3.5 Robots and Agents to Support Collaborative Learning

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Abstract: *This chapter examines how social components of robot and agent technology, combined with learning theories and methodologies, can develop powerful learning partnerships. Exploring ways to leverage the affordances of technology as peers and learning tools, can provide teachers with useful information to identify features and conditions for learning. This in turn can help design activities using pedagogical robots/agents to assist collaboration with and between students.*

Keywords: *robots, pedagogical agents, adaptive support, tutoring systems*

Introduction and Scope

As many broad definitions for collaborative learning exist, this chapter sees collaborative learning as a "...situation in which two or more people learn or attempt to learn something together" (Dillenbourg, 1999, p.1). This act of learning something together can relate to course content knowledge (e.g., mathematics, biology) or acquiring skills to perform learning activities (e.g., problem solving, reasoning skills, self-reflection). "Two or more people" can imply a pair, a small group, a class, a community, or all other intermediate levels, but much of the work introduced in this chapter, will involve collaborative learning between a pair (dyads) and a small group of people (triads). The chapter will focus beyond content knowledge, and examine the learning mechanisms that emerge from such collaborative processes and the role of robots and agents in supporting these processes. Collaborative processes are often complex, with both social and cognitive processes circulating and feeding into one another (Perret-Clermont, Perret, & Bell, 1991). Studying and identifying the practices that research indicates are successful can inform teachers about the affordances of robots and agents for supporting collaborative learning, as well as potential pedagogical risks when using these technologies. We argue that it is essential to understand the possibilities and the limits of technology-rich collaborative learning environments in order to design instruction that can support learning. Practice needs to be well grounded in theory to facilitate the exploration of how or why things work (Gomez & Henstchke, 2009) to ensure that learning trajectories are clear and robust for

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the classroom. This chapter does not reflect on advanced social and institutional factors, such as leadership and social norms, which may appear in large collaborative groups.

History and Development

A Brief Background of Robot and Agents in Education

Applying technology to educational content and pedagogy is not new. People have had high hopes for technology restoring personalized instruction as far back as Pressey's Testing Machine (Pressey, 1932) and Skinner's Teaching Machine (Skinner, 1986). Expert systems have been successful in their intended domain, but often evaluated unfairly because of the high expectations of the Turing Test (Hayes & Ford, 1995). Interestingly, much of the "learning" focused on programmed instruction and machine learning, where robot intelligence and expert systems guided or modeled human problem solving. Human behavioral models implemented into the system improved the quality of social interactions between humans and machines (e.g., conversational agents, intelligent tutoring systems). As a result technology was used to implement well-known teaching and tutoring strategies, but detecting the thought processes of children turned out to be quite difficult as it involved human learning, rather than machine learning. Early computerized automated instructions included teacher-student dialogues that asked questions to elicit responses. Frameworks such as Bloom's Taxonomy were used as a way to ask questions that required higher-order thinking processes to answer (Stevens & Collins, 1977). However, little evidence was found to support the correlation between higher-order questions and student achievement (Winne, 1979). Technological tools still seem to fall short when dealing with unfamiliar content.

The transition of technologically simple and single-minded artifacts to sociable, adaptable, and intelligent ones can pose controversies and open questions. Some of these controversies are decades old, but are still very much alive and well. Back when Skinner's Teaching Machine was first introduced, there was the fear that teachers would be replaced by machines. The role of the machines and the principles on which these teaching machines were based were misunderstood, which led to anxiety and high expectations that students would learn twice as fast. Today, we still see headlines in the media that say "Are robots going to replace teachers?" "Are robots going to be smarter than humans?" Back then and now, it appears that the role of machines and the principles on which these tools are based may continue to be misunderstood.

Recent advancements in digital manipulatives and technological artifacts (e.g., programmable building bricks) have helped expand the range of concepts children can explore with different robotic systems and machine platforms (Resnick, Berg, & Eisenberg, 2000). Robotics is an integrative discipline that brings together basic math, science, applied engineering, and computational thinking. Preparing pre-service teachers to teach STEM using robotics has been suggested as a promising way to improve students' experience of, and attainment in, science and mathematics. Modern robotic construction kits provide learning environments in which children can use their hands to touch and build concrete objects using familiar materials such as gears, motors, sensors, and computer-generated interfaces to program their creations (Bers, Ponte, Juelich, Viera, & Schenker, 2002; Resnick & Kafai, 1996). Cubetto, by Primo Toys, is another example in which a wooden robot is designed to teach children basic principles of coding using a tangible programming language (Bers & Horn, 2010). Influenced by the earlier work of Seymour Papert's LOGO (Papert, 1980) and Turtle Graphics, Cubetto uses a hands-on programming language to control a wooden robot that roams the checkerboard and completes clearly defined tasks. Students are less exposed to think about the social aspects of human-computer interactions (HCI), which is somewhat ironic, as more interest has been placed on the social effects of technology on human learning and behavior. Advancements in technology have enabled sensory technology to detect human behavior (e.g., physiological sensors, facial and voice recognition) and improve interaction between humans and machines for collaborative tasks (e.g., building and moving objects).

