AI Grand Challenges for Education

Beverly Park Woolf, H. Chad Lane,
Vinay K. Chaudhri, Janet L. Kolodner

■ *This article focuses on contributions that AI can make to address long-term educational goals. Challenges are described that support: (1) mentors for every learner; (2) learning 21st century skills; (3) interaction data for learning; (4) universal access to global classrooms; and (5) lifelong and lifewide learning. A vision and brief research agenda are described for each challenge along with goals that lead to development of global educational resources and the reuse and sharing of digital educational resources. Instructional systems with AI technology are described that currently support richer experiences for learners and supply researchers with new opportunities to analyze vast data sets of instructional behavior from big databases that record elements of learning, affect, motivation, and social interaction. Personalized learning is described that facilitates student and group experience, reflection, and assessment.*

Artificial intelligence affects growth and productivity in many sectors (for example, transportation, communication, commerce, and finance). However, one painful exception is education; specifically, very few AI-based learning systems are consistently used in classrooms or homes. Yet the potential exists for AI to have a large impact on education: As described by the articles on education in this and the previous *AI Magazine* issue, AI-based instructional software now routinely tailors learning to individual needs, connects learners together, provides access to digital materials, supports decentralized learning, and engages students in meaningful ways. As a society we have great expectations for the educational establishment (for example, train employees, support scientific and artistic development, transmit culture, and so on) and yet, no matter how much is achieved, society continues to expect even more from education. The current environment of fixed classrooms, lectures, and static printed textbooks is clearly not capable of serving a digital society or flexibly adapting for the future. Classrooms and textbooks are especially inappropriate for people who use mobile and digital technology every day. For example, digital natives learn and work at twitch speed, through parallel processing, and connected to others (Beavis 2010). For digital natives, information is instantly available, change is constant, distance and time do not matter, and multimedia is omnipresent. No wonder schools and classrooms are boring!

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Elementary School Children in Taiwan Draw Distinct Butterfly Pictures During a Field Trip and Wirelessly Transmit Them to the Local Server (a Teacher with a Notebook Computer and butterfly Database).

Photo courtesy of Tak-Wai Chan.

Research into the learning sciences and neuroscience provides essential insights into the intricacies of learning and the processes underlying learning, offering clues to further refine individual instruction. For example, students learn more when they work in teams on motivating and challenging group projects; they retain more when they immediately apply what they learn; and they learn more when they receive help from human tutors who respond quickly, in ways that reflect deep understanding of the learner's background, strengths, and weaknesses.

Applying such new insights about human learning in digital learning environments requires far deeper knowledge about human cognition, including dramatically more effective constructivist and active instructional strategies. AI techniques are essential for developing representations and reasoning about these new cognitive insights, for providing a richer appreciation of how people learn, and for measuring collaborative activity.

AI will be a game changer in education. In fact, education and AI can be seen as two sides of the same coin: education helps students learn and extend the accumulated knowledge of a society and AI provides techniques to better understand the mechanisms underlying thought, knowledge, and intelligent behavior.

The articles in this special issue of *AI Magazine* describe the use of AI technology in instructional software, for example, to support real-time understanding of student knowledge, individual differences, and learning preferences. In this article of the magazine, we take a brief tour of five proposed grand challenges for education: (1) mentors for every learner; (2) learning 21st century skills; (3) interaction data to support learning; (4) universal access to global classrooms; and (5) lifelong and lifewide learning. These challenges are aligned with the goals of making learning more social, collaborative, inquiry-based, ubiquitous, accessible, pervasive, secure, and available to people any time and anywhere. The challenges are intended to spur significant development in AI. Solving any one of these grand challenges could be a game changer for education.

Mentors for Every Learner: Grand Challenge One

Creating mentors for every learner requires research into how people learn. Research in the learning sciences (LS) has taught us a great deal about processes involved in learning; learning sciences addresses both how people learn and how to promote learning in real-world situations — how to capture learners' attention and keep them engaged, how to promote learning of difficult concepts, how to take advantage of the social and physical aspects of the classroom to promote reflection, the role of the teacher in promoting learning, and more. The first grand challenge focuses on applying these findings to the design and building of systems that can interact with learners in natural ways and act as mentors to individuals and collaborative groups when a teacher is not available.

Research in LS often utilizes design-based, experimental research methods in which interventions are implemented and evaluations developed to test the validity of theories and to develop new theories. For example, students learn best in collaboration, while working in small groups (Johnson and Johnson 1994). Current intelligent instructional software can support collaboration and personalize instruction to harmonize with learners' traits (for example, personality, preferences) and states (affect, motivation, engagement; see Conati and Kardan [2013], Lester et al. [2013]). Computational AI-based tools reason about a student's strengths, weaknesses, challenges, and motivational style as might human tutors while interacting with students (Arroyo et al. 2009). In general, many intelligent systems today are able to reason about student cognition, metacognition (thinking about learning), emotion, and motivation.

A Vision for Creating Mentors for Every Learner

> We are not going to succeed [in education] unless we really turn the problem around and first specify the kinds of things students ought to be doing: what are the cost-effective and time-effective and time-effective ways by which students can proceed to learn. We need to carry out the analysis that is required to understand what they have to do — what activities will produce the learning —and then ask ourselves how the technology can help us do that. — Herbert Simon (1998)

Boys Collaborate Informally on a Computer Activity.

Photo courtesy of Jessica Grant.

To mentor effectively and support individuals or groups while learning, an intelligent system needs to model the changes that occur in learners. Estimates of a learner's competence or emotional state, stored in user models, represent what learners know, feel, and can do. When and how was knowledge learned? What pedagogy worked best for this individual or group? Machine-learning and data mining methods are used to explore unique types of educational data and to better understand students and the settings in which they learn (see Conati and Kardan [2013], Koedinger et al. [2013]).

