An Analysis of the Failure of Electronic Media and Discovery-based Learning:
Evidence for the Performance Benefits of
Guided Training Methods[1].

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Abstract

This chapter will present a direct, evidence-based argument that while media provide economic benefits for training organizations, they have not and will not influence learning, motivation or work performance. We begin with a discussion of popular instructional design models based on discovery and problem-based learning and argue that a half-century of research has indicated that they are also ineffective for all but a small minority of learners. We will briefly describe the half-century of research that supports our conclusions and describe the consequences for business and education.   Contrary to popular belief regarding the importance of media in training, we will suggest that a handful of specific training methods are the only environmental factors that have been found to have a major influence on learning and performance. We will argue that the methods we describe are successful in many different delivery media because they support the mental process by which people learn complex knowledge. We will then describe an example of the current training models that promote guided learning. The chapter will conclude with a description of a powerful tool for selecting the most cost-beneficial media to deliver guided learning methods for nearly any training or performance goal.

Introduction

Education and training organizations are constantly alert to new developments that have the potential to increase the effectiveness and cost-benefit of instruction. This chapter will examine the research and best practice evidence for current and future instructional innovations that help and hinder instructional support for learning and performance. The discussion begins with a description of popular instructional approaches that have been found ineffective and/or to cause problems. We then go on to describe recent developments that appear to add significant value to learning and performance support systems.

Some of the innovations that have been a constant focus of attention in training are the exciting developments in new technologies such as computers, multimedia and virtual reality. The most common assumption is that new media are more motivating than older media and that increased motivation will lead to significantly more learning and performance. The discussion turns next to the evidence for these assumptions.

The Impact of Media on Learning

The past half-century of research, evaluation and best practice evidence about learning from instruction has established that the choice of media does not influence learning or motivation. While people have argued about this conclusion (see for example a review of the arguments by Clark, 1991, 2001), the current view that is most widely accepted in research and evaluation is that media only deliver instruction but do not influence learning. The reason for this conclusion is

that whenever we find a learning or performance benefit from instruction presented in a new medium or mix of media, we also find an equivalent increase in learning from a different medium or mix (Clark, 2001). If, for example, learning requires instructional strategies such as a demonstration of how to solve a class of problems and practice on an example of the problem while providing corrective feedback, the media used for the demonstration, practice and feedback will not influence learning. In the past decade or so many schools, business, government and military training organizations have made extensive use of computer and web or Internet-based "distance learning".   Many of those organizations have transferred instruction currently being offered in the classroom to the computer, Internet or multimedia and have evaluated both offerings before making a long-term commitment to distance education. These are interesting natural experiments because the skills and knowledge being taught in two versions of a course are similar, but the medium being used is different and sometimes instructional methods such as demonstration and practice are formatted differently in different media. Yet Bernard, Abrami, Lou, and Borokhovski (2004) surveyed all of the 688 comparisons they located of classroom and distance learning offerings of the same course content conducted prior to 2004 and found no differences in either learning or motivation. More recently, Sitzmann, Kraiger, Stewart, and Wisher (2006) reviewed 96 studies focused primarily on adults in business and college settings and found the same result. Web-based instruction and instructor-delivered, classroom-based instruction produced the same amount of learning, while classroom and web instruction were equally motivating. While some studies showed definite benefits from distance learning technology over the classroom, others showed better performance with classroom instruction. When this happens in research, it is most often the case that the instructional design is making the difference, not the medium used to deliver instruction. Even more of these studies show "no significant differences" between the classroom and the computer. Bernard et al. (2004) referenced five previous large-scale reviews of media comparison studies that have reached exactly the same conclusion. It is important to mention that both the Bernard and Sitzmann studies were comprehensive and inclusive. They included only studies in which different media were used to deliver the same course content, even when the instructional methods used had been reformatted to accommodate a newer media.

Arguments About the Impact of Media on Learning

Clark (2001) has reviewed all published studies and reviews of studies where the effects of different media were compared and reaches a conclusion identical to the Bernard and Sitzmann teams. He suggests that the reason some studies show benefits for certain media is because the researchers mistakenly inserted different information content or instructional methods in one of the media but not in the comparison media. In these poorly designed studies, differences in learning were due to providing more or different information and/or learning support to a group using one medium that was necessary to succeed at a test while

the same information or support was unintentionally denied to another group who received a different medium.

Robert Kozma (1994) has argued with the conclusion that media do not cause learning. He emphasizes the potential of different media to tailor instructional support to the unique learning needs of individuals and groups. He also argues that different media offer different kinds of instructional support, and so it is impossible to separate media from their unique learning support capabilities. The debates about this issue extended over a number of years but was finally resolved a few years ago when Kozma acknowledged (see Clark, 2001) that there was no evidence that media caused learning or that any one medium offered a unique learning support. Kozma remains optimistic that in the future we will learn more about the unique learning support capabilities of different media. However, at the present time it is simply not possible to identify any type of instructional support that is a function of any one medium. If more than one medium offer the same learning supports, then the choice between them is based on cost and availability – not on learning benefits.

Why Don't Media Make a Difference in Learning?

The reason media do not make a difference in learning is captured in the analogy that media are "mere vehicles that deliver instruction but do not influence student achievement, any more than the truck that delivers our groceries causes changes in our nutrition" (Clark, 1983, p. 445). Nutrition is a result of the way that food is grown, prepared, and consumed. Any food can be delivered by a variety of transportation vehicles, including trucks. Of course different kinds of food require different vehicle design. Frozen food requires insulation and refrigeration. Yet many different kinds of insulated vehicles can carry frozen food. The point is that if there is more than one medium that can carry instruction with the same learning outcome, and if this is the only conclusion possible from all the evidence at hand, then the only difference between those different media is their capability to influence the cost of instruction. Thus, it is important to focus our study and selection of media not on learning and performance gains, but on possible economic benefits.

Another analogy that illustrates why media do not cause learning can be found in the way that medication compounds are prepared for delivery. For example, aspirin is a special compound called acetylsalicylic acid and is incorporated into a number of inert "carrier" ingredients and delivered to the consumer in a variety of media such as tablets, liquid suspensions, candy or gum. All of these different media serve to deliver the same "active" aspirin ingredient with different levels of efficiency, but with equal effects on our physical symptoms. Media are not the active ingredients in instruction that causes learning, but simply the vehicles by which it is delivered.

If not Media, What does Cause Learning?

When the Bernard et al. (2004) and Sitzmann et al. (2006) research teams looked more closely at studies where either the classroom or the distance learning version of a course was more effective, they discovered the factor that appears to

cause most of the learning benefit. They called that factor "instructional methods." Instructional methods or strategies are the "active ingredients" in instruction in the same way that special compounds are the active ingredients in medications. The problem is that we have been tempted to assume that media are an active ingredient in learning and motivation.