Another question that comes to mind is how agents and robots are similar and/or different from one another. One common feature between "Agents," "Robots," and "Collaborative learning" is the wide variety of usage of these terms in different fields (e.g., cognitive psychology, artificial intelligence, social sciences), and variation in the degree of function and capability. While some agents and robots may be equipped with elaborate skills (e.g., have goals and knowledge, make decisions), others may have elementary skills (e.g., grammatical parser agent) and work in large numbers. Dillenbourg (1999) describes agents as a functional unit inside a system. Agents can have different skills and vary in number, representation, goals, and knowledge. Agents do not have to be autonomous or intelligent to impact learning; interactions with low functional units can also bring about interesting phenomena. On the other hand, robots can be seen as a physical platform with a system full of functional units that direct its behavior. These functional units can consist of multiple agents programmed to control humanoid robots to interact with, and respond to, a precise sequence of stimuli or systematic patterns. Robots may have more functional units within their system than agents, as they are not confined to a computer screen and have a physical presence, can take action, and manipulate objects in the real world.

State of the Art

Robots and Agents as Collaborative Learning Partners

The collaborative partner in learning has expanded from a human peer to include a virtual representation (agent) or a robotic peer. Advances in robotics technology have shifted the focus from supporting humans in industrial productivity (e.g., industrial robots, mobile agents) to supporting humans at a more personal level (e.g., companion robots, personal agents). One reason for this expansion may be the fact that many technological artifacts (e.g., humanoid robots, computer agents) now display biologically inspired human-like features and physical human behaviors that elicit social responses. Strong social metaphors enable students to share knowledge and build peer-like relations. Pedagogical agent programs can engage in contingent social dialog for a long time. The effects of socialness on learning are readily attributed to the timing and quality of information delivery, which computers can largely mimic and control in targeted ways (Kanda, Hirano, Eaton, & Ishiguro, 2004; Breazeal, Dautenhahn, & Kanda, 2016). Robots and agents are highly directable, and can create ideal circumstances that enable new ways for students to reflect, reason, and learn.

Collaborative learning with robots and agents is complex, as social metaphors are used to elicit engagement, and learning conditions are structured to induce cognitive processes in individuals and groups (Perret-Clermont, Perret, & Bell, 1991). This area of research may best be described along two continuums, the level of social metaphor, and who the targeted learner is (i.e., self, self-other, other). The amount of social interaction and verbal dialogue may differ based on the amount of social metaphor present and who the target learner is (self, self and other, or other). The next few sections will take a closer look into the collaborative learning processes and learning mechanisms that emerge from these interactions. Figure 1 attempts to position some of the work introduced in this chapter along these two continuums (i.e., social metaphor and target learner). Although some of the research introduced may not directly involve physical robots, the arrangements can be generalized to human-agent interactions, as much of the research and development with robots begins with human-modeled computer systems and virtual agent simulations.

Social Metaphors

Pedagogical agents with human-like appearances can be categorized according to the extent to which they include representations of social metaphors. We use the term “representations” because they are not mental models; they simply use technology to mimic schemas presumed to be present in the cognition of the humans with whom they interact. We call those representations social metaphors. However, as mentioned in an earlier section, not all technologies put the emphasis on direct social exchange with humans (e.g., industrial robots). Most fall somewhere in-between, and participate in both machine-like and human-like features.

It is important to note that direct interactions between an artifact and a user can occur without any real social elements. Socially indifferent systems usually have no social functions, social interests, or social abilities as part of human-machine interactions (e.g., statistical applications, word processors, industrial robots). Early examples of socially indifferent machines that assisted learner performance were the Testing Machine (Pressey, 1932) and the Teaching Machine (Skinner, 1986) mentioned earlier. Skinner’s Teaching Machine taught arithmetic: a sequence of math problems appeared on top of a machine box and guided the learner through programmed instruction. Even though both the testing and teaching machines had no social elements, they were somewhat successful in teaching mathematics to elementary, secondary, and college mathematics students. Modern robotic construction kits may also fit into this category, as children build and interact with concrete objects with no social elements, but still learn how gears, motors, and sensors work.

