Education + Technology + Innovation = Learning?

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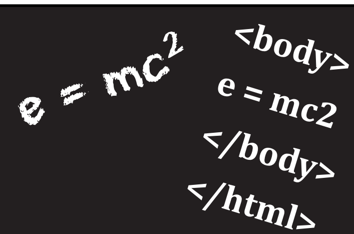

Part 3
Technology in Learning Innovation

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Close your eyes, and think of the word “technology.” What thoughts and images come to mind? Your smart phone? Computers? Hardware or digital things, or information in bits and bytes floating around in the “cloud” above your head? Now, pause to pay attention to the feelings that you associate with “technology”? Do you feel comfortable, or sense stirrings of concern? Is there eagerness, or do you have a sense that things could very easily be out of control?

Technology is the use and knowledge of tools, techniques, systems, or methods in order to solve a problem or serve some purpose. What we view as new technology evolves and advances persistently. A technological innovation—stone tools—is said to be a driver behind early human migration (Jacobs et al., 2008). Agriculture and pottery were innovative “technologies” to our Neolithic ancestors (Cole, 1970), as was the light bulb to Edison and his contemporaries (Hargadon & Douglas, 2001). Technology arose through our need to solve problems, whatever problems we as individuals or as societies were faced with at any given time. We learned to use materials from the environment (e.g., tools), or our own ingenuity (e.g., processes), to create new things and solve our problems. Across every endeavor known to mankind, we continue to advance knowledge and technology with each new discovery made or problem solved (Douglas, 2012). Innovative technology is rarely the result of a “eureka moment,” but of much more. Due to human endeavor, the march of innovation and new technology continues through time.

In 1968, at the dawn of the “modern” technology revolution, B. F. Skinner called for the development and growth of a “technology of teaching.” This technology would extend the progression of scientific discoveries made in the psychology laboratory into the school classroom. Although Skinner did create one of the first "teaching machines" (Skinner, 1968), he did not mean that teaching required machines. Instead, he advocated a "technology" of teacher/learner interactions that could greatly improve the likelihood of learner success (Skinner, 1954, 1984). As noted by Twyman (in press), Skinner outlined "a technology of instruction based on the behavioral principles of small, incremental steps, simple to complex sequencing, high rates of learner interaction, reinforcement of correct responses, and individual pacing" (n.p.) and thus commenced an instructional technology revolution featuring carefully designed instruction, thorough scientific validation, and automated (mechanical) delivery systems (Rumph et al., 2007).

Yet, almost 50 years later, Skinner's vision still has not come to pass. Few of the discoveries made in the psychological, behavioral, and cognitive laboratories have made their way into educational practice (Lagemann, 2002; Slavin, 2002). Instead, when we hear the words educational technology these days, we do not think of teaching processes or ways of learning; we think of laptops, tablets, apps, and other forms of hardware and software.

> ***Modern technologies allow data collection on student responses, learning patterns, content access, and a myriad of information on learning effects.***

There is a storied history of "hardware" technology invented for or used in the classroom. A timeline of classroom technology often includes advances from papyrus (at about 3000 B.C.), to the quill pen, the hornbook, the magic lantern, chalkboards, pencils, the overhead projector, the slide projector, the teaching machine, handheld calculators, the desktop computer, interactive whiteboards, student response systems, and now powerful, Internet-connected, mobile, personal digital devices, such as tablets and smartphones (Wilson, Orellana, & Meek, 2010). These more modern listings represent a tremendous evolution in the technology of "tools" used daily in schools. But has the technology in processes, in how we teach and learn, equally evolved? The answer, if we use student learning outcomes as our measure, is unfortunately "no."