Clark (1991) defines instructional methods as "any way to shape information that (supports)…the cognitive processes necessary for achievement … If students cannot (or will not) give themselves an adequate example, an instructional presentation must provide it for them…" (p. 34). An important cognitive process that is essential for learning is to connect new information to similar prior knowledge. This way students can draw on what they know in order to elaborate and understand something new. For example, after children learn to add and subtract whole numbers they are asked to learn fractions. The challenge of imagining "less than one" is daunting until instruction provides them with the "slice of pie" analogy. When reminded that one pie can be shared equally among many by slicing it and that each slice is a fraction of the whole pie, most students connect what they know about sharing pies and cakes and are well on their way to learning to add and subtract fractions. When the Bernard et al. (2004) and Sitzmann et al. (2006) research teams looked at instructional programs that produced more learning they found similar instructional methods. Later in the chapter we will describe what appear to be the most powerful instructional methods. At this point, the discussion turns next to evidence about the motivational qualities of media.

<div align="center">The Impact of Media on Motivation</div>

Nearly all educators have hoped that newer media will make instruction more engaging and interesting for learners of all ages. Most of us can recall painful memories of feeling trapped in a classroom and subjected to poor instruction. These memories help fuel interest in using technology to foster student excitement about learning. Following is a description of motivation and how it influences learning, and a review of the evidence about the motivational qualities of newer media.

What is Motivation?

Clark (2003) described motivation as:

> …the process that initiates and maintains goal-directed performance. It energizes our thinking, fuels our enthusiasm and colors our positive and negative emotional reactions to work and life. Motivation generates the mental effort that drives us to apply our knowledge and skills. Without motivation, even the most capable person will refuse to work hard. Motivation … nudges us to convert intention into action and start doing something new or to restart something we've done before. It also controls our decisions to persist at a specific work goal in the face of distractions and the press of other priorities. Finally, motivation leads us to invest more or less cognitive effort to enhance both the quality and

quantity of our work performance. (p. 21)
The best evidence supports the notion that motivation is the result of three things: 1) our values (we are more likely to choose to start and persist at goals we value), 2) our confidence that we can succeed at specific tasks (we invest more mental effort when tasks are perceived as challenging but possible to achieve); and 3) our mood or emotional state (positive mood states increase the likelihood that we'll start and persist at tasks) (Clark, 1999a). It is important to realize that motivation does not directly influence learning because it energizes the use of effective learning plans and strategies. It energizes us to start, persist and use adequate mental effort to apply learning methods. Successful learning always requires motivated effort and adequate prior knowledge. Without adequate prior knowledge, exceptionally high motivation will not produce learning and vice versa.

Are Newer Media More Motivating?

While most people can remember a situation where they were motivated by outstanding multimedia instruction, most can also remember a teacher or a book that was motivating. The large scale reviews of media evaluation and research studies by Bernard et al. (2004) and Sitzmann et al. (2006) both reached the conclusion that people are no more motivated when learning from new technology than they are by classroom instruction. This kind of finding suggests to many people that we should assign students to the setting they prefer if choices are available – or that we should develop and deliver instruction in the medium or mix of media that students prefer. It seems reasonable that if there are any motivational benefits to be gained from media, even for a minority of students, we should take advantage of their preferences. While this is a reasonable assumption, it turns out to be exactly the opposite of the evidence(Clark, 1982).

A landmark study by Salomon (1984) established that most people prefer media that they believe will make learning easier. Salomon asked people from Israel and the United States if they would rather learn from books or television and then assigned them to either a printed or televised lesson on the same topic. Israelis preferred books apparently because many of them had experienced an overwhelming amount of televised instruction and thought it was a "difficult medium". Americans had experienced television as an entertainment medium and thought it would make learning easier than books. What happened is that Israelis learned more from the televised lesson than from print and the Americans had the opposite result – they learned more from the print than from the televised lesson. Salomon measured the amount of mental effort learners in all conditions invested in learning and found that in general, we work harder under the conditions that we feel are more challenging. Israelis invested more effort in television because they believed it was difficult and Americans worked harder when given a printed lesson for the same reason. This study has been repeated many times with many different ages, nationalities, learning tasks and media and the same result occurs (see for example a discussion by Schunk and Pajares, 2004).

It appears that the choice of media does not help either student learning or motivation to learn. In fact, it is likely that allowing students to select media they

feel will make learning easier may actually cause many of them to loaf and learn less than if they feel challenged. Recent reviews of instructional research have indicated that learning is supported primarily by a limited set of powerful instructional methods.

What About Computer-based Educational Games?

        A number of studies and reviews of studies that examined the benefits of games have been conducted (for example, Chen & O'Neil, 2005; Gredler, 1996; Mayer, Mautone, & Prothero, 2002; Moreno & Mayer, 2005; O'Neil, Wainess, & Baker, 2005). All of the studies that have been published in reputable journals have reached a negative conclusion about learning from games. Apparently, people who play serious games often learn how to play the game and perhaps gain some factual knowledge related to the game – but there is no evidence in the existing studies that games teach anyone anything that could not be learned through some other, less expensive and more effective instructional methods. Even more surprising is that there is no compelling evidence that games lead to greater motivation to learn than other instructional programs.

        Chen and O'Neil (2005) and O'Neil et al. (2005) located over 4,000 articles published in peer-reviewed journals and found only 19 studies where either qualitative and/or quantitative data about learning or motivation from games had been assessed. Their analysis of the learning and transfer measures used in all 19 studies concluded, "… positive findings regarding the educational benefits of games…can be attributed to instructional design and not to games per se. Also…many studies claiming positive outcomes appear to be making unsupported claims for the media." (O'Neil et al., p. 461-462). Their use of the term "instructional design" was intended to highlight the occasional use of instructional methods such as providing examples, classification practice and problem solving routines. They conclude that all of the methods used in games have been used effectively in non-game instructional programs and are not unique to games.

        We might expect a less conservative and more optimistic view from industry, government or military sponsored surveys of gaming research because of the high level of investment in those sectors, especially the military. Military trainers in many countries have invested in serious games for training. Yet an excellent technical report by Hayes (2005) for the Air Force training command provides a particularly thorough review of the past 40 years of research and reviews of research on instructional games and "simulation games".   He concludes, " the research shows no instructional advantages of games over other instructional approaches...The research does not allow us to conclude that games are more effective than other well designed instructional activities" (p. 43). He makes the point that only poorly designed studies find learning benefits from games. In most cases poor design implies that the learning benefit of a game is compared to not receiving any game instruction or engaging in a non-educational exercise. What, he asks, can you conclude about the "relative" benefit of games when you do not compare them with any other way to teach or learn?

Chen and O'Neil (2005), O'Neil et al. (2005), and Hayes (2005) all suggest that most studies that report motivation benefits from games only ask students whether they were motivated – they do not provide any direct measures of motivation (such as increased persistence or mental effort). Student opinions about motivation have been found to be highly unreliable and often in conflict with performance-based measures when both are gathered (see, for example, a recent comprehensive review of reaction measures by Sitzmann, Brown, Casper, Ely and Zimmerman, 2008). Chen and O'Neil (2005) also note that many games appear to employ unguided, discovery, constructivist or problem-based learning pedagogy. Since this approach to instruction is also included in many of the applications of newer media, next is a review of discovery approaches to instruction.