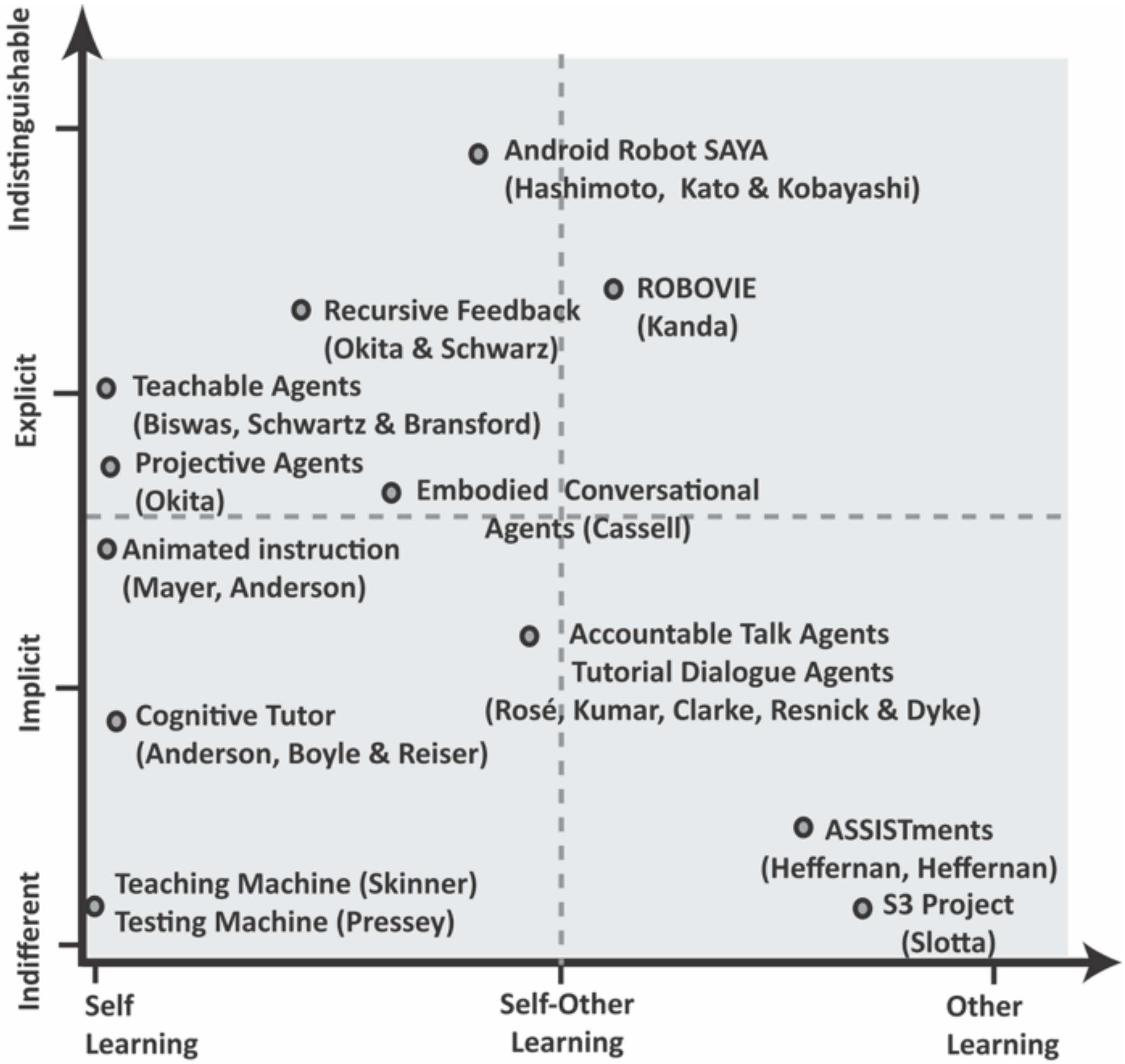

Fig. 1 Pedagogical robots and agents along social metaphor and target learner continuum.

Socially implicit systems draw on social patterns of interaction without trying to lead the learner to presume that they (i.e., the system) thinks like humans. Computer tutors, for example, incorporate interaction patterns known to be effective for tutoring, but they usually have a command-line interface and very little, if any, visual representation of an animated tutor character (Pane, Griffin, McCaffrey, & Karam, 2014). Anderson, Corbett, Koedinger, and Pelletier (1995) developed the Cognitive Tutor, an intelligent tutoring system and computational model that represented student thinking and cognition. The Cognitive Tutor contained a computational model representing student thinking and cognition, but the tutor, itself, appeared as disembodied text with no visual character (Anderson, Boyle, & Reiser, 1985).