Simulations and representations should dynamically explain themselves to learners and switch modalities as appropriate; for example, provide videos or appropriate animations. Learning should occur in authentic contexts and motivate information-seeking behaviors. We envision that the current paper textbooks will evolve into digital workbooks that are aware of such contexts and provide students with immersive learning experiences, breaking away from their current linear flow, to be adaptive to student's current state of learning, to embed simulation and virtual laboratories, and to more broadly engage in dialogues with students.

Learning is also fundamentally intertwined with social activities. Take for example an educational approach called Learning by Design that supports students working in teams on science problems (Kolodner 2002). The approach requires that learners design their own experiments; for example, to learn about forces and motion, students design and build miniature vehicles and propulsion systems and test their effectiveness. Thus students learn science in the context of trying to achieve design challenges. How can technology support these learners to become involved in the scientific concepts in services of completing their design. Having a technology mentor for every student will facilitate Learning by Design, which is otherwise difficult to accomplish in a classroom with many students/groups working on distinct projects.

Research to Create Mentors for Every Learner

AI provides the tools to build computational models of students' skills and scaffold learning. Further, AI methods can act as catalysts in learning environments to provide knowledge about the domain, student, and teaching strategies through integration of cognitive and emotional modeling, knowledge representation, reasoning, natural language question answering, and machine-learning methods (Woolf 2009). Such tools provide flexible and adaptive feedback to students, enabling content to be customized to fit personal needs and abilities. These are essential ingredients for achieving the vision of mentors for every learner and represent both ongoing and future areas of AI research.

Electronic tutors, an AI success story (Anderson et al. 1995), seek to move beyond domain dependence and to support learning of multiple tasks and domains (Bredeweg et al. 2009). The first way such systems must evolve is to directly address 21st century skills such as creativity, critical thinking, communication, collaboration, information literacy, and self-direction. We revisit such skills in the grand challenge two that follows.

Mentoring systems should also support learners with their decision making and reasoning, especially in volatile and rapidly changing environments. Learners need to make informed decisions and justify them with evidence, gathered through collaboration and communication (see Rus et al. [2013], Swartout et al. [2013]). Students need to learn science practices and scientific reasoning and how to apply facts and skills. In the example of Learning by Design, students share their experiences and ideas, persuade others to see their point of view, and articulate what they need to learn. They "mess about" and generate their own questions about the targeted science. Groups of students need to be supported as they discuss their methods and results, ask questions, and make suggestions. Technology can help by providing guidelines for groups and questions to students about their ideas.

Engagement in the information society often requires people to collaborate and exchange real-time responses over lengthy time periods. Modern problems are large (for example, climate change, sustainability, security) and are not typically solved by a single individual over a finite length of time. Technology is needed to support small group discussions, "white boarding," and the generation of new ideas. To support learners in groups, networking tools can facilitate individuals to learn within communities, communities to construct knowledge, and communities to learn from one another (Suthers 1999, Suthers 2003, Suthers and Hundhausen 2003, Woolf et al. 2010). How can software support students in collaboration, researchers to examine learning communities, and learning communities to morph into global communities? For example, how do learning communities sustain, build on, and share knowledge? School students clearly do not construct original knowledge in the same way as do research communities, but they can learn from community-based project work (Johnson and Johnson 1994).

Another key area for future mentoring research lies in helping students develop an understanding of what it means to be a productive and respected member of a community. Web-based services that enhance social networking are widely available, including Facebook, YouTube, pod- and video-casting, weblogs, and wikis. These and services result in a general decentralization of resources and a fundamental shift in agency towards learners who reason

Middle School Children Collaborate on a Classroom Science Project.

Photo courtesy of Mike Sharples.

about their own plans and solutions, away from teachers who simply broadcast information. Users increasingly select what information to access. In education, these trends have given rise to instructional programs based on group thinking and communities that share common aims and practices (Felner et al. 2007).

User models provide estimates that go beyond identifying the knowledge and skills mastered by the student. User modeling is beginning to support collaboration by representing students' communicative competencies and collaborative achievements. User models represent students' misconceptions, goals, plans, preferences, beliefs, and students' metacognitive, emotional, and teamwork skills. Models also track when and how skills were learned and what pedagogies worked best for each learner (Bredeweg et al. 2009, Lester et al. 2013).

By measuring changes in learning, instructional systems can assess student learning and adapt instruction (Shute et al. 2009). Based on user models messages are sent to the tutor controller to assign the most appropriate task (for example, select an easier or harder activity). Often, inferences about user/group models are based on parameterized probabilistic models. For instance, Bayesian Knowledge Tracing (Corbett and Anderson 1994) — a modeling approach frequently used to implement mastery learning — uses parameters that represent the probability that a learner did not know the answer, but only guessed. System developers are confronted with the problem of how to choose appropriate parameter values. VanLehn (2006) describes this specific decision process as part of a general model of the space of decisions made by tutoring systems. An "outer loop" manages learning activities (such as policies for selecting tasks) while an "inner loop" focuses on problem solving steps and moment-to-moment cognition.

User models might also include information about the cultural preferences of learners (Blanchard and Allard 2010) and their personal interests and learning goals. When modeling groups of learners, the model will make inferences to identify the group skills and behavior. Current approaches to user modeling do not scale well: they tend to require the construction of new models for each new system. Novel AI techniques are needed that focus on flexibility and reusability. For example, user models might be developed as shells that exist independent of the instruc-

Discovery Learning in a Classroom Field Trip.

Photo courtesy of Mike Sharples.

tional software and be attached only after such a system has been activated (Kobsa 2007). Instead of building a new user model for each software application, generic model shells might be defined separately for classifications of tasks.

