AI Grand Challenges for Education

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AI and Education

Artificial intelligence impacts growth and productivity in many industries (e.g., transportation, communication, commerce, and finance). However, one painful exception is education; today, very few AI-based learning systems are consistently used in classrooms or homes. Yet the potential for an impact on education is great: today's instructional software now routinely tailors learning to individual needs, connects learners together, provides access to digital materials, supports decentralized learning tools and engages students in meaningful ways. As a society we have great expectations from the educational establishment (train employees, support scientific and artistic development, transmit culture, etc.) and yet, no matter how much is achieved, society continues to expect even more from education. The current educational environment (fixed classrooms, repeated lectures and static printed textbooks) is clearly not capable of either serving society nor of flexibly changing for the future. Classrooms and printed textbooks are especially inappropriate for people who use technology on a daily basis. For example, digital natives learn and work at twitch speed, through parallel processing, with graphics and connected to others (vs. stand alone) (Beavis, 2010). For these digital natives, information is instantly available, change is constant, distance and time do not matter, and multimedia entertainment is omnipresent. *No wonder schools and classrooms are boring!*

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

Applying these 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 and for providing a richer appreciation of how people learn and for measuring collaborative activity.

Boys using mobile technology to collaborate on a project.
Photo Credit: Mike Sharples.

Artificial intelligence 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 understand the mechanisms underlying thought and intelligent behavior.

This special issue of AI Magazine describes the use of AI technology in instructional software, e.g., to generate real-time understanding of student knowledge, individual differences, and learning preferences. In this article, 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 life-wide learning.* These challenges are aligned with the goals of making learning more social, collaborative, inquiry-based, ubiquitous, accessible, pervasive, secure and available to people anytime and anywhere. They are intended to spur significant development in AI and highlight the richness of educational challenges. Solving any one of these grand challenges could be a game changer for education.

1. Mentors for every learner: Grand Challenge 1

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 world of the classroom to promote reflection, the role of the teacher in promoting learning, and more. Grand Challenge 1 in education is to apply these findings to design and build systems that can interact with learners in natural ways and act as mentors to individuals and collaborative groups when a teacher is not available.

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

1.1 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 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, *'What We Know About Learning,' 1*997

Middle school students use mobile devices to study butterflies .

Photo Credit: Tak-Wai Chan, National Central University , Taiwan

To mentor effectively and support individuals or groups while learning, an intelligent system needs to assess learning activities and 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 explore the unique types of data that derive from educational settings and use those methods to better understand students and the settings in which they learn (see Conati et al.; Koedinger et al., this issue).

Simulations and representations should dynamically explain themselves to learners and use multimedia to switch modalities as appropriate, e.g., provide explanations, videos or animations as needed by each learner. 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. The textbooks of the future will break away from the current linear flow in the paper textbooks, be adaptive to student's current state of learning, embed simulation and virtual laboratories, and more broadly have an ability to engage in a dialog with a student.

Learning is also a fundamentally intertwined with social activities and instructional approaches should reflect this important fact. Take for example an educational approach called Learning By Design™ that supports students working in teams on science problems (Kolodner, 2003). The approach requires that learners design their own experiments, e.g., 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 the design challenge before them? 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 to create designs.

1.2 Research to create mentors for every learner.

AI provides the tools to build computational models of skills, learning processes, and scaffolding of learning. Further, AI methods can act as a catalyst for computer-based learning environments through the integration of cognitive and emotional modeling, knowledge representation and reasoning, natural language question answering and machine learning methods, into software to provide knowledge about the domain, student and teaching strategies (Woolf, 2009). Such systems provide flexible and adaptive feedback to students, enabling content to be customized to fit personal needs and abilities and augment a teacher's ability to respond. 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 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 (Ashish, Burleson, & Picard, 2007; Dragon et al., 2006; 2010; 2013). We revisit such skills in Challenge Two below.

