

Pedagogical Agents: Back to the Future

W. Lewis Johnson, James C. Lester

■ *Back in the 1990s, we started work on pedagogical agents — a novel paradigm for interactive learning. Pedagogical agents are autonomous characters that inhabit learning environments to engage with learners in rich, face-to-face interactions. Building on this work, in 2000, together with our colleague Jeff Rickel, we published an article on pedagogical agents (Johnson, Rickel, and Lester 2000) that surveyed and discussed the potential of this new paradigm. We made the case that pedagogical agents that interact with learners in natural, lifelike ways can help learning environments achieve improved learning outcomes. This article has been widely cited, and was a winner of the 2017 IFAAMAS Award for Influential Papers in Autonomous Agents and Multiagent Systems.¹*

On the occasion of receiving the IFAAMAS award, and after 20 years of work on pedagogical agents, we take another look at the future of the field. We start by revisiting the predictions we made in 2000 for pedagogical agents, and examine which predictions panned out. Then, informed by what we have learned since then, we take another look at emerging trends and reexamine the future of pedagogical agents. Advances in natural language dialogue, affective computing, machine learning, virtual environments, and robotics are making possible even more lifelike and effective pedagogical agents, with potentially profound effects on the way people learn.

The Future of Pedagogical Agents as We Saw It in 2000

We envisioned that the ability of pedagogical agents to interact with learners in a natural, human-like way would make learning easier, more engaging, and more motivating. This deeper engagement, in turn, would result in improved learning outcomes.

At the time, prototype pedagogical agents capable of human-like interaction with learners were only just beginning to be developed. Figure 1 shows two such agents, which we cite as examples in the following discussion. Herman the Bug, on the left, observed the actions of learners interacting with the Design-a-Plant game and provided problem-solving advice, explanations, and hints (Lester, Converse, Stone, et al. 1997). STEVE (Soar Training Expert for Virtual Environments), on the right, inhabited the VET (Virtual Environments for Training) virtual environment and coached learners in the operation of a shipboard power plant (Rickel and Johnson 1999).



Figure 1. Example Turn-of-the-Century Pedagogical Agents.

We projected that the following pedagogical agent interaction capabilities would promote learning:

Expressing emotions. Agents can better engage and motivate learners by expressing emotional reactions through facial expressions and body movement.

Nonverbal feedback. Agents can give feedback nonverbally through shaking of the head, facial expressions, etc. Agents can use these cues to provide feedback continually, supporting learners without interrupting their activities. For example, when STEVE coached trainees in power-plant operations, he would watch and nod or shake his head as the learner performed each step of the procedure.

Gaze and gesture as attentional guides. Similarly, agents can use nonverbal cues such as gaze and gesture to direct focus of attention. For example, in figure 1 (right) STEVE is pointing at a button that the learner must press to start the power plant. Attentional guides such as these can make it easier for learners to follow complex procedures, and raise learners' awareness of events in the environment without interrupting them.

Conversational signals. Agents can use nonverbal signals such as backchannel head nods to regulate conversations with the learner, especially in the context of spoken dialogue. Nonverbal signals like these allow the agent to have a conversation with the learner while the learner is performing other tasks.

Adaptive pedagogical interaction. Combining the above capabilities, agents can respond adaptively to interruptions, conversational turn-taking, and learner actions in the course of an instructional scenario. For example, Herman the Bug provided visual problem-solving advice that was adaptively tailored to learners' individual needs as they designed virtual plants.

The capabilities of pedagogical agents make possible new types of interactions between learners and learning environments. Back in 2000, we identified two examples: interactive demonstrations and navigation guidance.

Interactive demonstrations. Agents such as STEVE can demonstrate tasks while at the same time explaining what they are doing, and why, directing the learner's attention to important features in the environment, and answering learner questions.

Navigational guidance. Agents can lead learners around a complex virtual environment, such as a power plant, and prevent them from getting lost.

We also foresaw that pedagogical agents could assume new roles in learning environments besides that of intelligent tutors. For example, they could act as virtual teammates and collaborate with learners in performing tasks.

How Did the Future Pan Out?

The fundamental hypothesis motivating our proposed research agenda was that pedagogical agents would improve learning. Early empirical work on pedagogical agents found the persona effect, which is that introducing pedagogical agents into learning environments can have a significant positive effect on learners' perception of their learning experience (Lester, Converse, Kahler, et al. 1997). However, the effect of pedagogical agents on learning outcomes had not been established. Educational psychologists greeted pedagogical agents with mixed reactions. Some were concerned that that they might prove to be "seductive details" (Garner, Gillingham, and White 1989) — interesting but irrelevant and distracting to learning. Others such as Clark (2001) argued that they were expensive to produce and that equivalent learning effects could be achieved through less costly means.

