Adaptive Educational Technologies

TOOLS FOR LEARNING and for LEARNING ABOUT LEARNING

Gary Natriello, *Editor*

National Academy of Education
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ADAPTIVE EDUCATIONAL TECHNOLOGIES PROJECT

Workshop Cochairs

Susan Fuhrman, Teachers College, Columbia University
James Gee, Arizona State University
Brian Rowan, University of Michigan

Staff

Judie Ahn, National Academy of Education
Katie Conway, Teachers College, Columbia University
Gregory White, National Academy of Education

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Executive Summary

With the spread of adaptive technologies that customize the user experience in response to individual users, it is not surprising that such experiences are increasingly found in educational settings or in tools to facilitate learning. The National Academy of Education commissioned a background paper and held two meetings of scholars, policy makers, and developers of adaptive educational technologies to consider the implications of such adaptive systems for education research and education researchers. This report highlights the issues discussed in those proceedings.

Recent progress in the development of adaptive educational technologies builds on several decades of efforts to use computer systems to offer tailored instructional experiences to students. Adaptive elements can be found in many forms and formats that support learning. Adaptive hypermedia learning systems, intelligent tutoring systems, adaptive elements embedded into online courses, and a variety of educational games and simulations can all be designed to tailor the learning experience to the needs of individual students. A wide array of information on learners can be used to shape the individual learning experience, including prior achievements, preferences, interests, traits, and the immediate learning environment. Whatever the individual learner characteristics or the dimensions of the learning experience represented in the system, the key defining feature of adaptive educational technologies is that one or more elements of the system are modified in response to information about the learner. It is this adaptivity that creates the personalized learning experience intended to maximize the learning of each student.

The growth of adaptive educational technologies offers some unique advantages as well as some new challenges for education research. Among the advantages are the ability to gather expanded learner profile metadata and aggregate it to allow us to learn more about the patterns of learning across venues, expanded data sources to make inferences about learning, and new techniques such as data mining and machine learning for making sense of information on learning. In addition, adaptive educational technologies can support learner agency by extending access to learner data systems to learners themselves, they can allow us to inquire into the impact of learner feedback in social systems by granting learners access to data on their own performance in relation to the performance of others, and they can provide large-scale test beds for experimentation.

In addition to new advantages, adaptive educational technologies also present some new challenges. Adaptive systems typically do not include contextual data beyond the system, they gather data in ways that are not easily organized for research and analysis, and they often produce data for which it is challenging to attribute meaning in the absence of a prior learning theory. In addition, there are unresolved concerns about the ownership of data on students as well as concerns about student privacy.

Although the era of adaptive educational technologies is just dawning, there are already several major areas of research. A number of studies have attempted to provide effective feedback to students as they utilize adaptive systems. Such studies have explored the possibility of providing advice to students in real time using ideas drawn from areas such as machine learning and social network analysis. A second group of studies has attempted to determine how to provide feedback to instructors as they utilize adaptive systems, including information on how to improve course structure, teaching styles, and student motivation. A third group of studies uses data from adaptive systems to provide insights into patterns of student learning in response to particular configurations of content. These studies of how students learn specific subject matter offer guidance for the development of efficient learning trajectories. A fourth group of studies draws on data from adaptive educational technologies to inform improvements to those same systems. A fifth and final set of studies uses data from adaptive systems to advance general theory.

Because adaptive educational technologies represent a substantially new research opportunity, making full use of them will require new types of infrastructure. Adaptive educational technologies present new kinds of data organized in fresh ways. These data exist in new configurations that vary from system to system. Moreover, the conditions under which data are gathered in these systems differ from those typically associated with education research activities. Dealing with the situations presented in adaptive educational technologies will require consideration of at least new training for researchers, development of new tools of analysis, specification of prototypes and standard protocols, and attention to the rights of individuals whose data are collected as part of the operation of these systems.

Education researchers will require new skills to make use of the data generated by adaptive technologies. Elements of an effective training infrastructure might include seminars and workshops on handling large and complex datasets; publications such as handbooks, textbooks, and journals to build the knowledge base on techniques for dealing with data from adaptive systems; specialized professional associations and related conferences; and courses, specializations, and degree programs in institutions that prepare education researchers. Developing prototypes and protocols to standardize the data produced by adaptive educational technologies could also support the greater use of such data by researchers. In addition, investments in the development of analytical tools to handle data from adaptive educational technologies could reduce the burden on education researchers and encourage greater use of data from such systems. Finally, developing models for the governance of the data generated by adaptive systems will be necessary to promote access for education researchers.

In view of the rapid growth of the use of adaptive educational technologies, workshop participants identified some possible next steps to protect the interests of the education research community. These include developing standards for data gathered through adaptive educational technologies to support education research, developing standards for credentials for education researchers to demonstrate proficiency in the handling of data from adaptive educational technologies, and guidelines for human subjects committees to facilitate the review of research projects involving data from adaptive systems.

The growth of adaptive educational technologies presents new opportunities for education research that can advance our understanding of student learning and performance. The full participation of the education research community is necessary to create the conditions that will guarantee that the promise of adaptive educational technologies is fully realized for research as well as practice.

