

Avoiding simplicity, confronting complexity: *Advances in studying and designing (computer-based) powerful learning environments*

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designing (computer-based) powerful
learning environments***

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PREFACE

Educational researchers are well aware of the complexity of learning and instructional processes. Over the years, they have looked for different ways to cope with this complexity. One of the coping strategies frequently used during the last century has been an analytical one. By focusing on particular bits and pieces, by thoughtfully reducing complexity, researchers have revealed the layered nature of learning and instructional processes. Unfortunately, this analytical approach has also often resulted in simplistic conclusions, simplistic interpretations of research and in simplistic solutions for complex instructional problems.

In order to more fully acknowledge the complexity of learning and instruction, various educational researchers in the last century have also attempted to study learning and instructional phenomena in their full complexity. While these holistic efforts have resulted in sincere accounts of how these phenomena can be dealt with, they have not in as much resulted in equally significant theoretical accounts of these phenomena.

Acknowledging the relevance of both coping strategies, this book addresses what is seen as one of the major issues in the further development of learning and instructional research, the issue of complexity of learning environments. It presents an overview of the current research done by researchers interested in the question on how to design powerful learning environments, and how to effectively integrate computers in instruction, without reducing this complexity. The different contributions all fit well in the overall theme of this book 'Confronting complexity, avoiding simplicity'.

All contributions attempt to empirically investigate this complexity by addressing design issues, or by identifying important variables influencing learning. One of the main research themes in these different contributions is how learners can be encouraged to use the different affordances offered to them, how learners exploit learning opportunities. Different contributions address the problem that learners do not or not optimally use support, or do not take the learning opportunities offered. Learners seem not to comply to the intentions of the designers, or those of the learning environment.

An additional theme that is addressed by different authors in this book is the aspect of visualization: visualization of aspects of the learning environments on the one hand (e.g., the application of multimedia principles), and visualization of communication aspects and learner's activities, often within collaborative learning environments, on the other hand.

Overall, the different authors in this book try to confront the complexity of learning environments, without reducing it to naïve simplicity. This is reflected in the variety of research questions addressed, and in the variety of methodologies used to answer these research questions.

This book constitutes the proceedings of the joint meeting of the special interest groups 'Instructional design' and 'Learning and instruction with computers' of the European Association for Research on Learning and Instruction.

For the second time the two special interest groups join their forces to exchange research issues addressed in the two groups. This is also reflected in the contributions of the four invited speakers, who either raise instructional design issues, or rather focus on the integration of technology in learning environments. The papers included in this proceedings, all went through a double blind peer review process. Each paper was read by two reviewers independently. The different nationalities of the contributors indicate that the issue of complexity is an issue that is fascinating to researchers all over the world.

For the special interest group 'Instructional design', this special interest meeting is organized for the second time in Leuven. While the idea to launch a special interest group on instructional design was reached at the EARLI-conference in 1991 in Madrid, the first special interest meeting was only held in 1994, with Joost Lowyck and Franz Schott as first SIG-coordinators. For the special interest group Instructional design it is already the 7th meeting. This 7th meeting of this group has a special meaning, since it is also the moment on which Joost Lowyck, one of the first coordinators is retiring. Joost Lowyck has been one of the researchers who always attempted to avoid simplicity and address complexity in his research. The theme of this joint meeting was selected as a tribute to his academic contributions.

Of course this second joint interest meeting and this book would not have been possible without the help of a large number of sponsors and people. As such, together with the editors of this book, the organizers of the second special interest meeting and the coordinators of the two EARLI SIG's involved want to explicitly express their gratitude to the following bodies for sponsoring this event: the European Association for Research on Learning and Instruction (EARLI); the National Science Foundation-Flanders; Groep T-hogeschool; the central educational support unit of the Katholieke Universiteit Leuven (DUO/ICTO); the academic institute for teacher training of the Katholieke Universiteit Leuven (AVL), and the scientific research community on 'Designing, developing and evaluating powerful learning environments' sponsored by the National Science Foundation- Flanders.