Since the publication of the Johnson, Rickl, and Lester (2000) article, a broad array of studies have formally investigated the effect of pedagogical agents on learning. These investigations have involved many

forms of pedagogical agents supporting diverse learner populations for a wide range of subject matter in different settings. A recent meta-analysis of pedagogical agents reviewed 43 independent studies with more than 3,000 learners (Schroeder, Adesope, and Gilbert 2013). Across all pedagogical agents, learner populations, settings, and subject matter, the meta-analysis found that agents improve learning relative to learning environments that do not use agents. Two additional findings were also revealed: in the analyzed studies, agents appear to be most effective for math and science and less so for the humanities, and they also appear to be more effective for younger learners (particularly K–12 students) than for older learners. At the same time, there are examples of pedagogical agent systems that depart from these general trends. For example, Alelo’s learning environments for foreign languages and cultures (humanities disciplines) are used widely by older learners in higher education and in the military in over twenty countries. In addition to the overall findings of the field, subtle interactions have also been found. For example, agents’ perceived level of intelligence can affect learners’ self-efficacy (Baylor and Kim 2004), agents’ gender can affect learners’ recall (Kim, Baylor, and Shen 2007), and learners’ personality traits can affect their emotional reactions to agents (Lallé et al. 2016).

With these foundational findings in hand, in the two decades since we began work on pedagogical agents we have been delighted to see the emergence of a broad range of pedagogical agent capabilities. Many of the nascent functionalities we envisioned for pedagogical agents in 2000 are *de rigueur* in today’s pedagogical agents. Learning environment designers routinely create pedagogical agents that monitor learners’ problem-solving activities and expressively respond with emotion, nonverbal feedback, gaze, and gesture. As learners interact with an environment, pedagogical agents provide hints, advice, and explanations, express emotion through facial expression and nonverbal behaviors, and direct learners’ attention to salient elements of a problem or a virtual environment with pointing gestures and gaze. For example, when learning progress slows or learners become frustrated, today’s pedagogical agents routinely respond empathetically and intervene with spoken encouragement. It is not uncommon for them to provide both cognitive (for example, task-oriented) and affective (for example, motivational) support.

In sum, in addition to significant use in experimental K–12 science, technology, engineering, and mathematics (STEM) learning environments, pedagogical agents are now being widely adopted in military training (Johnson et al. 2011; Johnson 2010) and higher education (Taglieri et al. 2017).² They have become an established part of technology-enabled learning in a range of disciplines.

Supporting Scientific Advances

Pedagogical agents have benefited considerably from advances in three adjoining fields. First, in the intervening 20 years since pedagogical agents first appeared, intelligent tutoring systems have steadily matured. In a development that surprised many in education, intelligent tutoring systems have become almost as effective as human tutors in one-on-one tutoring for STEM domains (VanLehn 2011). Many pedagogical agents today are driven by “back-end” intelligent tutoring systems that reason about the learner’s current competencies and dynamically adjust pedagogy by selecting and sequencing problems, delivering problem-solving feedback and support, conducting after-action reviews, and assessing learning (VanLehn 2006). However, rather than delivering these functionalities through traditional GUI elements, pedagogical agents create human-like interactions to support learners.

Second, significant advances in intelligent virtual agents have directly contributed to the maturation of pedagogical agents. Intelligent virtual agents, or virtual humans, are computer characters whose behaviors are dynamically generated to support rich interactions (Swartout et al. 2006). Early work on virtual humans focused on creating sophisticated theory-of-mind models (Pynadath and Marsella 2005) and enabling them to engage users in social dialogue (Bickmore and Cassell 2005), and these intelligent virtual agents can now develop rapport with human partners through artfully synthesized verbal and nonverbal behaviors (Huang, Morency, and Gratch 2011). Because pedagogical agents can be viewed as a specialized category of intelligent virtual agents (that is, those that target human learning support), pedagogical agent research readily draws on the increasingly sophisticated models of nonverbal communication and social interaction created in virtual humans research.

Third, advances in affective computing have propelled the development of emotionally responsive pedagogical agents. Affective computing encompasses three core capabilities: affect recognition, affect understanding, and affect synthesis. Affect recognition is the ability to recognize a user’s affective state from a stream of input signals that may include facial expression, heart rate, electrodermal activity, and speech (Calvo and D’Mello 2010; D’Mello and Kory 2015). Complementing affect recognition are affect understanding, which is the task of analyzing the recognized affective state and properly interpreting it in the wider cognitive and social context, and affect synthesis, which is the task of generating a system’s (typically an agent’s) expression of affect, including facial expression, posture, and gesture. A key objective of much work to date on affective computing has been to “close the affective loop” (Leite et al. 2010) by developing a tight integration of affect recognition, understanding, and synthesis to support empathetic interactions.

