EDITORS’ INTRODUCTION TO CHAPTER 31

Twenty years ago it would have been hard to imagine that computer networking would have such a profound influence on the field of instructional design and technology (IDT) and throughout society as a whole. The quest to build a better mouse trap is now guided by emerging technologies that continually strive toward being faster, smaller, more intelligent, and distributed. Predicting the future of IDT in this blur of technology innovation is at best a risky endeavor. In this chapter, John Jacobs and Jack Dempsey review a broad spectrum of emergent technologies in order to select those they think will have a growing impact on the IDT field over the foreseeable future. Even within this limited scope, they present evidence of a technology induced paradigm shift currently underway. The authors also describe ethical issues that may soon overtake the research community as it reaches out to incorporate advances within the related fields of cognitive science and neuroscience. We hope this chapter will spark an interest in the research of scientific fields that are on a convergent path with that of our field.

KNOWLEDGE AND COMPREHENSION QUESTIONS

1. What three technology areas are considered by the authors to have a meaningful influence on the field of instructional design?
2. What benefits are derived from development of distributed learning environments using an open architecture approach specified by Advance Distributed Learning (ADL)?
3. According to the authors, what central element is required in order to make the course management system of a distributed learning system functional? Why do you think this element is considered so important?
4. What types of instructional systems are characteristics of what the author's have described as information pull (I-PULL) and information push (I-PUSH) learning environments?
5. Why is it important to discuss ethical ramifications when contemplating the use of neural stimulation to enhance learning processes?

EMERGING INSTRUCTIONAL TECHNOLOGIES: THE NEAR FUTURE

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"What is the use of a book, thought Alice, without pictures or conversations?" -Lewis Carroll

INTRODUCTION

As in most professions, better tools make for better products. This also applies to the design of instructional systems. The past fifteen years have witnessed the development and continual upgrading of sophisticated computer-based programs that have revolutionized the way instruction is developed and implemented. Embedding any of a wide variety of media into the instructional environment can be done almost effortlessly. Similarly, course management functions at the individual and group levels can be implemented quickly and efficiently as can sophisticated assessment, feedback and branching capabilities. All in all it has never been easier to design, develop and implement effective instructional courseware. And yet a core element of developing effective instructional systems continues to involve activities completed before the development process begins: including requirements analysis, task/skill analysis, matching learning demands to instructional technologies, and so on. Technology-enhanced tools continue to pave the way for improvements in how instructional courseware is developed and implemented. It is the adherence to sound instructional theory throughout the entire design and development process, however, that will ensure the achievement of high impact learning outcomes.

This chapter reviews and discusses three emerging instructionally relevant technology areas that we believe will have a profound influence on the field of instructional systems, at least within the foreseeable future. The chapter also provides a glimpse of tools and trends that are likely to affect learning and instruction during the next ten to twenty years and forge an enduring relationship between distributed cognition and the craft of instructional design.

Three Emerging Influences

Three technology influences or forces that we believe will make a conspicuous contribution to the field are: (a) the proliferation of object-oriented distributed learning environments, (b) the use of artificial intelligence applications, and (c) the expanded effect of cognitive science and neuroscience.

OBJECT-ORIENTED DISTRIBUTED LEARNING ENVIRONMENTS

Object-oriented programming languages, such as C++ and JAVA, have been in use for several years and SmallTalk, the precursor to these languages, has been in use since 1970. Object-oriented programming currently has a dominant role in guiding the future of software application development, including those for designing and delivering instruction. Among the primary benefits of using an object-oriented programming language is the ability to separate programming function from associated data elements. This separation, in conjunction with a hierarchical layering of functional attributes, allows programmers to more easily re-use programming code and in many cases reduces the time and resources needed during software verification and validation (i.e., debugging). Object-oriented programming is being used increasingly to develop Internet applications because of its potential integration with HTML and XML. In the parlance of object-oriented programming language, program elements are linked rather than embedded. Conceptually and in practice, the notion of “linked objects” is creating a revolution in the way instruction is designed, developed and delivered.

Linked Objects

The conceptual underpinnings of distributed learning environments are relatively straightforward. The devil, as always, is in the details. For starters, take a typical stand-alone, technology-based training (TBT) program that can be generated using one of the many commercially available software applications. Now engineer it so that instructional materials (including text passages, graphic images, video, and audio files) are integrated into the program as linked objects. Increasingly, organizations are developing a repository of instructional content materials (i.e., learning objects), to include specific elements (e.g., text passages, photos, etc.) as well as more complex instructional chunks, that can be re-used via programming links as needed by one or more instructional platforms. Information content can be easily updated on an as-needed basis to ensure that the information is accurate, up-to-date, and tailored to the specific needs of individual learners.