Other systems build on explicit social metaphors of interaction and appearance that invite social interaction. Socially explicit systems consist of features that try to cue learners to think of social interaction, such as having an animation character interact with the student (Mayer & DaPra, 2012) or embodied conversational agents engaging in literacy learning with children (Cassell, Tartaro, Rankin, Oza, & Tse, 2007). Socially explicit systems usually consist of features that maximize social metaphors and perceptions of social presence to enable an affective social interaction to take place. For example, Honda's humanoid robot exhibits human-like movements and appearance, but also includes implicit features from cognitive models that invite social interactions (Ng-Thow-Hing et al., 2009). Robots in the socially indistinguishable category utilize extensive human mimicry. The social metaphor at this level usually involves high-fidelity appearance and behavior. A good example of this is the robots of Hiroshi Ishiguro (2007), who has been developing androids (i.e., realistic human-like robots) he calls "geminoids" and "actroids" that look and behave (almost) human. Mori's work on the uncanny valley indicates that the challenge in future development is to achieve total human mimicry (Mori, 1970). While androids are quite common in science fiction, material and design challenges still need to be resolved before they can become widely used in the real world. However, such ideas are starting to be tested in classrooms (Hashimoto, Kato, & Kobayashi, 2011).

Learner-centered interactions with and between pedagogical agents

Social interaction has been found to be quite effective in peer tutoring (Roscoe & Chi, 2007; Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001; Graesser, Person, & Magliano, 1995), reciprocal teaching (Palincsar & Brown, 1984), and behavior modeling (Anderson et al., 1995). Underlying these approaches is the view that individual cognition is shaped through social interactions and verbal dialogue plays a special role in learning and cognition (Wertsch, 1979). Such forms of collaborative learning are often seen as an optimal way to help people learn (Chi et al., 2001). While direct "in-person" human facilitation can indeed be effective, finding a peer learner that is a good match for learners with specific needs can be a challenge (Mandl & Ballstaedt, 1982). Human tutors that do not have the appropriate metacognitive abilities (e.g., unable to accurately monitor their pupils' understanding), skills, and patience, can negatively impact the tutee's learning outcomes (Chi, Siler, & Jeong, 2004).

One way to overcome the limitations of human peers is to involve computerized people (e.g., pedagogical agents and avatars) and/or computerized instructions (e.g., intelligent tutoring systems). Implementing teaching and tutoring strategies into technology has led to the development of pedagogical computer agents (Baylor, 2007). Like a human peer, a computerized peer can have limitations. The human learner may oftentimes be constrained by what the computerized peer agent or environment can do in response. However like a human peer, observing a computer-controlled agent, under peer tutoring circumstances, may trigger similar learning and reflection. The use of social metaphors and schemas makes interactions with humans more original and motivating (Bailenson, 2012; Baylor, 2007). When social metaphors in technology are combined with empirically supported learning methodologies and dialogic instructional repertoires, strong collaborative learning with and between students can occur with pedagogical agents.

Individual Self-Learning. There are several processes at work when individuals engage in self-learning. Some of the mechanisms involve students monitoring their own understanding through self-reflection, monologic reasoning, and self-regulation. Technological artifacts (i.e., pedagogical agents and robots) can provide a safe environment for students to externalize their own thought processes onto an artifact to make their thoughts more accessible for personal reflection (Shneiderman, 2007; Okita, 2014; Schwartz et al., 2009). For example, the Teachable Agent system (Biswas, Leelawong, Schwartz, Vye, & TAG-V, 2005; Schwartz et al., 2009) takes students' vague mental conceptualizations of a topic area, and produces more concrete representations using visualization tools (i.e., electronic concept map called Betty's Brain), which is interpreted and explored by the pedagogical agent. This allows the learners to reflect and structure their thoughts through social interactions with the agent, which in turn influences the development of metacognitive skills (Schwartz et al., 2009).

