, his script was a concatenation of the content of the Expert and Motivator scripts.

Table 2
Example Scripts for Each Agent in the Assessment Stage within MIMIC

Expert:	It is important to MATCH the assessment to the objectives to show that Anna learned the material. You should test whether Anna learned exactly what you intended that she learned, as set in the "Blueprints" stage. Depending on these initial goals, Anna could be tested with a traditional test, including multiple-choice items, True/False, short answer, or essay formats. Or, if your goals were more holistic, you could test her through demonstrations, portfolios, observations, or interviews.
Motivator:	Hmmm… developing assessment items for Anna. Um… This doesn't look easy – but I bet we can do it if we think about it.. Let's see …Think about if you took a class on how to do advance formatting of Microsoft Word. A meaningful test would test you in doing those types of formatting in Microsoft Word. And if you took a test in turning on and off a computer, a meaningful test would test you in how to actually turn it on and off! Yeah, I know this is just a really simple example. But I bet you can figure out how to create a good test for Anna. That would be a great way to show that you know how to do it!
Mentor:	I know we have to MATCH up our test questions with our objectives so that we can show that Anna learned the material. Hmmm…Let's see… If you were taking a computer class on how to use Microsoft Word, then would it be better to take a paper test to show you know it – or to demonstrate your ability using Word on the computer? And, if you took a test about turning on and off a computer, is it better for you to show your skill by taking a paper test or showing you can flip the switch on the computer? Yeah – these were just really simple examples. But I bet you can figure out how to create the right assessment for the material you are teaching. There are lots of ways to figure out if a student knows the material. The goal of assessment is to test a student in the best way possible to see if she understands the material.

Agent Development

The three pedagogical agents were developed using Poser 4 and implemented via Microsoft Agent. The agents were incorporated into the web-based research application, MIMIC (Multiple Intelligent Mentors Instructing Collaboratively) (Baylor, 1999b, 2002a), which facilitates students in learning the basics of instructional planning. MIMIC organizes instructional planning into four main stages: 1) Case Study, which describes the problem of a 13-year old girl struggling with the economics concepts of supply and demand; 2) Blueprints, where the learner describes the learning goals; 3) Planning, where the student develops the details of the instructional plan; and, 4) Assessment, where the student describes the assessment. Instructional planning is an appropriate content domain for students to learn, because it is ill-structured, somewhat difficult in nature, and requires creativity and high learner engagement (Jonassen, 1997), thus necessitating that learners seek assistance from the agents.

The MIMIC web application was developed in terms of functionality according to factors regarding learner and agent control (Baylor, 2001). Technically, it is comprised of a series of HTML forms within which the user interacts with the agents, programmed by Visual Basic Scripts. The core of the application's processing is done with server-side scripting, implemented with Cold Fusion. CFML (Cold Fusion Markup Language) is used to process all submitted forms, provide database interactivity, and allow the MIMIC environment to be set to variable configurations. Data was recorded to a Microsoft Access database.

Experimental Studies

Two controlled studies were conducted to examine 1) the learners' *perceptions* of the agent roles (Expert, Motivator, and Mentor) and 2) the actual *impact* of the roles on motivation and learning. Specifically, *role perception* refers to the learners' perception of the three agent roles and *role impact* refers to the actual instructional effects of the three agents on motivation and learning. The two studies differed by student participants, content, and intervention time (see Table 3). The initial study (Experiment I) examined role perception while the main study (Experiment II) examined both role perception and role impact.

Table 3
Samples and Interventions in Two Experiments

	Sample			Intervention		
	Participants	Number	Age	Content	Approx Time	Interaction mode
Role Perception Study (Experiment I)	Computer literacy students	78 (30% male & 70% female)	19.48 (SD=1.64)	Abbreviated version of MIMIC	20 minutes	Agent provided information
Role Perception & Role Impact Study (Experiment II)	Pre-service teachers	71 (12.5% male & 87.5% female)	19.60 (SD=3.93)	Instructional Planning (MIMIC)	90 minutes	Student requested information from agent

For both studies, agent gender, mouth movements, and script length were controlled to eliminate confounding effects. First, the male gender was adopted for all three agents to control for gender effects, given that female (and male) college students have found male agents as more facilitating of learning than female agents (Baylor & Kim, 2003) and also tend to more actively interact with males in other computer environments such as on-line communication (Jeong & Davidson-Shivers, 2003). Second, each agent used an identical standardized matrix for its mouth movement, based on evidence that students interpret an agent's message mostly relying on the shape of its mouth while speaking (Link et al., 2001).

Last, although the Mentor and Expert agents were designed to provide more *information* than the Motivator agent there was no significantly significant difference in the number of ideas conveyed across the three agent conditions.

EXPERIMENT 1 – ROLE PERCEPTION

The purpose of this study was to determine whether the students perceived the agent roles as motivational or expert-like. We predicted that the agents with expertise (Expert & Mentor) would be perceived as more expert-like, and that the agents with motivation (Motivator & Mentor) would be perceived as more motivational.

Measures

Role perception was assessed through learners' perceptions of the agent according to three properties: 1) its motivational qualities; 2) its expert-like qualities; and 3) its persona. Participants rated how motivational and expert-like the agent was in three areas: 1) animation, 2) affect, and 3) overall, each consisting of several items on a Likert scale ranging from 1 to 5. Agent persona was assessed using the API (Agent Persona Instrument), which includes four sub-scales of agent evaluation: Facilitating Learning, Credible, Human-like, and Engaging (Ryu & Baylor, in press). The API has been found to be reliable and valid in numerous other studies (e.g., Baylor & Ebbers, 2003a, 2003b; Baylor & Kim, 2003; Baylor et al., 2003a; Baylor et al., 2003b).