For example, say your organization developed instructional courseware using an off-the-shelf, TBT development platform. The courseware involved training newly hired employees to operate an existing piece of equipment. One module of the instruction involved completing maintenance tracking paperwork used to schedule ongoing preventative maintenance activities. Suppose also that the equipment is scheduled to be upgraded with new operating capabilities and that this will affect, among other things, the way equipment usage is reported. Using an object-oriented architecture, changes to the instructional modules involving the new equipment capabilities can be completed using resources developed by one group, while changes to the maintenance-tracking module can be completed by a separate group. The distributed nature of the instructional environment allows changes to be made to the central TBT program, which is then accessed by individual employees using a personal computer (PC) via a local- or wide-area networked communication link.

You can now begin to see the potential for such a centralized control, decentralized application instructional environment. To enhance learning effectiveness, a TBT program needs to measure and keep track of key learning events and activities at both the individual and group levels. This is where a distributed instructional environment can have a significant advantage over a stand-alone system. Within a distributed instructional environment, learning activities and events can be tracked within and across lessons or entire courses of instruction, making it possible to detect and address learning trends in a highly specific manner. It will be possible for distributed learning systems to integrate information about an individual's aptitude, learning preferences, goal orientation, and so forth within a tailored instructional program that matches learning needs to instructional technologies and activities.

Training Jackets

Storing information pertaining to individual learners is a key component of any TBT program. However, storing such information in a central location is problematic due to privacy issues and the need to establish secure data transmission channels. An electronic training jacket (ETJ) is currently being implemented by the Navy as part of the Navy Training Management and Planning System (NTMPS). The ETJ combines a variety of personal, administrative and educational/training data sources within a secure, centralized online data warehouse (see https://ntmpsweb.ntmps.navy.mil/etjclient/login.aspx). Over time, the Navy ETJ is expected to expand to incorporate a host of information related to the five “W” questions illustrated in Table 1, including a variety of job-related information (e.g., previous job assignments, licenses/qualifications, and awards).

Table 31.1

5 W's applied to a training jacket

Query	**Examples of Data**
Who is the trainee?	key biographical information such as name,identification number, position, aptitude, and learning styles
What is the trainee’s personal history?	key work experiences to include formal and informal education and training history

Where is the trainee headed?	types of operational assignments the trainee is likely to encounter.; overall career path goals/options
When will the trainee be expected to apply the training?	immediately versus sometime in the future, operate with or without job aids, work independently or with others
Why is this training being completed?	initial, remedial, or maintenance training; expected level of competence as a result of training (expert, journeyman, basic)

The electronic training jacket is considered a key component within a comprehensive integrated personnel management system (IMPS). For the ETJ concept to work, it needs to be transportable and to have an embedded capability for positively identifying individual trainees. One security-related application currently being implemented by the military, as well as industry and higher education, for accomplishing this task involves what is referred to as "smartcard" technology. These identification cards/units contain embedded microchips that providing positive identification using one or more of the following: thumbprint, voiceprint, retinal scan, DNA scan or some other as yet developed identification technique. If needed, the smartcard also can hold in its local memory the individual's ETJ information, making it readily transportable. Once the smartcard is activated using the positive identification technique, it has the capability to be inserted into a PC via a card scanner or other mobile computing device, thereby allowing the trainee to access the IMPS and initiate a training session. Interestingly, some relatively inexpensive and commonplace technologies such as WebTV, which provides Internet access via television, have smartcard capabilities.

The Advanced Distributed Learning (ADL) initiative (Department of Defense, 1999; see also www.adlnet.org) has been a major source of funding for over five years in the development of a comprehensive object-based distributed instructional courseware standard. This standard, referred to as Sharable Content Object Reference Model (SCORM), has now emerged from the prototype development phase into what developers hope becomes an implementation phase (Wisher, 2003). This initiative involves developing electronic “data tags” that will facilitate the development of an object-oriented, distributed training architecture to support military, industry and academia (Graves, 1994; Wagner, 2002). Such an instructional development environment, when fully developed and implemented, would establish an open architecture within which individual (proprietary) solutions could be implemented, but that allow information and resources to pass between proprietary instructional development and delivery platforms.