Even as our tools advance, there seems too little change in the way we teach (Allington, 1994). Just as the era when filmstrips and then the TV were introduced into classrooms, short videos accessed over the Internet are hailed as major breakthroughs, touted as revolutionizing education (Vetter & Severance, 1997). However, anything beyond a cursory look reveals that this "revolution" still relies on the age-old model of information presentation, individual or group study, some sort of test (perhaps), and then the hoped-for learning. And we have seen that these methods produce some students who do learn; however, most do not. Instructors may add questions and suggest discussion topics (as is often done by companies offering video selections from current television networks), but these are minor additions to what is otherwise a very noninstructional technological approach.

Other examples missing a true teaching technology abound. Search engines have dramatically increased our access to information. We live in an information-rich culture where there are few facts we can't locate in but a few minutes (Leu, Kinzer, Coiro, & Cammack, 2004; Smith, 2011). Yet these articles and webpages, just seconds away from our fingertips, are still mostly passive information for us to "absorb" and "retain" and even evaluate for reliability (Ybarra & Suman, 2006) the best we can. Most online courses tend to be replicas of traditional classrooms modified for asynchronous delivery. And much like the traditional classroom, some of these online courses are poorly organized and delivered, while others may be well organized and engaging; yet, pedagogically, there is little real difference between the two. Tablets put computing power (figuratively) in the hands of our children, providing 24/7 access if wanted (Shih, 2007). Touch interfaces invite interaction, and mastery of the interface often requires little training, but with what are our K–12 learners spending an average of 7.5 hours a day interacting (Means, Toyama, Murphy, & Jones, 2010; Rideout, Foehr, & Roberts, 2010)? This chapter, while providing an overview of current, mainstream K–12 hardware/software educational technology, will focus on more critical aspects of education technology: teaching and learning and how we can use a technology of teaching to improve outcomes for all learners.

The history of failure in education reform (Kazdin, 2000; Kliebard, 1988; Sarason, 1990) has caused many to ask, "What do we need to do, as a system and a society, to improve schooling?" We further the question by asking, "Can we do what has eluded us to this point, that is, create a real technology of teaching and learning? Is there any hope that our practices can be informed by the sciences of behavior, learning, and cognition? What role can current (and future) digital technology and new devices play in making this happen?"

The Technology of Tools

Technology tools, both hardware and software, have been lauded as the panacea for what ails the American classroom (e.g., Katten Muchin Rosenman, 2013). Whether or not they can or will fulfill that promise is still subject to great debate (Brady, 2012). While various tool technologies have improved some facets of education—such as greater information access, increased variety of content creation tools, broader access to instruction, automated data collection, and behavior management tools—the seamless blending of instructional design, pedagogy, and technology tools has been much harder to achieve. An example of that seamless blending is described in a recent white paper by Layng (2012):

> Imagine a reading comprehension program that was designed to take advantage of a wide range of technology available in a classroom, including computers, interactive whiteboards, and perhaps iPads. A teacher might begin

by assigning the first three lessons of the program to be completed online as homework (e.g., Leon et al., 2011). Learners could access the lessons using a notebook or iPad they have at home, or perhaps use a computer that may be located in a library or computer lab at school. The teacher could access reports that not only let her know if the work was done, but also describe the precise performance of each learner. The online application featuring continuous adaptation would catch and correct many of the errors made by the learner. The program would provide individualized correction based on the type of error that occurs. The teacher would know how many questions were answered correctly the first time, versus after a correction. Learners with many corrections would eventually answer correctly, but could be flagged as perhaps needing more attention. The teacher could then provide whole-classroom interactive whiteboard lessons that review and extend the material learned online. Learners would be able to participate and verbalize the strategies they learn. No interactive whiteboard? Teacher guides and learner response materials could be provided to help transfer and extend skills learned in the program.

The teacher may find that some of the learners do not have the basic decoding skills necessary for the lessons. A brief two-minute assessment administered to each learner might find that some need to begin in the second half of an online phonics program, while others need to begin earlier.