Participants

Seventy-eight undergraduate students (30.0% male and 70.0% female) enrolled in a computer literacy course participated in the study. The average age of the participants was 19.48 years (SD=1.64).

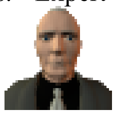
Procedure

Participants were randomly assigned to one of the three agent conditions in a between-subjects design. In the intervention, the agent introduced itself and provided comments (for approximately 10 minutes) in the "Planning" phase of MIMIC. The agent spoke without opportunity for the student to intervene or request more information, so that all had identical exposure. Following the intervention, participants answered questions regarding agent role perception. The whole session took approximately twenty minutes.

Design and Data Analysis

To analyze the data, two planned contrasts were tested. First, a *motivation contrast* tested the effect of the presence of motivation on role perception by comparing the Motivator and Mentor conditions versus the Expert condition. Second, an *expertise contrast* tested the effect of the presence of expertise on role perception by comparing the Expert and Mentor conditions versus the Motivator condition (see Table 4). The contrasts were tested by multivariate analysis of variance (MANOVA) with the three dependent motivational/expert-like measures (overall, animation, and affect), and four ANOVAs for each of the four API subscales (Facilitating Learning, Credible, Engaging, and Human-like). For all analyses, the significance level was set as < .05.

Table 4
Two Planned Contrasts, Experiment I

Contrast 1:	**Presence of Motivation**	Motivator and Mentor 	vs.	Expert 
Contrast 2:	**Presence of Expertise**	Expert and Mentor 	vs.	Motivator 

Results

The means and standard deviations of each measure are listed below in Table 5.

Table 5
Means and standard deviations, Experiment I

Dependent Variable	Properties	Sub-measures	Mean (Standard Deviation)		
			Expert (N=28)	Motivator (N=27)	Mentor (N=25)
Role Perception	Motivational	Overall assessment	2.28 (0.71)	3.00 (1.11)	2.60 (1.00)
		Animation	1.85 (0.84)	2.70 (1.20)	2.44 (0.96)
		Affect	1.82 (0.90)	3.03 (1.12)	2.80 (1.15)
	Expert-like	Overall assessment	3.89 (0.88)	2.51 (1.18)	2.96 (1.02)
		Animation	3.00 (1.05)	2.70 (1.06)	2.80 (1.04)
		Affect	3.42 (1.10)	2.48 (1.12)	2.68 (0.90)
	Persona	Facilitate learning	3.04 (0.85)	3.29 (0.86)	3.04 (0.76)
		Credible	3.92 (0.78)	3.10 (0.90)	3.52 (0.81)
		Human-like	2.90 (0.83)	3.44 (0.83)	3.22 (0.93)
		Engaging	2.74 (0.80)	3.75 (0.82)	3.66 (0.49)

Motivational Properties

The MANOVA revealed that the agents with motivation (Motivator & Mentor) were perceived as significantly more motivational than the agent without motivation (Expert), Wilks lambda=.78, F (3, 76) = 7.18, p<.001. Univariate analyses (ANOVA) indicated the same trend with significant differences occurring in all three dependent measures: overall assessment, $F=5.39$, $p<0.05$; animation, $F=19.62$, $p<0.001$; and, affect, $F=9.18$, $p<0.01$.

Expert-like Properties

The MANOVA revealed that the agents with expertise (Expert and Mentor) were perceived as significantly more expert-like than the agent without expertise (Motivator), Wilks lambda=.83, $F=5.03$ (3, 76), $p<0.01$. Univariate analyses (ANOVA) indicated the same trend with significant differences occurring in two of the three dependent measures: overall assessment, $F=12.97$, $p<0.01$; and, animation, $F=5.33$, $p<0.05$.

Agent Persona

For the Facilitating Learning sub-scale, there were no significant differences across the two contrasts. For the Credible sub-scale, the motivation contrast revealed that the agents with motivation (Motivator & Mentor) were perceived as significantly *less* credible than the agent without motivation (Expert), $F=9.79$, $p<0.01$. Similarly, the expertise contrast revealed that the agents with expertise (Expert and Mentor) were perceived as significantly more credible than the agent without expertise (Motivator), $F=9.71$, $p<0.01$. For the Human-like sub-scale, the motivation contrast revealed that the agents with motivation (Motivator & Mentor) were perceived as significantly more human-like than the agent without motivation (Expert), $F=4.6$, $p<0.05$. Similarly, the expertise contrast revealed that the agents with expertise (Expert and Mentor) were perceived as less human-like than the agent without expertise (Motivator), but the statistical significance was marginal, $F=3.7$, $p<0.06$. For the Engaging sub-scale, the motivation contrast revealed that the agents with motivation (Motivator & Mentor) were perceived as significantly more engaging than the agent without motivation (Expert), $F=32.65$, $p<0.001$. Similarly, the expertise contrast revealed that the agents with expertise (Expert and Mentor) were perceived as significantly *less* engaging than the agent without expertise (Motivator), $F=8.8$, $p<0.01$.