Finally, providing a mentor for every learning group means improving the ability of intelligent instructional systems to provide timely and appropriate guidance. In other words, the system needs to determine in real time what to say, when to say it, and how to say it. This grows more complicated as the skills demanded by society increase in complexity. The learning sciences has provided a wealth of knowledge about how to deliver effective feedback, but the challenge is to incorporate 21st century skills, such as creativity and teamwork. Rich, multifaceted models of instruction need to go beyond simple hints and to leverage increasingly more social and immersive strategies. Further, AI-based systems are emerging that focus on affective issues, such as emotional self-regulation and behavior change. These models require reconsideration of the role of feedback and seek to balance the cognitive aspects of learning with the noncognitive. Future learning environments should build student confidence, inspire interest, promote deep engagement in learning, and reduce or eliminate barriers to learning, as described in grand challenge five.

Learning 21st Century Skills: Grand Challenge Two

> The difference between stupid and intelligent people—and this is true whether or not they are well-educated—is that intelligent people can handle subtlety. They are not baffled by ambiguous or even contradictory situations—in fact, they expect them and are apt to become suspicious when things seem overly straightforward. — Neal Stephenson (2003)

The second grand challenge recognizes that citizens of the 21st century require different skills than did citizens from earlier centuries. Twenty-first century skills include cognitive skills (nonroutine problem solving, systems thinking, and critical thinking), interpersonal skills (ranging from active listening, to presentation skills, to conflict resolution). and intrapersonal skills (broadly clustered under adaptability and self-management/self-development personal qualities) (Pellegrino and Hilton 2012).

In a society built on knowledge, citizens need to acquire new knowledge quickly, to explore alternative problem solving approaches regularly, and to form new learning communities effectively. People need to tackle knowledge challenges and opportunities. For educators, this requires rapid revision of what is taught and how it is presented to take advantage of evolving knowledge in a field where technology changes every few years. As an example, the Internet first appeared for general use in the mid-1990s. In 2009, an estimated quarter of Earth's population used its services, and its countless applications were used in virtually every aspect of modern human life. As another example, online social networking hardly existed in 2007 and yet has become immensely popular. In many cases there are no names today for fields within which students of tomorrow will be engaged.

How can educators teach topics that barely exist one day and within a short time will change their students' lives? How can a curriculum teach about the next Internet-level change in society when it has not happened yet? One answer lies in improved and expanded learner competencies. Learners must be more creative, more agile, and more able to learn in groups; they must learn how to learn. Key features include skills in critical thinking, creativity, collaboration, metacognition and motivation.

One basis of a knowledge economy is continuing education and training of 21st century skills. Research shows that skilled workers have more job opportunities than do less skilled workers (Brynjolfsson and McAfee 2013). As technology advances, educated workers tend to benefit more, and workers with less education tend to have their jobs automated.

A Vision for Learning 21st Century Skills

The 21st century worker needs both "hard" skills (traditional domains, such as history, mathematics, science) as well as "soft" skills (teamwork, reasoning, disciplined thinking, creativity, social skills, metacognitive skills, computer literacy, ability to evaluate and analyze information). Further, working in today's knowledge economy requires a high comfort with uncertainty, a willingness to take calculated risks, and an ability to generate novel solutions to problems that evade rigorous description. Unfortunately, many of today's classrooms look exactly like 19th century classrooms; teachers lecture and students remain passive and work alone on homework problems that do not require deep understanding or the application of concepts to realistic problems. Our system of education is behind and the gap grows wider each day.

As we know, changes in educational policy, practice, and administration tend to happen slowly. For example, in the United States, about 25 years are required for an individual to receive a sufficiently well-rounded education to become a proficient educator (King, Sabelli, and Kelly 2009; Woolf 2009). The impact of that individual's teaching cannot be seen in subsequent learners for another 20 years. Thus the total cycle time for measuring teacher improvement is on the order of 45 to 50 years. Very few challenges in research or social policy cover such a long time scale (Roschelle et al. 2011).

A specific instance of this 21st century challenge is for citizens to apply what they have learned during school to novel problems encountered as adults. For example, students need to access and interpret science information learned in school and apply it to specific practical problems, judge the credibility of claims based on evidence, and cultivate deep amateur involvement in science.

Research to Support Learning 21st Century Skills

Research is needed to help students solve complex problems in innovative ways, remain comfortable with uncertainty, and think clearly about vast amounts of knowledge. Workers will need to solve problems across disciplinary domains in collaboration with people from other cultures and while immersed in inquiry reasoning. Technologies are needed that help develop alternative teaching modes, including rich computer interfaces, intelligent environments, and digital learning companions.

Creativity, curiosity, and intrinsic motivation can be enhanced as people begin to be involved in personal constructionist project-based activities (such as Learning by Design projects). A framework of using information technology to collect, relate, create, and donate resources can support creativity and motivation. Open-ended and exploratory inquiry-based systems support learners to question and enhance their understanding about new areas of knowledge (Dragon, Woolf, and Murray 2009; Dragon et al. 2013; Floryan and Woolf 2013). Innovative instructional approaches, such as preparation for future learning, have uncovered ways to increase comfort with uncertainty and promote development of adaptive expertise (Schwartz and Martin 2004). Returning to our example of Learning by Design, a design cycle interweaves design and investigation, so students become well versed in science practices. What type of technology is needed to mentor students as they learn, especially complex, ill-structured problems? How can technology support exploratory behavior and creativity?

Research is needed to develop resources for collaborative inquiry as students become exposed to diverse cultures and viewpoints. What is the process by which teams generate, evaluate, and revise knowledge? Research is needed to enhance learner's communication skills and creative abilities. Which tools match learners with other learners or mentors taking into account learner interests? Finally research is needed to support exploratory, social, and ubiquitous learning. How can software both support collaboration and coach about content? Can technology support continuous learning by groups of learners in ways that enable students to communicate what they are working on and receive help as needed? Learning communities, networking, collaboration software, and mobile and ubiquitous computing are being used

Classroom Assessment of Student Knowledge.