Creating affect-sensitive pedagogical agents attests to the growing recognition of the central role that emotion plays in learning (Baker et al. 2010; D'Mello et al. 2014; Pekrun et al. 2002; Pekrun 2011) and the importance of designing learning environments that respond to student affect (Rai et al. 2013; Sabourin and Lester 2014). Rather than conceptualizing learning as a purely cognitive endeavor, we now know that emotion profoundly affects learning, so work on developing pedagogical agents that recognize, understand, and synthesize emotion has become increasingly prominent.

The expression of affect can dramatically impact learners' perceptions of their interactions and even their learning performance. For example, agents that exhibit empathy significantly increase learners' perception of presence in a virtual environment (McQuiggan, Rowe, and Lester 2008), and a recent study that investigated whether human tutors' facial expressions influence learning in one-on-one tutoring found that tutors' use of facial expressions significantly improves learning performance when the expressions are contextually appropriate (Mudrick et al. 2017). Pedagogical agents that exhibit contextually appropriate affect may yield similar improvements in learning performance, and, conversely, pedagogical agents that respond inappropriately may cause confusion and harm learning, underscoring the importance of grounding agents' design in foundational research on human learning. Many experimental pedagogical agents have been developed with affect recognition capabilities that enable them to recognize when learners are confused or frustrated (Grafsgaard et al. 2013), and explorations are underway to understand the role that sensors can most effectively play in multichannel affect detection for learners (Paquette et al. 2015).

In addition to benefiting from research advances in these fields, two key enabling technologies have spurred the development of pedagogical agents. First, the proliferation of mobile computing and the low-cost computing power it has unleashed have created significant opportunities for pedagogical agent deployment. In 2000, we projected that pedagogical agents would be introduced into a wide range of learning environments. However, our vision focused on desktop and laptop devices: we did not anticipate the increasingly common adoption of pedagogical agents in tablet-based and phone-based learning environments.

Second, the character animation technologies provided by game engines are regularly used to create pedagogical agents. Rather than having to create and dynamically sequence agent behaviors programmatically, learning-environment designers often use off-the-shelf, commercial game technologies to orchestrate pedagogical agents' exhibition of gesture, posture, and gaze behaviors. In addition to freeing designers to focus on pedagogy, game engines allow

them to leverage ever-accelerating game engine graphics capabilities to introduce pedagogical agents directly into game environments. Game engines also enable pedagogical agents to be delivered in browser-based implementations, which is critical for many K–12 learning environments.

A development that has been somewhat surprising to us concerns agent presentation. We anticipated that with continued advances in graphics, pedagogical agents would become increasingly expressive, and this has happened in practice. In fact, pedagogical agents today can interact with learners via speech, facial expression, posture, and gesture with a fidelity that far exceeds our expectations given the graphics and animation capabilities circa 2000. That said, we did not anticipate that many pedagogical agents today would be developed with interfaces that are relatively impoverished, even relative to the standards of 2000. It is not uncommon to encounter pedagogical agents that are no more than still character images accompanied by speech balloons. Images or even stick figures are swapped in and out to convey different emotions, and speech-balloon text is updated to respond to learner actions. Some designers adopt this approach for the pragmatic reason of reducing production costs or download times. This simple approach is the presentation method of choice for many applications, and such an approach can yet yield very effective learning interactions.

Roles for Pedagogical Agents

In 2000, we projected that pedagogical agents would support what we called “face-to-face interaction” for a wide range of learning tasks. We expected that agents would support learners in much the same way that human tutors support learners: they observe learners progressing through problem-solving scenarios, they conduct interactive demonstrations, and they provide tailored problem-solving advice, all accompanied by context-appropriate nonverbal behaviors.

For example, the Crystal Island game-based learning environment for middle grades microbiology and literacy (Rowe et al. 2011) features as pedagogical agent a virtual nurse named Kim (figure 2). In Crystal Island, students play the role of a medical detective who is a member of a research team on a remote island where a mysterious disease is rapidly spreading. As students navigate through the environment, Kim monitors learners' progress and provides problem-solving advice as they diagnose the cause and source of the outbreak. Kim typifies the pedagogical agent we envisioned in 2000. She is a classic pedagogical agent who inhabits a virtual environment and adaptively scaffolds learning through interactions tailored to the needs of individual learners.