1

Introduction

We have reached a point where most people in modern societies have at least some experience with adaptive technologies, that is, systems that present themselves in ways customized to individual characteristics. Such systems are all around us: the lock that opens in response to your ID card, the ATM that retrieves your account information, the car seat that returns to the position you left it in when you insert your key (despite what other drivers may have done in the meantime), the thumbprint reader that allows only you to access your computer.

In the online world, the examples are even more powerful: personalized pages on Amazon that show items that may be of interest to you given your browsing and purchasing history, Google search results personalized in response to your search history, the personal account information displayed by your bank after you log in.

The behavior of these and similar systems is modified or adapted in response to individual users. The systems may respond to directions or information provided by the user, to an action or choice, or to information in the system or in connected systems.

With the spread of adaptive technologies into all aspects of life, it is not surprising that they are increasingly found in educational settings or as tools to support learners and to facilitate learning. The growth of such technologies has implications for educators, learners, and all those interested in using them in tools for learning.

The growing use of adaptive educational technologies as important elements in the education sector also creates new opportunities and challenges for education researchers. These tools generate new types of robust datasets that can offer new possibilities for education researchers. At the same time, these new opportunities suggest the need to enhance the skills of education researchers so that they can manage data from adaptive systems and utilize the data in a range of basic and applied studies.

Over the course of 2011, the National Academy of Education commissioned a background paper and convened two meetings to discuss these and related issues. An initial planning meeting was held in April to identify major issues and topics for a more extensive gathering in December. The December meeting included panels on learning, instruction, assessment, concerns, institutional responses and innovations, and developing infrastructure as well as demonstrations of a number of adaptive educational systems. Appendixes A and B contain the lists of attendees and panelists from the meetings. This report highlights the issues discussed in those proceedings.

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What Are Adaptive Educational Technologies?

The goal of responding to the needs of individual learners has received attention recently because of new demands on the educational system and new possibilities for providing personalized learning support. New demands for personalized learning stem from the growing sense that advanced economies require the vast majority of citizens to achieve high levels of learning throughout their lives. Such a massive increase in the demand for education may only be met with new tools, techniques, and learning resources.

Progress over the past decades in computing and communications technologies has set the foundation for a new learning infrastructure (Computer Research Association, 2005; National Science Foundation Task Force on Cyberlearning, 2008). Many computer-based systems engage students with educational opportunities, including instruction and resources. There has also been a shift from stand-alone hypermedia and tutoring systems to widely available Web-based systems. It is upon these technologies that new learning tools are being built to support individually responsive learning environments (Gardner, 2009; Maeroff, 2003) that promise to help greater proportions of the population to achieve higher levels of learning.

Adaptive educational technologies take account of current learner performance and adapt accordingly to support and maximize learning. By design, they present personalized educational experiences for each learner. Such technologies grow out of a long line of work on using computer systems to offer tailored instructional experiences to students (U.S. Congress, Office of Technology Assessment, 1988), beginning with Skinner's teaching machines in the 1950s (Skinner, 1986), and continuing on through the PLATO project at the University of Illinois in the 1960s (Smith & Sherwood, 1976), and the work of Suppes and Atkinson at Stanford on computer-assisted instruction in the 1970s and beyond (Suppes & Fortune, 1985).

Adaptive elements can be found in many forms and formats that support learning. They might involve ways of organizing resources or might involve complex learning environments. Adaptive hypermedia learning systems organize and present resources in ways that are tailored to individual student learning needs (Brusilovsky, 2001). Intelligent tutoring systems attempt to achieve the kinds of positive impact on learning long associated with one-on-one tutoring (VanLehn, 2011). The instructional elements of these systems, which are based on domain knowledge, knowledge of typical student learning patterns, knowledge of teaching strategies, and knowledge of methods for communicating with students (Woolf, 2009), adapt in response to individual students in order to maximize learning. Tutoring and other adaptive strategies can be embedded in online courses (Lovett, Meyer, & Thille, 2008). Additionally, a small but growing number of educational games utilize adaptive techniques to enhance the learning of individual players (Pierce, Conlan, & Wade, 2008; Barab, Gresalfi, & Ingram-Goble, 2010; National Research Council, 2011; Reese, 2012; Shute & Ventura, 2013).

A wide array of information about learners has been used to drive adaptation, including the learner's current state of knowledge and history of learning as inferred from his or her digital educational system interactions. Of course, both of these are considered within the context of the learning goals established within a particular system. More general characteristics of the learner—preferences, interests, and traits—are also used in some adaptive systems. The learner's experience with online environments and the immediate environment in which the learner is working may also be considered. Information on all of these factors can be used to generate the optimal personal learning experience through the adaptive system (Brusilovsky, 1996, 2001).

Brusilovsky (1996) specifies two broad techniques for adapting content to learners: adaptive presentation and adaptive navigation. Adaptive presentation involves tailoring the presentation of media content, presenting different text to different learners, and adaptation of the mode of presentation. Adaptive navigation involves techniques that help learners navigate content by adapting the way links are presented. Adaptive navigation techniques include providing direct guidance to learners, sorting links, hiding links, annotating links, generating links, and mapping links, all based on individual learner characteristics (Brusilovsky, 2001).