Photo courtesy of Djanogly Academy.

to create seamless social learning (Suthers 2003). Socially embedded and social-driven learning is pervasive. We no longer consider individual learners as working in isolation. Currently students work together in classrooms, but only during fixed time periods and with restricted team activities. Supported by AI-based technology, social learning is growing, continuing beyond the school day, involving continuous input from team members, and available whenever and wherever students want to learn.

Additionally, we need new intelligent information access to methods that enable ordinary citizens to access scientific information that is relevant to practical problems. Specific instances of such problems are decisions made during elections and choices for personal health. Many ballot measures (for example, one concerning genetically modified foods) require knowledge about science. Tools should enable citizens to access accurate and research-based information and reason through informed choices.

Interaction Data to Support Learning: Grand Challenge Three

The third grand challenge is about exploring and leveraging the unique types of data available from educational settings and the use of this data to better understand students, groups, and the settings in which they learn (Baker, Corbett, and Aleven 2008; Baker, Corbett, and Wagner 2006). Two distinct research communities have evolved to examine this data: learner analytics (LA) and educational data mining (EDM). The two areas have significant overlap both in their objectives and the methods and techniques used. Common goals include support individual learners to reflect on their achievements; predict students' requirements for extra support and attention; help teachers plan supporting interventions; and improve current courses or curriculum. One difference between the two communities is that the EDM community, originating from the intelligent tutoring systems community, often works on very small-scale cognition, for example, student mastery of specific topics, time spent on problems. Additionally EDM methods are drawn from a variety of disciplines, including data mining, machine learning, psychometrics of statistics, information visualization, and computational modeling. Learning analytics researchers are more focused on enterprise learning systems (for example, learning content management systems) and focus on issues such as student retention and test results; they often combine institutional data, statistical analysis, and predictive modeling to identify which learners need help and how instructors might change their pedagogical approach.

Both communities need to address the big neglected middle between cognition and test scores. The challenge is for both research communities to broaden what they do to begin to grasp more globally what learners (and groups of learners) are capable of and need. For example, we need analysis of systems thinking, critical thinking, self-regulation, and active listening. Data analysis should move across individual tutoring systems, games, classes, and so on to evaluate students' general competencies.

Data is available from many sources including interactions with other learners and with physical objects (for example, laboratory instruments). What data is needed and how can we collect and analyze it? How does this data support the four other challenges? How can we mine that data to improve learning? AI methods provide heuristics particularly adaptable to acquiring and analyzing educational data and discovery of novel and potentially useful information. How do we effectively store, make available, and analyze this data for different purposes and stakeholders?

School reform in the United States depends on data management and mining. Under the American Recovery and Reinvestment Act, states must make assurances that they are building data systems to track student achievement and teacher effectiveness, in addition to adopting rigorous standards that prepare students for success in college and the workforce.

> Hopefully some day we can track kids from preschool to high-school and from high school to college and college to career…. Hopefully we can track good kids to good teachers and good teachers to good colleges of education. – Arne Duncan (2009)

A Vision for Interaction Data to Support Learning

One vision for big interactive data includes making contributions to the evaluation of learning systems and development and testing of scientific theories about learning gains (Scheuer and McLaren 2011). Exploratory analyses identify regular (or unusual) patterns in data, for example, different problem-solving strategies between males and females (Arroyo et al. 2011) or patterns of successful and unsuccessful collaboration, thus helping to formulate new scientific hypotheses. EDM can be used to compare different interventions, for instance, how different teaching strategies compare to each other (for example, in online language learning courses, is it more efficient for students to reread the same stories or to read a variety of stories?). Computational methods have been used to randomize treatment assignment. Finally, EDM researchers have developed evaluation methods that are based on specific models of learning (for example, learning curves and Bayesian knowledge tracing).

Data of interest moves beyond the interaction of individual students (for example, navigation behavior, input to quizzes and interactive exercises) and includes data from groups of students in collaboration (for example, using chat), administrative data (for example, school, school district, teacher), and demographic data (for example, gender, age, school grades). Another focus is on student affect (for example, student motivation, emotional states), which can be inferred from physiological sensors (for example, facial expression, seat posture, and perspiration) (D'Mello, Graesser, and Picard. 2007; Arroyo et al. 2009). EDM uses methods and tools from the broader field of data mining (Witten and Frank 2005), a subfield of computer science and artificial intelligence that includes both theoretical (for example, investigating a learning hypothesis) and practical (for example, improving learning tools) features. Typical steps in an EDM project include data acquisition, data preprocessing (for example, data "cleaning"), data mining, and validation of results.

Research to Support Interaction Data for Learning

Research is needed to augment real-world equipment with data from instruments that can monitor learners' activities. For example embedded sensors in a laboratory science (for example, glassware that knows how much of a liquid a learner has added) might detect that a beaker has been placed on a Bunsen burner, monitor the rising temperature, and display the resulting graph (Bredeweg et al. 2009). Additionally, the simulation part of the environment might represent chemical interactions at the molecular level while the virtual part represents other team members in a group-based learning task. Intelligent environments will be aware of an individual's or groups' prior knowledge, skills, and abilities and provide appropriate coaching (Woolf et al. 2010).