As the program proceeds, skills learned online become the basis of collaborative in-class activities. The activities extend beyond the multiple-choice, inquiry-based lessons provided online, and give learners the opportunity to construct open-ended answers to literal, inferential, derived vocabulary, and main idea questions. Material from a range of subjects might be included in the collaborations as the programs progress and the learners master increasingly complex reading tasks. We should see learners eagerly extend their new comprehension abilities to new areas.

Other teachers may focus on the whole-classroom lessons, and reserve online or iPad work for those learners who seem to be having trouble in class. Yet others may rely on the online program and use the interactive classroom lessons for small-group instruction for targeted learners. And yet others may begin with the interactive whiteboard lessons and subsequently rely more on the online lessons as a result of acquiring iPads for their classrooms. The options are many and the flexibility great. What all of these teachers want, however, is content that will help them achieve their classroom goals—no matter what technology is theirs to use, or how they choose to use it.

In summary, schools need to be able to take advantage of any or all instructional technology found in any combination that meets their needs.
They might introduce iPads in one classroom, but have learners in other

> classrooms access the same lessons on a computer. If a classroom has no computers, but does have an interactive whiteboard, students should still be able to learn the same material. What's more, teachers should be able to take advantage of each technology's special features, such as whole-group or small-group instruction using interactive whiteboards, individualized instruction using computers, or mobile learning using iPads. (pp. 3–4)

This scenario may seem idealistic and futuristic, but, in fact, it exists today (see Layng, 2013a). We can learn a great deal about the use of education technology by examining what is involved in the scenario. First, there are the tools. The author talks about four: computers, interactive whiteboards, iPads, and (good old) print material. However, what makes their use compelling is not the individual devices, but how they all work together to achieve a valued educational outcome: reading comprehension. Further, all work together, not rigidly nor in a scripted lock-step curriculum, but afford a range of options that meet the learning goals. What ties the tools together is a unified curriculum instantiated within a software framework.

> ***Tools and their software must be considered as a unit and perhaps evaluated as such.***

The hardware/software technologies are tools that assist and enhance the learning process, but should not drive learning goals (National Education Association, 2013; see also McHaney, 2011). It is the software infrastructure across devices that combines each separate device into a unified whole. A teacher may choose a computer, an iPad, or an interactive whiteboard and also supplement with print if desired. While differential costs might influence use, it is the flexibility in how each is used that allows the teacher to meet the specific needs and technology requirements of the school, the classroom, and the learners. Thus, tools and their software must be considered as a unit and perhaps evaluated as such.

Tools and Data

We hear a great deal about data these days as well. The data generated by individual software programs and the instructional delivery platform that manages our learning tools are indeed important. Yet data alone may not be very helpful. In a recent demonstration of the use of "adaptive" data, a vendor proudly showed how the evening's homework assignment provided individualized, one-page reports for each subject in which each student was engaged. The data were displayed attractively; student strengths and weaknesses were highlighted. By examining the page, a teacher could spot certain learner weaknesses and subsequently design an intervention to address the problem. It all sounded quite compelling, that is, until one does the math. If a fifth-grade teacher teaches five subjects per day to 30 students, that means 150 pages of reports would be produced daily. How does one overworked teacher even begin to make use of that much data? Even in cases in which teachers may have time to contemplate a detailed report, what is to be done with the information? How is an instructional intervention or change designed and delivered, and how is it tracked and evaluated?

Data, instead of being a path to great outcomes, may instead lead to even greater stress on our teachers and principals (Cambell & Gross, 2012). Our data need to be tied to the practices of teaching and learning. Data should be smart (giving us insight), targeted (focused on the variables of concern), and informative (leading to immediate, evaluated interventions). What is needed are "smart reports" that provide critical information for 30 learners on one page, not 30 pages of reports. Our tools need to be linked in ways that provide continuous, formative evaluation, not of students, but of the effectiveness of the instruction or learning environment, and provide a basis to improve that effectiveness.