The Failure of Discovery-Based Instruction

One of the most popular approaches to instruction found in both schools and industry is based on the assumption that students will learn best if they are given a problem to solve or a task to perform and asked to work alone or to work collaboratively with a team to discover a solution. Those who use this discovery approach assume that the best learning occurs when people discover their own solution to a problem or task. Discovery learning can be provided in almost any instructional medium. It is often a key element in a computer-based course and is the essential pedagogical element in nearly all simulations and instructional games (Clark, 2007). Teachers in classrooms and trainers in work settings often use discovery to help students learn. Discovery is a defining element of many different approaches to instructional design including constructivism (Duffy & Jonassen, 1992); communities of practice (Brown & Duguid, 1991); problem-based learning (Schwartz & Bransford, 1998); inquiry learning (Kuhn, Black, Keselman, & Kaplan, 2000); collaborative learning (van der Linden, Erkens, Schmidt, & Renshaw, 2005); scaffolding (Pea, 2004) and discovery (Shulman & Keisler, 1966). It's origin probably extends back to work by Jerome Bruner (1961) who used early 1900's Piagetian child development theory (see Piaget, 1928) to support discovery learning.

Evidence about Discovery Learning.

Recent reviews of the research and evaluation evidence for discovery approaches by Mayer (2004) and Kirschner, Sweller and Clark (2006) have provided compelling evidence that discovery is almost always less effective than giving students a guided solution in a demonstration based on task analysis and accompanied by practice and feedback. Mayer (2004) reviewed the past 50 years of research and found consistent evidence against discovery and in favor of guided instruction for all ages, all tasks and all contexts. Kirschner, Sweller and Clark (2006) reached the same conclusion as Mayer and focused their examples on the teaching of mathematics in schools and the education of physicians. The difficulty with asking people who are learning complex knowledge to discover all or part of the knowledge they are learning is that the discovery process requires a huge amount of unproductive mental effort. Even if a minority of learners

succeed and discover what they need to know, the discovery process does not teach them how to discover and the effort required could be invested in more efficient learning from demonstrations and practice exercises. Problem-solving during learning is desirable but discovering how to solve a problem in order to learn to solve a problem is not helpful or desirable. If all serious reviews of the evidence about discovery learning have been negative for the past 50 years (see for example, a very early and very negative research-based critique by Shulman & Keisler, 1966), how is it possible that discovery is our most popular instructional method in schools and industry?

Why is Discovery Learning so Popular?

Most of us remember vividly those times when we have experienced an important insight after investing effort to solve a problem. In fact, nearly all novel insights throughout the history of human beings has occurred as a result of discoveries. Most psychologists agree that learning is a process whereby people construct new knowledge by adding to what they already know about a topic. Because we are all unique, the result of the knowledge construction process is somewhat different for every individual. Discovering and constructing knowledge are common experiences for all of us. Thus, it seems intuitively correct to assume that in order to learn, we have to allow people to construct their own knowledge. Yet because learning requires construction it does not follow that construction or discovery is the most effective or efficient way to instruct or to help people learn. In fact, the evidence best supports the claim that we are born with a mental architecture that makes learning by discovering or constructing knowledge almost impossible for complex tasks. This applies to all but a small minority of the most able and knowledgeable learners (Kirschner, et al., 2006).

Our Mental Architecture Resists Discovery Learning.

In many ways it is not surprising that our most common assumptions and practice in instruction are at odds with the evidence about what works. The approaches we are using now were developed in the past century when our understanding of the architecture of the mind was based on a "black box" metaphor. Since we could not directly measure mental reactions to different instructional techniques, we had to make assumptions about what would work from our own experience and the way that learners reacted to different methods of teaching. With the development of direct measures of mental processes using the technology of neuroscience and more sophisticated measures of learning and performance, we are in a transition period to a new instructional psychology. We have achieved a number of new insights about the structure of our minds that will eventually change our approach to instruction. One compelling aspect of these new insights that is relevant to multimedia instruction is called Cognitive Load Theory.

Cognitive Load Theory and Multimedia Design

Sweller (2007) provides a compelling case for the fact that our minds have evolved to make new learning difficult in order to protect us from quick,

extensive and radical changes in thinking and behavior that might threaten our lives. Because all learning is novel, it is potentially as harmful as it is beneficial. The information processing system that protects us from learning rapidly has many features. On the one hand, our minds simply will not permit us to think about more than about 3 to 4 new things at once. This information-processing limit is a major speed bump since all learning is novel and subject to this limitation. This new estimate of mental processing limit by Cowan (2001) reduces by more than 50 percent our former estimate (Miller, 1956) of a 7 to 9 chunk thinking capacity. This much lower capacity estimate is further reduced by learner anxiety. Not only do these limitations on thinking slow down our learning, but if we try to exceed this 3 to 4 chunk information processing limit, a processing routine shuts down our conscious mind in the same way a fuse disconnects an overloaded electrical circuit. When we are disconnected our focus tends to switch to daydreaming (see for example a review of the research and a more complete description of this process by Clark, 1999b). Anyone who has attempted to study a difficult chapter in a textbook after reading for 10 to 20 minutes or more realizes that they can not remember much of anything they have read. This describes the phenomenon of cognitive overload.

Another recent insight from extensive research on cognitive load theory (Mayer, 2004; Sweller, 2007) about the destructive power of common features of multi-media instruction raises an even larger cause for concern. Mayer (2001; 2005) has identified and studied the most common multimedia screen and instructional design strategies that overload learners mentally and cause learning problems. In nearly all cases, overload is caused by providing students with information in any form that distracts them from processing the essential conceptual or procedural knowledge required to perform the task they are learning. Since we all have a limited capacity to think when learning we must use our thinking capacity to process relevant information. When instruction provides distractions such as music, animated agents who give us advice, tabs that allow us to get additional information, pages of text to read on the screen and key information embedded in irrelevant contextual information, we must spend effort ignoring the irrelevant to select and learn the relevant information (Clark & Choi, 2007). Mayer (2001) identifies a number of multimedia design principles that if implemented, tend to help us avoid cognitive overload and help learning (see Table 1).