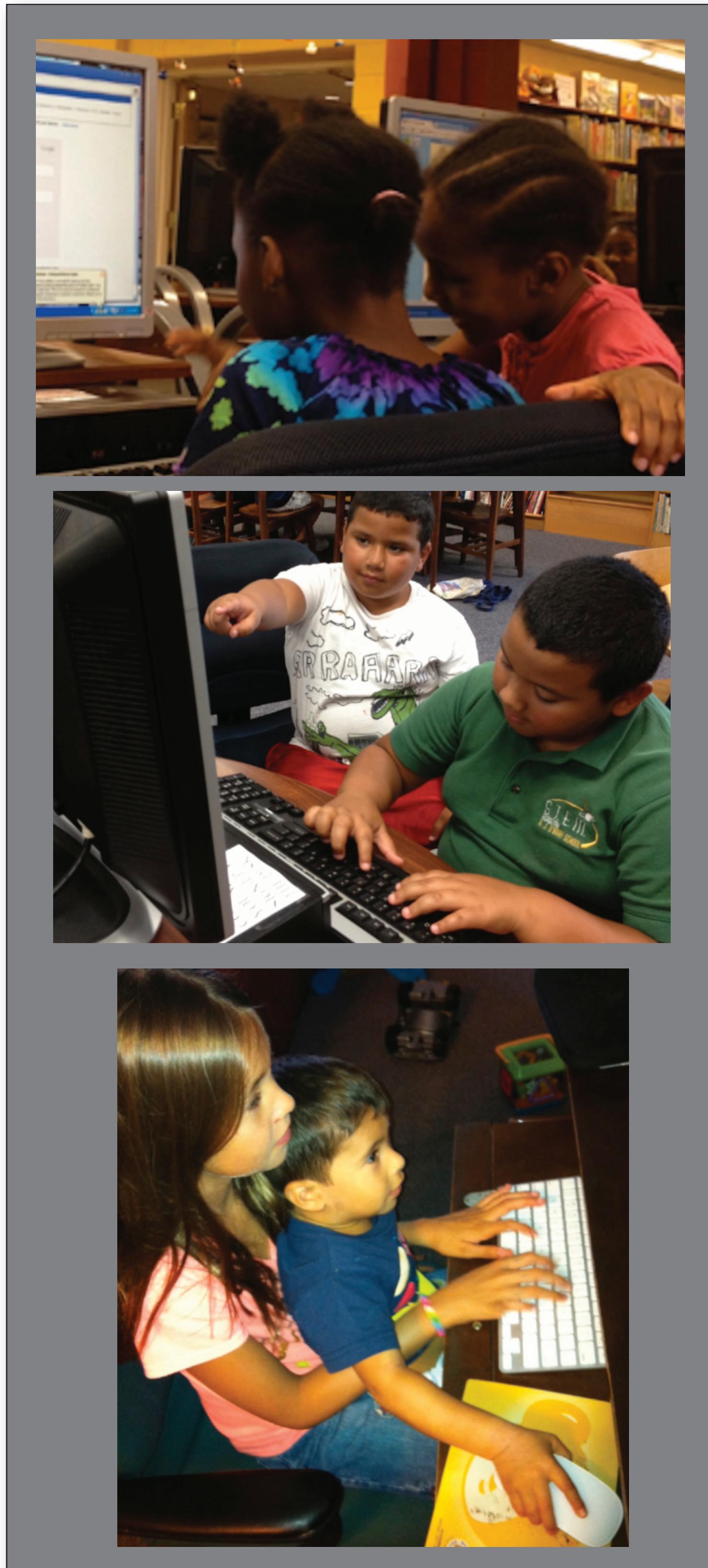
Machine-learning (ML) techniques are promising tools when systems repeatedly observe how students react and then generalize rules about the domain or student (see Conati anf Kardan 2013, Kobsa 2007). For example, ML techniques are used to augment user and group models automatically. Observation of prior students' behavior provides training examples that form models to predict future actions (Webb, Pazzani, and Billsus 2001). These techniques are used to acquire models of individual students and groups classified into patterns of users with common interests or skills. ML paradigms support tutors to adapt to new environments, use past experience to inform present decisions, and infer or deduce new knowledge. Intelligent environments use ML techniques to acquire new knowledge about students and groups and to predict student affect and learning (Johns and Woolf 2006; Arroyo and Woolf 2005).

Research is also needed to study how to achieve increased software flexibility and reduced cost, which are two sides of the same coin. If instructional environments were more flexible and could learn more about and accommodate their instruction to new student populations, the per student training cost would be reduced. Currently many person-years are required to construct a single instructional environment; for example, a detailed cognitive task analysis might take six months. Research is needed to support development of user models that adapt to new student populations to counter the typical inflexibility of educational systems that fossilize a teaching system to a single domain and instructional approach (Sison and Shimura 1998). Clearly inflexible instructional software is let loose in constantly changing environments (for example, the Internet) under conditions that cannot be predicted (Vassileva 1998). This method is limited and shortsighted for many reasons. The original authors had incomplete knowledge about the domain, as do most authors. They also had incomplete knowledge about students and teaching strategies, and thus portions of the system remain forever incomplete. This lack of flexibility is a contributing factor to the high development cost and effort required to construct intelligent tutors.

Research has shown that intelligent instructional software needs to reason about uncertainty. Older educational software represented student knowledge using formal logic (for example, student *A* knows skill *X*). However, this representation does not include the fact that authors cannot know with certainty how to represent student skills or whether students actually know these skills. Knowledge in educational software is incomplete and therefore reasoning under uncertainty is required. ML techniques use approximations to reach weaker conclusions as compared to formal logic techniques, for example, "This student will succeed on the next problem with a probability of *N* percent." ML both makes this process more complex and provides an opportunity to solve more interesting problems.

Research is needed to examine the expected data deluge from lifelong chronicles of student learning. New data sources will provide knowledge to find clusters of children with similar learning difficulties; identify success and failures in teaching strategies; generate a deeper understanding of learning; and shed light on key questions in education and psychology. Research is needed to consider issues of time, sequence, and context; this involves massive nonindependence. Research is needed to record and analyze fine-grained interaction data from pedagogical systems, as well as from servers that provide tools for assessment and collaboration across networks.

Effective use of interaction data is dependent on effective assessment of learning. Given a world where learners use a variety of electronic learning objects and those objects are continuously assessing learner progress on a variety of measures, it is possible to assess each individual across a wide variety of activities (Shute et al. 2009). The distribution of assessment information to a broader variety of members of the educational establishment improves the odds that



Informal Education: Children Working on Computers in a Library.

Photo courtesy of Melissa-Sue John.

Young Girl Pushes on a Robot that Readjusts Its Vertical Position.