While "*collaborative dialogue with oneself*" may sound puzzling, "*conflict with oneself*" may sound more familiar (Dillenbourg, 1999). As explored by Mead (1934) and Vygostky (1978), *thinking* can be viewed as an internalized dialogue with oneself (e.g., self-regulation, self-explanation, cognitive conflict). Self-explanation is a process whereby students explain to themselves or externalize their knowledge or understanding in the form of verbal utterances (Chi, Bassok, Lewis, Reimann, & Glaser, 1989). Early automated instructions involved pedagogical agents and chatbots that helped scaffold students' verbal reasoning through questions that elicited explanations from students (Stevens & Collins, 1977). Through self-explanations, students "fill in" missing or not yet understood parts of phenomena (i.e., knowledge integration) in order to provide a complete explanation. King (1999) found that when students were trained to use such self-regulation techniques to monitor their own understanding, they were more effective at problem solving than students who were not trained. Learning by explaining to oneself has received great attention in machine learning (Mitchell, Keller & Kedar-Cabelli, 1986) and in cognitive modeling (VanLehn, Jones, & Chi, 1992).

Self-learning can involve both indirect and direct interactions with others, where the interaction can shift back and forth between monologic and dialogic interactions, but still focus primarily on individual self-learning. Interactions that involve the "thought of others" or the "anticipation of a social interaction" has led to learning with pedagogical agents and avatars (Okita, Bailenson, & Schwartz, 2007). Studies have found that asking students to "prepare to teach" can lead to more learning compared to students who are asked to study for themselves (Bargh & Schul, 1980). The mere presence of others or studying among peers can also be useful in learning. Learning can occur by comparing ourselves to peers or observing others to develop a better understanding of the self. Even if a student cannot solve a math problem, observing someone else may help. This is because the person they are observing can provide a model of competent performance. Self-reflection while problem solving is challenging because of the cognitive demand of solving the problem and simultaneously reflecting on one's own performance (Gelman & Meck, 1983). A projective pedagogical agent, "ProJo," was designed to openly display its reasoning when solving math problems. This relieved the cognitive load and allowed learners to monitor ProJo and "look for mistakes" (Okita, 2014). The additional benefit of monitoring the work of others for mistakes is located in the act of wrestling with potentially inferior solutions (Kruger, 1993). ProJo is based on the premise that externally monitoring the reasoning of a pedagogical agent's problem solving can help students turn their monitoring skills inward, and eventually self-correct when solving math problems (Karmiloff-Smith, 1979).

Learning by Teaching (LBT) through Teachable Agents has created an ideal situation for self-learning, where the student takes on the role of a peer tutor and teaches a computerized pupil agent (Bargh & Schul, 1980; Leelawong & Biswas, 2008; Biswaset al., 2005). LBT consists of a phase that further shows desirable effects called Recursive Feedback (Okita & Schwartz, 2013), which refers to information that flows back to tutors when observing their pupils' subsequent performance while interacting with others (e.g., football coach seeing his team competing out on the field). Tutors can map their understanding by observing how their pupils apply their teachings through interaction with others. Any discrepancies they notice leads to the realization that potential deficiencies in pupil understanding are not due exclusively to how the material was taught per se, but rather a lack of precision in the tutor's own content knowledge. When studies compared human pupils to computerized pupil agents, similar results were found in a virtual reality environment (Okita, Turkay, Kim, & Murai, 2013).

Self-learning can benefit from intelligent tutoring systems that use behavioral data of other students and instructors, even if they do not have direct contact with them. Research on intelligent model-based agents has focused on personalized instruction involving multifaceted systems that leverage rich models of students and pedagogies to create complex learning interactions. Systems such as Cognitive Tutors (Anderson et al. 1995; Pane et al. 2014) have tens or hundreds of thousands of users, and have gathered performance and behavioral data (e.g., how to teach, study what worked, when it worked), which has contributed to the design of current intelligent tutoring systems. Cognitive Tutors can provide support to and anticipate the student's thinking processes (VanLehn et al 2005) based on experiential data from other students, and model complex teacher and student pedagogical strategies (Heffernan & Koedinger, 2002). Research on intelligent tutoring systems has been successful at producing impressive technologies based on knowledge modeling with Bayesian Knowledge tracing and production-rule models to represent skills (Pane et al., 2014; Corbett, Koedinger, & Hadley, 2001).

Self-learning can also have limitations. While elaboration of one's own thinking is good for individual performance, ignoring the views of peers and their ideas can limit opportunities to reflect on and develop reasoning skills. Barron (2003) has found that this is especially true in group problem solving, where the absence of engagement with others' reasoning, or the excessive use of one's own thinking, can lead to poor overall group performance.

Self-Other Learning. This section covers pedagogical agents and robots that focus on Self and Other's learning, which is important in dyads, triads, and small group activities that involve more ideas and perspectives from the participants (i.e., learner and their peers). Self-Other learning with pedagogical agents often involves different discussion methods (e.g., "talk moves," script-based, and dynamic dialogic instruction) that help set up systematic differences among learners and elicit rich interactions that improve students' reasoning skills. Reasoning skills are developed through self-other interactions that trigger cognitive and socio-cognitive conflict, develop group knowledge integration, and build consensus from discussions (Kuhn, Zillmer, Crowell, Zavala, 2013).