Meta-Data Tags

Meta-data tags refer to “data about data” (see http://www.imsglobal.org/metadata/index.cfm) and are used to label the wide variety of learning resources needed to manage and deliver instruction within a distributed learning environment. Meta-data tags can index an individual learning resource (object) using multiple attributes. According to the Institute for Electrical and Electronics Engineers (IEEE) standard used at the time of this writing, meta-data tags cover the following five areas:

- General – Information describing the learning object as whole
- Lifecycle – Historical and current state information about the object
- Metametadata – Information related to features of the description as opposed to the resource (e.g., identifying label, who contributed what, etc.)
- Technical – Information about format, size, location, platform requirements, etc.
- Educational – Information about educational or pedagogical nature of the object

The meta-data tag and associated sub-level attributes facilitate re-use of a given learning object across various courseware boundaries and within certain levels of granularity (e.g., course, unit, lesson, procedure, illustration). As an example, an animated graphic depicting the integration of various systems (hydraulic, electrical, mechanical, etc.) within an aircraft landing gear can be used in several lessons within the same curriculum that deal with aircraft maintenance, troubleshooting, system integration, hydraulic systems, electrical systems, mechanical systems and so on. Similarly, other course developers involved in developing courseware supporting an entirely new curriculum can use this same learning object. The IMS standards are aggressively promoting an open, distributed-learning architecture that supports a wide variety of instructional development platforms. Due in part on the rapid and sometimes unpredictable advances driving the information technology fields, the ongoing IMS standards development process is slowly growing into market share acceptance. One can participate in or simply become a spectator in the ongoing SCORM development process by participating in IMS-sponsored “plugfests,” that bring together vendors, content developers, and tool creators for the primary purpose of conducting cross-platform interoperability tests.

From an educational research perspective, acceptance and widespread use of a standard set of meta-data tags may allow the field of instructional systems to develop theoretically-based, empirically-validated courseware design principles at a level of specificity as yet unimagined. For example, by collecting data across various instructional platforms and information content areas, it will be possible to determine what instructional features (e.g., media type, level of interactivity, etc.) interact with specific learning styles or preferences to produce above average gains in learning and knowledge transfer. The key to making this a reality is to establish research-reporting guidelines to ensure that individual study results can be integrated within a larger body of knowledge and that support analysis using meta-analytic or other useful quantitative and qualitative review procedures (Hays, Jacobs, Prince, & Salas, 1992).

It may even be worthwhile to consider setting up a central data repository for the field of instructional design and technology. Why not? Such an effort is not unprecedented. Researchers in the area of neuroimaging are currently attempting to archive brain scan images from selected resources (i.e., peer reviewed studies) within a centralized database in an attempt to assist the research community’s ability to answer longstanding questions related brain function and associated behavior in humans and certain animals (Van Dorn & Gazzaniga, 2002). A similar effort to archive selected instructional data using a systematic approach could facilitate answering longstanding questions concerning the nature of human learning and performance as they relate to cognitive processing and instructional technologies.

THE APPLICATION OF ARTIFICIAL INTELLIGENCE

Instructional systems of the future will be able to perform a number of high-level activities involved in monitoring and regulating the instructional environment at individual and group levels. At the individual level, future instructional systems will diagnose learning needs, learning aptitudes and styles, develop instruction tailored to pre-identified needs and aptitudes, modify the level and type of feedback and instructional strategy based on learner responses and progress, and implement best practices guidelines based on up-to-date research findings. At the group level, future instructional systems will monitor and allocate instructional resources (e.g., schedule team activities or computer simulator time), collect and analyze data across individuals, tasks and settings, and generate lessons learned, best practices guidelines, and so forth for use by instructional systems researchers and practitioners.

These high-level functions can only be accomplished by integrating some form of artificial intelligence (AI) within the course management component of instructional systems architecture. There are several approaches that have been used by AI researchers to embed “intelligence” within computers (Gardner, 1985; Pew & Mavor, 1999). What follows is a brief description of two basic instructional approaches that we believe will integrate AI functionality and in so doing open up new vistas in development of future instructional systems. Several examples are included within this discussion that exemplify IA-based instructional applications and associated research currently underway related to these two approaches.