Photo courtesy of Stephen Woolf.

more learners will succeed. For example, young learners could benefit from their parents being informed early about possible learning deficiencies and the need for additional help or motivation (Heffernan and Koedinger 2012). Teachers might benefit from seeing a real-time summary of areas of weakness of students in the class; such a report could guide teachers to immediately alter their teaching methods to accommodate student strengths and liabilities. Consideration of the social processes of learning will also affect the nature of data communication in connection with assessment of learning. Digital assessment and feedback should result in more effective, efficient, and enjoyable instruction, especially when data technologies enhance learners' experiences (Shute et al. 2009). Current large educational data repositories, such as the DataShop from Pittsburgh Science of Learning Center (see Koedinger et al. [2013], Koedinger et al. [2008]) contain data from hundreds of thousands of students; these efforts have already greatly increased access for interested researchers.

As the variety of electronic learning objects grows, the likelihood of becoming drowned in details increases. Research needs to address this deluge with development of new data mining, security, and database techniques. Who are the potential consumers of this data, for example; how can data be distilled for assessment content so it is useful for each stakeholder?

The current educational technology community needs frameworks for orientation and assessment materials, for example, a shared data dictionary that prevents duplication of efforts and streamlines the use of nomenclature and categorization. This is done regularly by other computer scientists: for example researchers in compilers have preset data sets that many people use; similarly researchers in operating systems, databases, and computer architectures have preset databases.

For example, a vision has been proposed for a lifelong user model to exist as a first-class citizen, independent of any single application and controlled by the learner (Kay 2008). This envisioned taxonomy would first be established by corresponding researchers, populated during a student's life, and disseminated (and perhaps governed) by a body similar to other shared standards as coordinated by the IEEE or ISO.

Research is also needed to develop algorithms for educational data, for example, integration between psychometric and machine-learning methods for bringing together data miners and psychometricians. In addition, recent work has often integrated the results of one model into a second model. For instance, models of learning have been key components in models of other constructs such as gaming the system (Baker et al. 2008). Applicability of models within other models is likely to have a multiplier effect, making it easier to make effective models of a variety of constructs. Another area of significant promise is "discovery with models," in which a machine-learned model of a construct is developed and then utilized in a broader data set, in conjunction with other models or other measures (for example, survey measures), in order to study the associations between the constructs studied. This type of research can be conducted quickly and inexpensively once the models have been developed and validated for generalizability.

Boy Writes on his Computer Screen.

Photo courtesy of Tak-Wai Chen.

Universal Access to Global Classrooms: Grand Challenge Four

The fourth grand challenge is directed at providing learning that is universal, inclusive, available any time/anywhere, and free at the point of use. Universal access to global classrooms was first discussed at the AAAI 2008 Fall Symposium (Cohen 2009). One goal is to identify steps toward such global Internet classrooms, in which every student everywhere learns at a level that only the best students can learn today.

A Vision for Universal Access to Global Classrooms

Global classrooms could potentially support individuals and groups to learn remarkably better than if they were taught by a single human teacher. Such systems would be available all the time and provide an unlimited supply of people with whom students could converse about topics. Such broad access and availability of rich resources should significantly improve learning. Recent implementations of this vision are in their infancy. For example, massively open online courses (MOOCS), such as Coursera, Udacity, and Edx, contain a wealth of resources and provide higher education courses from excellent teachers for free.

Unfortunately these large online courses do not yet solve the global classroom problem. Currently MOOCS are personalized to only a very limited degree, are not inquiry based, have a huge dropout rate, and have been shown to be successful only with learners already at a very high level of background knowledge and motivation. Which AI techniques can help learners to engage well with global learning content and with other learners? How can AI techniques support learners to meet other learners with similar interests? What techniques are needed to help learners manage language and cultural issues and support access to labs and resources that are in short supply or are not local?

Research to Support Universal Access to Global Classrooms

Universal access to global classrooms requires asking questions that are increasingly complex and computational. One goal is to develop cyberspace as a collaborative and cognitively supportive learning environment. For example, instrumented instructional systems might detect student position, emotion, and behavior (through physical sensors, models, and log data). Assessing student learning involves building multidimensional models and measurement methods; indexing and organizing data to be searched, identified, and retrieved remotely; and the design, development, delivery, and analysis of online modular assessment. One example of student assessment includes online student grading and the use of education data mining to study student errors.

Global classrooms can help learners to collaborate on real projects, either at a distance or in local spaces (for example, coffee shops). What is the role of AI in global classrooms? Apparently what's problematic about MOOCs can be addressed by many of the challenges provided here (MROE 2013). Thus we need to solve nearly all the challenges described in this article in order to achieve successful global classrooms.

Human-Computer Interfaces. Global classrooms should include dynamic assessment and learning

Lifelong Learning: Within Personalized Outdoor Experiments Using Informal Learning and Location-Based Delivery of Content.

Photo courtesy of Mike Sharples.

Students on a Forest Field Trip Use the One Laptop per Child System to Make Observations.

Photo courtesy of One Laptop per Child (DesignApplause).

models that represent what learners know, along with when and how knowledge was learned (grand challenge one). How can algorithms identify pedagogy that worked best for each individual and reason about student cognition? What interfaces best support computer-supported collaborative learning, both collocated and at a distance, both synchronous and asynchronous? Student models would extract what learners are thinking and support student engagement, cognition, metacognition, and affect during project activities.

Student Data. Global classrooms should use educational data mining and machine learning to effectively store, make available, and analyze data for different purposes (grand challenge three). Data about student and group interaction should be protected, stored, and analyzed to evaluate how students performed. Hundred of thousands of visitors could access these portals daily and global classrooms would produce a substantial improvement in learning, based, in part, on analyzing prior learners who interacted with these same systems (Koedinger et al., 2013). How do we ensure security and privacy in global classrooms and distill data for assessment content so it is useful for each stakeholder? How will automated grading of complex student input inform new algorithms for data mining of like complex structures?