In terms of the more complex learning arrangements of virtual worlds and games, the possibilities for adaptation become greater and less generic. In the panel on instruction, Sasha Barab talked about "adapting whole story lines, whole worlds, whole roles, not just conceptual ideas. . . ." Indeed, such complex learning environments allow elements such as role specifications and entire story lines to respond to individual learners and their unique characteristics (Barab, Gresalfi, & Ingram-Goble, 2010).

Whatever the individual learner characteristics or the dimensions of the learning experience represented in the system, the key defining feature of adaptive educational technologies is that one or more elements of the system are modified in response to information about the learner. It is this adaptivity that creates the personalized learning experience intended to maximize the learning of each student.

3

The Potential of Adaptive Educational Technologies in Education Research

Because adaptive educational technologies collect data on individual students and student performance, they generate datasets that offer both new opportunities and new challenges for education researchers.

Unique Advantages of Using Data from Adaptive Learning Technologies

In the panel on learning, Roy Pea identified six ways in which adaptive learning technologies can help us learn about learning:

1. Adaptive learning technologies provide expanded learner profile metadata and aggregate them to allow us to capture the benefits at scale of learning more about the patterns of learning across diverse schools, districts, and states.
2. They expand the data sources we use to make inferences about learning and its conditions.
3. Through the use of techniques such as data mining and machine learning, we can expand our sense-making techniques for understanding learning and related conditions as a basis for guiding more effective learning.
4. Adaptive learning technologies can extend access to learner data systems to the learners themselves to enhance agency, self-assessment, and self-regulation.

5. They can also extend learner access to data about their own performance in relation to the performance of others to support inquiry into the functioning of learner feedback in social systems.
6. Adaptive educational technologies can also provide large-scale test beds for experimentation.

These new opportunities afforded by adaptive educational technologies suggest three courses for education research. First, they offer new possibilities for education researchers to examine problems and issues previously examined in other data. Second, they allow new kinds of research questions that have previously eluded empirical examination. Third, they have the potential to generate research questions as a result of examinations of large new datasets. However, as is discussed below, the data generated by adaptive systems come with special challenges as well.

Unique Challenges of Using Data from Adaptive Learning Technologies

The data generated by adaptive educational technologies present challenges for analysts trying to extract meaning and address research questions, and also present some special issues worth noting:

1. Although data gathered through adaptive systems can offer insight into important relationships among the variables included, they typically do not include contextual data beyond the system itself. Thus, for example, data on events preceding student engagement with the system, or data on contemporaneous events outside the system such as conversations between students and teachers or learning experiences in the home or community, would not be available without additional efforts to collect data. In addition to such traditional out-of-system events, during the meeting of the panel on learning, Jim Gee highlighted the independent growth of affinity spaces where users of systems gather to share knowledge; activity in such spaces would not be captured in the data generated by the adaptive system. If the adaptive system generates data over a considerable period of time, the lack of data on other aspects of the students' educational and life experience may compromise a researcher's capacity to develop a clear understanding

of the impact of experience on learning. Thus, researchers relying solely on data from the adaptive system might not appreciate the contextual factors.

2. Adaptive technologies gather data in ways that are optimized for the efficient operation of the system, including adjustment of what the system presents to students. Such data are not organized in ways that are amenable for analysis. At the meeting, Brian Rowan described the challenge of taking data from adaptive systems and processing them to make them suitable for analysis. Preparing data from adaptive systems for analysis is a very substantial task. As a result, it may be more accurate to view the data preparation stage as another step of data collection as the researcher selects and reorganizes the data to address the research questions (Romero & Ventura, 2007).
3. While adaptive educational technologies tend to produce data tightly linked to specific student actions, the meaning of such data is often unclear. For example, the kind of keystroke data typically gathered may raise questions about the proper unit of data for analysis. Less detailed and more meaningful actions are both easier to handle (Stephens & Sukumar, 2006) and potentially more useful for research purposes (Mislevy et al., 2010). Other student movements (e.g., drawing on a tablet or making gestures) are challenging to interpret, and attributing meaning requires additional data, assumptions, or, ideally, a framework of meaning.
4. Although there are ongoing efforts to address issues of data ownership and access (Office of Science and Technology Policy, 2012), the ownership of and access to data from adaptive educational systems is complicated. Education researchers are accustomed to negotiating access with students, parents, and schools, but adaptive educational systems introduce another player into the mix: the system developer or provider. System providers may assert rights to the use of data for system development, and they may be reluctant to share proprietary data rights with education researchers. Of course, commercial providers are not unique in that regard as John Stemper suggested in the panel on concerns when he explained the challenge of encouraging researchers to share data in open repositories.
5. Because adaptive educational technologies gather information on individual students through online applications, they inherently raise three types of privacy concerns. First is the

set of concerns related to the status of students as individual citizens or consumers in a networked world where valuable access to networked resources requires the exchange of personally identifiable information (Nissenbaum, 2010). Second is the set of concerns related to the status of many students as children whose privacy may require additional protections by virtue of their youth (Pitman & McLaughlin, 2000). Third is the set of concerns related to the role of students within educational institutions, a role that entails the gathering of particular kinds of information in the educational process (Glenn, 2008). Developers, providers, and adopters of adaptive educational technologies must confront these multiple layers of concerns for the privacy of student users of such technologies. Education researchers intent on using the data generated by adaptive technologies must be accountable for understanding these various privacy concerns and the procedures for addressing them in the applications that generate data used in their research.