Table 1
Mayer's (2001) Multimedia Design Principles

Principle	Guideline
Multimedia	Students learn better from words and pictures than from words alone.
Spatial Contiguity	Students learn better when corresponding words and pictures are presented near rather than far from each other on the page or screen.
Temporal Contiguity	Students learn better when corresponding words and pictures are presented simultaneously rather than successively.
Coherence	Students learn better when extraneous words, pictures, and sounds are excluded rather than included.
Modality	Students learn better from animation and narration than from animation and on-screen text.
Redundancy	Students learn better from animation and narration than from animation, narration, and on-screen text.
Individual Differences	Design effects are stronger for low-knowledge learners than for high-knowledge learners and for high-spatial learners rather than for low-spatial learners.
Signaling	Students learn better when cues (e.g. underlining, arrows) are added that highlight the main ideas and organization of the words.
Pacing	Students learn better when they control pacing of segmented narrated animations rather than continuous pace.
Concepts First	Students learn better when new terms are learned before introducing complex processes, principles or procedures.
Personalization	Students learn better when narration is conversational and uses personal pronouns such as "you" and "yours".
Human Voice	Students learn better when a human voice is used for narration rather than a machine voice or foreign accented voice.

Mayer's principles apply to what most people call screen design (for computer or multimedia-based training), or graphic design for the printed page. They are all intended to focus people's attention on only relevant portions of instruction and not to distract them with irrelevant and dysfunctional depictions of information. Yet much more is necessary to support learning than simply helping learners avoid distracting elements in instruction. The additional learning support elements are most often called instructional principles and related instructional methods or strategies. What follows is an examination of the most powerful methods available that can be included in nearly any instructional design or delivery system.

Powerful Instructional Methods

Instruction has at least two major components – the first is to provide information that we want people to learn (instructional content) and the second is to structure that information in order to help students learn it (instructional methods) without being distracted by instructional displays (screen or graphic design). Simply giving people information is not instruction - or as the book by Stolovitch and Keeps (2002) makes clear "Telling Ain't Training". Instruction can fail because the information we give students is incomplete or inaccurate and/or because we do not provide adequate learning support. Complicating the search for the best instructional methods is the fact that there are hundreds of different descriptions of instructional methods that have been recommended in the past century (see for example discussions by Cronbach & Snow, 1977; Pea, 2004; and Kirschner et al., 2006).

A Fragmented Instructional Design Community

What makes the search for the most important instructional design principles and related instructional methods challenging is both the variety one finds in use and the intense advocacy of people who market their own design system. Advocates of different instructional theories and models tend to define and operationalize instructional support in very different ways. These different theories often spring from different models of learning and sometimes different belief systems, inquiry methods and philosophies (Cronbach & Snow, 1977; Jonassen, 1991; Merrill, 2002; Romiszowski, 2006). To some extent, these differences reflect the increased specialization and fragmentation in educational research and theory over the past half century (Winthrop, 1963; Ravitch & Vitaretti, 2001) and a growing fragmentation among various sub-specializations in educational research. One result of this phenomenon is that researchers who favor a specific theory or point of view tend to isolate themselves and limit their research, while reading and collaborating with only the journals and professional associations or divisions of associations that emphasize their perspective. For example, it is our experience that the groups who educate classroom teachers for K-12 education and the large number of faculty who teach in our universities tend to ignore the instructional theory and instructional design models generated by people who develop instructional programs and media for K-12, university and industry education. Business and military trainers are more open to instructional design but tend to confuse media with instructional method. Even various instructional design models tend to attract advocates who do not examine alternatives or look carefully at evidence that does not support the model they advocate. Encouraging dialogues between these diverse groups and individuals who are concerned with instruction and learning will help bridge this gap in the future.

David Merrill's Five Star System

David Merrill (2002; 2006) has bucked the fragmentation trend by selecting the most powerful instructional principles from among the many instructional design systems that are available. In a study supported by the American Society for Training and Development, he identified a number of

current systems that could present strong research and evaluation evidence to support their effectiveness. He was curious about the instructional methods that reflect each of the principles that are the common foundation of the design systems he located. After an extensive and systematic analysis, he identified five instructional principles and the related instructional methods that all of these powerful systems use. He then looked broadly at the research on instructional methods (Merrill, 2006) and confirmed that each of these five received strong validation in both laboratory and field based experiments.

Five instructional design principles. The five principles Merrill (2002) found in the most powerful design systems suggest that "learning is promoted when the learner: 1) Observes a demonstration – demonstration principle; 2) Applies the new knowledge – application principle; 3) Undertakes real-world tasks – task-centered principle; 4) Activates existing knowledge – activation principle; and 5) Integrates the new knowledge into their world – integration principle" (Merrill, 2006, p. 262).   Merrill describes a situation where the corporate training group NETg revised one of their own Excel spreadsheet application courses to reflect these five principles (Thompson Inc, 2002). When they compared the new and old versions of the application, they found huge differences in performance favoring the five principles. The students in the five principles course completed complex spreadsheet tasks more quickly (29 minutes versus 49 minutes) and effectively (89% versus 68% performance improvement) than students in their standard course. "Effectiveness was measured by the learners' ability to complete three complex tasks which required them to develop three different spread sheets given a set of data and analysis requirements" (Merrill, 2006, p. 264). He also describes a study reported in a conference paper by Barclay, Gur and Wu (2004) who analyzed the extent to which these principles were included in the hundreds of training courses presented on over 1400 web sites in five different nations (Australia, China, France, Turkey and the U.S.). The best training courses in each of these countries implemented only half of the principles, and the national average for all courses in each nation was about one principle per course.

From Instructional Principles to Instructional Methods

Principles predict what will happen if a type of instruction is offered to students. Instructional methods are strategies for implementing the principles. Nearly all principles and methods can be implemented and delivered in nearly all media. One way to translate Merrill's (2002) five principles into instructional methods is described as follows:

1) Provide realistic field-based problems for students to solve;
2) Give students analogies and examples that relate their relevant prior knowledge to new learning;
3) Offer clear and complete demonstrations of how to perform key tasks and solve authentic problems;
4) Insist on frequent practice opportunities during training to apply what is being learned (by performing tasks and solving problems) while receiving corrective feedback; and

5)   Require application practice that includes "part task" (practicing small chunks of larger tasks) but also "whole tasks" (applying as much of what is learned as possible to solve the complex problems that represent challenges encountered in operational environments) both during and after instruction.

Merrill's instructional methods and the principles upon which they are based can be integrated into nearly any instructional design system or used to construct a new design system tailored for the needs of specific organizations and/or groups of students (See Clark & Estes, 2008 for an approach to developing tailored applications of Merrill's principles to different cultural contexts).