Mentoring systems should also support learners with 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.; Swartout et al., this issue). Students need to learn science practices and scientific reasoning and how to apply the facts and skills they are learning. In the example of Learning by Design above, students to share their experiences and ideas, persuade others to see their point of view, and articulate what they need to learn more about. They "mess about" and generate their own questions about the targeted science. Students need to be supported to discuss their methods and results with peers, to ask questions and to make suggestions. Technology can help by providing guidelines for groups, questions about ideas and responses to student suggestions.

Engagement in the information society often requires real-time responses over lengthy time periods; modern problems are not typically solved by single individuals over a finite length of time. Technology should support small groups, class discussions, "white boarding," literature about science content, generation of questions as well as additional investigation. To support learners in groups, networking tools need to be enhanced to work in educational practice to facilitate individuals to learn *within* communities, communities to *construct* knowledge, and communities to learn from one another (Suthers, 1999; 2003; Suthers & Hundhausen, 2003). How can software both support collaboration and coach students about content? How do researchers examine learning communities? How do learning communities morph into global communities with orientations beyond education? 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 & Johnson, 1994).


Boys collaobrating on a science prject
Photo Credit: Mike Sharples, ICCEE 2008

Another key area for future research on mentoring systems lies in helping students develop an understanding of communities, and what it means to be a productive and respected member of one. Web-based services that enhance social networking are widely available, including Facebook, YouTube, pod- and video-casting, weblogs, wikis. These services result in a general decentralization of resources that reflect a fundamental shift in *agency* towards learners who reason about their own plans and solutions and away from teachers who simply broadcast information. This shift is also propelled by user-led media content consumption, in which users increasingly select what information to access and what music or films to watch and when. In education, these trends have given rise to instructional programs based on group-thinking and communities who share common aims and practices, and leverage community-based content creation (Felner et al., 2007).

User modeling must be advanced to provide mentoring systems estimates that go beyond what knowledge and skills have been mastered. They must support learning that occurs in groups by representing student communicative competencies and collaborative achievements. They must also represent students' metacognitive skills, emotional states, and teamwork skills. These models must also track when and how skills were learned and what pedagogies worked best for each learner (Bredeweg et al., 2009; Lester et al., this issue).

By measuring changes in learning in many areas, instructional systems assess student learning and adapt instruction (Shute et al., 2009)**.** Based on a user model, a message might be sent to the tutor controller to assign the most appropriate task (e.g., select an easier or harder exercise). Often, inferences about user/group models are based on parameterized probabilistic models. For instance, *Bayesian Knowledge Tracing* (Corbett & Anderson, 1995) – a modeling approach frequently used to implement mastery learning – uses parameters to represent the probability that a learner only guessed the correct solution. System developers are confronted with the problem of how to choose appropriate parameter values. VanLehn (2008) describes this specific decision 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 modeling systems should also leverage more advanced reasoning and inference-making tools from AI, represent *inferences* about users, including their level of knowledge, misconceptions, goals, plans, preferences, beliefs, and relevant characteristics (stereotypes) along with records of past interactions with the system. They might include information on the cultural preferences of learners (Blanchard & 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 models for each new system. New AI techniques are needed that focus on flexibility and reusability. For example, user models might be developed as *shells* that exist independent of the instructional software and attached only after such a system has been activated (Kobsa, 2007). Instead of building a user model for each software application, generic model shells might be defined separately for classification of tasks.


Hispanic girl showing grandmother how to use computer
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Finally, providing a mentor for every learner and groups of learners means improving the ability of systems to provide timely and appropriate guidance. In other words, the determination of *what* to say to learners, *when* to say it, and *how* to say it grows more complicated as the skills demanded by society also increase in complexity. The learning sciences has provided a wealth of knowledge about how to deliver effective feedback, but the challenge to incorporate 21st century skills, such as creativity and teamwork, present new challenges. Rich, multi-faceted models of instruction and coaching will be needed that go beyond simple hinting – these systems must leverage advances in new user modeling techniques and the richness of modern learning environments that are increasingly more social and immersive. Further, AI-based systems are emerging that focus on affective issues, such as *emotional self-regulation* and *behavior change.* These require reconsideration of the role of feedback and more robust systems that seek to balance the cognitive aspects of learning with the non-cognitive. Future learning environments should seek to build confidence in learners, inspire interest in important topics like science, promote deep engagement in learning, and reduce or eliminate the barriers to learning present in the world today.