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We hope you enjoy the contributions in this book and look forward to your comments

Geraldine Clarebout and Jan Elen
Leuven, May 10, 2006

INVITED SPEAKERS

RICHARD E. CLARK

NOT KNOWING WHAT WE DON'T KNOW: REFRAMING THE IMPORTANCE OF AUTOMATED KNOWLEDGE FOR EDUCATIONAL RESEARCHⁱ

INTRODUCTION

All theory is against the freedom of the will; all experience is for it.
Samuel Johnson (1791), *Boswell's Life of Johnson*

Scientific progress sometimes comes not from new methods or technologies but from new ways of framing old problems. The purpose of this paper is to suggest that we reframe the importance of evidence gathered in the past two centuries about automated, unconscious cognitive processes (also called procedural, implicit and tacit knowledge and strategies). The suggestion is based on the assumption that we do not yet fully appreciate the impact of automated processes on complex learning, motivation and problem solving. This situation may have caused important gaps in the design of instructional research and practice and in instructional design theories and models.

We seem tempted to view evidence about automated mental processes as an odd and unimportant sideline in education and psychology. The avoidance of evidence that unconscious processes control much of our learning and performance have led us to adopt questionable assumptions to support our instructional research and design theories as well as the measures we use for assessing the impact of instruction. The goal of this paper is to encourage a refocusing of our future research and development efforts to fully integrate what we know about automated knowledge into both research and practice.

AUTOMATED COGNITIVE PROCESSES AND SELF-REGULATION

For at least the past two centuries philosophers and psychologists have commented on the existence of automated and unconscious mental processes. From Samuel Johnson's 18th century contrarian views on the exercise of free will to the more recent evidence on controlled and automated processes presented by researchers such as Schneider and Shiffrin (1977) and Daniel Wegner (2002), evidence about the ironic impact of automated processes has been constant but largely ignored in education. Estimates suggest that as adults are consciously aware of as little as 10 percent of our cognitive operations and automated procedural knowledge and so as much as 90 percent of our learning and problem solving may be automated and unconscious (Bargh, 1999, Bargh & Chartrand, 1999). In spite of this, most of our

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instructional research and indeed most of educational “science” emphasizes the learning of conscious, declarative knowledge and more or less ignores automated unconscious knowledge (Sun, Sluzarz, & Terry., 2005). Is it possible that we have developed an educational science that emphasizes only 10 percent of our self regulatory and learning processes?

Automated Routines for Automating Knowledge

We appear to have innate, unconscious routines for automating all behavior that is perceived as successful and is repeated over time (cf. Kunst-Wilson & Zajonc, 1980). Perhaps we have ignored automated knowledge because we are not at all aware of the automatization process. In addition, neuroscience evidence indicates that the expression of automated behavior appears to be pleasurable (Helmuth, 2001). Brain imaging has revealed that behavioral addiction may largely be due to non-conscious memories of environmental conditions triggering automated behaviors. Behavioral addictions appear to use the same neural reward process (albeit to a lesser degree) activated in drug addictions. Furthermore, in a recent review, Zajonc (2001) cogently argues that emotion-laden preferences for routine may be conditioned via benign and repeated exposure to the environmental conditions that elicit automated behavior. Moreover, these preferences may be stronger if repeated exposure occurs outside of conscious awareness! Thus, not only may automated behavior be addictive and its formation automated, but our expression of automated knowledge may be pleasurable as well. Investigation of this process in learning is the subject of John Anderson’s (1995) view of cognitive architecture and processes. His ACT-R theory describes a compelling, evidence-based version of the stages and events in the process by which learning objectives engage cognitive automaticity routines to gradually transform conscious declarative knowledge into automated procedural routines over time.

Perhaps it is too difficult for us to accept evidence that not only are we unaware of important cognitive processes but that some of those unconscious processes cause us to wrongly believe that we exercise effortful, effective self control. Evidence against our deliberate self control comes from diverse areas such as research on stereotypes, the development of our beliefs about the influence of our willful decisions, the accuracy of our memory for past expectations about future events; the processes that support complex learning and problem solving as well as the development of advanced professional expertise.