6. Because data gathering in adaptive systems is integrated with program delivery in a way seldom encountered in education research activities that are typically grafted on (often over considerable resistance) to the regular business of educational programs, the opportunities for research have the potential to expand exponentially.

The unique opportunities afforded education researchers by data from adaptive educational technologies have been and will be sufficient to generate the interest and effort necessary to address the unique challenges presented by their use in research. Indeed, some of the challenges noted can be reduced or eliminated over time. For example, as learning scientists become more involved in the design and development of adaptive learning systems, these systems are likely to be designed with research and data interpretation in mind. As adaptive systems become more widely used, issues of data ownership, handling, and privacy are likely to be resolved.

Even at this early stage, adaptive educational technologies are supporting fruitful lines of inquiry. In the next section are some examples of research drawing on data from adaptive systems.

4

Examples of Research Drawing on Adaptive Educational Technologies

Several attempts to characterize and classify research that makes use of data from adaptive educational technologies (Baker & Yacef, 2009; Castro, Vellido, Nebot, & Mugica, 2007; Romero & Ventura, 2007) highlight the breadth of possibilities. To illustrate the types and range of studies, five categories are highlighted below with the caveat that some studies may fall into more than one category.

Major Areas of Research on Adaptive Educational Technologies

- Research that informs student users of adaptive systems
- Research that informs teacher users of adaptive systems
- Research that informs curriculum development
- Research that informs the design and improvement of adaptive systems
- Research that advances general theory and practice

Research That Informs Student Users of Adaptive Systems

A number of studies have attempted to determine how to provide effective feedback to students as they use adaptive systems. These studies have explored the possibility of providing advice to students in real time using ideas drawn from, among other areas, machine learning and social network analysis. Examples of this type include the following:

- Hwang (1999) investigated a system to provide learning advice to students.
- Heraud, France, and Mille (2004) used student log data to guide students in a tutoring system.
- Kelly and Tangney (2005) employed machine learning techniques to generate information on student learning styles.
- Romero, Ventura, Zafra, and De Bra (2009); and Tang and McCalla (2005) provided personalized content for students, the former via Web-usage mining, and the latter through social network analysis.

Research That Informs Teacher Users of Adaptive Systems

Studies in a second group have attempted to determine how to effectively provide feedback to instructors as they utilize adaptive systems, including information on how to improve course structure, teaching styles, and student motivation. Examples of this type include the following:

- Feng and Heffernan (2007) provided live reporting to teachers on student performance in the ASSISTment System.
- Romero, Venturo, and De Bra (2004); Tang, Lau, Li, Yin, Li, and Kilis (2000); and Vialardi, Bravo, and Ortigosa (2008) provided general insights for course development and improvement.
- Roll, Aleven, McLaren, and Koedinger (2011) drew on students' help-seeking to infer learning.
- Hurley and Weibelzahl (2007) provided insight into student motivation.
- Crespo, Pardo, Perez, and Kloos (2005); and Zakrzewska (2008) developed information to guide group formation.

Research That Informs Curriculum Development

Some studies using data from adaptive systems provide insights into patterns of student learning in response to particular configurations of content. These studies of how students learn specific subject matter offer guidance for the development of efficient learning trajectories. Examples of this area of research discussed at the meeting include the following:

- Baker (2007), Jong, Chan, and Wu (2007), and Muehlenbrock (2005) worked to detect student responses to the learning of specific content areas.
- Simko and Bielikova (2009) developed concept maps of specific subject-matter areas with the goal of allowing instructors to automatically create graphs showing the relationships among concepts and the hierarchical nature of knowledge in those domains.
- Pavlik, Cen, and Koedinger (2009) analyzed learning curves to generate domain models.

Research That Informs the Design and Improvement of Adaptive Systems

Other studies have attempted to draw on data from adaptive educational technologies to inform how improvements to the design of these systems might be made most effectively. For example, studies have attempted to understand how different types of students respond to various adaptive educational technologies. Others have focused on the delivery models for different forms of content or across different subject matter, and still others on the efficacy of various pedagogical strategies. Examples of this area of research include the following:

- Chi, VanLehn, Litman, and Jordan (2010) examined pedagogical approaches that lead to effective tutoring experiences.
- Superby, Vandamme, and Meskens (2006) identified factors that predict student failure in college.

Research That Advances General Theory and Practice

A fifth and final type of study has attempted to use data from adaptive systems to advance general theory. Self-regulation is one area where general theory has been used in research on adaptive systems (Lajoie & Azevedo, 2006). Research on the impact of hypermedia environments on self-regulated learning provides a good example of work that uses data from adaptive systems to refine understanding of theory and ultimately improve practice beyond the immediate adaptive system. Specific examples include the following:

- Azevedo, Guthrie, and Seibert (2004) examined student use of self-regulated learning processes and the impact on learning.
- McManus (2000) analyzed the relationship between levels of learner control in hypermedia environments and student self-regulatory skills for their impact on learning.