2. Learning 21st century skills: Grand Challenge 2

> “Nell," the Constable continued, indicating through his tone of voice that the lesson was concluding, "the difference between ignorant and educated people is that the latter know more facts. But that has nothing to do with whether they are stupid or intelligent. 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, *The Diamond Age*

Grand Challenge 2 in education is to recognize that citizens of the 21st century require different skills than did citizens from earlier centuries. 21st century skills include *cognitive skills* (non-routine 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) (Koenig et al., 2011).

In a society built on knowledge, citizens need to acquire new skills 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 among today's school-aged children. 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 in a short time have changed 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 able to learn in groups; *they must know how to learn*. Key features include skills in critical thinking, creativity, collaboration, meta-cognition and motivation.

Research shows that in a knowledge economy skilled versus less skilled workers have more job opportunities as a result of skill-based technical change (Brynjolfsson & McAfee, 2013). As technology advances, *educated* workers tend to benefit more, and workers with *less educated* workers tend to have their jobs automated.

2.1 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) (Shute et al., 2009). 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 USA about 25 years are required for an individual to receive a sufficiently well-rounded education to become a proficient educator. The impact of that individual's teaching cannot be seen in subsequent learners for another 20 years. Thus the total cycle time for learning 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 challenge is for citizens to apply what they learned about a specific topic, such as a science discipline, during their school years to novel problems that they encounter during their daily lives. We need to equip students to access and interpret the science information they need in response to specific practical problems, judge the credibility of scientific claims based on both evidence and institutional cues, and cultivate deep amateur involvement in science.

2.2 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, while using inquiry reasoning. Technologies are needed that can help develop alternative teaching modes, including rich computer interfaces, intelligent environments, learning companions, and tools that detect and respond to student emotion.

Creativity, curiosity, and intrinsic motivation can be enhanced as people have increased opportunities to work on personal constructionist project-based activities (such as Learning by Design™ projects). A framework of using information technology to collect, relate, create, and donate resources will support creativity and motivation (Ashish, Burleson, & Picard, 2007). Inquiry-based systems that are open-ended and exploratory in nature, allow learners to question and enhance their understanding about areas of knowledge in which they are motivated to learn (Dragon et al., 2009). Innovative instructional approaches, such as *preparation for future learning*, have uncovered ways to increase comfort with uncertainty and promote the development of adaptive expertise (Schwartz & 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 and guide these students as they learn science content, especially complex, ill-structured problems deeply? How can technology support a curriculum designed to engage children and encourage curiosity?

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 and/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 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 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 methods that enable ordinary citizens to access scientific information that is relevant to practical problems they are facing. Specific instances of such problems are decisions made during elections and the choices for personal health. Many ballot measures such as the one concerning genetically modified foods require knowing about science. Information access tools should enable citizens a way to access accurate and research-based information about such topics, and help them reason through informed choices.

3. Interaction data to support learning: Grand Challenge 3

Grand Challenge 3 is to explore and leverage the unique types of data available from educational settings and to better understand students, groups and the settings in which they learn (Baker et al., 2008b; 2006). Two distinct research communities have evolved, learner analytics (LA) and educational data mining (EDM). The two areas have significant overlap both in their objectives and the methods and techniques used. Their 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 research, originating from the community of intelligent tutoring systems researchers works on very small-scale cognition, e.g., student problem solving, time spent on problems. 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 (e.g. learning content management systems) and focus on issues such as retention and test results; they combine institutional data, statistical analysis, and predictive modeling to identify which learners need help and how instructors can change academic behavior


Middle School children collaborating on a science project.

Photo Credit: Mike Sharples, ICCEE 2008

We need to address that big neglected middle between cognition and test scores. The challenge is for both research communities to broaden what they do now 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, etc. and evaluate students' competencies.