Early automated instructions with static interactions were limited in monitoring and responding to learners. These interactions eventually evolved into more elaborative speech acts that have social and intellectual functions (Greeno, 2015), and trigger cognitive processes through elaboration and self and other reasoning (Resnick, Michaels, & O'Connor, 2010). Speech acts like Accountable Talk moves scaffold collaborative knowledge building and reasoning and have been shown to support learning, long-term retention and development in reasoning. Pedagogical agents that elicit talk moves in a collaborative learning situation have been successful at producing similar performance effects (Adamson, Dyke, Jang, Rosé, 2014; Dyke, Adamson, Howley, & Rosé, 2013). The pedagogical agent takes on a 'facilitator' role rather than a 'tutor' role, because the agent only minimally intervenes to scaffold group discussions with human peers (Dyke et al 2013, Kumar, Rose, Wang, Joshi, & Robinson, 2007). However, even minimal intervention of this kind (e.g., prompting a student to reason about their peers reasoning), carries both a conversational implicature whereby the student shares their thinking verbally with their peers, as well as a cognitive implicature – simply prompting the target student to reason by virtue of that request.

Script-based methods (Dillenbourg, 1999; Kollar, Fischer, & Hesse, 2006; Kobbe et al., 2007) comprise different scaffolding techniques that involve structuring tasks into phases, introducing interaction rules, or employing role playing during collaborative interactions. A script can be used to define a wide range of features in collaborative activities (e.g., methods, tasks, roles, timing, patterns of interactions). Static scripts provide the same support for all participants, regardless of participant behavior during a collaborative interaction. Dynamic scripts provide a different response tailored to a participant's or group's performance or context of discussion as it unfolds. Scripts with a strict model can easily be encompassed in the design of the agent system, and may use dialogues intended to be adopted by the participants (e.g., "follow me" style prompts) to more subtle suggestions of behavior (e.g., "Each come up with three ideas, then discuss the ideas as a group"). Strict scripts can minimize the gap in group learning experience and performance and establish uniformity in discussions between the groups. Such semi-structured interfaces that include pre-defined scaffolds have helped grouped students to focus more on the task and produce less off-task comments (Baker & Lund, 1996). Over-scripting can have negative implications by limiting the creative thought process and the contributions students can make (Dillenbourg & Hong, 2008).

Over the years there has been more interest in dialogue-rich instruction that involves dialogue with discussants who engage students in inter-mental reasoning processes. In inter-mental reasoning processes students explain, reflect upon, and elaborate on their own and their peers' understanding of domain concepts, and collaboratively engage in a sense-making process (Clarke, Resnick, & Rosé, 2015). Engaging in dialogue with another creates conditions for challenges, disagreements, and contradictions of opinions and ideas.) This process can lead to cognitive restructuring where students begin to integrate new perspectives into their own understanding (Kruger, 1993). Early pedagogical agents that use dialogic instruction have been programmed to elicit conceptual depth by using generic prompts that encourage learners to articulate and elaborate their own lines of reasoning and to challenge and extend the reasoning of their peers. Recently, more dynamic dialogical instructions support learners by adapting the strategy by taking into account emergent characteristics of a discussion. Pedagogical agent systems, also referred to as "Tutorial Dialogue Agents," help lead students through directed lines of reasoning to construct their conceptual development from the Knowledge Construction Dialogues developed by Rose and VanLehn (2005). Dynamic dialogical instruction engages the group in a dynamic interchange of input by producing and receiving ideas, and negotiating for meaning. Tutorial dialogue agents are interactive, and have the ability to conduct multi-turn directed lines of reasoning with students who respond to their prompts (Kumar & Rose, 2011). A notable framework, Academically Productive Talk (APT), is used to elicit rich interactions (Kumar et al, 2007) and can be triggered through real-time analysis of collaborative discussions (Dyke et al 2013; Kumar et al, 2007, 2010). Students using tutorial dialogue agents with APT have engaged in directed lines of reasoning that have led to significantly more learning than those with no support. Studies have found a number of important mechanisms in dialogue-rich discussions or dialogic instruction where individuals articulate their thinking, listen to their peers, and try to negotiate meaning while integrating their input.