Discussion

As summarized below in Table 6, results indicated that the Motivator and Expert (and the Mentor implicitly) effectively simulated the intended instructional role, according to the learners' perceptions. Specifically, the agents with motivation (Motivator and Mentor) were perceived as more motivational, human-like, and engaging and the agents with expertise (Expert and Mentor) were perceived as more expert-like and credible.

An obvious limitation with this initial study was that participants were asked only to evaluate the roles after a relatively short period of time of exposure to the agents (approximately 20 minutes), and did not have the opportunity to interact with and learn from the agents. Thus, it was necessary to replicate these results by studying a different population who could interact with and learn from the agents for a longer period of time. Additionally, participants revealed through an open-ended question that the agent voice was a key factor in their ratings, so we wanted to include voice as part of the role perception measures.

Table 6
Results of Role Perception Study, Experiment I

Contrast 1:	**Presence of Motivation**	Role Perception: • More motivational (overall, affect, animation) Persona: • less credible • more human-like • more engaging
Contrast 2:	**Presence of Expertise**	Role Perception: • More expert-like (overall, animation) Persona: • more credible • less human-like • less engaging

EXPERIMENT 2 – ROLE PERCEPTION AND ROLE IMPACT

The purpose of Experiment II was twofold: 1) to replicate the results from Experiment I with a different population, more intensive tasks, and a longer duration of time, while also assessing agent voice; and, 2) to examine the impact of the three roles (Expert, Motivator, and Mentor), that is, the effects of the three roles on actual motivational and learning outcomes.

Together with predicting the same role perception results from Experiment I, we also hypothesized that the motivational agents (Mentor and Motivator) would lead to increased learner motivation toward instructional planning and that the Mentor would be most effective for learning and motivation.

Measures

The dependent variables were *role perception* and *role impact*. Role perception was assessed as in Experiment I, with the addition of a measure to assess the qualities of agent voice as motivational/expert-like. Role impact was examined by the effects of the agents on learner motivation and learning as described next.

Motivation

Motivation was assessed with two sub-measures: self-efficacy and disposition. For self-efficacy, a one-item question was based on Bandura and Schunk's (1981) guidelines, given that self-efficacy is the degree to which one feels capable of performing a specific task at certain designated levels (Bandura, 1986): "How sure are you that you can write a lesson plan?" on a scale ranging from 1 (not at all sure) to 5 (Extremely sure) before and after the intervention. For disposition, participants' personal attitudes regarding instructional planning were assessed before and after the intervention. The participants were asked to write two adjectives to "Describe what you think about instructional planning." This method was employed to obtain the participants' personal affect regarding instructional planning as opposed to the response set that could bias them to choose more favorable adjectives if adjectives were presented in a list. The adjectives were coded according to three levels: as -1 if both were negative, as 0 if one was negative and the other positive, and as +1 if both were positive. Two raters coded the items independently. Inter-rater reliability was established at $r = .95$. The concurrent validity of this measure was supported in Kitsantas and Baylor (2001) by a significant positive correlation between initial disposition and initial self-efficacy scores. Prior research has shown that self-efficacious students generally have a positive affect (Bandura, 1986).

Learning

Learning was assessed by a post test to measure transfer of learning to a new scenario. The participants were provided with the following instruction:

> *Applying what you've learned, develop an instructional plan for the following scenario:* You are a sixth grade teacher of a mathematics class. A member of the president's advisory committee is visiting today and wants to see an example of your instruction to teach multiplication of fractions. For a 40-minute class period, you decide to teach your students how to multiply fractions. Please be as specific as possible in the space below.

Each instructional plan was scored holistically according to a scale (where 1=poor and 5=excellent) in terms of how well the participants applied their knowledge of instructional planning to this particular situation. Three researchers discussed together what characterized a score of 1 through 5 while evaluating ten sample plans. Following that, each researcher independently scored the same 10 instructional plans to establish inter-rater reliability. After establishing the inter-rater reliability at $r>.90$, one of the researchers then scored the remainder of the instructional plans using the same scale. In scoring each instructional plan, the researchers were blind as to the participants' conditions.

Participants

The participants included seventy-one pre-service teachers (12.5% male and 87.5% female) enrolled in an introductory educational technology class in the same university as Experiment I. The average age of the participants was 19.6 years (SD=3.93).

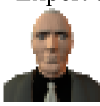
Procedure

The experiment was conducted during a regular session of the course and students used headphones so that they would not be distracted by the other participants. The participants were randomly assigned to one of the three agent conditions (Expert, Motivator, and Mentor) within MIMIC. In this study, participants had the opportunity to interact with the agents. After the agent provided an initial observation upon entering each of the four MIMIC planning stages, the agent was available to provide additional advisements when selected by the participant. The available advisements (specific to each instructional planning stage) would appear in a pop-up box for the participant to select. Within this study, there were a total of 13 agent advisements, including the advisement presented automatically as the participant entered each stage. There were no differences across conditions in terms of number of agent advisements selected. Most participants (over 90%) selected all agent advisements. Following their work within MIMIC, participants answered post test questions, and were given as much time as needed to complete the tasks. The whole session took approximately 90 minutes with individual variations.