Data is available from many sources including interactions with other learners and with physical objects (e.g. laboratory instruments). What data is needed and how can we collect and analyze it? How does this data support the four other challenges? What do we know about learning, student attitudes and student retention? 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 US 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 pre-school 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, Remarks at the National Press Club, 1999

3.1 A vision for interaction data to support learning

The vision for interactive data includes EDM contributing to the evaluation of learning systems and development and testing of scientific theories on technology-enhanced learning (Scheuer and McClaren, 2011). Exploratory analyses identify regular (or unusual) patterns in data, e.g., problem-solving strategies of students and 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 types of practice compare to one another (e.g., in language learning, is it more efficient to reread the same stories or to read a variety of stories?). Computational methods have been used to randomize treatment assignment and to capture data. Finally, EDM researchers have developed new evaluation methods that are based on specific models of learning (e.g., learning curves and Bayesian Knowledge Tracing).

Data of interest moves beyond interactions of individual students (e.g., navigation behavior, input to quizzes and interactive exercises) and includes data from groups of students in collaboration (e.g., text chat), administrative data (e.g., school, school district, teacher), and demographic data (e.g., gender, age, school grades). Another focus is on student affect (e.g., motivation, emotional states), which can be inferred from physiological sensors (e.g., facial expression, seat posture and perspiration) (CITE D'mello; arroyo). EDM uses methods and tools from the broader field of *Data Mining* (Witten & Frank, 2005), a sub-field of computer science and artificial intelligence. EDM features include both the theoretical (e.g., investigating a learning hypothesis) and practical (e.g., improving learning tools). Typical steps in an EDM project include data acquisition, data preprocessing (e.g., data "cleaning"), data mining, and validation of results.

3.2 Research about interaction data to support learning

Research is needed to *augment* real world equipment with data from instruments that can monitor learners' activities. For example embedded sensors in the lab (e.g., 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 and the groups' prior knowledge, skills and abilities and provide appropriate coaching (Ashish, Burleson, & Picard, 2007)

Student with disabilities using a computer.
Photo Credit: ???

ML techniques are promising where systems repeatedly observe how students react and generalize rules about the domain or student, (see Conati et al. in this issue; Kobsa, 2007). For example, machine learning (ML) techniques are used to augment user and group models automatically. Observation of prior students' past behavior provides training examples that form models to predict future actions (Webb et al., 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 enable 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 affect and their learning (John & Woolf, 2006; Arroyo & Woolf, 2005).

Research is needed to study how machine learning (ML) techniques can achieve *increased software flexibility* and *reduced cost*, which are two sides of the same coin. If instructional environments were more flexible and could learn about and accommodate their instruction to new student populations, the per-student training cost would be reduced. Currently many person-years are needed to construct a single environment; for example, a detailed cognitive task analysis might take six months. Research is needed to support user models to *adapt to new student populations* to counter the typical inflexibility of educational systems that fossilizes a teaching system to a single domain and instructional approach (Sison & Shimura, 1998). Clearly inflexible instructional software is let loose in a constantly changing environment, (e.g., 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 student and teaching strategies, and thus portions of the system remain forever incomplete. This lack of flexibility is a contributing factor in the high development cost and effort in construction of tutors.

Research has shown that *reasoning about uncertainty* is needed for educational software. Most educational software represents student knowledge using formal logic, (e.g., student A knows skill X). However, this representation does not include the fact that authors cannot know with certainty how to represent skills or whether students actually learned these skills. Knowledge in educational software is incomplete and therefore reasoning under uncertainty is needed. ML techniques use approximations to reach weaker conclusions than do traditional tutors, e.g., "This student will succeed on the next problem with a probability of N%." ML both makes this process more complex and provides an opportunity to solve more interesting problems.