Where this kind of agent might be particularly useful is in augmenting a teachers' facilitation of face-to-face whole class discussions. Several studies have documented how rare it is to find classrooms where teachers lead students in rich discussions of this kind (Kane & Staiger, 2012; Pimentel & McNeil, 2013). In addition, few professional learning interventions have been successful in supporting teachers in learning how to facilitate discussions that engage students in deep reasoning and argumentation (Clarke et al., 2013). Studies have documented that teachers rarely use probing questions or help students think with peers during classroom discussions (Pimentel & McNeil, 2013). Thus, effective tools/methods aimed at improving teachers' classroom talk skills are in much demand and can support teachers in facilitating discussions that support learning (McLaren, Scheuer, Miksako, 2010 p. 387). Tutorial dialogue agents can be useful for pre-service and in-service teachers in managing group collaborative interactions in the classroom and monitoring the interactions occurring in different places and/or at different times. Not only is initiating small groups of students into dialogic discussion practices using computer support beneficial, but the findings also show that dynamic support by tutorial dialogue agents poses positive effects on teacher uptake of dialogic facilitation practices in classroom discussions (Clarke et al., 2013).

Others' Learning. Pedagogical agents can also provide information on "others' learning" to help people such as teachers and parents make instructional decisions, select appropriate course content, and monitor academic performance. Applying algorithms such as Bayesian Knowledge Tracing (BKT) to intelligent tutoring agents can model the learner's mastery of knowledge, and predictive analytics can identify potential struggles students may have (Corbett & Anderson, 1995). While such interventions are sophisticated and prescriptive (i.e., an automated system taking specific action to a given situation), there are challenges in accommodating the effects of human intervention (e.g., teachers taking action after seeing student performance) in the system's automated instruction process.

Studies have also found that teachers and parents tend to favor technology that depends more on simple and straightforward heuristics to assess student mastery (e.g., Get three in a row right, move to next level) (Heffernan & Heffernan, 2014). Another approach is to use information on others' learning to provide useful descriptive information to a third party (i.e., teachers and parents). Recent open-learner models and reporting systems use educational data mining and learning analytic methods to extract important information and present data using visualization techniques to indicate student progress and behavior. Instead of having the system make the decision, the system uses information from others' learning to present options for teachers and parents from which they can make intelligent informed decisions (Baker, 2016).

The Purdue Course Signal System (Arnold & Pistilli, 2012) offers predictive analytics in student success and early warnings for instructors when a student is at risk. Course Signals attempts to scaffold effective practice by suggesting actions to instructors based on student performance and behavior. In ASSISTments, teachers examine student's interaction data and performance reports on assignments, to design next day lectures, and better predict exam outcomes (Feng, Heffernan & Koedinger, 2009; Heffernan & Heffernan, 2014). ASSISTments all provide extensive professional development for teachers to share and disseminate effective practices. The S3 project (Tissenbaum & Slotta, 2019) allows teachers to monitor ongoing student activities through software agents that process student interactions in real time. This allows teachers to receive notifications that help orchestrate student groups, dynamically control classroom flow, and allocate necessary resources to students in a timely manner. Other systems have also made available to instructors real-time information on student participation through chat messages, so instructors can take immediate action to improve the collaborative discussions among students (Van Leeuwen et al., 2014).

Linking Theory to Practice using Robots and Agents in Learning

Some have argued that by making machines smarter, good teaching and tutoring strategies can be implemented, and thus more learning will occur. Intelligent agent systems and robots alone do not guarantee learning, and we would argue that they should not be considered the panacea for supporting collaborative learning either. They cannot replace the intelligence of a teacher, but when deployed strategically the affordances of these technologies can foster processes of collaboration and thinking practices that are supportive of individual and collaborative learning.

Other factors can influence learning (e.g., motivation, engagement, trust) and application in classrooms. Learners may not understand sophisticated artifacts; thus, they may not trust them or may over trust them by attributing too much intelligence to them. Also, some worry that making learners too dependent on sophisticated features will cause them to cease acting, thinking, and learning independently and depend on machines to make decisions for them (advice giver, expert system, information system management). According to Salomon, Perkins, and Globerson (1991), student performance with technology can be assessed in two ways. One is the way students perform while equipped with or interacting with technology. Usually, this means that technology plays a significant part in the cognitive process that students would usually have to manage manually on their own. Just handling a computer-based tool with no guidance can make the user (teacher or student) lapse into meaningless activities. A positive impact of interaction with these computer-based tools would be lasting cognitive changes that equip students with thinking skills, depth of understanding, and strategies to continue solving math problems (e.g., similar to internalizing the abacus) even when away from technology.