Though comprehensive, Merrill's (2002) principles do not provide a complete model for designing at the lesson level. Moreover, instructional methods alone do not give guidance about what knowledge and skills have to be taught to achieve performance goals. To determine instructional content requires the use of task analysis methods to identify the conceptual and procedural knowledge necessary to perform a task (Jonassen, Tessmer, & Hannum, 1999). As tasks become more complex, they require the use of both controlled (conscious, conceptual) and automated (unconscious, procedural or strategic) knowledge over an extended period of time (Clark & Elen, 2006; van Merriënboer, Clark, & de Croock, 2002). Thus, a valuable approach to task analysis is to capture both the observable actions and the underlying "cognitive" knowledge experts use to successfully and consistently perform a complex task (Clark & Estes, 1996). Optimized instructional design methods, then, should integrate both cognitive task analysis (CTA) and Merrill's five principles. Currently, at least five major instructional design systems take this approach: 1) The Integrated Task Analysis Model (ITAM; Redding, 1995; Ryder and Redding, 1993); 2) the Ten Steps to Complex Learning systematic approach to four-component instructional design (van Merriënboer & Kirschner, 2007; van Merriënboer, Clark, & de Croock, 2002); 3) Task-Centered Instructional Strategy (Merrill, 2007); 4) e-Learning and the Science of Instruction model (R. C. Clark & Mayer, 2007); and 5) Guided Experiential Learning (GEL; Clark, 2004, 2006). To more fully illustrate how these integrated instructional design models work, we describe GEL in the next section.

Guided Experiential Learning

Clark (2004, 2006) describes one possible list of the instructional methods that most evidence-based instructional design systems use at the lesson level in a design system called "guided experiential learning" (GEL). He specifies how Merrill's five principles could be combined with currently used training methods by requiring that all lessons include the following elements in the following sequence: 1) Objectives (specify actions, conditions and standards that must be achieved in a lesson); 2) Reasons for learning (advantages of learning and risks of failure to learn and transfer); 3) Overview (knowledge models and content outline); 4) Conceptual Knowledge (concepts, processes and principles necessary to learn to perform a task or solve a problem with examples and analogies that

support learning); 5) Demonstration of the procedure (a clear "how to" description for all elements of a task or solution); 6) Part and whole-task practice of procedures with corrective feedback; 7) Challenging, competency-based tests that include reactions (trainee confidence and value for the learning) and learning performance (memory for conceptual knowledge and application skill for all procedures).

Cognitive and Behavioral Task Analysis: When subject matter experts are available, implementing Merrill's (2002) five principles and the GEL design at the lesson level also requires the use of cognitive task analysis (CTA) to determine training information content Clark (2004, 2006). CTA methods capture accurate descriptions of the performance objectives, equipment, conceptual and procedural knowledge and performance standards that experts use to perform complex tasks (Clark, Feldon, van Merriënboer, Yates, & Early, 2007). CTA can be viewed as extending, not replacing, behavioral task analysis. CTA not only records observable activities, it also seeks to capture the unobservable cognitive processes that underlie expert task performance. The results of CTA provide the instructional content that "populates" each instructional element in the GEL system.

Why is CTA important? Experts are often called upon to provide their knowledge and skills for training development and delivery. Behavioral task analysis has historically served as the primary approach to capturing experts' observable actions for these purposes. However, replicating expert performance that originates from behavioral task analysis alone is problematic, especially for complex tasks involving unobservable cognitive activities, such as analysis, judgments, and decisions (Yates, 2007). Experts achieve high performance in a domain as a result of continuous and deliberate practice in solving problems over a long period of time (Ericsson, Krampe, & Tesch-Römer, 1993). Through practice, expert's new knowledge and skills become automated and unconscious (Anderson & Lebiere, 1998) to an extent that perhaps up to 90% of all knowledge is unconscious (Wegner, 2002). As a result, when called upon to describe how they achieve their high performance levels, experts are often unable to completely and accurately recall the knowledge and skills they use, often resulting in significant omissions that can negatively impact the effectiveness of instruction and lead to subsequent difficulties for learners (Chao & Salvendy, 1994: Feldon, 2007; Hinds, 1999). Studies have shown that training based only on expert self-report information has been found to lack approximately 70% of the information necessary for training and performance (Feldon & Clark, 2006).

Training based on the results of cognitive task analysis methods, on the other hand, has been shown to be substantially more effective than training developed through other means. In Merrill's (2002) study comparing discovery learning with direct instruction in the use of spreadsheets, the direct instruction training was based on strategies elicited from an expert spreadsheet user. In a problem-solving task, learners in the CTA-based instruction group scored 89% versus 34 % for the discovery group. The CTA-based group also required less time to complete the task with an average of 29 minutes versus an average of more than 60 minutes for the discovery group.

CTA-based instruction has also been shown to be more effective for training in troubleshooting. Schaafstal, Schraagen, and van Berlo (2000) compared a preexisting training course in radar system troubleshooting with a newly-designed course based on content elicited using CTA methods. Although participants had equal scores on pre-tests of basic knowledge, participants in the CTA-based training were able to identify more than twice the number of malfunctions, and in less time, than the participants in the traditionally trained group. In addition, these results were replicated in all subsequent implementations of the CTA-based training designs.

Evidence from the use of CTA in various areas of medicine indicates important implications for medical training as well as the treatment of patients. For example, in a CTA study of medical school surgical instruction (Velmahos, et al., 2004) researchers found that when medical professors taught medical students to perform surgery, the professors tended to accurately describe their own visible actions but consistently omitted most of the key decisions they made when describing their approach to a surgery. In this study, information captured from CTA interviews with expert surgeons were used to train half of the annual surgical residents in a large urban teaching hospital and the other half of the surgical residents experienced a traditional "see one, do one, teach one" pedagogy (Halsted, 1904). The experts who taught the traditional group were the same experts interviewed for the CTA. In the year following the training, senior surgeons observed the surgical residents whenever they performed the task without knowing how they'd been trained. Results indicated that the residents who received the CTA-based description of the surgical procedure made about 60 to 70 percent better decisions with patients than those who only observed the procedure and heard expert surgeon explanations. CTA trained students were more accurate about where to perform the procedure, what instruments to choose when patients were seriously injured and what to do when a step did not have an intended outcome. As a result, the surgeons who experienced the CTA-based training made no serious errors when using the procedure with patients whereas the experimental group made a number of damaging decision errors (although not more errors than had been typical in the past for this procedure). Similar results in studies of the diagnostic expertise of top neonatal nurses have been reported by Crandall & Gretchell-Leiter (1993) who described a similar study where CTA of expert neonatal nurses exposed a strategy for diagnosing life-threatening infections in premature infants that was significantly more effective than the textbook method taught in universities.

To determine the generalizability of the effectiveness of CTA-based instruction, Lee (2004) conducted a meta-analytic review of the training literature. Meta-analysis is a statistical method of aggregating and comparing the findings of different research studies within a common topic (Lipsey & Wilson, 2001). Her search for training studies based on CTA methods resulted in 39 comparisons of the average effect size differences between pre- and post-test measures of training performance. Lee reported an overall average post-training performance gain of about 53% (d = 1.72) for CTA training when compared to more traditional training design using expert-based task analysis.