5

Infrastructure Needed to Support Research Drawing on Adaptive Educational Technologies

Because adaptive educational technologies represent a substantially new research opportunity, making full use of them will require new types of infrastructure. These technologies present new kinds of data organized in fresh ways. These data exist in new configurations and in ways that vary from system to system. Moreover, the conditions under which data are gathered in these systems differ from those typically associated with education research activities. Dealing with the situations presented in adaptive educational technologies will require consideration of at least four responses: training for researchers, development of new tools of analysis, specification of prototypes and standard protocols, and attention to the rights of individuals whose data are collected as part of the operation of these systems.

Training for Researchers

Education researchers will require new skills to make use of the data generated by adaptive technologies. Such skills are necessary for the tasks that are involved in taking the data from adaptive systems and making them manageable in analyses. Education researchers will also require skills in analyses that are more common in data mining typically conducted by computer scientists and systems engineers (Romero, Ventura, Pechenisky, & Baker, 2011). Moreover, if researchers wish to participate in the development of adaptive systems and thereby have a say in the data that are collected, they will require knowledge of the designs and the design possibilities of the systems. Otherwise, researchers will be limited to data available from systems designed without their research questions in mind.

With a relatively well-defined set of skills to be conveyed to education researchers, several elements of what might become an effective training infrastructure are essential:

1. Seminars and workshops devoted to handling the large and complex datasets generated by adaptive learning technologies could provide focused training and practice opportunities. A model for such activities can be found in the institutes and workshops sponsored by the National Center for Education Statistics to prepare researchers to work with national datasets. Another option would be to organize such activities through a network of regional institutionally based programs. Examples of this approach can be found in the Pittsburgh Science of Learning Center's summer school on mining of data from adaptive learning technologies and the Learning Analytics Summer Institutes at Stanford.
2. A variety of publications might contribute to a knowledge base on techniques for dealing with data from adaptive systems. These might include publications such as the *Handbook of Educational Data Mining* (Romero, Ventura, Pechenisky, & Baker, 2011) as well as textbooks and other professional books highlighting the evolving set of analysis issues and techniques. Specialized journals, such as the recently launched *Journal of Educational Data Mining* and the *Journal of Learning Analytics,* could offer outlets for publication and modes of studies using the new kinds of datasets.
3. Specialized professional associations might be formed to create opportunities for education researchers to learn from one another via conferences and other activities. Education researchers could also join existing communities of researchers in intelligent tutoring systems, artificial intelligence in education, educational data mining, learning analytics and knowledge, and the International Society of Learning Sciences.
4. Perhaps the most substantial element of a new training infrastructure would be the incorporation of courses, specializations, and degree programs in the graduate schools where education researchers are prepared and in collaborative efforts to create joint programs with departments

of computer science, statistics, psychology, and sociology where big data science is being developed and where education research topics are coming to be addressed. This, of course, would require the preparation of faculty to handle such efforts.

Prototypes and Protocols

Providing training to education researchers to take on the currently nonstandard and unwieldy datasets emanating from adaptive learning technologies is only one approach to developing an infrastructure to support education research on adaptive systems. Another approach involves the development of prototypes and protocols that could lead to greater standardization of the data produced by adaptive educational technologies. Education researchers have a role in developing prototype systems, particularly around data gathering and reporting. In addition, organizations such as the U.S. Department of Education with its Learning Resource Metadata Initiative and Learning Registry and the Schools Interoperability Framework Association with its SIF protocol offer models of the kind of standard setting that may alleviate some of the difficulties of accessing data from diverse systems from any number of providers. Investments in the development of publicly shareable prototypes and protocols could accelerate the use of data from adaptive technologies in education research.

Tools

The tools used for the analysis of data from adaptive learning technologies have not been developed with education researchers in mind. Most of the tools are generic and have a steep learning curve for scholars outside the specialized areas of inquiry, often in computer science, for which they have been developed. This means that education researchers new to adaptive technology will need to invest considerable time and resources to make good use of the available tools. Investments in the development of tools would reduce the burden on researchers and encourage use of data from adaptive technologies for education research. These investments could take the form of improved documentation, more intuitive and understandable interfaces, and enhanced technical support.

Issues in Creating a Data Governance Model

Education researchers are accustomed to dealing with the complexities of securing access to data about students and their learning. Such efforts address issues of informed consent and the protection of human subjects. They meet the requirements of human subjects committees at the institutions where the research is based as well as requirements of the schools and districts where the data are gathered.

The data gathered via adaptive educational technologies present new complexities for all concerned. Adaptive systems capture data on students and their learning in ways that may not be transparent to either students or their parents. Because adaptive systems are often operated by software vendors, publishers, or other third parties, and because the data are often located in systems physically outside the schools and districts where they are collected, the various rights to the data may not be clear. This, coupled with the standards common for other education research (e.g., informed consent), currently presents barriers that make it difficult for researchers to use data from adaptive systems for education research. However, there are efforts under way to overcome such barriers through the development of principles, policies, and practices to leverage the value of individual data while protecting the privacy rights of individuals. Such efforts include those of the U.S. Department of Education (2012), the OECD (2012), and the World Economic Forum (2012). Nevertheless, challenges to the evolving policies regarding student data suggest that issues involving student data are far from settled (Electronic Privacy Information Center, 2013).