Mobile Computing. How will mobile computing be leveraged to support education? What is the nature of student/faculty interaction through mobile computing and how do we facilitate improved education with physically distributed course projects (for example, involving data collection) (grand challenge three)?

Social Computing. Once global classrooms are embedded in larger social contexts, how can computational systems support student collaboration and engagement (grand challenge two)? What is the process by which teams work in virtual, collaborative learning environments (grand challenge one)?

Online teaching resources now provide easy access, interoperable standards, and numerous APIs. They are beginning to be available in multiple languages and for multiple cultures. Another goal is to support global classrooms to acquire new knowledge. Global classrooms might one day support teachers to write thousands of new online problems (Heffernan and Koedinger 2012) or support grade school students to create new problems (Beal 2013). Funding agencies might support establishment of vertical systems (for example, generic user/domain models) and target new funds for horizontal efforts (for example, tutors in new domains that use existing shell user/domain models).

Lifelong and Lifewide Learning: Grand Challenge Five

The final (fifth) grand challenge addresses lifelong and lifewide learning or learning continuously over the entirety of one's life (lifelong) and across all aspects of that life (lifewide). Assuming that grand challenges one through four can be achieved, affordances of each challenge will help people to learn throughout their lives. Cultivating a culture of learning in society and promoting adaptive thinking connects challenge five directly to challenge two (21st century skills). Education must adapt to promote the joys of learning and provide authentic learning opportunities that blur the distinction between learning and life. This challenge refers to access to resources and to facilitating people to interact who are interested in the same topic. It also refers to adapting resources to a persons' level of understanding and doing so throughout life and in ways that are highly relevant to those learners.

> Many individuals do not participate in any meaningful learning at all throughout their adult lives and many others have only sporadic and highly interrupted patterns of engagement. These inequalities are highly dependent on an individual's age and stage of life, as well as patterned in terms of income, gender and social class. — Diana Laurillard (2008)

A Vision of Lifelong and Lifewide Learning

Education and learning are clearly not equivalent. Learning takes place naturally and continuously, especially for younger people; it is possible in any place at any time. Education seems to be fixed in terms of time, place, and prescribed activities. This fifth challenge asks us to reexamine the unnatural boundaries established by the education community: students, teachers, and activities are organized into levels (school, college, university, and professional development), places of study (home, work, institutions), types of learning (formal and informal learning), and by personal ability (special and typical students) (Laurillard et al. 2008). Each organized group has defined boundaries, which in turn constrain learning and limit transfer of learning across all boundaries.

However, people clearly learn across all these boundaries. One feature of mobile technology and social networks is to provide seamless and ubiquitous learning across established boundaries. For instance, the distinction between formal (in the classroom) and informal (outside of the classroom) education may disappear as learners gain knowledge equally well outside and inside the classroom.

An additional aspect of lifelong learning is to develop teacher professional training so teachers might keep up with the next generation of education standards and pedagogical approaches. Teachers' knowledge and practice have a direct correlation with student achievement.

Information technology increases opportunities for lifelong and lifewide learning, both inside and outside of the traditional education structure. In the end, we cannot discuss the need for formal education without also acknowledging the need for custodial care of young people, even at a time when we may see less need for constrictive classrooms and daily routines (King, Sabelli, and Kelly 2009). Given well-managed technology, education can better match the long-sought-after goal of lifelong learning.

Young Boy Plays Ball with Robots.

Photo courtesy of Stephen Woolf.

Research to Support Lifelong and Lifewide Learning

Research to support lifelong and lifewide learning might focus on how learning fundamentally occurs within humans; one perspective is that human learners are typically more alike than they are different (Pashler et al. 2008). Such a perspective focuses on theories of learning that are rigorously proven, such as aptitude treatment interactions among novices and experts (Shute 1992). Another perspective seeks to identify distinguishing factors among mature learners, such as biological or age-related sensory changes, longer records of life experiences (social, professional, health, and so on), more complex psychological development and increased capacity for transformative self-reflection. In the new knowledge economy, career development may be measured as much by the acquisition and development of valuable and relevant knowledge across a lifetime of employment, as it is by the rank and title

Young Girls Collaborate to Interpret Graphics in a Classroom.

Photo courtesy of One Laptop per Child (DesignApplause).

of each particular job (Inkson 2007). In this context, "career," metaphorically, can be characterized as a repository of knowledge (Bechr 1987).

Future research should also support learners at a personal level (for example, building on hobbies and unique interests) and seek not just to convey knowledge, but to inspire and cultivate interest in learning. We need to spread infectious enthusiasm and help learners become passionate about things they care about. This is addressed, in part, by bringing together much of what the first four challenges involve, but also by supporting all citizens to be lifelong and lifewide learners.

Animated and AI-based agents that act as facilitators have been integrated into many learning environments (Swartout et al. 2013, Lester et. al. 2013, VanLehn et al. 2009). Learning systems use agents to respond to users' interests, intentions, and goals and might motivate them based on their age, economic, and cultural considerations. Agents have taught within practical/real-life contexts and taken on authentic role models as virtual learning companions and teachers (Arroyo et al. 2011). They promote positive attitudes and build self-efficacy (Lane et al. 2013) and may request particular topics and knowledge components on behalf of users. They might provide complete user models; for example, orchestrate their own interactions, allowing certain (evaluated and approved) active objects to place themselves in context and expect objects to self-assemble and adapt to the learner's characteristics (for example, cognitive, previous skills, culture) and their needs (disabilities, learning difficulties).

Learners might call upon virtual characters as virtual teachers and companions (see Swartout et al. [2013], Bredeweg et al. [2009]). These characters would not only be knowledgeable, but also carefully reflect the characteristics of people they model. They might enhance professional development or skills and best practices training for job advancement, career counseling, or retraining for new vocations. They might support people in sports and outdoor

Young Children Learn Naturally and All the Time. They Also Explore Computers.