How is CTA conducted? CTA refers to a variety of interview and observation techniques used to elicit and represent the knowledge, goals, strategies, and decisions that underlie observable task performance. Although there are many types of CTA methods (for a review see Clark et al., 2007), CTA methods share a common goal of capturing the knowledge of subject matter experts (SMEs) who have demonstrated consistent proficiency in performing a task over the long period of time. CTA is most commonly performed in five stages:

1. Identify the tasks to be analyzed and acquire general knowledge of the domain in which the tasks are performed.
2. Identify the types of knowledge required to perform the tasks and sub-tasks.
3. Elicit the knowledge required to perform the tasks using multiple SMEs.
4. Analyze and format the elicited knowledge and verify for accuracy and completeness by reviewing transcripts and crosschecking with multiple SMEs.
5. Format the knowledge for its intended application (e.g. procedures that include action and decision steps, general strategies or rules of thumb, and job aides).

The GEL design system incorporates a CTA method that includes the five stages. After identifying the required knowledge types and becoming familiar with the area of interest, three multiple subject matter experts are interviewed followed by cycles of expert self- and peer-review to capture the automated and unconscious knowledge acquired through experience and practice. The initial, semi-structured interview begins with a description of the CTA process by the analyst. The SME is then asked to list or outline the performance sequence of all key sub-tasks necessary to perform the larger task being examined. SMEs are also asked to describe (or help the interviewer locate) at least five authentic problems that an expert should be able to solve if they have mastered the task, the benefits of solving the problems and the risks of not being able to solve the problems. Problems should range from routine to highly complex whenever possible. The resulting sequence of tasks becomes the outline for the training to be designed or the job description produced after the CTA is completed. Starting with the first subtask in the sequence, the analyst asks a series of questions to collect:

(a) The sequence of actions (or steps) necessary to complete the task and all sub tasks;
(b) The decisions that have to be made to complete the sub task, when each must be made, the alternatives to consider, and the criteria to decide between the alternatives;
(c) All concepts, processes and principles that are the conceptual basis for the experts' approach to the sub-task;
(d) The conditions or initiating events that must occur to start the correct procedure;
(e) The equipment and materials required;

(f) The sensory experiences required (e.g., the analyst asks if the expert must smell, taste or touch something in addition to seeing or hearing cues in order to perform each sub task), and

(g) The performance standards required, such as speed, accuracy or quality indicators.

The interview is repeated for each SME, with each recorded and transcribed verbatim. The transcripts are then analyzed to generate consistently formatted protocols containing the results of each interview. After each SME has corrected their own protocol, they are then exchanged with the other SMEs for verification and correction. An aggregated "gold standard" protocol is produced and submitted to each SME for final approval.

How are the results of CTA used in the GEL system? The GEL design technology combines the five training principles that Merrill (2002) identified as the active ingredients of the most effective, evidence-based pedagogical systems current in use with CTA methods that effectively capture the knowledge and skills that underlie expert task performance. Table 2 shows how the results of CTA provide the content for a GEL designed course and each of the seven elements within a GEL lesson.

Table 2
Incorporating CTA Results for GEL Lesson Design

CTA Result	GEL Lesson Element
Course Design	
Five large authentic field problems, ranging from easy to complex, that illustrate the performance of the task.	Sequence groups of problems into lessons: - First performed in the field are first taught - If no fixed sequence, then easy to difficult
Conceptual knowledge about field problems: - New concepts (definitions and examples) - Process (how it works – big picture) - Principles (what causes something to happen) - Procedures (how to do it, conditions and consequences)	Identify prior knowledge and pre-requisite knowledge that must be taught first.
- Authentic field problems - Action and decision steps - Conceptual knowledge	Challenging, competency-based assessment – provide whole-task tests that include reactions (trainee

• Standards	confidence and value for the learning) and learning (memory for conceptual knowledge and application skill for all procedures).

<table>
<tr><td colspan="2" align="center">Lesson Design</td></tr>
<tr><td>• Conditions or initiating events
• Performance standards
• Equipment and materials
• Sensory experiences</td><td>1. Objectives – specify the actions, conditions and standards that must be achieved.</td></tr>
<tr><td>• Authentic field problems
• Benefits of solving
• Risks by not solving</td><td>2. Reasons for learning – state the benefits of learning and the risks of failure to learn and transfer.</td></tr>
<tr><td>• Authentic field problems
• Conceptual knowledge</td><td>3. Overview – relate the knowledge to be learned to learners' prior knowledge; provide the position of the lesson in the overall course.</td></tr>
<tr><td>New conceptual knowledge for each lesson:
• Concepts
• Process
• Principles</td><td>4. Conceptual Knowledge – provide knowledge necessary to perform the task or solve a problem with examples and analogies that support learning.</td></tr>
<tr><td>• Authentic field problem
• Action steps and decisions steps with alternatives and criteria for deciding</td><td>5. Demonstration – provide a "how to" demonstration of the procedure for all elements of a task or solution using an authentic field problem.</td></tr>
<tr><td>• Authentic field problems
• Action and decision steps</td><td>6. Part and whole-task practice – provide opportunity to practice procedures using authentic field problems and provide corrective feedback</td></tr>
<tr><td>• Authentic field problems
• Action and decision steps
• Conceptual knowledge
• Standards</td><td>7. Challenging, competency-based assessment – provide part-task tests that include reactions (trainee confidence and value for the learning) and learning (memory for conceptual knowledge and application skill for all procedures).</td></tr>
</table>

How does GEL develop flexible expertise and learning transfer? The purpose of learning is to develop flexible skill expertise and to transfer that expertise to solving novel problems. After an extensive review of the transfer literature, Perkins and Grotzer (1997) and Clark and Blake (1997) argue that

flexibility can be taught in a way that facilitates the solution of novel and challenging problems. They describe strategies that have been used in successful programs.   De Corte (2003; Masui & De Corte, 1999) draw on these reviews and others to provide a description of aspects of learning environments that facilitate the development of the necessary characteristics for successful transfer of existing skills to novel problems in which orienting (problem framing) and self-judging were taught according to the following guidelines:

- *Environment*: Skills and knowledge instruction must be taught in environments that reflect the application environment as much as possible to highlight the importance of relevant cues.
- *Motivation:* Task motivation must be linked to tangible and personally relevant outcomes.
- *Increasing novelty***:** Training must be sequenced to allow for gradually increasing levels of novelty and challenge (see also extensive research on the design of instruction using worked examples: Atkinson, Derry, Renkl, & Wortham, 2000; Paas & van Merrienboer, 1993; Sweller, 1999).
- *Variable Practice*: The characteristics of learning and performance tasks must be variable over the course of instruction to maximize opportunities to develop flexibility.
- *Targeted Feedback*: Students must be provided with opportunities to receive targeted feedback and consider alternatives to more effective approaches.

These guidelines reflect a similar list suggested by Merrill (2006) who analyzed the key features of new training design systems that appeared to be successful at developing flexible expertise and recommended similar design features.