In summary, the successful integration of a technology tool for learning generally goes hand-in-hand with changes in teacher training, curricula, and assessment practices (Ertmer, 1999; Kopcha, 2012). Integration must occur not only with current devices, but with evolving devices as well. A school should not constantly face the threat that devices purchased this year will be totally useless in two years. This will require the development of software in the form of an instructional delivery platform that evolves to integrate old devices with new, across device manufacturers, for both the individual and whole classroom. These tools, while being developed and tested, are not yet ubiquitous (Edutopia, 2007). These devices are not cheap, and investments must be protected. Systems that rely on a single device or operating system are too limiting and restricting. Devices need to be integrated such the data produced are useful, easy to use, and easy to apply. And, if we have all this, will we be in reach of providing the very best education for our learners? The answer is, sadly, not quite.

The Technology of Process

Duke Ellington has been quoted (Markle, 1990) as saying, "Beauty without utility is an ornamental lump." Regrettably, our tools of technology may end up being just that. One approach to solving this dilemma is to focus on improving what is actually done with the tools, that is, to focus on the practices used in teaching and learning. We often hear that "teaching" remains largely an art. But recent advances in the technology of the teaching and learning process suggest we may be beginning to combine the science of learning with the art of teaching. There are three nonexclusive ways in which we may do this. One uses a technology of data analysis to make explicit currently implicit practices that may succeed, or at least provide information about what will happen to our learners given certain curricula (see Anderson, Gulwani, & Popovic, 2013; and the series of articles by Layng, Sota, & Leon, 2011; Leon, Layng, & Sota, 2011; and Sota, Leon, & Layng, 2011). A second approach systematically applies a scientific research and development process in the production of the software applications sold to schools (Layng, Stikeleather, & Twyman, 2006). The third explicitly applies practices that the learning sciences have determined to be effective, thereby making use of work in the experimental and applied learning sciences in our teaching (see Twyman, Layng, Stikeleather, & Hobbins, 2004).

Big Data: Making the Implicit Explicit

One approach employs "big data" to mine the art of teaching in order to provide effective practices. Proponents of big data maintain that solutions for teaching and learning can emerge from collecting and analyzing as much data as we can from as many learners as we can (Greller & Drachsler, 2012; West, 2012). But what is meant by "big data," and what does it mean for education?

Using data to drive decision making is not new to school districts. In fact, most districts are flooded with data. Everything from attendance, to bus ridership, to number of cafeteria meals served, to program usage rates, to teacher sick days, to student test scores and more are collected and used to make decisions. Many schools have adopted classroom reporting systems that describe what students are doing, their grades, homework, and so forth. These data are often available to students and parents as well. Schools strive to find data that help them make sense of what they are trying to do, and perhaps indicate what works, and even predict outcomes given certain practices. Often the word most frequently used is "accountability" (Ehren & Swanborn, 2012). Data are frequently used to compare outcomes between schools. Sometimes data are used to help identify successful practices that might be shared in some way, yet at other times they are used to reward or punish administrators or teachers (Burnett, Cushing, & Bivona, 2012).

Big data is none of that. Big data often makes few or no assumptions about what the data show. Data are not chosen to show this or that. Instead, every bit of data collected, from just about every source, is used. For schools, this would mean all the data listed above and more—including data publicly available but not collected by the school, such as census data. This inclusiveness is why it is called "big data." But it is not simply the amount of data, but how the data are used that is important (Greller & Drachsler, 2012; Siemens & Gasevic, 2012). In most instances, "genetic algorithms" are used to find patterns and highlight relationships in the data (Beasley, Martin, & Bull, 1993; see also Ryan Baker's chapter on data analytics in this *Handbook*). Used correctly, these algorithms can potentially diagnose learner problems, suggest solutions, make predictions, and even design instruction.