Addressing the complexities of data rights will require the development of a management governance process to specify the various rights to data. Elements of the management governance must include:

1. A clear understanding of the kinds of data gathered by adaptive educational technologies;
2. Specification of the various rights that may be associated with data (e.g., the right to delete or modify data, and the right to use data to enhance the educational experience, for system improvement, and to address general research questions);
3. The parties who have an interest in the data on students and their learning (e.g., students, parents, teachers, schools, districts, states, system providers, colleges, employers, governance organizations);

4. The relationships among the various parties;
5. The conditions under which specific rights may be exercised; and
6. The precautions required to protect the interests of each party involved.

Developing one or more models for a data rights governance process will save considerable time and expense for all concerned as they develop data-sharing arrangements.

Additional Reading

For more on the topic of data mining and adaptive learning technologies, see *Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief*, published by the U.S. Department of Education. Copies are available at: http://www.ed.gov/edblogs/technology/files/2012/03/edm-la-brief.pdf.

6

Next Steps

The rapid growth of the utilization of adaptive learning technologies has implications for all concerned: students, parents, educators, educational agencies, system developers and providers, and education researchers. Workshop participants suggested some possible next steps to protect the interests of the education research community and the opportunities for and integrity of the education research process.

Step 1. Standards for Research Data

The education research community could develop standards for data gathered through adaptive educational technologies to support education research. Ideally, these standards would be developed by a consortium of research associations. These standards could be used to encourage developers to make provisions for gathering data as part of the design and development process. Additionally, the research community could offer a review procedure leading to the designation of an adaptive technology system as meeting research standards.

Step 2. Credentials for Education Researchers

The education research community could develop standards for a program of study leading to proficiency in using data from adaptive educational technologies. Such standards might be developed by a group of graduate programs in conjunction with one or more research associations. The completion of the program of study or individual components of study could result in a certificate or other credential.

Step 3. Guidelines for Human Subjects Committees

The education research community could develop guidelines for human subjects committees to facilitate the review of research proposals that involve data from adaptive educational technologies. These guidelines might address the major concerns posed by the more complicated data-gathering processes, more elaborate data structures, and more distributed ownership patterns associated with adaptive systems. The guidelines could be issued by a consortium of research associations, government agencies, and graduate programs in education research. At the closing session of the meeting, Bob Hauser noted that the federal government had issued notice of proposed rulemaking in the area of human subjects in July 2011 and that a key response document had been prepared under the leadership of Felice Levine of American Educational Research Association representing the work of a collectivity of social science groups and organizations. The National Academies' Committee on Revisions to the Common Rule for the Protection of Human Subjects in Research in the Behavioral and Social Sciences is currently working in this area with a report expected later in 2013 (see http://www8.nationalacademies.org/cp/projectview.aspx?key=49500 for a description of the project).

The growth of adaptive educational technologies presents new opportunities for education research that can advance our understanding of student learning and performance. The full participation of the education research community is necessary to create the conditions that will guarantee that the promise of adaptive educational technologies is fully realized for research as well as practice.

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Appendix A

Workshop Agenda

Planning Meeting
May 12, 2011
Keck Center—Room 101
500 Fifth Street, NW
Washington, DC 20001

MEETING AGENDA

Thursday, May 12

8:00-8:30 am	**Breakfast**
8:30-8:40 am	**Welcome and Meeting Overview** Susan Fuhrman, *Teachers College, Columbia University; President, National Academy of Education*
8:40-9:00 am	**Participant Introductions**
9:00-10:00 am	**Product Demonstrations—Envisioning the Scope of AETs** *Chair: Susan Fuhrman* *15-minute demos—focused equally on the product and on the data captured* • MasteringPhysics (Rasil Warnakulasooriya) • WISE (Marcia Linn) • ASSISTments (Neil Heffernan)

10:00-10:30 am	**Discussion—Analysis of Data from AETs** • 10-minute presentation on the literature (Ken Koedinger) • 20-minute group discussion
10:30-11:00 am	**Student Learning from AETs** • 10-minute presentation on data archiving (John Stamper, PSLC Datashop) • 20-minute group discussion
11:00 am-12:00 pm	**Roundtable—Developing Models Using Data from AETs** *10-minute presentations, followed by group discussion* • Student Affect (Bob Dolan) • Social Networks (Shane Dawson) • Teacher Implementation (Brian Rowan) • Intervention Effectiveness (Guido Gatti)
12:00-12:30 pm	**Working Lunch: Discussion of Background Paper** *Chair: James Gee, Arizona State University*
12:30-3:30 pm	**Addressing the 3Q's and Identifying Topics for the Summit** *Chair: Brian Rowan, University of Michigan* Discussion of Question #1: • What research opportunities are possible using these data? Discussion of Question #2: • What kinds of analyses have researchers conducted in the past using such data? And, what has been learned from such analyses? Discussion of Question #3: • What more is needed to develop research in this area? — What are the costs and benefits of using such data for research?

— What kind of organizational supports would be needed from developers if data were used for research and program improvement?
— What other accommodations might be needed for researchers (e.g., to ensure confidentiality of data, allow data to be processed statistically, etc.)?