Based on the DeCorte (2003) and Merrill (2002) design criteria and the studies cited above, the GEL design system attempts to promote the development of flexible expertise through applying all of the empirically identified training methods that promote flexibility:

- *Environment*: Where possible, GEL lessons are situated in the environment where skills and knowledge will be applied. Environment is reflected in a series of application scenarios (similar to case studies) and demonstration videos. GEL also attempts to prevent cognitive overload by focusing novice trainees on only the key elements of an application environment.
- *Motivation*: GEL requires motivating statements of tangible and personally relevant "benefits and risks" associated with each task to be learned.
- *Increasing novelty*: GEL requires the collection of five, increasingly novel and challenging scenarios (similar to case studies or authentic problems) for use in practice exercises, checks on learning and testing. The variation in novelty for a GEL course is greater than any other design system.

- *Variable Practice*: GEL requires both part task practice (during lessons) and whole task practice where trainees are required to apply what they have learned as they attempt to solve the problems and scenarios described in the point above.
- *Targeted Feedback*: GEL requires targeted feedback on trainees' attempts to apply what they have learned from demonstrations and attempts to practice when given scenarios and problems. GEL feedback strategies draw on the most current research on feedback and performance to support flexible expertise.

Additional features of GEL designed to promote flexible expertise:

- *Analogical Connections to Prior Knowledge*: GEL requires the presentation of analogies and varied examples in each lesson in order to help trainees connect to prior knowledge and to promote flexible application of skills and knowledge. The strategy reflects research by, for example, Gentner, Lowenstein and Thompson (2003).
- *Open Questions during Feedback*: When application practice feedback is given, trainees are asked for their reasoning about their problem solving strategies and are given the opportunity to examine alternatives rather than being "told the correct path".

In summary, we have described a powerful instructional design system that translates Merrill's (2002) five principles to instructional methods and specifies a sequence of cognitive events for the course and each lesson. We have also described a method to capture the knowledge and skills subject matter experts use to solve complex problems in the training domain. With the instructional design and content in place, we now turn the discussion to describing a powerful approach for selecting the optimal delivery media based on supporting the cognitive processes necessary for meaningful learning within the GEL system.

A Two-Stage Cognitive Approach to Media Selection

Sugrue and Clark (2000) provide an in-depth analysis of the use of media, media attributes, and instructional methods as part of their comprehensive approach to media selection for training. They suggest that the difficulty in choosing among media options either prior to, or after instructional design, stems from the confusion between media and methods and between media and media attributes. Each have a role to play in media selection; however, only instructional methods are directly related to the cognitive processes involved in learning, whereas the choice of media has a direct link to cost, access, or time to learn.

To begin the discussion we return to the definition of an instructional method as an external (environmental) activity that supports internal cognitive process necessary for meaningful learning (Clark, 1983, 1994). The degree to which a method provides a level of support varies according to the amount of intrinsic cognitive load on working memory imposed by the instructional content.

A method is further defined according to the cognitive process it supports. For example, presenting a learner with reasons for the training, the benefits of learning a task, and the risks of poor performance support the cognitive process of goal elaboration. Similarly, demonstrating how to perform the steps in a task supports the cognitive process of compiling procedures by presenting examples (Anderson, 1993; Anderson & Bothell, et al., 2004; Anderson & Fincham, 1994).

Sugrue and Clark (2000) refer to Levie's (1989) definition of a media attribute as the specific feature of a medium that provides the functionality of transmitting information to trainees or cognitive processing responses from trainees. Examples include functions that transmit audio and video, display text, provide searchable access to information, or that give feedback during practice. A more specific example would be the "zooming" attribute of real time video camera lenses. This attribute allows a designer to "zoom in or out" and so to visually select a small aspect of a visual or pull back to a wide shot of a complex visual. A medium, then, is defined as an external resource that contains media attributes or capabilities (Kozma, 1991). In short, a medium's attributes enable the delivery of methods that have cognitive consequences, and therefore, the best approach to selecting media is based on its ability to perform instructional functions relative to other media. Sugrue and Clark's (2000) analysis of the instructional influence of media and methods is summarized in Figure 1.

Figure 1. Outcomes of instruction influenced by media and instructional methods. (From Clark, Bewley, & O'Neil, 2006. Reprinted with permission.)

	Access	Cost (Development & Delivery)	Efficiency (Time to Learn)	Learning and Motivation
Media	X	X	X	
Methods			X	X

Sugrue and Clark (2000) propose that media selection begins first with the selection of instructional methods that support the cognitive processes necessary to perform the task to be trained and then continues with an analysis of media based on their ability to provide the type of method, amount (hint or provide), timing (now or later) and control (learner or media) of methods. Final media selection is based on the most economical, assessable, and cost efficient media that incorporate the required attributes.

In their discussion of media selection issues, Clark, Bewley, and O'Neil (2006) recommend following Sugrue and Clark's (2000) cognitive process for determining instructional methods. However, in their examination of media attributes, they found that "three of the most common instructional methods can be only presented via a limited number of media" (p. 136) based on the methods'

requirements for 1) sensory information; 2) conditional knowledge; and 3) synchronous feedback.

As a result, we propose a two-stage process for media selection that incorporates both approaches.

Selecting instructional methods. Sugrue and Clark (2000) propose a model of instructional methods that includes six categories. The model is based on Glaser's (1992) model of the cognitive components of expertise, Anderson's (1993) theory of learning, and theories of the components of self-regulated learning (Corno & Mandinach, 1983; Flavell, 1979; McCombs, 1988; Pintrich & DeGroot, 1990; Salomon, 1984) and is consistent with Merrill's (2002) five principles and the GEL (Clark, 2004, 2006) system. Each of the categories, the cognitive process they support, and a mapping with the instructional components of the GEL system are listed in Table 3.

Table 3
Instructional Methods (Sugrue & Clark, 2000) and GEL Components (Clark, 2004, 2006)

Instructional Method	Cognitive Process	GEL Component
Goal Elaboration	Explains the goal and its demands	Objectives, Reasons, Overview
Information	Provides task related information	Conceptual knowledge Demonstrations
Practice	Provides opportunities in varied contexts	Practice
Monitoring	Observes performance	Feedback
Diagnosis	Identifies causes of error	Feedback
Adaptation	Modifies goal, information and practice	Assessments Demonstration Practice and Feedback

Thus, within the GEL design system, the question to be answered during the first stage of media selection is: *What type, amount, timing, and control of Objectives, Reasons, Overview, Demonstration, Practice, Feedback and Assessments methods must be provided?* Based on the responses to this question, Table 4 provides a procedure for selecting instructional methods.

Table 4

Procedure for Instructional Method Selection (Sugrue & Clark, 2000)

	Instructional Method Selection Procedure
	Select:
Step 1	Type of goal elaboration (description and/or demonstration)
Step 2	Type of information (description and/or demonstration)
Step 3	Type of practice (high and/or low contextual authenticity)
Step 4	Type of support for monitoring (data collection or guidance)
Step 5	Type of support for diagnosis (analysis or guidance)
Step 6	Type of adaptation (goal/information/practice; or guidance)
Step 7	Amount of each method (low or high; fixed or variable)
Step 8	Timing of each method (fixed or variable; immediate or delayed)
Step 9	Locus of control for each method (system, trainee, or shared)

Selecting media. The second stage of the media selection process is choosing the media that best provide the selected type, amount, timing, and control of methods that support the cognitive processing necessary for learning.