Since 2000, we have seen pedagogical agents evolve from classic pedagogical agents like the ones we envisioned, such as Crystal Island's Kim, to

include three additional families of pedagogical agents that serve functions very different from, but also complementary to, the classic pedagogical agents we proposed: teachable agents, learning companions, and role-playing agents. While classic pedagogical agents are fundamentally teachers, teachable agents (Biswas et al. 2005) are fundamentally students. Learners interact with teachable agents by “teaching” them: learners introduce new concepts and explain the relationships between concepts to teachable agents, usually through a GUI that supports concept map creation. For example, in Betty’s Brain, students teach teachable agent Betty (figure 3) about science topics, and they monitor Betty’s learning as she takes quizzes and responds to questions (Biswas et al. 2005). Interactions with teachable agents elicit the self-explanation effect (Chi et al. 1989), which promotes deeper learning through knowledge integration and mental model refinement. Teachable agents also appear to elicit the protégé effect (Chase et al. 2009), which is that learners seem to feel responsible for their teachable agents and to exert more effort to learn for their agents than when learning alone without an agent.

While classic pedagogical agents teach and teachable agents learn, learning companions, such as those depicted in figure 4 (Karumbaiah et al. 2017), act as peers to learners (Chou, Chan, and Lin 2003). Rather than acting didactically as an authority figure or requesting assistance as a student, learning companions act as knowledgeable peers, and play an important social role in learning (Kim and Baylor 2006). Learning companions can serve a key motivational function, which can be moderated by many factors such as gender. For example, a recent study found that a learning companion deeply integrated into the narrative of a game-based learning environment produced experiences that were significantly more engaging for girls than for boys compared to a learning companion without the same backstory and personality, even holding task support constant and controlling for learners’ prior knowledge and video game experience (Pezzullo et al. 2017). In addition to “pure” learning companions, some learning companions provide both a cognitive and social role.

Cai et al. (2014) have experimented with “trialogues” where learners interact with a pair of agents that combine these agent roles. One agent plays the role of expert agent and another the role of fellow student. Including role-playing agents makes it possible to vary the interaction strategy depending upon the learner’s level of ability. Low-ability learners can learn vicariously by watching the expert agent teach the student agent. Medium-ability learners can engage the expert agents in tutorial dialogue. High-ability learners can teach the student agent.

Agents increasingly play roles as participants within interactive learning scenarios and games. In our 2000 paper, we suggested that agents could act as vir-



Figure 2. Pedagogical Agent Kim in the Crystal Island Game-Based Learning Environment.

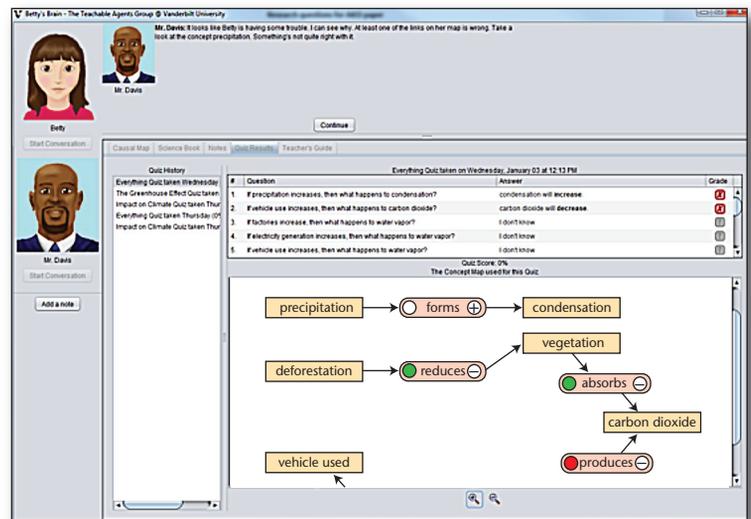


Figure 3. Teachable Agent Betty in the Betty’s Brain Learning Environment.

tual teammates, which has proven to be hugely important for learning foreign languages, cross-cultural skills, and interpersonal skills more generally. Applications first appeared in military training (Johnson 2010) and are now being used in healthcare (Taglieri et al. 2017), education, and corporate training. Such agent-based scenarios help learners gain skills that readily transfer to the real world by enabling them to learn in safe environments where they can practice and make mistakes with impunity, in contrast to live role-play exercises where learners often feel that they are performing before an audience and are being judged.

Figure 5 shows a combination of agents used in VCATs (Virtual Cultural Awareness Trainers) (Johnson et al. 2011), web-based cultural awareness courses that have trained over 100,000 military service members and are available for over 90 countries. A