Design and Data Analysis

The design and data analysis were the same as in the initial study for agent role perception but with the addition of one planned contrast (see Table 7 below) to assess agent mentorship, thus contrasting the Mentor agent with the Expert and Motivator. To analyze self efficacy and disposition, a split-plot factorial design was employed to test within subject (repeated measures) and between subject (agent role) effects. No initial differences were found for pre-test scores across groups for self-efficacy and disposition. For analyzing transfer of learning, univariate analysis of variance (ANOVA) tests were conducted for the three contrasts. For all analyses, the significance level was set as □ < .05, while considering for family-wise error (3 contrasts per analysis). Cohen's *d* values were calculated as an estimate of effect size, where d=.2 indicates a small effect, d=.5 a medium effect, and d=.8 a large effect.

Table 7
Additional Planned Contrast for Experiment II

		Mentor	vs.	Expert and Motivator
Contrast 3:	**Presence of Mentorship**			 

Results

Role Perception – Motivational Properties

From the overall MANOVA, there was no significance for the motivational contrast. However, the univariate results revealed significant (or marginally significant) differences between the agents with motivation (Motivator & Mentor) and the agent without motivation (Expert) for several of the sub-measures. For overall assessment and animation, the Motivator and Mentor were rated as more motivational than the Expert, both approaching statistical significance, F=2.85, p=.09, d=.40, and F=2.98, p=.09, d=.40, respectively. For affect, the Motivator and Mentor were significantly more motivational than the Expert, F=5.27, p<0.05, d=.56. For voice, there was no significant difference.

Role Perception - Expert-like Properties

It was revealed through MANOVA that the agents with expertise (Expert and Mentor) were perceived as significantly more expert-like, Wilks lambda=.83, $F=3.37$, $p<0.05$. Univariate analyses (ANOVA) indicated the same trend with significant differences occurring in two of the four dependent measures: overall assessment, $F=8.46$, $p<0.01$, $d=.76$ and voice, $F=5.27$, $p<0.05$, $d=.58$.

Role Perception - Agent Persona

The agents with motivation (Motivator & Mentor) were perceived as significantly more <u>human-like</u> ($F=7.19$, $p<0.01$, $d=.85$) and <u>engaging</u> ($F=22.56$, $p<0.001$, $d=1.76$) than the agent without motivation (Expert). The agents with expertise (Expert and Mentor) were perceived as significantly more <u>credible</u>, $F=15.64$, $p<0.001$, $d=1.13$, and more <u>facilitative of learning</u>, $d=.55$, $F=2.74$, $p<.05$ than the agent without expertise (Motivator). The agent with mentorship (the Mentor) was perceived as significantly more <u>facilitative of learning</u>, $d=.49$ $F=2.74$, $p<.05$, and <u>engaging</u>, $F=6.99$, $p<0.01$, $d=.80$, than agents without mentorship (the Expert and Motivator).

Role Impact - Self-efficacy

The results revealed that the interaction of agent role (between-subject) and self-efficacy (pre and post measures) approached statistical significance. The increase of self-efficacy of the students who had the agents with motivation (Motivator and Mentor) was higher than of those who had the agent without motivation (Expert) $F=2.83$, $p=.09$. Also, in the mentorship contrast, the increase of self-efficacy of the students who worked with the Mentor was marginally higher than of those who worked with the other agents (Expert and Motivator) $F=2.66$, $p=.10$.

Role Impact – Disposition

There were no significant differences for disposition toward instruction planning for each contrast.

Role Impact – Learning

The learning results revealed that the Mentor led students to have significantly higher transfer scores than students working with the other agents (Expert and Motivator), $F=3.89$, $p<0.05$, $d=.50$. Additionally, students who worked with the agents with expertise (Expert and Mentor) had significantly higher transfer scores than those who worked with the agent without expertise (Motivator) $F=3.89$, $p<0.05$, $d=.44$.

Below, Table 8 presents the means and standard deviations of three agent conditions for the dependent measures of Experiment II.

Discussion

As summarized below in Table 9, results generally confirmed the role perception results of Experiment 1, and also indicated that the roles had the intended *impact* on motivation and learning. For role perception, results confirmed that the Motivator and Expert (and the Mentor implicitly) effectively simulated the intended instructional role. The results were not as strong, though, in showing that the agents with motivation (e.g., Contrast 1) were perceived as motivational. Unlike Experiment I, (where there were no significant differences), the agent persona characteristic of "facilitating learning" was significantly greater for agents with expertise, and also for the Mentor alone. In terms of motivational impact, it was found that students' self-efficacy was improved (approaching statistical significance) when they worked with the motivational agents. In terms of impact on learning, the transfer scores of the students working with the expertise-possessing agents (Expert and Mentor) were significantly higher.

Table 8
Means and Standard Deviations, Experiment II

Dependent Variables	Properties	Sub-measures	Mean (Standard Deviation)		
			Expert (N=29)	Motivator (N=24)	Mentor (N=20)
Role Perception	Motivational	Overall assessment	2.17 (1.19)	2.75 (1.22)	2.47 (0.84)
		Animation	1.83 (0.93)	2.33 (0.92)	2.05 (0.91)
		Voice	2.07 (1.22)	2.54 (1.41)	2.42 (1.01)
		Affect	1.82 (1.03)	2.42 (1.18)	2.47 (1.17)
	Expert-like	Overall assessment	3.31 (0.97)	2.25 (0.94)	2.52 (1.07)
		Animation	2.48 (1.12)	2.29 (0.86)	2.10 (0.99)
		Voice	3.37 (1.15)	2.41 (1.14)	2.57 (0.90)
		Affect	2.86 (1.21)	2.50 (0.78)	2.26 (0.93)
	Persona	Facilitate learning	3.27 (0.80)	2.90 (0.99)	3.26 (0.90)
		Credible	3.99 (0.73)	2.88 (0.95)	3.36 (0.86)
		Human-like	2.74 (0.81)	3.38 (0.71)	3.06 (0.78)
		Engaging	2.63 (0.84)	3.50 (0.86)	3.66 (0.75)
Role Impact	Motivation	Self-efficacy	3.03 (0.73)/ 3.06 (0.92)[1]	2.67 (0.82)/ 2.96 (0.86)	2.50 (1.10)/ 3.05 (1.14)
		Disposition	0.17 (0.85)/ 0.14 (0.74)	0.54 (0.72)/ 0.33 (0.70)	0.45 (0.69)/ 0.25 (0.76)
	Learning	Transfer	2.85 (1.26)	2.54 (1.02)	3.15 (0.81)