Ironic Cognitive Processes Cause Attribution and Performance Errors

Wegner (2002) has provided very compelling evidence that while most of us believe that we exercise conscious, deliberate control over our own decisions and actions, this belief is largely an illusion. Wegner (2002) argues persuasively that our behavior is mostly caused by a range of both physical and automated mental mechanisms that are largely automated and only occasionally influenced by will and intention. Yet, he argues, our attributions for our behavior will either focus

exclusively on conscious will as the primary agent of our behavior or attribute causality to external events. Wegner (1997) also presents evidence for an automated “ironic” monitoring and control sub-system for cognition that attempts to help us avoid mistakes but often produces errors. He gives evidence that when cognitive load exceeds working memory capacity the condition produces an unconscious, uninterruptible, cognitive process that “...searches for mental content signaling a failure to create the intended state of mind” and introduces “...different, unwelcome and unintended behavior” (p. 148). This phenomenon may help explain a wide range of human errors from “slips of the tongue” in stressful speaking situations to the documented inability most students experience when attempting to overcome previously learned and automated “misconceptions” when learning science principles or a new language.

Teachers as Experts Who May Not Be Able to Describe What They Know

Even more compelling for education is evidence that automated knowledge may prevent teachers and other experts from accurately describing to students the very effective analytical strategies they apply and the decisions they make when they solve problems in their area of expertise. Chao and Salvendy (1994) used four different strategies to study the explanations expert computer programmers gave trainees when describing three highly structured tasks such as how to diagnose and solve bugs in complex computer programs. They found that even top experts who were motivated to share their expertise described an average of only 41 percent of the important strategies they used often. When tasks were fairly simple and involved fewer decisions, the expert descriptions were 50 percent accurate. However, for more complex tasks requiring many decisions, their accuracy slipped to only 21 percent. If two or more experts were consulted about the same task, the accuracy of the reports increased by an average of only about 12 percent with each new expert. Feldon (2004) found a 70 percent gap in the explanations about the design of memory experiments given by psychology and education professors who taught research design. Feldon asked his subjects to use a computer program that permitted them to design memory experiments and then are presented with the data their experiment produced. He asked them to explain how they made decisions and compared their explanations with the decisions they actually made as recorded by the program. Is it possible that the most expert teachers unintentionally withhold 70 percent of their expertise from their students while believing that they have given 100 percent? Is this unintentional withholding a reasonable explanation for the evidence provided by Hinds (1999) that teachers and other experts significantly under-estimate the difficulty level novices experience when trying to learn to perform complex tasks

Explicit and Implicit Beliefs and Attitudes About Ourselves and Others

Another compelling example of this phenomenon can be found in research on stereotypes. Most of us believe that we are fair and impartial when dealing with

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others and yet that belief seems to conflict with the implicit attitudes reflected in the biased decisions subjects make about other when they are stressed and/or cognitively overloaded in experiments (Devine, 1989; Greenwald & Banaji, 1995). Mental operations that were once thought to require conscious, effortful processing, such as the reduction of “cognitive dissonance” when our values or beliefs conflict, now appear to be largely automated and effortless. Lieberman, Oshner, Gilbert, and Schacter (2001) present evidence from a series of studies that attempts to exert conscious control over mental conflict reduction does not change the outcome for most subjects but does make the eventual resolution of the conflict much less efficient. In their study, amnesiacs who could not remember that they had experienced a conflict about choices were much more effective and efficient in resolving the conflict than university students who reached similar conclusions more slowly - apparently because their conscious reasoning interfered with an automated cognitive process.

Hindsight Bias Revises our Memory for Expectations

If we accept the evidence about the “hindsight bias” phenomenon studied by Hoffrage and his colleagues at the Max Plank Institute in Berlin (Hoffrage et al., 2000), even our memory for our past actions and beliefs are not free of automated distortion. It appears that in most instances we remember having made an accurate prediction when in fact our earlier expectations were far from accurate. They document many cases in which we unconsciously “reconstruct” a “memory” for our previous expectations and predictions about the outcome of a future event only after the event has occurred.

EXPLANATIONS FOR THE BENEFITS AND COSTS OF AUTOMATED COGNITIVE PROCESSES

Cognitive psychologists concerned with learning and problem solving (e.g. Anderson, 1995; Anderson & Lebiere, 1998; Newell, 1990; Schneider & Chein, 2003; Sweller, 2006) have suggested that we need automated, “unconscious” knowledge to circumvent the processing limits on consciousness (working memory). Past estimates (Miller, 1955) placed the information capacity of conscious working memory at approximately seven (plus or minus two) chunks of related declarative knowledge. Yet that number has been cut in half recently as a result of an extensive review by Cowan (2001) whose estimate of three (plus or minus one) chunk limit is now generally accepted. Sweller (2006) speculates that the evolutionary purpose of severe limits on how much information we can consciously consider is to protect us from rapid changes in our knowledge. He suggests that if we were able to learn a great deal of untested and/or faulty new routines quickly we might learn and express self-destructive behavior. Automated knowledge is difficult to learn and apparently cannot be automated until it is perceived as useful and successful with repetition over time.