Instructional systems of the future will combine information content with automated teaching and learning principles (i.e., pedagogy) to create combination information push-pull learning environments. Information push (I-PUSH) learning environments will be based on an expanded use of intelligent tutoring system (ITS) applications. Information pull (I-PULL) learning environments will be based on intelligent interfaces allowing learners to construct their own learning experiences using integrated tool sets. These tool sets will include the capability to conduct concurrent information search and analysis operations and to rapidly develop simulated environments for testing ideas or fostering knowledge transfer to real-world settings.

Recent advances in the expanding fields related to AI provide a provocative view of technologies that will support such I-PULL tool sets. For example, data mining technologies are currently being developed that allow atmospheric scientists to scan large visually complex data sets (Hsu, Welge, Redman, & Cluster, 2002) and assisting executives when making critical business decision by mining complex, and often incomplete and mismatched (i.e., dirty) data sets (Kim, Choi, Hong, Kim, & Lee, 2003; Macedo, Cook, & Brown, 2000). Research in other AI fields, such as expert systems and intelligent autonomous agents, provide evidence of capabilities which can lead to tool sets that can aid in locating and translating knowledge, as well as enhancing creativity (Laine, 2002) by using single and multi-agent systems (Williams, 2004).

ITS applications have been effectively employed in a variety of content areas (Zackary, Ryder, Santarelli, & Weiland, 2000) and have been shown to produce results approaching those attributed to one-on-one tutoring (Merrill, Reiser, Ranney, & Tafton, 1992). At their heart, ITS frameworks are viewed as highly interactive, computer-based instructional environments whose goal is to actively guide (i.e., push) learners toward achieving expertise within a given content area. Within an ITS framework, interrelated models are generated and used to guide the instructional process: one depicting how an expert would perform, another depicting how a novice would perform, and a pedagogy model for guiding instructional/learning processes (Ohlsson, 1986; McCarthur, Lewis, & Bishay, 1993). The expert model reflects an ideal solution path typically in the form of goals and sub-goals that are generated by conducting an in-depth analysis of the cognitive process steps a typical subject-matter expert performs when faced with the same problem or problem type. Similarly, the novice model may encompass several sub-models, each of which depicts an erroneous solution path that a novice learner may explore when faced with a given problem or problem type. In addition, a pedagogy model is used to guide instructional/learning activities, such as the amount and type of feedback as well as the use of branching. The key elements of ITS that set it apart from conventional computer-based instruction are an ability to accurately diagnose learning errors by matching error patterns to pre-defined models of novice performance, and tailoring subsequent instructional activities (e.g., via feedback, branching, etc.) so that learner performance more closely matches that of the expert model.

In their paper describing applications related to executable cognitive models, Zachary,Ryder, Santarelli, & Weiland (2000) describe progress made using a cognitive modeling system, called the COGNET/BATON framework. The COGNET system models human decision processes in complex real-time, multi-tasking environments, such as decisions made by an air traffic controller. BATON is an executable cognitive architecture that represents three human information processing subsystems that work in parallel: sensory/perception, cognition, and action/motor. The paper describes several successful COGNET/BATON applications related to a) integrating multiple telephone operator job functions, b) developing performance support system (i.e., intelligent agent) for assisting fire support operations aboard a new class of Navy destroyer, and c) providing intelligent embedded training for Combat Information Center teams aboard Navy Aegis cruisers. Interestingly, these researchers note that the highly complex and time-consuming work needed to develop a given cognitive model can produce multiple applications, to include intelligent tutors/embedded instructors, decision and performance support systems, autonomous agents, and design/interface guidance advisors. Thus, these researchers contend that ITS and related AI (cognitive modeling) applications have matured significantly over the past ten years and are now poised to successfully tackle a wide range of content areas.

Within a typical ITS framework the tutor provides information, examples, feedback, and so forth, necessary for learning to take place. McArthur, Lewis, and Bishay (1993) contrast instruction-led approaches engendered by the ITS framework with learner-centered approaches (in their words “interactive learning environments” or ILEs), that in our view can be characterized as an I-PULL learning environment. Within

ILEs, the learner takes on the primary responsibility of managing the learning process, typically by employing tools that allow information to be collected, manipulated, and represented.

Our vision of I-PULL learning environments expands the concept of ILEs on several fronts. For example, I-PULL intelligent interfaces will be off-the-shelf platforms that can be trained to work closely with an individual user/learner. Initially, an intelligent interface will gather information about an individual's learning style and information processing strengths and weaknesses based on the results of an extensive questionnaire coupled with the results from a series of pre-programmed learning assessment exercises. As individuals interact with the software tools to locate, store and use information for ongoing work and leisure pursuits, the intelligent interface will provide suggestions on how to improve learning efficiency and effectiveness based on validated learning-to-learn principles and personal usage characteristics.