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Dialogic instruction has been shown to support learning, retention, and reasoning development, and has made this form of instruction a widespread practice that is promising; however, scaling this practice is not easy. Training teachers to use dialogic instructions effectively is a challenge, especially in low-performing schools (Clarke et al., 2013). Despite the decades of work on knowledge modeling in Intelligent Tutoring Systems, the approaches favored in practice (or at scale) are fairly simple (Heffernan & Heffernan, 2014). It is difficult for a pedagogical agent to recognize that an intervention is not working as students adapt faster than automated systems. It is not that such changes and updates are impossible, but they take time and require constant attention. Humans are flexible and intelligent, but going through large amounts of information takes time. Baker (2016) suggests that rather than building sophisticated intelligent tutors, tools need to be designed more intelligently using Educational Data Mining (EDM) and Learning Analytics to augment human cognitive abilities and performance.

Future Prospects of Robots and Agents in Education

In this chapter we examined how social metaphors in robot and agent technology, combined with learning theories and methodologies, reveal powerful learning partnerships and new insights into the role of social relationships in learning. Winograd and Flores (1986) remind us that people develop tools, but tools need to be refined and used by intelligent individuals based on practice. There is much educational research that looks into developing guidelines for practice and design (Bransford et al., 2010) and educational data mining methods (e.g., learning decomposition) that show strategies that work (Beck & Mostow, 2008). By identifying the kinds of practices that research suggests are successful, we can work to maximize benefits from technology (pedagogical agents and robots, and robotic systems). Salomon et al. (1991) remind us that cognitive effects gained through technology depend greatly on the meaningful engagement of learners in the tasks afforded by these technological artifacts. It is essential to design a collaborative learning relationship with pedagogical robots and agents that do not cease independent thinking but promote lifelong learning.

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Additional Reading

Johnson, W. L., & Lester, J. C. (2018). Pedagogical Agents: Back to the Future. *AI Magazine*, *39*(2), 33-44.

Johnson and Lester revisit their 2000 survey on research pedagogical agents - agents that engage with humans to support their learning. In the (Johnson, Rickel & Lester, 2000). In this 2018 update, they revisit their 2000 predictions for developments in the area of pedagogical agents, and consider the current state of the art. This article provides a survey of pedagogical agents developed over the last 20 years, classified in terms of the ways in which they engage with humans to support learning. In addition to examples of pedagogical agents, this article discusses the underlying technological architecture that has been driving developments of pedagogical agents.

Le, N. T., & Wartschinski, L. (2018). A Cognitive Assistant for improving human reasoning skills. *International Journal of Human-Computer Studies*, *117*, 45-54.

This article reports on an evaluation of LIZA, an adaptive *conversational* agent that interacts with humans through text-based natural language processing. Le and Wartschinki examine whether engaging with Liza increases a humans' skill of reasoning through discussions about reasoning, heuristics and biases. This article provides an example of a system as a thought partner for solving problems. In addition, this articular of how a system's mimicry of human-like interaction through natural conversation, can elicit cognitive processes of humans that are productive for learning.

Shiomi, M., Kanda, T., Howley, I., Hayashi, K., & Hagita, N. (2015). Can a social robot stimulate science curiosity in classrooms?. *International Journal of Social Robotics*, *7*(5), 641-652.

This article reports on a field study of Robovie in an elementary school. Robovie is a social robot designed to socially engage with children. In this study, the researchers explored how social

interaction with Robovie about science might stimulate children's interest and curiosity about science. This article provides a concrete application of the use of robots as a collaborative learning partner in schools and an evaluation of its affordances for development interest in science.

Timms, M. J. (2016). Letting artificial intelligence in education out of the box: educational cobots and smart classrooms. *International Journal of Artificial Intelligence in Education*, *26*(2), 701-712.

This article invites the field of artificial intelligence in education to imagine systems that are purposefully designed for teaching and learning, rather than adapting systems from business industries to support teaching and learning. In proposing the former, the author invites the field to imagine the kind of technological support for teaching a teacher might desire, and the kind of technological support for learning a student might desire. This article identifies some of the constraints of off the shelf systems for pushing the field forward in terms of designs for supporting teaching and learning.

Wise, A. F., & Schwarz, B. B. (2017). Visions of CSCL: Eight provocations for the future of the field. *International Journal of Computer-Supported Collaborative Learning*, *12*(4), 423-467.

This article presents a series of questions and tensions for the field of CSCL to wrestle with, or perhaps reconcile, for future research and development. Amongst these questions and tensions are several issues at the edge of current research and development on robots and agents. This article is useful for identifying potential new directions for designing robots and agents for collaborative support of learning.