John Anderson's ACT-R (e.g., Anderson & Lebiere, 1998) theory describes the automatization process in specific, evidence-based detail. Anderson's learning theory has provided the key components of some of the most effective of our newest and most effective instructional design theories for learning complex knowledge (c.f. van Merriënboer, 1997; Merrill, 2002a, 2002b). The presumed benefits of automated knowledge in the form of analytical and decision strategies and procedures is that it allows us to circumvent limits on conscious thinking and express tested and effective learning and problem solving routines while leaving working memory space to process the novel components of tasks.

STRATEGIES FOR RESEARCH ON AUTOMATED COGNITIVE PROCESSES IN LEARNING AND INSTRUCTION

The primary goal of this paper is to suggest that we need to encourage a more intense and focused dialogue about the evidence for automated knowledge and its potential impact on our understanding of the processes that surround learning and instruction. A partial list of the questions and issues that, if developed, might provide considerable benefit follows. The reader will no doubt think of many other issues that deserve attention.

1. *Examine problems encountered in currently popular research topics that might be solved by including hypotheses related to the automatization of cognitive processes and/or automated procedural knowledge.*

One positive consequence of automated knowledge is that many areas of educational research may be ripe for reconsideration. One way to describe Sweller's (2006) cognitive load theory is that it describes the conditions under which automated processes protect working memory. Cognitive load theory has already made a highly significant contribution to research on the design of multi-media instruction and other forms of instructional presentations (for example, Mayer, 2001).

Self-Regulation

Other areas that might benefit from a consideration of automated processes include, for example, research on self-regulation of learning and motivation (e.g. Baumeister & Vohs, 2004). Studies that attempt to teach learners to control self-regulatory strategies in short treatments might be one of the most likely causes of evidence about failures in attempts to deliberately control cognitive processing (Molden & Dweck, 2006; Efklides, 2005). Is it possible that self-regulatory strategies have to be taught as procedures and practiced over time under the conditions where they must be expressed until they become automated? Is it also possible that the most effective self regulatory strategies will be very context or condition specific?

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Misconceptions

The role of misconceptions in learning (e.g., Kendeou & van den Broek, 2005) may also need to be reframed since misconceptions may be automated and very difficult to either change or replace. Is it possible that the reason this area is receiving less attention in recent years is because studies that attempted to modify misconceptions have largely failed (e.g., Vosniadou, 1994)? Is it also possible that studies focused on ways to change automated knowledge might breathe new life into the study of misconceptions in learning science and other topics (e.g., Vosniadou, 2002)? While this literature has focused primarily on science learning, is it also possible that misconceptions might inhibit learning in nearly all areas where prior experience and expectations conflict with new learning?

Unguided Inquiry-based and Constructivist Learning

Studies on unguided constructivist and inquiry-based learning are problematical since only learners with advanced prior subject-matter knowledge appear to thrive in unguided learning settings (Mayer, 2004). Learners, who lack adequate automated learning strategies for specific domains, may need instructionally based guidance to learn and instruction in problem solving or learning strategies might need to be implemented in the same way that other cognitive strategies are taught – and automated (Kirschner, Sweller, & Clark, 2006). Merrill (2002a, b) has reviewed current, popular instructional design theories and has recommended five types of guidance that appear to underlie the most effective systems. A critical component of the most effective guidance seems to be showing learners how to decide and act to accomplish authentic tasks and problems, then providing increasingly challenging part and whole-task practice and corrective feedback until learning occurs. Similarly, previously automated skills are the most likely reason why learners with high prior knowledge do not require procedural instruction in the form of demonstrations or worked examples but those with intermediate or lower prior knowledge find it difficult or impossible to succeed without them (e.g., Kalyuga, Chandler, Sweller, & Clark, 2001).