Clark et al. (2006) state that the three instructional methods that often limit instructional media selection are: "the sensory modes required for learning concepts, processes, and procedures; 2) conditional knowledge requirements for

the use of learned information; and 3) the need for synchronous feedback when complex knowledge is being learned" (p. 136).

Some training may require sensory information beyond the visual and aural senses. Firefighting, for example, relies heavily on smell and tactile modes. Currently, electronic media can only provide visual and aural information, therefore, any part of the training that requires smelling, tasting, or touching something must be conducted "in person." For the media selection process, then, the guideline is that if any sensory-based information is absolutely necessary to learn concepts, processes, and procedures, then it must be presented during that particular part of the training (Clark, et al., 2006).

Conditional knowledge is information about when and where to perform a task and must be depicted during training. One way of thinking about conditional knowledge is that it represents the first part of an "if-then" statement. A manufacturing example might be: If an order is received, then follow the procedure for processing payments and shipping the product. Some conditions are more complex and require greater authenticity, such as a fire, an urban setting, or a confrontation with people. As a guideline, the media selected must adequately depict the conditions required for learners to apply the new training (Clark, et al., 2006).

Synchronous feedback refers to observation and corrective feedback provided by a live "expert coach" when trainees engage in complex practice exercises (Clark et al., 2006). Complex knowledge is defined as "requiring the integration and coordinated performance of task-specific constituent skills rather than merely recalling definitions and other conceptual knowledge about concepts, processes, and principles" (p. 137). In other words, complex knowledge is more than the sum of its parts, so trainees cannot practice each part and then be expected to perform the whole task successfully. Whole task practice is required to integrate and coordinate all parts of a task (see van Merriënboer, 1997 and van Merriënboer, Clark, & de Crook, 2002 for a complete discussion). As a guideline, if complex knowledge is the focus of the training, the media selected for complex practice exercises must support synchronous feedback for trainees through real time observation and both verbal and visual feedback by a coach.

The objective of the media selection process is to determine the most cost beneficial media delivery platform for effective training and education (Clark et al. 2006). For the purposes of media selection, Clark et al. classify media platforms as either classroom or distance, which includes multimedia transmitted over the Internet, and/or recorded on CD or DVD. To apply the procedure for selecting media, they recommend first determining the training requirements with respect to sensory modes, conditional knowledge, and practice and feedback. It is also necessary to collect information about the learning objectives, the location and number of learners, and the cost of delivering the training on all possible platforms. With this information in hand, the procedural steps in Table 5 are followed to select the optimal media.

Table 5
Training Delivery Platform Selection Procedure (Clark et al., 2006)

Training Delivery Platform Selection Procedure	
Steps	Decisions and Actions
1	Can both a distance and a classroom platform simulate all of the necessary conditions in the job setting where the learner will apply their skills and knowledge? If yes, go to Step 2. If the answer is no for any platform, select the platform that will provide the necessary conditions.
2	Can both platforms provide the required immediate (synchronous) and delayed (asynchronous) information and corrective feedback needed to achieve learning objectives? If yes, go to Step 3. If the answer is no for any platform, select the platform that will provide the necessary feedback.
3	Can both platforms provide the necessary sensory mode information (visual, aural, kinesthetic, olfactory, tactile) required to achieve all learning objectives? If the answer is no for any platform, select the platform that will provide the necessary sensory mode information.
4	If both distance and classroom platforms have survived as viable options, subject both to cost-per-student (Steps 4A and 4B) and (if desired) value-enhanced-cost (Step 4C) analysis.
4A	Derive the cost of each platform by listing and summing the costs associated with a specific course. Derive two sums, one for distance delivery and one for classroom.
4B	Divide the projected cost of each platform by the number of learners to be trained to determine the cost-per-student of each platform. Either select the platform with the lowest cost per student or go on to Step 4C.
4C	To determine the value-enhanced-cost for classroom or distance platforms, survey key stakeholders to determine their preference or value for each platform. Subtract the percent of average value assigned to the preferred platform by the stakeholders from the cost-per-student of that platform to derive a value-enhanced-cost.
5	Select the delivery platform option that survived Steps 1-3 and

> that has the lowest cost-per-student and/or lowest value-enhanced-cost from Step 4.

To arrive at the cost-per-student value, all direct and indirect costs of resources should be calculated for each platform version under consideration, including design, development, transmission, travel and cost of materials. The total cost for each platform is then divided by the number of trainees scheduled to complete the course. For example, if a distance-delivered training is projected to cost $450,000 and will be delivered to 6,500 trainees, then the cost-per-student is $69.23.

In some instances, key stakeholders may place a value on particular media to deliver training based, for example, on the public relations value of using the latest technology or the "face time" with employees that live training provides. Clark et al. (2006) define value-enhanced-cost as "the percent of value (relative strength of the preferences) stakeholders place on their preferred delivery platform above the value they place on their less preferred option multiplied by the cost-per-student" (p. 140). For example, assume that the stakeholders prefer distance training to live training by 27% and the cost of the distance option is $69.23 per student. The value enhanced cost would be $50.54 calculated as $69.23 \times .27 = \$18.69$ and $69.23 - 18.69 = \$50.54$. Thus, the value-enhanced-cost provides a lower cost advantage when comparing platforms. In short, the final media selection decision is based on a combination of the instructional methods, cost-benefit ratios, and stakeholder values.

Conclusion

In seemingly parallel paths, dramatic changes are occurring in the organizational climate for training, research in cognitive psychology, and the capabilities provided by multimedia technology. However, high expectations that the convergence of these advances would benefit business and education have not been realized. In training environments, research has shown that, for all but a few learners, popular discovery-based instructional methods, including those being used in simulations and "serious games", are largely ineffective. Instructional content is largely drawn from incomplete and inaccurate subject matter expert descriptions of learning tasks, rather than capturing the unobservable decisions, judgments, and analysis they use to solve complex problems. And regardless of the evidence that media does not influence learning, most training delivery decisions are based primarily on media preferences, rather than supporting the cognitive processes involved in meaningful learning.

In this chapter, we have illustrated a complete system that integrates three components of evidence-based practice that have been demonstrated to result in successful training and education: 1) a cognitive task analysis process that captures nearly all of the knowledge and skills experts use to solve complex problems in a domain in a way that can be used by novices; 2) a guided experiential design process that integrates expert knowledge and skills with instructional methods that support learners' cognitive processing during learning and transfer of what is learned; and 3) a media selection process to achieve the

most effective and efficient delivery of these instructional methods. As education and training stakeholders who hold diverse positions in all three areas engage in dialogs and implement integrated instructional systems, we will benefit not only from additional research data supporting their effectiveness, but also the impact of highly educated and trained people ready to compete in the global marketplace.

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