The algorithms are referred to as "genetic" because the principles of selection, much like those found in nature, are applied to the outcomes of looking for relations in the data (Johnson, 1999). By looking at learner characteristics, academic history, economic and social demographics, assignments made, assignments completed, quiz scores, grades on projects, and so forth, one algorithm may predict at a 50% correct rate that learners who have certain characteristics and experience may be successful in a given curriculum, and another algorithm might predict at a 60% correct rate that learners who have slightly different characteristics and experience may be successful in the curriculum. Thus, an initial population of hypotheses is generated. The "fitness" of each hypothesis is computed based on how closely each hypothesis predicts actual outcomes. Two hypotheses from the old generation are selected for mating; that is, genetic operators are used on this pair to create at least two offspring. The fitness of the two offspring is computed, and the ones selected that make the better prediction, these offspring are added to the new generation. This process continues until the best possible algorithm evolves that results in the most accurate predictions. Since this is done with very powerful computers, calculations occur very rapidly. With these data, a school knows which learners with identifiable characteristics will likely succeed with a given curriculum. The school can now more effectively match learners to curricula. Sometimes, hundreds of algorithms can be tested against one another in just a few minutes. Such procedures can make very clear, more quickly and reliably than ever before, that certain methods have not worked with a particular group of learners while another has. Or, based upon data not previously considered, schools might be better able to identify and assist those at risk. For example, it may be found that attendance for the first 20 days of high school predicts the graduation rate for a particular set of high schools. With those data, a school could immediately target students likely not to graduate. There would be no need to wait for test scores or other results. It may well be possible to then predict which intervention may be more likely to succeed.

This process continually learns from itself with new incoming data. Ultimately, the data generated from a great variety of sources gets combined with the day-to-day activities of teachers to produce and test more algorithms. Everything a teacher does, the lesson plans, the worksheets, the projects, the homework, and all the student data from all of those elements would be fed into the database. Data from thousands and perhaps someday millions of learners would be entered daily into the programs. In time, the most effective practices would emerge. As these practices are used and teachers vary the recommendations, these data would find their way back and new practices would be selected. In theory, the very best educational practices should emerge that most closely meet the requirements of each learner. Further, if instruction is being designed, the paths in the instruction can quickly be evaluated and altered until the best instructional sequence emerges.

There are critics of this use of big data (see Simon, 2013). One clear challenge is privacy (see Strauss, 2013). By its very nature, big data searches and keeps searching for every bit of data collected about a person, generating an unfathomable 2.5 quintillion bytes of data about our existence every single day (IBM, 2013). In education, this includes everyone—administrators, teachers, and students. While big data advocates argue that the individual data is not important apart from the whole, it is still collected and stored. Further, are there questions of the data that should not be asked? What may prevent data from being used to single out a small group and sort the remaining into tracks with fewer resources? Careful consideration must be given to the types of data stored, how it is stored, and who has access to it. The U.S. Department of Education has recently released two publications (including policy drafts) to assist educators and administrators with understanding and using digital big data (see U.S. Department of Education, 2012a, 2012b).

The Scientific Research and Development Process

Another approach that can contribute to a technology of learning is to be found in the learning sciences laboratories and in scientifically designed learning environments. In the latter, learning scientists use scientific methods to actually design or "engineer" the learning environment. This approach is highly dependent on a very precise, integrated research and development process, a type of scientific formative evaluation. Layng, Stikeleather, and Twyman (2006) described it in detail; we have paraphrased it below:

> Scientists and engineers whose responsibility it is to design complex systems, such as an airplane, rely on thorough formative evaluation to produce a vehicle that will fly the first time. For example, careful wind tunnel and other experiments test how the materials perform, how much lift is provided by the wings, and how the overall aerodynamics are implemented. Each revision is retested until the component meets a predetermined standard. Only after thorough testing of the components, both separately and together, is the final question asked, "Does it fly?"
>
> Each flight is considered a replication; the more conditions encountered, the more systematic the replication. Design modifications determined from test flights improve stability and reliability even more. Rigorous formative evaluations can have the same effect on instructional program development. By ensuring that each component meets a specified quality standard, which in the case of instruction would be a high mastery standard achieved by the learners tested, we can design and build instructional programs that have the same high likelihood of success as when building a modern aircraft. Rigorous "single-subject" iterative cycles (test–revise–test) provide great confidence that all aircraft built in accord with the design and development process will fly—without the need for tests comparing groups of aircraft. A similar approach to educational program development can provide comparable confidence.