Task Analysis, Self Report and Think Aloud Protocols

Studies that make heavy use of self-report strategies for capturing the knowledge of subject-matter experts through task analysis and “think aloud” protocols (e.g., Davison, Vogel, & Coffman, 1997) are most likely flawed because once cognitive processes are automated they are no longer available for conscious monitoring and so cannot be accurately and completely described during a task analysis or think aloud protocol (Feldon, in press; Wheatley & Wegner, 2001). The more promising Cognitive Task Analysis strategy (e.g., Clark & Estes, 1999; Schraagen, Chipman, & Shalin, 2000) seems more likely to capture the cognitive operations that experts have automated and therefore find difficult to describe completely and accurately. Cognitive task analysis is one of the important and underappreciated features of

instructional design systems that specialize in complex knowledge (e.g., van Merriënboer, 1997).

It may also be necessary to rethink the measures we use for assessment including our reliance on the immediate post testing of declarative knowledge in instructional research and the use of self-report measures to assess motivational processes and outcomes (e.g., Stone et al., 2000).

For example, using secondary (speed of response to random cues during problem solving) measures of distraction and automaticity of knowledge, both Gimino (2000) and Flad (2002) found preliminary evidence that self report measures of how much mental effort learners invested to achieve learning goals may be flawed because of automated defaults that occur when working memory is overloaded (Clark, 1999). In addition, if the gradual automation of procedural knowledge results in increased speed and automaticity is it possible that two learners with the same score on an application exercise or learning test where time to respond is not controlled or measured might actually have very different amounts, stages and types of learning? Is it possible that a learner who has attained very high levels of expertise may not be able to describe the cognitive strategy they used to solve problems as accurately as a less expert student? In our laboratory we have examined the use of “think aloud” instruction used by professors of surgery to teach new surgeons. We divided one year’s class of surgical trainees into two groups and gave one group cognitive task analysis (CTA) worked example descriptions of a common surgical procedure while the control group received “think aloud” demonstrations from top surgery professors. We monitored the surgical trainees as they performed the procedure in the hospital for the next year (Velmahos et al., 2004). The results indicated that the CTA group made significantly fewer mistakes than the control group who made some very serious mistakes (but the number and type were consistent with “think aloud” taught surgeons in previous classes. Most interesting was the finding that both groups performed equally well on the part of the procedure they could visually inspect but the experimental group excelled in areas that involved critical decision making. We can observe and model what we can perceive but we cannot observe the making of decisions.

2. *Conduct studies that examine methods of circumventing, changing and/or replacing automated knowledge.*

The costs and negative impact of automated knowledge are due to its inaccessibility and the many ways that it silently interferes with our learning, some of which are described in the introduction to this paper. One other important difficulty is that automated knowledge is extremely difficult and perhaps impossible to modify when it is no longer functional and may be interfering with performance (Sasaki, 2004). While automated routines are difficult to learn and require many hours of application to speed and automate (Anderson, 1995), once automated they appear to be very difficult or impossible to modify, eliminate or “unlearn”.

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Sasaki (2004) has reported on the efforts we have invested in my center over the past five years to monitor research in this area. He describes three strategies that appear to have been tested: 1) over learning new knowledge that replaces existing knowledge by extending practice so that new knowledge is stronger (e.g., Zajonc, 2001); 2) goal substitution or circumventing the expression of maladaptive knowledge or processes by strengthening intentions to pause and implement new learning so that environmental conditions lead to the expression of new routines (e.g. Gollwitzer, 1999), and 3) activating an automated process to modify or replace maladaptive, activating automatic processes such as those described by Lieberman et al., (2001). We have found that the greatest interest and most systematic research on changing automated routines can be found among our colleagues in psychotherapy and counseling psychology (e.g., Bargh & Chartrand, 1999). It appears to be likely that complex learning most often requires a change in previously learned routines and thus learning difficulties might be due in part to the change-resistant qualities of automated prior knowledge and processes. Given the evidence about the reward potential of automated cognitive processes because of their links to addictive neural pathways and reward centers (Helmuth, 2001) some researchers (e.g. Prochaska DiClemente, & Norcross, 1992) are exploring the use of powerful psychological interventions used in the treatment of drug addictions to change many individual and organizational behaviors.