1. Pre and post test scores are separated by a slash (/) for self-efficacy and disposition.

OVERALL DISCUSSION

By empirically validating these particular role instantiations of pedagogical agents as Expert, Motivator, and Mentor, the studies indicated that pedagogical agents can authentically simulate instructional roles. Given that a large number of pedagogical agents have been employed in intelligent systems without systematic assessment of agent features on specific educational outcomes, this is a main strength of these preliminary studies. From an educational perspective, this suggests that such agents can be implemented as "virtual human instructors" for instructional interventions and be perceived by learners as intended, when designed with the correct persona and media features.

Table 9
Results of role perception and impact study, Experiment II

Contrast 1:	**Presence of Motivation**	Role Perception: • Affect more motivational • Overall and animation more motivational * Persona Features: • less credible • more human-like • more engaging More self-efficacy *
Contrast 2:	**Presence of Expertise**	Role Perception: • More expert-like (overall, voice) Persona Features: • more credible • more facilitative of learning • less human-like • less engaging More transfer of learning
Contrast 3:	**Presence of Mentorship**	Persona Features: • more engaging • more facilitative of learning More transfer of learning More self-efficacy *

* *approaching statistical significance (p<.10)*

Specifically, results revealed that the motivational agents (Motivator, Mentor) were perceived as more human-like and led to improved learner self-efficacy. Yet, this affective encouragement and support was not sufficient for the learners to write better instructional plans (i.e., to facilitate learning). On the other hand, the agents with expertise (Expert and Mentor) led to improved learning outcomes and were also perceived as such (as facilitating learning and as more credible). Of the two agents with expertise, the Mentor was perceived to be more engaging and also led to improved self-efficacy, thus having the overall best impact on learning and motivation, paralleling the literature on human instruction.

The longer intervention time in the second study led to slightly different results, which highlights certain characteristics of the agent roles. In the longer study, the agents with expertise were perceived as more facilitative of learning, perhaps because students had more time to interact with them. On the other hand, the motivational agents were not perceived to be as motivational in the longer study, perhaps because the learners became somewhat disillusioned when they realized the agents were not going to provide any substantive information, only verbal encouragement and emotional support. Even so, the motivational agents still positively influenced learner self-efficacy, most likely because they were perceived as a less-knowledgeable peer, and "if he can do it, so can I." To support this explanation, we found similar results when manipulating agent competence, finding that students have increased confidence when working with less competent agents (Kim & Baylor, To appear).

Designing and testing the viability of agent role differentiation is important, particularly for implementation within multi-agent learning systems (see Odell et al., 2003). As Norman (1997) implored several years ago, it is critical that the user's *expectations* of the agent functionality matches its actual functionality. Thus, it is important to ensure that agent functional roles are perceived by users as intended by the system designers. And, assuming that the pedagogical agent role is well-designed, it could positively contribute to the learners' perceptions and expectations of a learning system's interventions. For example, adding such an interface agent (e.g., an "Expert") to an existing intelligent tutoring system would likely facilitate the learner in understanding and interacting with the system more fluidly and authentically.

From a design standpoint, the generic agent roles employed in these studies could serve within different content domains. The Expert would be appropriate to introduce new content or demonstrate a procedure within a well-defined subject area, (e.g., Steve teaching how to operate a piece of equipment in Navy ships, or Adele in medical simulations, Johnson, 2001). The Motivator may be more appropriate in ill-structured domains or constructivist learning environments, where learners' voluntary engagement is more critical than their knowledge acquisition. Also, the Motivator may work more effectively with low achieving students, who are sometimes motivated by working with those who are of a similar competency level (Bandura, 1997; Hietala & Niemirepo, 1998). The Mentor could serve effectively in many types of learning situations where *both* learning and motivation are key outcomes.

It may seem to be a limitation that the agents employed in these studies were not particularly "intelligent" but rather were pre-scripted to ensure similar learner experiences. Other research that we have conducted has shown that learners assume agents such as these are providing dynamically-generated and adaptive responses, even when they are not (e.g., Baylor & Chang, 2002). Thus, we found that the advantage of controlling the agent-learner dialogues outweighed the possible loss of ecological validity (e.g., by not using truly conversational agents). Further, it is necessary to better understand learner interactions with interface agents before examining more complex intelligent agents. As Norman (1997) suggested, learners interact with agents as represented through their interface (e.g., persona), not through their underlying algorithms.