Two middle school girls sharing a mobile tool in a Biology project.
Photo Credit: Tak-Wai Chan, National Central University , Taiwan

Research is needed to examine the data deluge from lifelong chronicles of student learning: provides knowledge to find clusters of children with similar problems; identifies success and failures in teaching strategies and generate a deeper understanding of learning; sheds light on key questions in education and educational psychology

Research is needed to consider issues of time, sequence, and context; massive non-independence. Research is needed to record and analyze fine-grained interaction data from pedagogical systems, as well from servers that provide tools for assessment and collaboration across and among networks.

Distribution of well-managed and well-mined learning data is closely related to 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 learners will succeed. For example, young learners could benefit from their parents being informed about learning deficiencies and providing additional help or motivation (Heffernan & Koedinger, 2012). Teachers might benefit from seeing a 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. Assessment will result in more effective, efficient, and enjoyable instruction when data technologies enhance the learner's experience and support network (Shute et al., 2009). Current efforts such as the DataShop from Pittsburgh Science of Learning Center (see Koedinger et al., in this issue; Koedinger et al., 2008) have been utilized for data from hundreds of thousands of students; these efforts have already greatly increased access for interested

As the variety of electronic learning objects grows, the likelihood of becoming drowned in details increases. Research needs to address this deluge of data, by development of new *data mining, security and database* techniques. Who are the potential consumers of this data, e.g., how can data be distilled for assessment content so it is useful for each stakeholder? Research is needed to provide frameworks for orientation and assessment materials, e.g., a shared data dictionary that prevents duplication of efforts and streamlines the use of nomenclature and categorization. A vision has been proposed for a lifelong user model to exist as a first class citizen, independently of any single application and controlled by the learner (Kay, 2008). This envisioned taxonomy would first be established by corresponding researchers and then disseminated (and perhaps governed) by a body similar to other shared standards as coordinated by the IEEE or ISO.

Research is needed to make data available to the broader research community, and for the greatest possible diversity of learning environments. This is done regularly by other computer scientists: compilers have preset data sets that everybody uses; databases, operating systems, and computer architectures do the same.

A classroom of students in a developing country using XO computers.
Photo Credit: One Laptop Per Child

Research is needed to develop *algorithms* for educational data.. For example, we need to consider 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., 2008a) We need to determine how models and model-creation software can be made available for broader use of this nature, and for studying questions of validity. 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 (e.g. 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.

4. Universal access to global classrooms: Grand Challenge 4

Grand Challenge 4 is directed at learning that is universal, inclusive, anytime, anywhere, and free at the point of use. Universal access to global classrooms was first discussed at a AAAI Fall Symposium (AAAI 2008). 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.

4.1 A vision for universal access to global classrooms

Global classrooms should support individuals and groups to learn remarkably better than when taught by a human teacher. Since they are available at all times and have a non-limited supply of people with whom to converse about the topic of learning, they should also significantly improve rational/creative problem solving. Recent implementations of this vision can be seen through the providers of the massively open online courses (MOOCS) such as Coursera and Udacity that have focused on providing the best courses from best teachers for free.

Unfortunately these courses do not yet solve the 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 engage well with the learning content and with other learners? How can AI support learners with similar interests? What techniques are needed to help learners manage language and cultural issues and to support access to labs and resources that are in short supply or are not local?

4.2 Research to support universal access to global classrooms

Universal access to global classrooms requires asking questions that are increasingly *complex* and *computational*. Research is needed to explore technical issues around tracking, personalizing supporting multiple learning activities and reasoning about students and group cognition. Computational architectures and algorithms are needed that capture, store and support student and collaborative behavior as well as engagement in pedagogical dialogue.

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 multi-dimensional models and measurement methods; data indexed and organized 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, using education data mining to study errors in a logic tutor, using a taxonomy and pattern matching.

Global classrooms can help learners to collaborate on real projects, either at a distance or in local spaces (e.g., coffee shops). What is the role of AI in global classrooms? Apparently what's problematic about MOOCs can be addressed by the challenges enumerated here (CRA CCC, 2011). Thus we need to solve nearly all these challenge to make global classrooms work well.