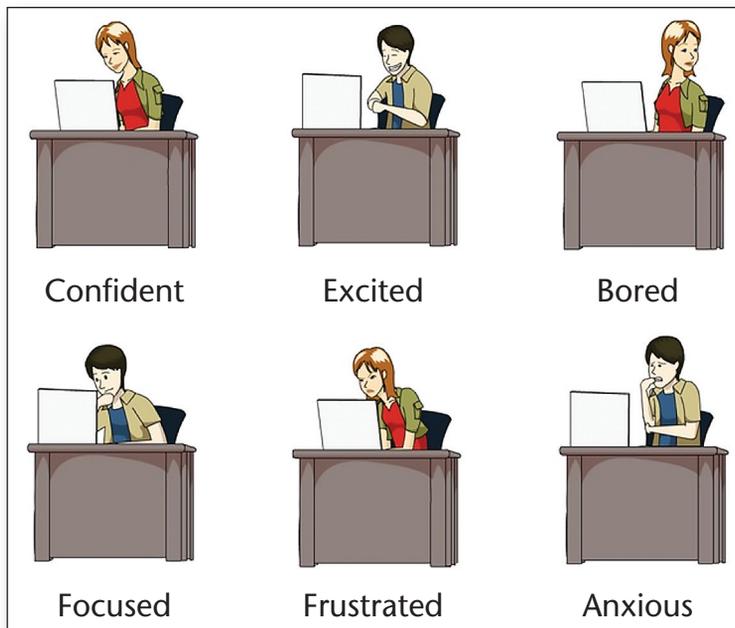


Figure 4. Learning Companions in MathSpring.

virtual coach, a classic pedagogical agent, introduces instructional topics (left) and provides feedback throughout. Learners then practice and demonstrate their mastery of cultural skills in role-play scenarios (right). Learners learn from the reactions and feedback of the virtual role-players, as well as from the virtual coach.

Figure 6 shows the cloud-based Alelo Enskill platform for virtual role-play, which is being used by higher education institutions in over a dozen countries to help students develop their spoken English skills.² Learners engage in task-oriented spoken conversations with virtual agents on a range of topics. Enskill provides learners with hints and feedback, evaluates their performance, and provides personalized instruction on skills they are having difficulty with. Simulation objectives are aligned with can-do statements in the Common European Framework of Reference for Languages (CEFR) (Council of Europe 2017), the most widely recognized standards for proficiency in foreign languages. This curriculum alignment means that as learners master conversational skills in Enskill, they make progress toward spoken proficiency as measured by CEFR-aligned language assessments.

Back to the Future

The field of pedagogical agents continues to develop. As we have seen, new types of agents continue to emerge that interact with learners in new ways and that benefit from advances in the underlying technologies. We now discuss what we envision for the future of pedagogical agents, drawing lessons from what we have learned so far.

Factors Driving Demand for Pedagogical Agent Development

We believe that three factors will drive demand for improved pedagogical agents: the need for scalable online learning that engages and retains students; the demand for higher-level skills; and the needs of lifelong learners.

The need for scalable online learning that engages and retains students. As enrollments in online learning grow, so does student attrition. Students in conventional e-learning courses often feel isolated and disengaged. Can agents help engage and retain students in online courses?

The demand for higher-level skills. Employers and educators alike are concerned about the gap between the knowledge that students attain in school and the skills that they need to be productive members of the workforce. Increasing emphasis is being placed on so-called 21st-century skills: critical thinking, communication, collaboration, and creativity. Pedagogical agents have a role to play in promoting higher-level learning and 21st-century skills.

The needs of lifelong learners. Today's learners must continue to learn and develop new skills throughout their lives. But when learners leave school, they no longer have the same access to teachers and tutors to guide their learning and provide feedback. Can pedagogical agents fill the gap?

Advances in Conversational Agents

In recent years, there have been rapid advances in speech and language technology, leading to a wide range of voice-enabled consumer products. Cloud-based cognitive services make it easier to integrate speech and language technology into learning products as well. Examples include the Alelo Enskill platform, which leverages Microsoft's speech and language technology, and Georgia Tech's virtual teaching assistant, which uses the IBM Watson platform (Goel and Polepeddi 2017). Now that learning products are available that utilize dialogue technology, there will be a constant push to improve their dialogue capabilities. This push for conversational capability will result in pedagogical agents that are increasingly able to communicate with learners in new ways that promote learning.

The Alelo Enskill platform is a case in point. Enskill currently supports dialogue at the A level on the CEFR proficiency scale. The institutions and instructors using Enskill's A-level modules are now demanding dialogues at the B level and above, and so Alelo is currently enhancing Enskill's dialogue capabilities to meet this demand. Extending dialogue to higher levels of proficiency has the added advantage of making Enskill applicable to a wider range of skills that involve spoken communication in areas such as healthcare, hospitality, sales, customer service, and collaboration in the workplace, to name a few.