It is, however, necessary to simulate these agent roles with female agents and agents of other ethnicities given that it has been found in other research that agent gender and ethnicity can impact student motivation (Baylor & Kim, 2003; Baylor & Plant, 2005; Baylor et al., 2003b). Also, the participants here were limited to college students, and different results may be obtained with other age groups. Further, these studies did not examine the effects of the *individual components* of the roles (e.g., image, animation, voice, affect, and script), but rather looked at the composite "agent role." The relative effect of the Expert's script (as compared to other media features) on learning is of particular interest. Consequently, more research is needed to determine the relative contribution of these media features in influencing learner role perception and impact.

In general, are efforts to understand the impact of pedagogical agents worthwhile? Empirical research to date suggests so. For example, manipulating an interface agent's image alone can significantly enhance learner motivation, with large effect sizes (Baylor, 2005; Baylor & Plant, 2005). Such results powerfully illustrate that it is not advisable to figuratively "tack on" an interface agent to an existing ITS system without a better understanding of the possible implications. Further, the nonverbal communication of the agent (e.g., deictic gestures versus emotional expression) can differentially impact procedural and attitudinal learning outcomes (Baylor et al., 2005), thus suggesting the need for more empirically-based design principles for employing agent animation. Similarly, it is of importance to consider the overall agent persona and functional role, particularly as more realistic multi-modal and technologically-advanced pedagogical agents are constructed.

Yet, *maintaining* such agent instructional roles in the longer-term suggests new challenges. In particular, research is needed with respect to the relative importance and interaction of the following two psychometrically-derived latent constructs of "pedagogical agent persona:" 1) the informational usefulness of the agent's instructional messages (related to credibility and facilitation of learning) and, 2) the affective interactions of the agent (related to human-likeness and engagement) (Ryu & Baylor, in press). This psychometric model suggests that maintaining agent credibility in a long-term instructional relationship may be attributed to informational usefulness (e.g., underlying instructional strategies and dialogue) more than to affective interactions. While systematic long-term research with pedagogical agents is lacking, Bickmore (2003) implemented a PDA-based relational agent, "Laura," (operationalized to incorporate meta-relational communication, empathy, sincerity and politeness) to promote human exercise behaviours over the course of a month. As he attests, maintaining agent credibility over the longer term brings new difficulties of addressing repetitiveness (e.g., making both verbal and nonverbal responses less predictable) and sustaining engagement (Bickmore & Picard, in press). Thus, both components of the agent persona – informational usefulness and affective interactions – may be equally critical, yet only further research can confirm their relative contributions.

Overall, given that learners viscerally respond to agents in human-like ways (e.g., Reeves & Nass, 1996), better understanding of learner response to the overall agent persona and role will continue to be of importance. New instructional roles for pedagogical agents, including agents as "learning companions" (Kim & Baylor, submitted) and as persuasive social models (Baylor & Plant, 2005), have the potential to facilitate learning in new ways. The studies described here can serve as a foundation for evaluating and authenticating such new agent roles at the macro-level.

ACKNOWLEDGEMENTS

This work was sponsored by National Science Foundation (NSF) Grant # IIS-0218692.

REFERENCES

Aimeur, E., & Frasson, C. (1996). Analyzing a new learning strategy according to different knowledge levels. *Computers & Education,* 27(2), 115-127.

Atkinson, R. K. (2002). Optimizing learning from examples using animated pedagogical agents. *Journal of Educational Psychology*, 94, 416-427.

Bandura, A. (1986). *Social foundations of thought and action: A social-cognitive theory*. Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: W. H. Freeman.

Bandura, A., & Schunk, D. H. (1981). Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. *Journal of Personality and Social Psychology,* 41, 586-598.

Baylor, A. L. (1999a). Intelligent agents as cognitive tools for education. *Educational Technology,* 39(2), 36-40.

Baylor, A. L. (1999b). Multiple intelligent mentors instructing collaboratively (MIMIC): Developing a theoretical framework. In Proceedings of International Cognitive Technology Conference, San Francisco, CA.

Baylor, A. L. (2000). Beyond butlers: Intelligent agents as mentors. *Journal of Educational Computing Research,* 22(4), 373-382.

Baylor, A. L. (2001). Investigating multiple pedagogical perspectives through MIMIC (Multiple Intelligent Mentors Instructing Collaboratively). In J. D. Moore, C. L. Redfield, & W. L. Johnson (Eds.) *Artificial Intelligence in Education: AI-ED in the Wired and Wireless Future, Proceedings of AI-ED 2001*. Amsterdam: IOS.

Baylor, A. L. (2002a). Agent-based learning environments for investigating teaching and learning. *Journal of Educational Computing Research*, 26(3), 249-270.

Baylor, A. L. (2002b). Expanding preservice teachers' metacognitive awareness of instructional planning through pedagogical agents. *Educational Technology Research & Development,* 50(2), 5-22.

Baylor, A. L. (2005). The impact of pedagogical agent image on affective outcomes. Proceedings of Workshop on Affective Interactions, Intelligent User Interface International Conference, San Diego, CA.

Baylor, A. L., & Chang, S. (2002). Pedagogical agents as scaffolds: The role of feedback timing, number of agents, and adaptive feedback. In Proceedings of the International Conference of the Learning Sciences, Seattle, WA.

Baylor, A. L., & Ebbers, S. J. (2003a). Evidence that multiple agents facilitate greater learning. In U. Hoppe, F. Verdejo, & J. Kay (Eds.) *Artificial Intelligence in Education*. Amsterdam: IOS Press

Baylor, A. L., & Ebbers, S. J. (2003b). *The pedagogical agent split-persona effect: When two agents are better than one.* Proceedings of ED-MEDIA, Honululu, Hawaii.