The following two examples provide a glimpse of adaptive learning environments that integrate what can be considered I-PULL functionality. Woods (2001) describes a math tutor system called the QUADRATIC tutor that uses scaffolding and contingent tutor design principles. These instructional design principles are based on research involving the amount and type of help that a learner seeks when he or she is provided tutoring assistance, to include self-regulation of time on task. For these researchers, one interesting and potentially useful instructional characterization that can be made comes from assessing the extent to which a learner is likely to perform self-corrections and whether they refuse help or over rely on help (in his words, “help refusers” versus “help abusers,” see Woods, 2001, p. 285).

Another instructional system that includes adaptive elements that appear to support individual user needs through I-PULL type functionality is described by Weber and Brusilovsky (2001). Their instructional system, referred to as ELM-ART, is a web-based adaptive interactive textbook. The authors suggest that the system provides intelligent adaptive functionality for the primary purpose of enhancing system versatility. Versatility, they contend, is a key instructional design characteristic because it offers the opportunity to collect information about a given learner’s knowledge, preferences and interests. In so doing, the system can provide more effective adaptive (and intelligent) tools for assisting learner performance when navigating within the instructional environment. For example, tools that that help the learner choose what to learn next or what problem/assignment will promote knowledge transfer, when and how best to engage in a discussion forum, what hyperlinks to explore, or when to attempt a quiz or test. One important component of the ELM-ART system that helps promote versatility and thus adaptive intelligent functionality is its reliance on what is called collaborative student modeling. As described previously, ITS applications typically involve a “novice” model the system uses to determine the current performance level for the learner. Collaborative student modeling refers to the ability of learners to inspect, and in some cases modify, their respective student (novice) model employed by the system at any given time. The system does, however, collect performance data in the form of time spent accessing one or more pages, embedded questions or problems answered correctly, quiz/test items answered correctly, and so on in order to validate the accuracy of the model.

Among the more valuable tools increasingly available to instructional designers are simulations and simulation games (Jacobs & Dempsey, 1993; Dempsey, Lucassen, Gilley, & Rasmussen, 1993; Aldrich, 2003). Simulations and simulation games will be used within both I-PUSH and I-PULL learning environments. A wide variety of simulation techniques, such as 2D & 3D modeling, role playing, video, and case studies will increasingly be used to create realistic environments for developing and testing new ideas or practicing specific tasks and associated skill sets. Once created, simulation environments will be capable of being exported so others can use them for individual training or as part of a distributed simulation activity involving two or more participants. Intelligent computer-generated agents will also be included within the simulation environment to allow realistic collaborative interaction. Any Internet search will identify a number of companies offering instructional simulation-based products and services as well as several industry reports and articles suggesting simulation tools are a rapidly growing niche within the instructional technology sector. Whenever artificial intelligence learning systems are discussed one question invariably materializes. When will AI systems truly demonstrate human-like "intelligence" in the form of learning (i.e., the ability to change behavior based on past experience) and flexible problem solving? It is our belief these momentous achievements will occur at a modest level within the next decade due to developments in related fields. First, AI researchers have used a variety of cognitive modeling approaches that more closely mimic the functioning of human information processing to investigate such critical performance issues as situational awareness, decision making, and knowledge acquisition (Pew and Mavor, 1998). Second, recent advances in parallel processing offer a possible breakthrough in raw computing power, which have impeded the ability of AI researchers to write programs performing relatively simple cognitive tasks (e.g., object recognition) under real-time constraints. In addition, there are alternative technologies offering great promise. One such technology is field-programmable gate array (FPGA), a relatively new type of integrated circuit that can be thought of as intelligent hardware (Faggin, 1999). Using FPGA, future computing systems can not only be the size of the current microchip, they can have inherent hardware architectures incorporating properties that are found only in biological neural networks. Learning systems using FPGA technology may be capable of displaying such key intelligent functions as real-time learning and self-repairing. When used in combination with increasingly sophisticated and powerful cognitive processing software approaches, these hardware advances will usher in the beginning of a revolutionary era in intelligent computing that will greatly influence the field of instructional systems.