Natural language dialogue has many advantages as a vehicle for promoting learning. First, it is high-

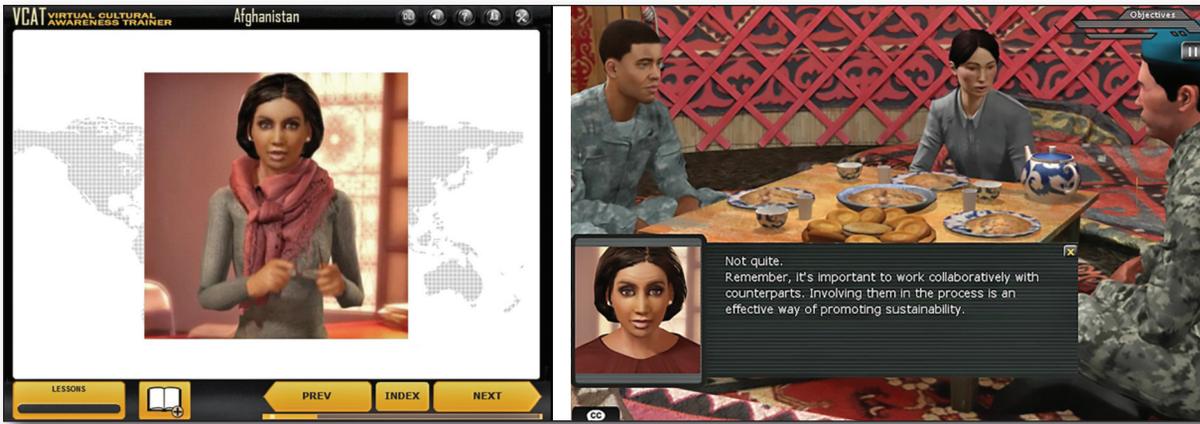


Figure 5. A Combination of Agents Used in VCATS.

VCAT Virtual Coach (left) and Virtual Role-Play (right). ©Alelo Inc. Reproduced with permission.

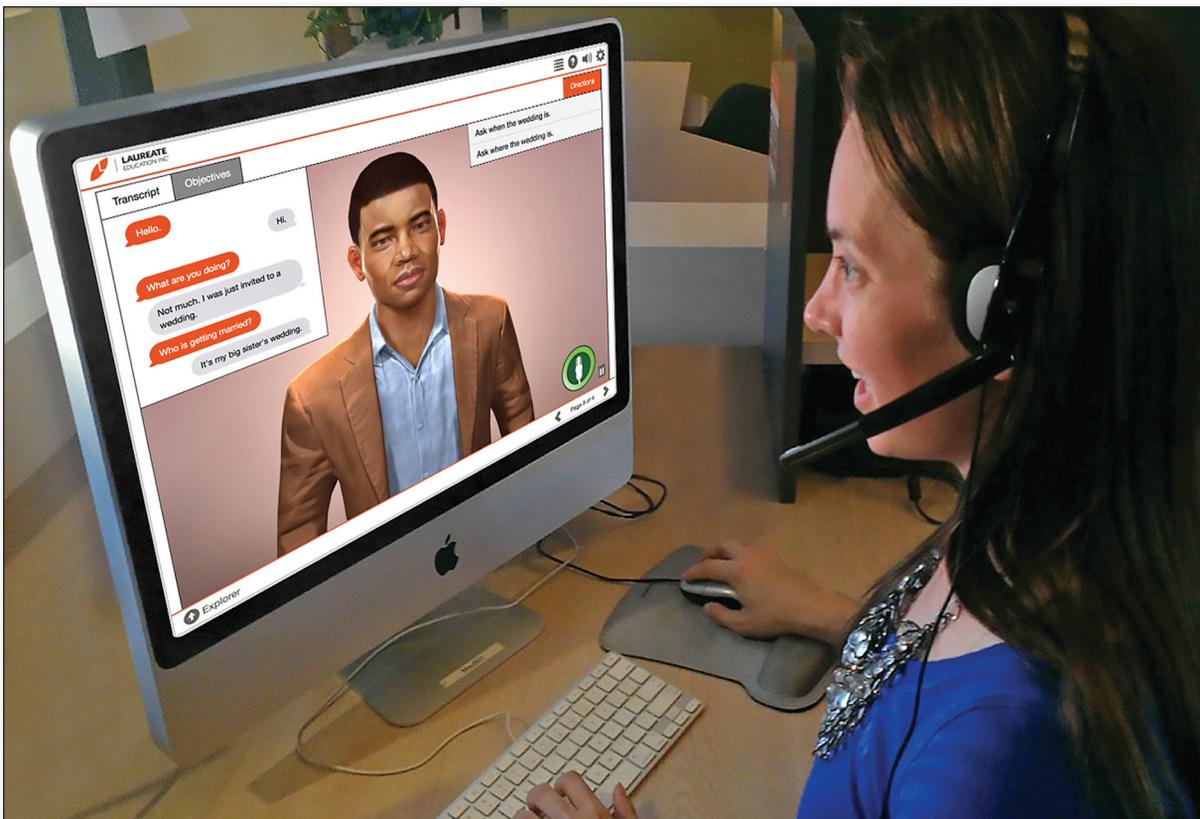


Figure 6. Enskill Simulated Dialogue with Pedagogical Agents.