Baylor, A. L., Kim, S., Son, C., & Lee, M. (2005). The impact of pedagogical agent emotive expression and deictic gestures on attitudinal and procedural learning outcomes. To appear in Proceedings of Artificial Intelligence in Education (AI-ED) International Conference, Amsterdam. Manuscript available from the authors.

Baylor, A. L., & Kim, Y. (2003). *The role of gender and ethnicity in pedagogical agent perception.* In Proceedings of E-Learn (World Conference on E-Learning in Corporate, Government, Healthcare, & Higher Education), Phoenix, Arizona.

Baylor, A. L., & Plant, E. A. (2005). Pedagogical agents as social models for engineering: The influence of agent appearance on female choice. To appear in Proceedings of Artificial Intelligence in Education (AI-ED) International Conference, Amsterdam. Manuscript available from the authors.

Baylor, A. L., & Ryu, J. (2003). Does the presence of image and animation enhance pedagogical agent persona? *Journal of Educational Computing Research,* 28(4), 373-395.

Baylor, A. L., Ryu, J., & Shen, E. (2003a). The effects of pedagogical agent voice and animation on learning, motivation and perceived persona. In Proceedings of ED-MEDIA, Honululu, Hawaii.

Baylor, A. L., Shen, E., & Huang, X. (2003b). Which pedagogical agent do learners choose? The effects of gender and ethnicity. In Proceedings of E-Learn (World Conference on E-Learning in Corporate, Government, Healthcare, & Higher Education), Phoenix, Arizona.

Beishuizen, J. J., Hof, E., Van Putten, C. M., Bouwmeester, S., & Asscher, J. J. (2001). Students' and teachers' cognitions about good teachers. *British Journal of Educational Psychology,* 71, 185-201.

Bickmore, T. (2003). Relational Agents: Effecting Change through Human-Computer Relationships. PhD Thesis, Media Arts & Sciences, Massachusetts Institute of Technology.

Bickmore, T. and Picard, R. (In Press) Establishing and Maintaining Long-Term Human-Computer Relationships. *ACM Transactions on Computer Human Interaction* (TOCHI).

Bull, S., Greer, J., & Gord, M. (2003). The caring personal agent. *International Journal of Artificial Intelligence in Education*, 13(1), 21-34.

Cassell, J. (1998). A framework for gesture generation and interpretation. In R. Cipolla & A. Pentland (Eds.) *Computer vision in human-machine interaction* (pp. 191-215). New York: Cambridge University Press.

Chan, T. W., & Baskin, A. B. (1990). Learning companion systems. In C. Frasson & G. Gauthier (Eds.) *Intelligent tutoring systems at the crossroads of artificial intelligence and education* (pp. 7-33): NJ: Ablex Publishing Corporation.

Chan, T. W., & Chou, C. Y. (1997). Exploring the design of computer supports for reciprocal tutoring systems. *International Journal of Artificial Intelligence in Education*, 8, 1-29.

Cooper, B. (2003). Care-making the affective leap: More than a concerned interest in a learner's cognitive abilities. *International Journal of Artificial Intelligence in Education*, 13, 3-9.

Dillenbourg, P., & Self, J. (1992). People power: A human-computer collaborative learning system. In G. G. C. Frasson, &G. McCalla (Eds.) *The 2nd international conference of intelligent tutoring systems, lecture notes in computer science* (Vol. 608, pp. 651-660): Springer-Verlag.

Driscoll, D., Craig, S. D., Gholson, B., Ventura, M., Hu, X., & Graesser, A. (2003). Vicarious learning: Effects of overhearing dialogue and monologue-like discourse in a virtual tutoring session. Journal of Educational Computing Research, 29, 431-450.

Driscoll, M. P. (2000). *Psychology of learning for instruction.* Boston: Allyn & Bacon.

Erickson, T. (1997). Designing agents as if people mattered. In J. M. Bradshaw (Ed.) *Software agents* (pp. 79-96). Menlo Park, CA: MIT Press.

Ericsson, K. A. (1996). The acquisition of expert performance: An introduction to some of the issues. In K. A. Ericksson (Ed.) *The road to excellence: The acquisition of expert performance in the arts, sciences, sports, and games* (pp. 1-50). Hillsdale, NJ: Erlbaum.

Ericsson, K. A., Krampe, R. T., & Tesch-Romer, C. (1993). The role of deliberate practice in the acquisition of expert performance. *Psychological Review,* 100(3), 363-406.

Gonzales, M., Burdenski, T. K., Jr., Stough, L. M., & Palmer, D. J. (2001). Identifying teacher expertise: An examination of researchers' decision-making. Paper presented at the American Educational Research Association, Seattle, WA.

Goodman, B., Soller, A., Linton, F., & Gaimari, R. (1997). Encouraging student reflection and articulation using a learning companion. In B. du Boulay, & R. Mizoguchi (Eds.) *Artificial Intelligence in Education* (pp. 151-158). Amsterdam: IOS

Graesser, A. C., Person, N. K., Harter, D., & Group, T. T. R. (2001). Teaching tactics and dialog in Autotutor. *International Journal of Artificial Intelligence in Education*, 12, 257-279.