3. *Focus research on instructional methods that most effectively teach automated knowledge and instructional design models that incorporate this research.*

Most of our current instructional design models and nearly all instructional research is narrowly focused on the learning of conscious, declarative knowledge. This generalization extends to studies of social learning and motivational process as well as issues connected to school and classroom culture. John Anderson's systematic research on learning provides strong evidence that declarative knowledge, when used to accomplish tasks and solve problems gradually transforms into automated procedural knowledge (Anderson, 1995; Anderson & Lebiere, 1998). His research, extending over a quarter century, makes a very compelling case that all effective applied knowledge must be proceduralized and automated in order to circumvent the limits on working memory. While other researchers have developed slightly different views of this process (cf. Sun et al., 2005), most reach a similar conclusion about the importance of the automaticity process. Thus we must encourage more research that attempts to improve our support for automatization processes during learning and problems solving. Since declarative and procedural knowledge appear to interact constantly to support performance on all complex tasks, we must also examine the interaction between these two types of knowledge. The best current example of this approach can be found in the exceptional instructional design theory of van Merriënboer and colleagues (Paas, Renkl, & Sweller, 2003; van Merriënboer, 1997; van Merriënboer, Kirschner, & Kester, 2003). Van Merriënboer 4C/ID model is solidly

based on Anderson's ACT-R theory and related studies. The design activities that flow from his model support the learning of both declarative and procedural knowledge. While van Merriënboer design model has been primarily field tested by applying it to training in large government organizations, it would be very interesting to develop a version of the approach for application on a large scale in formal primary, secondary and post secondary educational settings.

A misconception that has plagued the development of advanced instructional design theories and models is the assumption that every context or setting requires a different design model. This belief has resulted in a huge variety of models whose differences are not readily apparent (Merrill, 2002a, b). Clark and Estes (1999, 2000) suggested an alternative that might help us reduce redundancy and focus our development on a few different models. Their suggestion is that we develop two stage design models. The first stage of the models would describe a research-based "generic" approach to designing all instruction for any type of learning task and the second stage specified how the design would be 'translated' for the culture, expectations and delivery media found in specific educational settings where the design would be used. The 4C/ID model (and similar complex knowledge design models) could be thought of as first stage models that would require a translation plan for implementing them in different cultural settings. Clark and Estes (2002) suggest an approach to cultural translations.

It would also be helpful if we provided greater support for instructional research that extends beyond a 30-minute segment of learning in order to better understand the mechanisms that influence the gradual automatization of knowledge and the instructional methods that will provide effective external support for learning over time. We might also benefit from improvements in the technology available to support the measurement of various stages in the development of both declarative and procedural knowledge including both dual-task (e.g. Gimino, 2000; Flad, 2002) and neurological (Feldon, 2004) measures.

CONCLUSION

Reframing the importance of automated knowledge may help us solve some persistent and difficult problems in a number of research areas, including instructional design theories and models. If we are successful at integrating automated processes into our instructional theories, research and practice, we may solve many of our most difficult and long-standing teaching and learning problems. If we delay, we may find that our prominent role in educational research and development is gradually replaced by newer neuroscience and computational or connectionist learning and performance theories that focus on automated routines.

NOTES

ⁱ The ideas presented in this paper were developed over time in collaboration with a number of colleagues including Sean Early, David Feldon, Julie Flad, Amy Gimino, Fredric Maupin, Hiro Sasaki, and Kenneth Yates. Requests for copies should be sent to clark@usc.edu

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FROM LEARNING TO INSTRUCTION: ADVENTURES AND ADVANCES IN INSTRUCTIONAL DESIGN

INTRODUCTION

The practice of planning and implementing instruction has experienced many transformations over the years, many of which are associated with advances in cognitive psychology and with new technologies available for learning and instruction. Nonetheless, no single model or theory of instructional design has been widely embraced by the instructional design community, and there are relatively few empirically established principles to guide the design of effective instruction. While these two claims may be challenged by some, the discussion will proceed as if they are not controversial. Basic learning principles and promising technologies that seem to have implications for instructional design practice will be reviewed. A key issue in determining the efficacy of proposed applications of learning principles to design practice will be examined – namely, how to determine progress of learning in complex domains and associate changes in learning and performance with specific aspects of instructional interventions. A promising approach to this central challenge that makes use of dynamic problem conceptualizations will be presented, and problematic aspects of this approach will be examined and discussed.

In the Preface to *Impact of Research on Education: Some Case Studies*, Patrick Suppes (1978) said “all of us on occasion probably feel that there is little hope that research, given the small national effort devoted to it, will seriously affect practice” (p. xiii). In spite of much research on learning and instruction, there is still much that we do not understand and much more that could be done to improve learning and instruction based on what we do understand. Meanwhile, cognitive psychology moves on and technologies that are used to support learning and instruction change. In 1972, in his keynote address to the Association of Computing Machinery, Edgars Dijkstra said that “the electronic industry has not solved a single problem, it has only created them, it has created the problem of using its products” (p. 861).