Human-Computer Interfaces. Global classroom should include dynamic assessment and learning models that represent what learners know, along with when and how knowledge was learned (Grand Challenge 1). 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 so as to be helpful with engagement, cognition, meta-cognition 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 3). Data about student and group interaction should be protected, stored, and analyzed to evaluate how students performed. Assessment by machine learning algorithms will improve individual instructional systems. Hundred of thousands of visitors could access these portals daily and these systems would produce a substantial improvement in learning, based, in part on analyzing prior learners who interacted with these systems (Koedinger et al., in this issue). 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 best to support education? What is the nature of student/faculty interaction through mobile computing and how do we facilitate higher education with physically distributed course projects (e.g., involving data collection) (Grand Challenge 3)? **Social Computing.** Once online higher education in embedded in larger social contexts, how can computational systems support student collaboration and engagement (Grand Challenge 2)? What is the process by which teams work in virtual, collaborative learning environments (Grand Challenge 1)?

Online teaching resources now include 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. For example such systems would support teachers to write new content. Teachers might help write thousands of problems in high school geometry/algebra problems (Heffernan & Koedinger, 2012) or support grade school students to create new problems (Beal, 2012). Funding agencies would support establishment of vertical systems (e.g., generic user/domain models) and target new funds for horizontal efforts (e.g., tutors in new domains that use existing shell user/domain models).

5. Lifelong and lifewide learning: Grand Challenge 5

Grand Challenge 5 in education addresses lifelong and lifewide learning. Or, in other words, learning continuously over the entirety of one's life (lifelong) and across all aspects of that life (lifewide). Assuming the Grand Challenges 1-4 were achieved, affordances of each of these challenge will help us to learn throughout our life. Cultivating a culture of learning in society and promoting adaptive thinking links this Challenge 5 directly to Challenge 2 (21st Century skills). Education must adapt to promote the joys of learning and seek to provide authentic learning opportunities that blur the lines between learning and life. This challenge refers to access to resources and to people interested in the same things. 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.

Photo Credit: Tak-Wai Chan, National Central University , Taiwan

> "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."
> — Laurillard et al., "Learning Through Life: The Role of Technology," 2008

5.1 A vision of lifelong and lifewide learning

Education and learning are clearly not synonymous. Learning takes place naturally and continuously, especially for younger children; it is possible in any place at any time. Education seems to be fixed in time, place and prescribed activities. This fifth challenge asks us to re-examine the unnatural boundaries established by the educational 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 group has defined boundaries, which in turn constrain learning and limit transfer of school learning into everyday life.

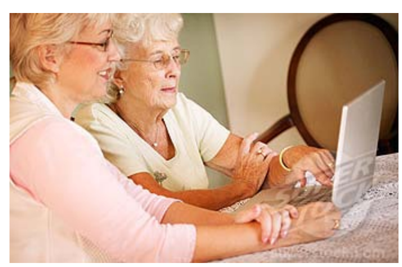
However, people clearly learn across these boundaries. One feature of mobile technology and social networks is to provide seamless and ubiquitous learning across established boundaries. For instance, the distinction between formal (in the classroom) and informal (outside of the classroom) education may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

An additional important aspect of lifelong learning is to provide professional development to teachers so that they can keep up with next generation of education standards and pedagogical approaches. Teacher's knowledge and practice have a direct correlation with the student achievement.

Information technology increases opportunities for lifelong and lifewide learning. It might even produce more learning outside the educational apparatus than within it, although this is difficult to measure. 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 et al., 2009). Given well-managed technology, education can better match a long sought after goal of lifelong learning.

5.2 Research to support lifelong and lifewide learning

Some distinctions between learners, such as generational differences, are highly relevant in informal learning contexts. These include biological or age-related sensory changes, a longer record of life experience (social, professional, civic, family, health, etc.), more complex psychological development, capacity for transformative self-reflection, differentiation and reintegration, and assumptions of adult agency and self-direction, are some distinguishing factors for mature learners. In any case, we focus on how learning fundamentally occurs and support findings that suggest learners are typically more alike than different (Pashler, et al., 2008), despite different settings where learning can formally take place. We look at theories of learning that are rigorously proven, such as Aptitude Treatment Interactions among novices and experts (Shute, 2008). In the new knowledge economy, career development may be measured as much by acquisition and development of valuable and relevant knowledge across a lifetime of employment, as it is by the rank and title of each particular job (Inkson, 2007). In this context, "career", metaphorically, can be characterized as a repository of knowledge (Becher, 1987).