3:30-4:00 pm **Wrap-up, concluding comments, and next steps**

4:00 pm **Meeting adjourned**

WORKSHOP PARTICIPANT LIST

May 12, 2011, Planning Meeting

Co-Chairs:

Susan Fuhrman, Teachers College, Columbia University
James Gee, Arizona State University
Brian Rowan, University of Michigan

Participants:

Judie Ahn, National Academy of Education
Roger Azevedo, McGill University
Sasha Barab, Indiana University
John Behrens, CISCO
Larry Berger, Wireless Generation
Christopher Brown, Pearson Foundation Research Program
Allan Collins, Northwestern University
Katie Conway, Teachers College, Columbia University
Shane Dawson, University of British Columbia
Andrea diSessa, University of California, Berkeley
Bob Dolan, Assessment & Information, Pearson
Guido Gatti, Gatti Evaluation, Inc.
Richard Halverson, University of Wisconsin-Madison
Michael Hansen, Urban Institute and CALDER
Aaron Harnly, Wireless Generation
Neil Heffernan, Worcester Polytechnic Institute
Paul Horwitz, Concord Consortium
Caitlin Kelleher, Washington University in St. Louis
Ken Koedinger, Carnegie Mellon University
Carol Lee, Northwestern University
Marcia Linn, University of California, Berkeley
Robert Mislevy, University of Maryland
Fred Mueller, Pearson Learning Technologies Group
Gary Natriello, Teachers College, Columbia University
Zoran Popovic, University of Washington
Seth Reichlin, Pearson
Erin Reilly, University of Southern California
Steve Ritter, Carnegie Learning
Dan Schwartz, Stanford University
David Shaffer, University of Wisconsin-Madison
John Stamper, PSLC DataShop
Elizabeth Tipton, Teachers College, Columbia University

Kurt VanLehn, Arizona State University
Rasil Warnakulasooriya, Pearson Learning Technologies Group
Gregory White, National Academy of Education

APPENDIX B

Summit Agenda

Agenda for December 1-2, 2011 Summit

Keck Center
500 Fifth Street, NW
Washington, DC 20001
All locations are Keck 100 unless otherwise specified

Day 1: Where We've Been

8:30–9:00 am	**Continental Breakfast**
9:00–9:30 am	**Welcome**
9:30–11:00 am	**Demonstrations** (Keck 100 and Breakout Rooms)
11:00 am–12:15 pm	**Learning Panel** This panel is about our ability to learn about learning through AET data analysis. The panel will focus on cognition, and social and emotional learning, as well as contextual factors. It will include theory building opportunities and the development of new learning models, as well as the possibilities to conduct pioneering studies in learning and development. **Moderator: Susan Fuhrman, Teachers College, Columbia University** **Panelists:** **Jere Confrey, North Carolina State University** **James Gee, Arizona State University** **Roy Pea, Stanford University**
12:15–12:30 pm	**Keynote Address: Senator Michael Bennet**
12:30–1:15 pm	**Lunch** (Keck Cafeteria, 3rd Floor)

1:15–2:30 pm	**Instruction Panel** This panel will focus on how instructional practices have changed because of new technologies, as well as how they contribute to the ability to assess the effects of instructional approaches. **Moderator: Brian Rowan, University of Michigan** **Panelists:** **Sasha Barab, Arizona State University** **Arthur Graesser, University of Memphis** **David Pritchard, MIT**
2:30–2:45 pm	**Break**
2:45–4:00 pm	**Assessment Panel** This panel will focus on the immediate feedback on student progress allowed by these technologies and the possibilities for tailoring instruction as a result. **Moderator: James Gee** **Panelists:** **Robert Mislevy, University of Maryland, College Park** **David Shaffer, University of Wisconsin–Madison** **Valerie Shute, Florida State University**
4:00–5:15 pm	**Concerns Panel** This panel will focus on how to best address privacy and proprietary concerns, ensure quality control, and ensure theoretically sound analyses. **Moderator: Brian Rowan** **Panelists:** **George Alter, Inter-University Consortium for Political and Social Research, University of Michigan** **Gary Natriello, Teachers College, Columbia University** **Lauren Resnick, University of Pittsburgh** **John Stamper, Carnegie Mellon University and Pittsburgh Science of Learning Center DataShop**

5:15 pm	**Reception** (Keck Atrium, 3rd Floor)

Day 2: Where We're Going

8:30–9:00 am	**Continental Breakfast**
9:00–10:15 am	**Institutional Responses and Innovation Panel** This panel focuses on how AETs influence institutions and on providing data-based feedback to schools and other learning settings. **Moderator: Susan Fuhrman** **Panelists:** **Richard Halverson, University of Wisconsin–Madison** **Ken Koedinger, Carnegie Mellon University** **Marcia Linn, University of California, Berkeley**
10:15–11:30 am	**Developing Infrastructure** This panel includes the roles for public and private enterprise in building AET data analysis as a field. It will also focus on roles for a variety of stakeholders, including researchers, instructors, developers, and end users. **Moderator: James Gee** **Panelists:** **John Behrens, CISCO** **Ed Dieterle, Bill & Melinda Gates Foundation** **Carl Wieman, Office of Science and Technology Policy, Executive Office of the President**
11:30 am–12:00 pm	**Closing**