Photo courtesy of Stephen Woolf.

recreation or instructional skills-based learning. Other areas of lifelong and lifewide learning include travel (directional way-finding), daily life (legal issues and civic responsibilities), and health care (medical and pharmacological information, self-care strategies, distance medicine).

Just as we expect rich AI-based interfaces to permeate throughout life experiences, we expect tools and interfaces to support lifelong learning (longitudinal), and ubiquitous (embedded) experiences (Ashish, Burleson, and Picard 2007). Persistent interfaces can adapt to learners across life transitions and stages. In many ways, such systems may come to know the learners better than learners know themselves. As tools they will be available to enhance and facilitate learners' life aspirations, reflections, and engagements. Harnessing new technologies and social media can also be a critical enabler in facilitating teacher professional development, which has the potential for providing "just-in-time assistance" and is potentially more scalable than approaches that rely on limited physical one-on-one training.

Discussion and Conclusion

This article described five challenges for AI and education and provided a vision and brief research agenda for each. These challenges include development of support for (1) mentors for every learner; (2) learning 21st century skills; (3) interaction data to support learning; (4) universal access to global classrooms; and (5) lifelong and lifewide learning. Several computational ideas were suggested for each challenge and long-term goals described, such as providing access to global educational resources and the reuse, repurposing, and sharing of digital educational resources.

This article focused on contributions that AI can make to address long-term educational goals. Specifically, personalized learning can be supported by tools that enhance student and group experience, reflection, analysis, and theory development: most of all we expect systems with AI technology to support richer experiences for learners who will then be able to reflect on their own learning. Learning scientists with AI tools will have new opportunities to analyze vast data sets of instructional behavior collected from rich databases, containing elements of learning, affect, motivation, and social interaction.

Technology cannot affect education in isolation; rather it operates as one element in a complex social and political system that must consider content, pedagogy, and the environment that students, instructors, and technology cocreate (Oblinger 2012). Education is vital to increased earning power in most countries. For example, a typical worker in the United States with a bachelor's degree earns 80 percent more than does a high school graduate (Porter 2013).

Additionally, a country that does not leverage the enormous payoff for investment in preschooling is being deficient in its entire approach to education. The payoff for investment in preschool can be measured in improved college success, higher income, or even lower incarceration rates (Porter 2013). For example, education in the United States does not focus on preschooling and therefore does not redress the inequities that begin at birth (resulting from rich/poor parents) and does not improve the lot of disadvantaged children as they grow up. Difference in cognitive performance between rich and poor is just as big at age 18 as it is at age 3, before students enter school. Thus, the current education system in the United States is failing its citizens. Income inequality in the United States is passed down through the generations. Parents who are able have opted out of the U.S. educational setting entirely; for example, 5 million students are in alternative schools, including home schooling, online schools (27 states have virtual schools), charter, and magnet schools.[1] By focusing its funding on high school and college students, and less on preschooling, a country is subsidizing the wrong people, at the wrong time, and in the wrong way.

AI and education researchers need to be driven by the problems of education practice as they exist in school settings. The emerging forms of technology described here will challenge, if not threaten, existing educational practices by suggesting new ways to learn (McArthur, Lewis, and Bishay 1994). Policy issues that involve social and political considerations need to be addressed, but are beyond the scope of this document.

The technologies discussed in this article are not exhaustive and many others might be considered instead. Many of the technologies described already exist in some form in laboratories and many features have been tested in classrooms. Yet current intelligent instructional systems have not been combined in large scale nor in optimal ways for education; they often provide single fixes or add-ons to classroom activities. One overarching challenge for the community of researchers in the field of AI and education is to move beyond the realm of isolated projects in which each research team develops idiosyncratic conceptual frameworks and methods (Dede 2009). Instead, to realize progress in AI and education, the community of researchers needs to undertake collective scholarship that both integrates long-term overall goals and subdivides the resulting tasks.

Many learners have the potential to be more successful than they are in the current education system; computational systems offer the potential to both help learners succeed and help further research in the learning science. If we do not adopt new strategies afforded by AI technology, even students who succeed today will likely fail to meet tomorrow's challenges. AI techniques are already extending the success of today's learners in individual studies. We look forward to witnessing how these technologies empower learners everywhere, expand opportunities for learning, and provide rich, engaging interactive experiences for people of all ages and at all times.

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Note

1. See the National Center for Education Statistics, 2012, nces.ed.gov/pubs2013/pesschools10/tables/table_02_asp.

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Beverly Park Woolf is a research professor in the School of Computer Science at the University of Massachusetts-Amherst. She is a fellow of the American Association of Artificial Intelligence and develops intelligent tutors that model students' cognitive knowledge and affective behavior. Woolf received her Ph.D. in computer science and an Ed.D. in education from the University of Massachusetts-Amherst. Currently she is a Presidential Innovation Fellow and is on loan to the US National Science Foundation.

H. Chad Lane is a research scientist at the University of Southern California's Institute for Creative Technologies. His research involves the application of entertainment and intelligent technologies to a variety of challenges, including education and health behavior, and investigates the many roles virtual humans can play in virtual learning environments, such as coach and colearner, as well as in the context of mobile educational games. Lane received his Ph.D. in computer science from the University of Pittsburgh.

Vinay K. Chaudhri received his Ph.D. in computer science from University of Toronto, Canada, and is currently a program director in the Artificial Intelligence Center at SRI International. His research focuses on the science, engineering, and application of large knowledge base systems.

Janet Kolodner is a Regents' Professor in the School of Interactive Computing at the Georgia Institute of Technology. She was founding editor-in-chief of *The Journal of the Learning Sciences* and her research has addressed issues in learning, memory, and problem solving in computers and in people. At present, she is on loan to the U.S. National Science Foundation, where she is the lead program officer for the program Cyberlearning: Transforming Education.