COGNITIVE SCIENCE AND NEUROSCIENCE CONTRIBUTIONS

Advances in the related fields of cognitive science and neuroscience have been based, in part, on the ability of researchers to monitor electro-chemical activity within the brain and to more accurately match brain structure and associated neural activity to overt actions, such as psychomotor behavior, recall of information, and decision making (Davidson & Irwin, 1999; Tononi, Edelman, & Sporns, 1998). Technology improvements in this area, such as combining standard imaging techniques like positron emission tomography (PET) with other promising magnetoencephalography (MEG) or magnetic-source magnetic resonance imaging (msMRI) methods, continue to enhance the level of precision with which neural activity can be monitored. Innovations in this area will likely include the ability to influence brain activities affecting learning and these innovations will be incorporated into advanced instructional systems. One promising technique, called transcranial magnetic stimulation (TMS), is being used as both a “brain mapping” tool, as well as a potential therapy (Hallett, 2000). Brain mapping tools such as these will open up a new vista for instructional technology research that will have direct application to the design of instructional systems. For example, researchers are studying brain regions that appear to give rise to memory and retrieval process (Buckner & Wheeler, 2001; Simons & Spiers, 2003) thereby making it possible to monitor the level of knowledge acquisition and retention by measuring the relative amount of brain activity as well as the specific neural pathways being activated. This may even give rise to a new class of learning objectives that describe this unique learning activity. For instance, “The learner will demonstrate understanding of the concept of ‘network interoperability’ by exhibiting neural activity in .04% of his/her superior temporal gyrus mass and by exhibiting cross modal activation starting in the temporal lobe and moving to the pre-frontal lobe.”

In the area of interdependent learning, where two or more individuals must collaborate their efforts to enhance team or group performance, much has been written about the need for establishing a shared mental model across team members (Stout, Cannon-Bowers, Salas, & Milanovich, 1999). By monitoring the timing and extent of neural activities across the various team members, it may be possible to determine what activities enhance team collaboration, cohesiveness, and overall performance effectiveness.

What if a learner is having difficulty assimilating new information? Can a gentle electrical impulse focused on a specific brain region spur acquisition and recall of to-be-learned information? If a learner is temporarily unable to focus on the task at hand or is experiencing a more general sense of low motivation, can focused neural stimulation assist the learner to re-focus his/her attention or generate a more general sense of purpose and self-efficacy? These questions focus attention on much bigger issues that need to be addressed as research in this area expands. Indeed, researchers are actively studying neurobiological activities related to reward and expected reward (Jones, 2003; Schultz, 2000). Certainly, as one crosses the line between passive monitoring of neural activities and into active manipulation of these activities, there is the need to pay heed to ethical and legal issues related to free will and mind control.

For researchers and practitioners in the area of instructional technology, monitoring neural activity associated with learning is intriguing because of the opportunity for obtaining direct feedback related to mental processes. Tracking internal activities at the neural level is important, but provides only a partial solution for advancing the field of instructional technology. Another important component involves the ability to track learner performance and provide effective feedback. The following section discusses advances in these two key areas.

Advanced Performance Tracking

Imagine your goal is to improve your serve in tennis. Now imagine slipping into a tight fitting leotard-type outfit that fully covers your body from head to feet. This “body glove” incorporates an intricate electrical grid that transmits precise body position and relative movement information to a personal computer (PC) located several feet away.

The PC has attached to it a large, flat panel display system that visually simulates your movements in real-time using a realistic 3-dimensional model that matches your body type, weight, and so on. Next, you begin practicing your serve. After three or four tries, the system provides a verbal and visual (using the flat-panel display) critique of key elements that make up an effective serve, such as initial stance, ball toss, and arm and racket motion. Your 3-D image is superimposed upon an ideal image modeled after a highly proficient service motion of someone your age and with your ability level. The program then provides you with verbal and visual instructions on each service element individually, and then gradually combines two or more elements until you are now practicing the entire serve as one fluid motion.

After several much-improved practice serves, you check your progress on the computer by reviewing your three most recent service motions superimposed on top of the ideal image. In addition, you request an analysis and progress report from the program. Alas, your forward arm motion and wrist snap just prior to striking the ball needs additional work because it produces a slower than expected serve that has too much side spin. After several more attempts at self-correction (with verbal and visual prompts and feedback generated by the program), you decide you need more direct help. You now slip your arm into a device that looks like a long glove that reaches to your shoulder. This device is slightly thicker than your body glove performance tracking system and has embedded into it what the manufacturer refers to as micro-hydraulic capabilities.