Hietala, P., & Niemirepo, T. (1998). The competence of learning companion agents. *International Journal of Artificial Intelligence in Education,* 9, 178-192.

Jeong, A., & Davidson-Shivers, G. V. (2003). Gender interactions in online debates: Look who's arguing with whom. Paper presented at the Annual Meeting of the American Educational Research Association, Chicago.

Johnson, W. L. (2001). Pedagogical agent research at carte. *AI Magazine, Winter,* 85-94.

Johnson, W. L., Rickel, J. W., & Lester, J. C. (2000). Animated pedagogical agents: Face-to-face interaction in interactive learning environments. *International Journal of Artificial Intelligence in Education,* 11, 47-78.

Jonassen, D. H. (1997). Instructional design models for well-structured and ill-structured problem-solving learning outcomes. *ETR&D,* 45(1), 65-95.

Kearsley, G. (1993). Intelligent agents and instructional systems: Implications of a new paradigm. *Journal of Artificial Intelligence and Education*, 4(4), 295-304.

Kim, Y., & Baylor, A. L. (To appear). Pedagogical agents as learning companions: The role of agent competency and type of interaction. *Educational Technology Research & Development (ETR&D)*. Manuscript available from the authors.

Kim, Y., & Baylor, A. L. (Submitted). A social-cognitive framework for designing pedagogical agents as learning companions. *Educational Technology Research & Development (ETR&D)*. Manuscript available from the authors.

Kim, Y., Baylor, A. L., & Reed, G. (2003). The impact of image and voice with pedagogical agents. In Proceedings of E-Learn (World Conference on E-Learning in Corporate, Government, Healthcare, & Higher Education), Phoenix, Arizona.

Kitsantas, A., & Baylor, A. L. (2001). The impact of the ipsrt (instructional planning self-reflective tool) on preservice teachers' performance, disposition, and self-efficacy beliefs regarding systematic instructional planning. *Educational Technology Research & Development*, 49(4), 101-110.

Koedinger, K. R., & Anderson, J. R. (1997). Intelligent tutoring goes to school in the big city. *International Journal of Artificial Intelligence in Education*, 8, 30-43.

Kort, B., Reilly, R., & Picard, R. W. (2001). An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion. In *Proceedings IEEE International Conference on Advanced Learning Technologies*, 43-46.

Link, K. E., Kreuz, R. J., Graesser, A. C., & Tutoring Research Group. (2001). Factors that influence the perception of feedback delivered by a pedagogical agent. *International Journal of Speech Technology,* 4, 145-153.

McNeill, D. (1992). *Hand and mind: What gestures reveal about thought*. Chicago: University of Chicago Press.

Moreno, R., Mayer, R. E., Spires, H. A., & Lester, J. C. (2001). The case for social agency in computer-based teaching: Do students learn more deeply when they interact with animated pedagogical agents? *Cognition and Instruction,* 19(2), 177-213.

Nass, C., & Brave, S. (In Press). Wired for Speech: How Voice Activates and Advances the Human-Computer Relationship. Cambridge, MA: MIT Press.

Nass, C., & Steuer, J. S. (1993). Computers, voices, and sources of messages: Computers are social actors. *Human Communication Research*, 19(4), 504-527.

Norman, D. A. (1997). How might people interact with agents. In J. M. Bradshaw (Ed.) *Software agents* (pp. 49-56). Menlo Park, CA: MIT Press.

Odell, J., Parunak, H. V. D., & Fleischer, M. (2003). The role of roles. *Journal of Object Technology,* 1, 39-51.

Palinscar, A., & Brown, A. (1984). Reciprocal teaching of comprehension-fostering and comprehension-monitoring activities. *Cognition and Instruction,* 1(2), 117-175.

Picard, R. W. (1997). *Affective computing*. Cambridge, MA: MIT Press.

Prendinger, H., & Ishizuka, M. (2001a). Carrying the role-playing metaphor to interactive learning environments. In Proceedings of the International Conference on Intelligent User Interfaces (IUI). Santa Fe, New Mexico.

Prendinger, H., & Ishizuka, M. (2001b). Social role awareness in animated agents. In *Proceedings of the International Conference on Autonomous Agents* (pp. 270-277). Montreal, Quebec, Canada.

Reeves, B., & Nass, C. (1996). *The media equation*. Stanford, CA: CSLI Publications.

Roth, W.-M. (2001). Gestures: Their role in teaching and learning. *Review of Educational Research,* 71(3), 365-392.

Ryu, J., & Baylor, A. L. (In Press). The psychometric structure of pedagogical agent persona. *Technology, Instruction, Cognition & Learning (TICL)*.

Saarni, C. (2001). Emotion communication and relationship context. *International Journal of Behavioral Development*, 25(4), 354-356.

Schunk, D. H. (1989). Social cognitive theory and self-regulated learning. In B. J. Zimmerman & D. H. Schunk (Eds.) *Self-regulated learning and academic achievement: Theory, research, and practice* (pp. 83-110). New York: Springer-Verlag.

Soller, A. (2001). Supporting social interaction in an intelligent collaborative learning system. *International Journal of Artificial Intelligence in Education*, 12, 40-62.

Ur, S., & VanLehn, K. (1995). Steps: A simulated, tutorable physics student. *Journal of Artificial Intelligence in Education*, 6(4), 405-435.

Vygotsky, L. S. (1978). *Mind in society*. Cambridge, MA: Harvard University Press