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ly engaging. Instead of being passive recipients of knowledge, learners actively use and construct their knowledge through dialogue. They must formulate their own responses instead of selecting from multiple-choice responses that the learning system presents to them. As dialogue-based systems become more widespread, we predict that they will

result in higher levels of engagement, higher levels of learning, and better retention in learning programs.

The challenge for agent developers now is to leverage dialogue technologies to support multimodal dialogue and to promote better learning. Whereas natural-language-processing services focus solely on text

and language, pedagogical agents integrate verbal and nonverbal communication in rich learning interactions. Dialogue with pedagogical agents takes place in the context of a learning activity, and agents can exploit this context to evaluate the learner's responses and provide feedback. They can assess the learner's progress toward mastery of the target skills, and share those assessments with teachers as well as learners. This assistance helps teachers in blended learning programs to focus on areas where learners are experiencing difficulties and relieves them of the burden of having to evaluate learner responses themselves.

Not all learning applications employing natural language dialogue will feature animated pedagogical agents; some applications on mobile devices will likely rely on text messaging and social media, just as their human users do. However, animated interfaces will continue to be essential for many types of agents, including role-playing agents and relational agents.

The Future of Relational Agents

Recent new developments are relational agents, which are virtual agents that engage in relationship-building behaviors with users. Relational agents are used extensively in healthcare applications to develop rapport with patients, and there have been initial experiments with pedagogical agents that use relationship-building behaviors (Bickmore, Pfeifer, and Schulman 2011). We predict that future agents will combine affective computing technologies with relationship-building behaviors, resulting in empathetic pedagogical agents that develop and maintain relationships with learners (Walker and Ogan 2016). Such agents will not only express emotions and react to learner emotional states, but also infer psychological characteristics such as personality (Robison, McQuiggan, and Lester 2010), demonstrate empathy, and be emotionally supportive. Such qualities are essential for good teachers but tend to be neglected in educational software.

Relational agents could be useful in promoting growth mindsets and teaching grit. They could be particularly useful as a companion for lifelong learners. Lifelong learners are likely to engage in a diverse set of learning activities over the course of their careers. Conventional domain-specific learner models may be useful for pedagogical agents in the short term, but they will be of limited value over time as learners move between learning experiences. Relational pedagogical agents that develop models of each learner's character traits and establish relationships with them could be more effective in supporting learners. Such emotional support is currently lacking in personal assistants for learning such as PERLS (Freed et al. 2014) that have models of learning paths but not of the emotional dynamics, the frustrations and joys, associated with learning journeys.

The Future of Colocated Agents

Our 2000 paper conceived of pedagogical agents as "cohabiting" learning environments with learners. We saw virtual environments as making it possible for learners and agents to share the same space and interact with each other — even if virtual-reality technology was not yet ready for widespread use in educational contexts. Recent advances in virtual reality, augmented reality, and robotics now make it much more feasible to colocate agents and learners in the same space, resulting in more engaging and effective learning experiences.

Alelo has experimented with different ways of colocating learners and agents, using virtual reality, augmented reality, and robotic agents. In general, we find such immersive environments to be highly engaging for learners. They have more control over where to go and where to focus their attention, compared to desktop displays. Learners can enter complex environments, containing multiple agents, that challenge their skills. For example, we can seat the learner at a banquet table with multiple guests (figure 7) to test the learner's cross-cultural communication skills. The learner must decide from moment to moment which agent to talk to and then observe how the other agents react. Learners have the freedom to make cultural mistakes (for example, addressing an interpreter or lower-ranked guest instead of the more senior guest). Low-cost head-mounted displays such as Google Cardboard and mobile VR technologies such as WebVR make it possible to distribute VR-based agent applications widely. We predict widespread use of such applications in the near future.

Robotic agents with expressive faces (figure 8) are highly engaging for face-to-face communication, much more so than screen-based agents. People react in a very visceral way when a robotic agent responds to what they say. However, virtual agent technology is more versatile than robotic technology, and humanoid robots are prone to mechanical failures. Therefore, for many applications we expect virtual agents to be used instead of or in addition to robotic agents. Students who tested the RALL-E language learning robot shown in figure 8 very much liked the experience of interacting with the robot, but still wanted a version that they could run on their smartphone and take home with them.

Agents in Digital Ecosystems

Emerging interoperability standards make it possible to integrate agent-enhanced learning environments into digital ecosystems.³ This trend is likely to accelerate the adoption and innovation of pedagogical agent technologies.

In the digital ecosystem approach, agent-enhanced learning activities such as role-play simulations and games exist alongside other digital learning materials to provide learners a seamless learning experience. Agent platforms such as Alelo Enskill can



Figure 7. A Virtual-Reality Environment for Learning Cross-Cultural Skills.

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draw on cloud-based cognitive services and, in turn, can offer cloud-based learning services. Developers can create agent-enhanced learning objects and distribute them to other providers, or make them available publicly as open educational resources (OERs).