Responding to the verbal directions from the program, you set your body position to a point where your forward arm motion is to begin. You now feel a warm sensation in your arm, wrist and hand as the micro-hydraulic arm gently shows you the correct arm and wrist motion. During the next 20 or so practice swings you feel less and less influence from the micro-hydraulic device and, in fact, the program confirms that your muscle memory has now been altered slightly to incorporate the newly corrected arm motion and wrist snap. This result is confirmed by a the program's analysis indicating key elements of your service motion more closely match that of the ideal model and your serve is now 5-10 miles per hour faster than before.

The previous example provides a vision of what an advanced performance tracking and feedback system can offer in the way of enhanced training processes and outcomes. Real-time body position and motion capture is now a reality. A search of body tracking capabilities on the Internet will produce numerous academic institutions and commercial enterprises actively involved in developing and marketing systems of this nature. Note also the system's ability to diagnose training needs prior to prescribing remedial training. Future instructional systems will have embedded in them the ability to conduct performance assessment at the whole-task or part-task level.

A LITTLE FARTHER DOWN THE ROAD: CYBERNETICS AND NANOTECHNOLOGY

For nine days in August of 1998, Kevin Warwick, a professor of Cybernetics at the University of Reading wore a tiny capsule measuring 23mm by 3mm surgically implanted in his left arm. The capsule contained a power source and microprocessors. Warwick, an expert on intelligent buildings, programmed the implant to open doors, have his computer speak to him about his e-mail, run baths, and chill wine (Witt, 1999; Warwick, 2002). There are a number of authors who consider activities like Warwick’s either self-aggrandizing and idiotic (Horgan, 2005) or right on track (Kurtzweil, 1999). Although it may be awhile before we can control computers directly from our nervous system (Brooks, 2002), it is something that even the middle-aged authors of this chapter are likely to see in their lifetime. Highly miniaturized, powerful computer implants will be available (at least for those who can afford it) and will likely be a more common elective operation than cosmetic surgery.

There are many implications of Professor Warwick's implant. For instructional designers, the question is an old one. "Would a job aid be more practical or effective than an instructional program?" Many well-known performance-technology authors (e.g., Mager & Pipe, 1970) have been asking that question for decades. If there is something too cumbersome to remember, why shouldn't we cart the knowledge as an external memory source, perhaps even one that can be inserted and removed as we now do with removable storage on a personal computer? Recall that 10 years ago the idea of 1GB of data on something the size of SD media was incredible! Just as Moore's law, which originally stated that the amount of data storage that a microchip can hold doubles every 18 months (Raymond, 1994) is now outdated, looking at computer-based electronic performance support systems (EPSS) as static is unrealistic. We will learn more and more, yes. But we will also carry our knowledge with us. Although less invasive "wearable technology" will be more commonplace than implants, humans and technology will interact in ways that we are just beginning to envision.

Just as H.G. Wells was a leading visionary for many of the inventions that took place in the mid-twentieth century, Neal Stephenson (1992; 1995) is emerging as a prophet for the future of learning technologies. Stephenson's novels contain many plausible future technologies that impact learning. In Stephenson's novel, *The Diamond Age, or a Young Lady's Illustrated Primer*, for example, hundreds of new technologies are made available through nanotechnology, based on the manipulation of individual atoms and molecules to build structures to complex, atomic specifications (Drexler, 1986). In Stephenson's future, the age of "could" be done is replaced with the age of what "should" be done much more so than the 20th century when, at times, we had initiated irreversible error. Regardless of how we attain them, we will unquestionably have available to us many new technology-generated tools in the very near future. For instance, in *The Diamond Age*, the "primer" from which the protagonist learns is made of “smart paper," which is very thin sheets consisting of infinitesimal computers sandwiched between "mediatrons" that project necessary images. Far into the future? Xerox Parc and MIT, for example, have independently developed commercially viable electronic paper technologies that are lightweight and as flexible as newsprint. This electronic paper stores images viewable in reflective light, has a wide viewing angle, is relatively inexpensive, and is electrically writable and erasable. Like many of the newer innovations, electronic paper is fast on its way to becoming a commonplace fact of life.