In spite of so much enthusiasm about information and communications technologies, there is the fact these technologies change frequently and introduce the problem of learning to use them effectively – this is particularly a challenge in educational contexts (Spector, 2000). The changing nature of technology and the associated challenges for learning and instruction are too numerous to mention here. However, the fact that an important educational resource, the Education Resources Information Center (ERIC) Clearinghouse on Information and

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Technology, was closed, along with all 16 ERIC clearinghouses and 10 adjunct clearinghouses, represents the impact of changes in technology. These clearinghouses had been serving various educational constituencies since 1966 and had attracted large groups of users all over the world, including researchers, teachers, students, librarians, media technologists, and administrators. ERIC continues but without those clearinghouses. Perhaps the service and support is as good as it had been – many do not think so since much less is now available. Regardless, those who were used to the resources made available through those clearinghouses have had to adjust what they do. Technology changes.

Technology changes what people do. More importantly, technology changes what people can do. People can teach and learn with technology (see, for example, Jonassen, 2006; Lowyck & Elen, 2004; Spector & Anderson, 2000). New technologies provide new opportunities to improve learning and instruction. However, in spite of significant investments in research and technology, education has not changed all that much. If one judges educational improvements by their impact on society, then one can see, what led to the negative view about educational research to which Suppes (1978) referred. I am reminded of the opening words in a well known Biblical text which can be loosely translated as follows: In the beginning there were chaos and confusion. Before modern research on learning and instruction, there were, perhaps, chaotic and confused approaches to teaching, with various teachers using different strategies and resources and aiming to achieve quite different things. One might conclude that not much has changed since that inauspicious beginning. What have ensued might be called adventures although some would like to claim them as advances. I am not convinced.

RESEARCH ON LEARNING AND INSTRUCTION

What has been established by learning research in the last 50 years or so? Cognitive psychology has established much about memory and its role in learning. There are limitations to what individuals can hold in short term memory that do not seem to vary significantly with age, gender, experience or other individual differences (Miller, 1956). The cognitive architecture developed by Anderson and colleagues (2004) is widely accepted and based on multiple types of representations in memory – textual and visual, primarily. Paivio (1986) and others argue that multiple perceptual cues can facilitate storing and retrieving specific items from memory. Cognitive psychologists have contributed much more in terms of our understanding about learning than these few items (see, for example, Kintsch, 1993; Polson, 1993).

It is clear that learning implies that an individual has changed in some way. Changes may involve abilities, attitudes, behaviors, beliefs, mental models, skills or any combination of these. Typically, observing changes, and thereby establishing that learning has [or has not] occurred, involves identifying relevant response patterns involving these abilities, attitudes, behaviors, beliefs, and so on. Many things make it difficult to determine that learning has occurred or why

learning did or did not occur as expected. First and foremost, there is the fact that humans are naturally engaged in learning most of the time. Much of what we learn occurs incidentally or accidentally or unintentionally. In order to conduct research on learning, we typically focus on intentional learning that occurs in somewhat structured settings (such as schools) in which there is a goal or aim or objective that can be identified and clarified or negotiated and against which progress of learning can be assessed.

Cognitive researchers readily admit that many non-cognitive aspects influence learning, including such affective factors as motivation and prejudice. Motivation plays an especially significant role in the development of expertise (Ericsson, 2001). Social and incidental interactions with others affect how well one learns and performs (Moreno, Mayer, Spires, & Lester, 2001; Salas & Fiore, 2004).

Many of the findings pertaining to research on learning are summarized in Bransford, Brown, and Cocking (2000). Among these findings are the following:

- Students have preconceptions about how things work, and these preconceptions (often misconceptions) need to be taken into account in learning activities.
- The development of competence requires foundational knowledge, a conceptual framework, and the ability to organize and retrieve knowledge.
- Metacognitive approaches can facilitate learning and improve performance.

These findings are consistent with and reinforced by model-facilitated learning (Milrad, Spector & Davidsen, 2002), cognitive apprentice (Collins, Brown, & Newman, 1989), model-centered learning (Seel, 2003) and other such instructional design approaches.