Older women with technology
Photo Credit: Design Pics / *SuperStock* 1889R-25417-R-X999

Future research must address learners outside of school, and work to bridge learning that happens in all contexts. Attention must be paid to support learners at a personal level (e.g., building on hobbies and unique interests) and instill more permanent change. Future intelligent technologies should seek to not just convey knowledge, but to inspire and cultivate interest in important topics. We need systems that spread infectious enthusiasm and help kids 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 focusing everybody as lifelong and lifewide learners.

Intelligent agents that act as facilitators have been integrated into many existing learning environments (Swartout et al., Lester et. al., in this issue; VanLehn et al., 2009). Learning systems can take into account the interests, intentions, and goals of users and might motivate them based on a user's age, economic, and cultural considerations. Agents might teach within practical/real-life contexts and include authentic role models as virtual learning companions and teachers (Arroyo et al., 2011), and work to promote positive attitudes and build self-efficacy (Lane et al., 2013) **.** These agents may request particular topics and knowledge components on behalf of users and may interact with each other. They might provide complete user models; e.g., 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 (cognitive, previous skills, culture) and their needs (disabilities, learning difficulties). These agents 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 recreation* or instructional skills-based learning. Other areas include: *travel* (directional way-finding); interpretive tourism (learning about heritage and cultural attractions); *home life (h*ome repair and how-to knowledge); *hobbies and avocational interests* (skills acquisition, social networking, product information, best practice); *daily life* (driver education, learning about laws, legal issues, and civic responsibilities, news acquisition, consumer information awareness); and *healthcare (*medical and pharmacological information, self-care strategies, distance medicine).

Learners could call upon *virtual characters* as authentic role models (based on *real people*) as virtual teachers and companions (see Swartout et al., in this issue; Bredeweg et al., 2009). These characters would not only be knowledgeable, but also carefully reflect the characteristics of people they model. Simulations and augmented reality will not only represent learning situations, but also allow learners to represent or model their own thoughts and responses, and those would be interpreted by the system.

Longitudinal and lifelong learning will be enhanced: 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, & Picard, 2007). Persistent interfaces can adapt to learners across life transitions and stages. In many ways, such systems they 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.

Photo Credits: Mike Sharples, ICCEE 2008

Harnessing the new technologies and social media can be a critical enabler in facilitating the ongoing teacher professional development. Online professional development for teachers has the potential for providing "just in time assistance", and it is potentially more scalable than approaches that rely on limited local resources. Research needs to be undertake to understand how we can leverage such affordances for teacher professional development.

As the default boundaries of schools and traditional educational institutions vanish due to abundant computer-based components, it will become important to create a meta-framework to reference new student achievements and goals (Bredeweg et al., 2009). How do we establish *benchmarks, standards,* and further means to *index* and *classify* educational materials, certificates, institutes, etc.?

Discussion and Conclusion

This article described five challenges for AI and Education, and provided a vision and brief research agenda for each. It identified several computational ideas applied to human learning that address these challenge and ultimately provide access to global educational resources and the reuse, repurposing, and sharing of such resources.

We do recognize that technology cannot impact education in isolation, rather it operates as one element in a complex adaptive system that considers domain knowledge, pedagogy and the environment that students, instructors and technology co-create (Oblinger, 2012). United efforts are needed by educators, psychologists, learning scientists, and sociologists to create information and knowledge components that are easily accessible and usable by third parties. Many students have succeeded in the past in our current educational model, which is static, passive, primarily text-based and not collaborative. Yet *far too many* have failed. In fact, some studies imply that the United States' entire approach to education is faulty as we have not leveraged the enormous payoff for investment in pre-schooling, whether measured in improved success in college, higher income or even lower incarceration rates (Porter, 2013). Education in the USA does not redress inequities at birth (a result of having either rich or 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 was at age 3, before students entered school.