By employing a scientific formative evaluation process that saw its beginnings in the 1950s (Markle, 1967) and has continued today (Layng et al., 2006;

Twyman et al., 2004), learning environments may be created that are the products of rigorous developmental testing and that will produce the outcomes required for learner success. Efforts are underway to help automate this process, thereby making it accessible to a larger curriculum development community (see Anderson, Gulwani, & Popovic, 2013). This process is increasingly used by educational publishers and others looking to build replicable and scalable learning environments. Those purchasing applications for their tablets, computers, or whiteboards should determine if those applications have gone through such a process (see Leon et al., 2011, for an example of this process applied to teaching reading comprehension.)

One major question raised by this technology is, "Who pays for it?"

One major question raised by this technology is, "Who pays for it?" The scientific development process is not cheap. Few start-ups can afford it, and few established publishers feel the need to do it since districts may often purchase "good enough" products, particularly if "good enough" is less expensive (see Janzen & Saiedian, 2005).

Direct Application of Learning Science to Teaching

Educational practices can also be informed by the work of learning scientists as they increasingly attempt to bring the laboratory to school. The results of years of important learning sciences research has yet to find its way into the classroom. This is troublesome. Scientists have investigated all types of learning and have often developed optimal strategies for producing each type. Different types of learning have been identified, and researchers have found that teaching methods appropriate for one type of learning is not appropriate for another. Various categorizations of content analysis and matched teaching applications have been proposed, categorizations which are intended to provide a useful guide for the analysis of content and the application of effective teaching/learning methods.

One categorization (Tiemann & Markle, 1991) separates learning into three main categories: psychomotor, simple cognitive, and complex cognitive. Though the categories offer broad classification, learner behavior may not necessarily fall cleanly into one or the other. Each category can be further subdivided into basic relations, linked relations, and combined relations. Within the psychomotor category, the focus is on learning how to physically do something. Holding a pencil properly (basic relation), swinging a golf club (linked relation, a component is dependent on preceding one), and performing a complex ice-skating routine (combined relation, components are combined and recombined to form new routines) all fall in this psychomotor learning category. What separates psychomotor learning from other types are the physical training required and the events (kinesthetic stimuli) that guide behavior often arise from within one's own body. Simply showing a learner how something is done is seldom adequate. Learners must learn to sense changes in muscle movement and certain temporal–spatial relations (see Mechner, 1994 for a comprehensive discussion).

Within the simple cognitive category, basic relations include (a) paired associate learning (e.g., given a country, name its capital), multiple discrimination learning (e.g., shown numbers 0 through 9, pick out each when asked), and simple serial learning (e.g., counting). Linked relations include sequence learning (e.g., recite *Macbeth*), conditional sequence (algorithms) learning (e.g., complete a long division problem), and combined relations learning (such as verbal relations in which performances are described but not necessarily demonstrated, e.g., describe how a play at third base is made). The primary goal for simple cognitive learning involves learning to perform a task one can already do in the presence of new events. Testing for simple cognitive learning typically involves determining if the learner can do precisely what has been taught. Here, providing enough practice and proper presentation of events to be learned is important.