DISTRIBUTED COGNITION AND INSTRUCTIONAL DESIGN

The last decade has brought some dissatisfaction and, in certain cases, caustic criticism of the traditional ADDIE (analyze, design, develop, implement, and evaluate) approach to instructional design (e.g., Gordon & Zemke, 2000). These critics charge that ISD is too slow and clumsy to meet today's challenges and (ironically) is too process-driven especially for use by less experienced designers who look at the instructional design models more linearly. Related criticisms contend that

ISD is not a real "science." Although, as with most arguments, there are contrasting views (e.g., Merrill, Drake, and Pratt, 1996), these criticisms attract notice to the changing nature of instructional design. The exciting developments in learning technologies that we have discussed will no doubt shape the way future instructional programs are developed and implemented. Even so, advanced technology applications will not make up for a lack of sound instructional theory and educated instructional design professionals.

What is needed in our view are instructional design strategies and research aimed at identifying how best to implement emerging instructional technologies so that they increase learning outcomes while ensuring individual privacy and promoting the highest possible ethical standards. We are not advocating letting the technology drive the instructional design process. Rather, to aid learners in their attempts to “construct” meaning from information/knowledge, instructional designers will rely more and more on emerging educational technology. This not so subtle shift toward a learner-centered instructional environment will, in our view, usher in a new instructional systems paradigm that has an increased emphasis on developing new technology-based tools for aiding learning processes.

Much of what we have discussed in this chapter has been centered in instructional technologies that we believe to be viable in the foreseeable future. Many of these technologies employ what Salomon (1996) and others refer to as distributed cognition. In essence, distributed cognition recognizes that a person solves a problem or performs a task with the aid of other resources. The knowledge brought to bear on the task is distributed among the individual and other resources (e.g., computers or other people). Perkins (1996) refers to this as "person-plus." The theory of distributed cognition hypothesizes that information is processed between individuals and the tools and artifacts provided by the environment or culture. A primary force causing us to move toward distributed cognition is the limitation of the individual, unaided human mind. Professionals in most fields have jobs that are increasingly more complex, more specialized, and require access to exponentially increasing domain knowledge. Distributed cognition is a compelling response to this limitation (Norman, 1988).

During the next few years, we will see the accelerated effect of distributed cognition affecting both learning and the field of instructional design. Distributed cognition and efficacious instructional design approaches (and cybernetics, for that matter) are all about humans and technology interacting as complimentary infrastructures. Things (often sophisticated computer technologies) that can store, retrieve, and analyze information are becoming an integral part of our learning opportunities. Humans (teachers, coaches, other specialized professionals) have shared understandings and experiences that are unavailable in things. Even in the near future, instructional design certainly must become more facilitative in creating environments in which the learner interacts smoothly with these two infrastructures. The traditional instructional systems approach that seeks to engineer learning through a more or less linear approach is giving way to a new instructional paradigm that places a premium on learner control and the emergence of educational technologies that facilitate the learner’s ability to construct meaning out of a rich pool of available information.

SUMMING UP

As acquaintance of ours shared a story of a vacation trip that she took with her young daughter to an historical settlement such as Williamsburg, Virginia or Plymouth, Massachusetts where past technologies are actively recreated. The mother spent the day explaining to the child the different functions of the various tools and furnishings within the aged buildings. We imagine the conversation went something like…

"What's this place, Mother?"

"Well, this is bakery, dear. Where they made bread."

Entering another building the girl asked, "What did they do here, Mother?"

"Well here is where they used this big spinning wheel to make clothes."

Their tour progressed in a similar fashion until they came to a place where the technology seemed very familiar to the suddenly excited child. "I know what this is, Mother," she cried out with absolute assurance. "This is a school! It's set up just like my classroom!"

As the story suggests, education (and training) has for years been the most conservative of fields. Our use of technology has largely been pedestrian, isolated, and uninspired. In this chapter we discuss learning tools and technologies that we believe are likely to make a conspicuous impact. At least two implicit themes emerge. First, it is clear that learning in many environments will take place in much different ways in the future than it has in the past. Research in the effective use of these new technologies of learning is sorely needed.

Second, the accelerated rate of technological change is forcing instructional design, comfortable in its traditional models, to move to address these astounding changes. Our impact as a professional field will increasingly be linked with our ability to do so.

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APPLICATION QUESTIONS

1. Using the example from the chapter as a model, write a new learning objective that would reflect the possible influence cognitive science research, such as brain mapping, might have on the instructional design process. Compare your response to others in your learning group.
2. Describe how nanotechnology could be used to improve a specific job or task with which you are familiar.
3. Working with a group, brainstorm ways that education and training are likely to change in the next 30 years. List these changes. Next to each change, list the impact that change could have on the processes of learning.