Yet, education is vital to increased earning power. A typical worker with a bachelor's degree earns *80 percent more* than does a high school graduate (Porter, 2013). By focusing our educational system on high school and college students, we are subsidizing the wrong people and the wrong way. Income inequality in the United States is passed down the generations. Parents who are financially able to, have opted out of the standard educational setting entirely, e.g., 5 million students are in alternative schools, including home schooling, online schools (27 states have virtual schools) and magnet schools (NCES, 2010).

This article focused on contributions that AI can make to education. Specifically, p*ersonalized learning* can be supported by AI tools that enhance student and group experience, reflection, analysis, and theory development: most of all we expect systems to lead to rich experiences that incorporate opportunities for learners to reflect on their own learning. Learning scientists, using 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. AI techniques will support the tracing patterns of learning and engagement over lifetimes, leading to new theory developments with powerful impacts. Learners have the opportunity for one-on-one instruction from embodied, ambient, and embedded virtual agents; co-located and distributed human peers and mentors; community members, teachers, and parents, each enhanced by information from rich interfaces and diverse sources of guidance for providing actualizing social and motivational feedback opportunities and interactions.

A middle school boy using mobile technology to measure the temperature of a tree.

Photo Credits: Mike Sharples, ICCEE 2008

Lifelong learning facilities will transcend traditional educational institutions and begin to impact aspects of continuing education and professional development. Content, delivery, personalization, and *adaptivity* of instructional systems can support seamless, ubiquitous access to lifelong learning facilities at home, at work, in schools and universities. Changes in education can deliver new ways of organizing learning delivery that go *beyond teacher-centric* models and include flexible and adaptive learner-centered, learner-controlled models of distributed lifelong learning.

The selected technologies in this article are not exhaustive and many others might be considered. Many technologies in the vision already exist in some form in laboratories and many features have been tested in classrooms. Yet current intelligent instructional systems have not been combined on large scales nor in optimal ways for education; they often provide single fixes or add-ons to classroom activities.

One overarching challenge for researchers in the field of AI and Education is to move beyond the realm of isolated projects in which each research group uses idiosyncratic conceptual frameworks and methods (Dede, 2009). Instead, to realize progress in AI and Education, researchers as a community need to undertake collective scholarship that subdivides the task of responding to the challenges. AI and Education researchers also need to be driven by the problems of education practice as they exist in school settings. This will ensure that emerging forms of technology described here will also challenge, if not threaten, existing educational practices by suggesting new ways to learn or offering new support for students (McArthur et al., 1994). Policy issues that involve social and political considerations, need to be addressed, but are beyond the scope of this document.

Hardware and software components, tools, and methods are also needed to support a service-oriented model of education. Communication (e.g. natural language—speech and writing), gestures and facial expressions are needed along with pedagogical agents that use speech with intonation, facial display, head and eye movement, and gestures. A semantic web is needed that reasons about the effectiveness of web pages and the impact of instruction tutors on classifications of students, e.g., students with disabilities.

Since many learners have the potential to be more successful, we need to explore the type of rich computational interfaces that will both help learners to succeed and help advance learning science. If we do not adopt new strategies afforded by AI technology even students succeeding today will likely fail to meet tomorrow's challenges. AI techniques and rich computational tools are already extending the success of today's learners in individual studies. We look forward to witnessing how AI will empower learners everywhere, expand opportunities for learning, and provide rich, engaging interactive experiences for all learners, of all ages, everywhere and at all times.

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- AI and Education
- 1. Mentors for every learner: Grand Challenge 1
  - 1.1 A vision for creating mentors for every learner
  - 1.2 Research to create mentors for every learner.
- 2. Learning 21st century skills: Grand Challenge 2
  - 2.1 A vision for learning 21st century skills
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