Hosting digital ecosystems in the cloud provides access to learner data. As learners access learning services in the cloud, the services can capture and analyze the learners' responses. Machine learning algorithms can then be applied on the captured data both to improve agent behavior models and to develop models of common learner errors. We foresee a transition to a data-driven approach to pedagogical agent development, where agents act as data collection tools as much as learning tools. This double focus will further accelerate the development and adoption of agents and lower production costs.

Outstanding Research Questions

Although there have been significant advances in the science and technology of pedagogical agents, there remain important outstanding questions. Such questions are likely to guide future research in the field.

Although there is evidence of effectiveness overall, and evidence that agents support certain types of learners, there are also exceptions. More research is needed relating the characteristics of agents, learners, and domains with learning outcomes. We now recognize that there are multiple types of agents and that these agent types differ in terms of the learners and domains that they benefit. Classic pedagogical agents are well suited for younger learners, while role-playing agents can benefit adult learners as well. Classic pedagogical agents benefit low-performing

learners, while teachable agents benefit high-performing learners. By analyzing each type separately and comparing results through meta-analyses, it will become clearer how to use agents most effectively.

Further research should also consider cost-effectiveness, to determine whether the benefits of agents justify the cost in particular applications (Schroeder et al. 2011). In practice, there are ways to manage costs, such as using a combination of animation and still images, as shown in figure 5 (right). In the past, some researchers have questioned the value of agents altogether, arguing that when agents are found to enhance learning, a less expensive and less distracting alternative has equal or greater benefits (Clark and Choi 2007). We think that it depends upon the pedagogical use of the agents. As the above examples illustrate, pedagogical agents make possible new types of interactive learning experiences that are difficult to match using static multimedia presentations. They engage learners emotionally and socially, not just at a cognitive level. Meanwhile, machine learning and data-driven approaches will continue to drive down development costs, shifting the return on investment (ROI) breakeven point in the direction of more highly capable pedagogical agents.

Concluding Remarks

Back in the 1990s, when we started work on pedagogical agents, we saw a bright future for the technology. Much has been accomplished in the past 20 years; agents have become established as learning tools and continue to improve. So we continue to be excited about the new possibilities that the technol-



Figure 8. Dialogue with a Robotic Pedagogical Agent.

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ogy has to offer. Looking back at what the field has accomplished makes us anticipate even more eagerly the new developments yet to come.

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Note

1. www.aamas2017.org/result-awards_aamas2017.php.
2. See *Alelo's Enskill Platform Expands into Sixteen Countries*, www.prweb.com/releases/2017/12/prweb14976697.htm.
3. See *Cloud-Based Cognitive Services for Learning*, mediax.stanford.edu/page/lewis-johnson-ai-ecosystems.

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Conference Chair

Vasile Rus
vrus@memphis.edu
University of Memphis, USA

Program Chairs

Keith Brawner
keith.w.brawner.civ@mail.mil
Army Research Lab, USA

Roman Barták
bartak@ktiml.mff.cuni.cz
Charles University, Czech Republic

Special Tracks Coordinator

Eric Bell
Eric.Bell.FLAIRS32@gmail.com
USA

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The 32nd International FLAIRS Conference

Lido Beach Resort, Sarasota, Florida, USA

May 20-22, 2019

In cooperation with the Association for the Advancement of Artificial Intelligence

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W. Lewis Johnson is an internationally recognized expert in AI in education. For his work on the first Alelo immersive game, *Tactical Iraqi*, he won DARPA's Significant Technical Achievement Award. Johnson served as president of the International AI in Education Society, and was cowinner of the 2017 Autonomous Agents Influential Paper Award for his work in the field of pedagogical agents. He has been invited to speak at international conferences such as the International Conference on Intelligent

Tutoring Systems, and he presented a Distinguished Lecture at the National Science Foundation. Under his leadership, Alelo has developed into a well-recognized producer of innovative learning products employing the virtual role-play method. It's cultural awareness training courses are now available for over 90 countries and the Enskill platform is in use in multiple countries in Latin America, Europe, and Asia.

James C. Lester is a distinguished professor of computer science at North Carolina State University, where he is director of the Center for Educational Informatics. His research on personalized learning technologies ranges from intelligent tutoring systems and game-based learning environments to pedagogical agents, affective computing, computational models of narrative, and natural language tutorial dialogue. The adaptive learning environments he and his colleagues develop have been used by thousands of students in K-12 classrooms throughout the US and internationally. He is the author of more than two hundred publications and is cowinner of the 2017 Autonomous Agents Influential Paper Award for his work in the field of pedagogical agents. He has served as editor-in-chief of the *International Journal of Artificial Intelligence in Education*, and is an AAAI fellow.