SUMMIT PARTICIPANT LIST

December 1-2, 2011 ,Summit

Chairs:

Susan Fuhrman	Teachers College, Columbia University
James Gee	Arizona State University
Brian Rowan	University of Michigan

Participants:

George Alter*	University of Michigan
Eva Baker	UCLA
Marni Baker	Columbia University
Ryan Baker	Worcester Polytechnic Institute
Marianne Bakia	SRI International
Sasha Barab*	Arizona State University
John Behrens*	CISCO
Randy Bennett	ETS
Marie Bienkowski	SRI International
Christopher Brown	Pearson
Jack Buckley	National Center for Education Statistics
Jamika Burge	DARPA (i_SW)
Steve Cantrell	Bill & Melinda Gates Foundation
Isabel Cardenas-Navia	Office of Naval Research
Karen Cator	U.S. Department of Education
John Cherniavsky	NSF Division of Research on Learning
Jody Clarke-Midura	Harvard Graduate School of Education
Stephen Coller	Bill & Melinda Gates Foundation
Allan Collins	Northwestern University
Jere Confrey*	North Carolina State University
Lyn Corno	Teachers College, Columbia University
William Cox	DSA Capital
Richard Culatta	U.S. Department of Education
Phil Daro	University of California, Berkeley
Shane Dawson	University of British Columbia
Arlene de Strulle	National Science Foundation
Chris Dede	Harvard University
Ed Dieterle*	Bill & Melinda Gates Foundation
Bob Dolan**	Pearson

[* panelist]
[** demonstration]

Nancy Doorey	ETS
Janice Earle	National Science Foundation
John Easton	IES, U.S. Department of Education
Stuart Elliott	National Research Council
Robert Floden	Michigan State University
Daniel Goroff	Sloan Foundation
Art Graesser*	University of Memphis
Richard Halverson*	University of Wisconsin-Madison
Jane Hannaway	CALDER/AIR
Aaron Harnly**	Wireless Generation
Robert Hauser	National Research Council
Ryan Heath	Columbia University
Neil Heffernan	Worcester Polytechnic Institute
Laurence Holt**	Wireless Generation
Paul Horwitz**	The Concord Consortium
Kim Jacobson	Junyo
Thomas James	Teachers College, Columbia University
Caitlin Kelleher	Washington University in St. Louis
Anthony Kelly	George Mason University
Diane Jass Ketelhut	University of Maryland, College Park
Don Knezek	International Society for Technology in Education (ISTE)
Kenneth Koedinger*	Carnegie Mellon University
Janet Kolodner	National Science Foundation
Keith Krueger	Consortium for School Networking
Andrew Latham	ETS
Eric Lindland	Frameworks Institute
Marcia Linn*	University of California, Berkeley
Christopher Lohse	Council of Chief State School Officers
Ellen Meier	Teachers College, Columbia University
Edward Metz	IES, U.S. Department of Education
Natalie Milman	George Washington University, GSEHD
Jessica Mislevy	SRI International
Robert Mislevy*	ETS
Gary Natriello*	Teachers College, Columbia University
Brian Nelson	Arizona State University
Kenny Nguyen	Friday Institute for Educational Innovation
Barbara Olds	National Science Foundation
Nicole Panorkou	North Carolina State University
Roy Pea*	Stanford University
Kathy Perkins**	University of Colorado at Boulder
Jefferson Pestronk	U.S. Department of Education

Penelope Peterson	Northwestern University
Dave Pritchard*,**	MIT
Lauren Resnick*	University of Pittsburgh
Steven Ritter**	Carnegie Learning
Patrick Rooney	U.S. Department of Education
Mark Schneiderman	Software & Information Industry Association
Steve Schoettler	Zynga
Marilyn Seastrom	NCES, U.S. Department of Education
David Shaffer*	University of Wisconsin–Madison
Russell Shilling	DARPA
Valerie Shute*	Florida State University
Chuck Simon**	Pearson Digital Learning
Emily Dalton Smith	Bill & Melinda Gates Foundation
Mike Smith	Carnegie Foundation for Advancement of Teaching
Sarah Sparks	Education Week
John Stamper*	Carnegie Mellon University
Constance Steinkuehler Squire	White House, OSTP
Ken Stephens	Pearson plc
James Stigler	UCLA
Martin Storksdieck	National Research Council
Jana Sukkarieh	ETS
Elizabeth Tipton	Teachers College, Columbia University
Greg Tobin	Pearson
Robert Torres	Bill & Melinda Gates Foundation
Elizabeth VanderPutten	National Science Foundation
Hugh Walkup	U.S. Department of Education, Office of Educational Technology
Denny Way	Pearson plc
Sandra Welch	National Science Foundation
Carl Wieman*	White House, OSTP
Lauren Young	Spencer Foundation
Sabine Zander	Teachers College, Columbia University

Staff:

Judie Ahn	National Academy of Education
Katie Conway	Teachers College, Columbia University
Regan Ford	National Academy of Education
Philip Perrin	National Academy of Education
Jennifer Tinch	National Academy of Education
Gregory White	National Academy of Education