The complex cognitive category involves concepts such as solid, liquid, and gas (basic relations), which are defined by a set of "must have" features that every instance of the concept shares, but each instance also has certain "can have" features that are not shared and do not enter into the definition of the concept. The goal is to have learners classify instances versus non-instances based on the "must have" features and be able to identify instances not provided during instruction as an example of the concept. Further, learners must be able to correctly reject noninstances that lack one or more of the "must have" features. Next come principles and other higher order linking of categorical learning (linked relations). A principle, for example, describes the relation between concepts, and can often be stated as an if–then relation. It may be a statement of a law such as, "for every action, there is an equal and opposite reaction." The four key concepts being linked are equal, opposite, action, and reaction. The application of the principle, even if one can state it, will be determined, in part, by how well one understands the four concepts. Not being able to distinguish action from reaction and not being able to recognize each instance across a wide range of "can have" features make understanding the principle nearly impossible. Strategies (combined relations) make up the last category of complex cognitive relations. These are self-discovery strategies that learners use to analyze and create new insights and rules. Considerable work has been done on how to teach learners these strategies (see Robbins, 2011; Whimbey &Lochhead, 1999). Rarely do we see them used in the classroom.

Though materials are available for training teachers in these methods, one will not likely find them in colleges of education. Yet more are being developed all the time. It is now possible using new learning technologies to rapidly teach vocabulary (four new words fully taught in 5 minutes), by combining research in what is called "stimulus equivalence" with research in what is called "fast mapping" (Sota, Leon, & Layng, 2011). We can even teach for generativity and recombinatorial insights (Robbins, 2011). A technology of learning is possible.

Interestingly, some of these methods have been available for decades. For example, there is consensus on how best to teach concepts, whether using direct teaching, peer-teaching, inquiry, games, or projects (e.g., Layng, 2013b). As early as 1971, D. Cecil Clark reviewed about 235 concept-learning studies from a range of laboratories and applied classroom experiments. He found a remarkable consensus on what is effective when teaching concepts (Clark, 1971). Inexplicably, even though subsequent work over the years has supported Clark's conclusions, the methods have yet to be incorporated into classroom teaching, the design of textbooks, or apps.

To make these methods available to schools would, of course, require a massive investment in professional development. Where does that money come from? Who determines where to start? How are teachers supported as they try to introduce these methods into their classroom?

We have briefly addressed two types of learning technologies: tools and processes. Now, what would happen if these three technologies of process were combined with the rapidly growing technology of tools? We may be able to overcome the shortcomings and challenges of each. Educators can encourage vendors, device manufactures, and developers to provide tools that include technologies for the collection and use of big data and content products that are based on a strong scientific formative evaluation—the results of which inform and are continually informed by big data—and to ensure that these tools and products use the most up-to-date learning sciences methods as possible. Further, these products should come with professional development that itself is informed by and informs all of these. By allocating scarce resources to those who provide these tools, districts can help ensure they are investing in more than ornamental lumps.

Action Principles

State and Local Education Agencies

a. Ensure equity of access to broadband Internet, for all students.
b. Ensure that technology and digital tools work together, in concert, to produce educational outcomes.
c. Provide administrators with training and guidelines on how to make informed decisions about purchasing equipment, technology use, educational applications, and data systems.
d. Provide assessment and accountability systems (or guidelines for careful development) that ensure academic integrity and accurately measure the impact on students in terms of psychomotor, simple cognitive, and complex cognitive learning.

e. Foster in-house "big data" expertise, including developing a training plan for analytical skills and the understanding of interrelationships between data sets.
f. Collaboration with a national agency and work towards competency certification for teachers of online learning.
g. Encourage preservice and inservice programs to provide instruction and professional development related to the application of learning science principles, including making use of work from the experimental and applied learning sciences in teaching.
h. Encourage preservice and inservice programs to provide instruction and professional development related to the successful engineering of learning environments.

Schools and Classrooms

a. Provide ongoing professional development for all personnel on how to use technology effectively. This includes access to relevant, high-quality, interactive professional development on how to integrate the technology of tools and the technology of process into their instruction and practice.
b. Provide all educators with training and assistance in determining what procedures and products use the most up-to-date findings from the learning sciences for effective teaching and learning.

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