Lowyck and colleagues (Lowyck & Elen, 2004; Lowyck, Pöysä, & van Merriënboer, 2003) also provide a compact and meaningful summary of the findings of learning research that have implications for instructional design and the effective use of technology. Their findings pertaining to goal-directed learning include the following:

- Learning is an active process that typically involves mental effort.
- Learners interpret their experiences and construct internal representations.
- Learning is cumulative; new knowledge is most useful when it is integrated with prior knowledge.
- Effective learning is self-regulated.
- Learning occurs in contexts that include both physical and socio-cultural aspects.

The mental effort that is associated with intentional learning has been explored by cognitive load researchers (Paas, Renkl & Sweller, 2003; Sweller, 2003), who distinguish intrinsic cognitive load (largely due to factors in the problem itself), extraneous cognitive load (largely due to incidental aspects in the presentation of the problem or in the environment in which it is presented), and germane cognitive

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load (generally beneficial to learning and dependent on individual characteristics and circumstances).

Merrill (2002) develops a set of first principles for the design of instruction based on an examination of the leading success stories in educational research and instructional technology, namely: Star legacy (Schwartz, Lin, Brophy, & Bransford, 1999), McCarthy's (1996) 4-Mat, Andre's (1986) instructional episodes, Gardner's (1999) multiple intelligences, Nelson's (1999) collaborative problem solving, Jonassen's (1999) constructivist approaches (1999), and Schank's learning by doing (Schank, Berman, & Macperson, 1999). These approaches and their associated learning systems, along with those mentioned earlier and others which could easily be named, represent the great adventures in instructional design research and technology. Merrill's (2002) principles include adopting a problem-centered instructional approach, activating relevant knowledge structures and expectations in learners, demonstrating how to solve problems, providing problem solving practice and opportunities for applying knowledge, and integrating what has been learned into meaningful activities.

Spector (2001) provided a synthesis of this general body of educational research as follows:

- Learning is fundamentally about change – change in attitudes, behavior, beliefs, capabilities, mental models, skills, or a combination of these.
- Experience is the starting point for learning and improved understanding.
- Context determines meaning as interpreted and constructed by individuals.
- Relevant contexts are often broad and multi-faceted; effective learning integrates multiple aspects of new contexts with existing knowledge and understanding.
- Effective learning begins from a position of humility and uncertainty – that is to say, with an admission (explicit or tacit) of not knowing or understanding.

These various summaries indicate a high degree of agreement among educational researchers about the implications of research on learning for the design of instruction. Why, then, is there so little application of these findings beyond the involved research groups to improve learning and instruction systemically? Moreover, why have we not seen systematic benefits accrue to society from improved learning and instruction? Perhaps educational practice is not as evidence-based as one would like to imagine.

ASSESSING LEARNING IN COMPLEX DOMAINSⁱ

I believe the answer to the previous questions about apparent lack of progress in reaping the benefits of research on learning and instruction are a result of a failure to deal effectively at many levels with educational systems. Indeed, it is the inability to conceptualize education as involving complex and dynamic systems

that inhibits progress. In this section, I shall provide an overview of research related to learning in and about complex systems and focus in particular on an assessment methodology that is pertinent to evidence-based decision making in learning and instruction.

Systems-based approaches to learning and instruction have been around for more than fifty years and have recently been integrated into assessment and evaluation (Seel, 2003; Spector & Koszalka, 2004). Findings from systems-oriented research on learning and instruction in complex, ill-structured problem domains suggest that learners often fail to comprehend the nature of a system – how various factors are interrelated and how a change in one part of the system can dramatically affect another part of the system (Dörner, 1996; Spector & Anderson, 2000). A number of instructional approaches already mentioned address this deficiency directly, including problem-centered learning (Merrill, 2002) and variations such as model-centered learning (Seel, 2003) and model-facilitated learning (Milrad et al., 2002).

A common theme in systems-based approaches is the notion that the full complexity of a problem situation should eventually be presented to the learner, and that helping the learner manage that complexity by gradually introducing additional problem factors can contribute to effective learning. Challenging problems typically involve a complex system, and instruction should be aimed not only at a specific facet of the problem but also at the larger system so as to help learners locate problems in their naturally larger contexts; this has been called a holistic approach (Spector & Anderson, 2000) or a whole-task approach (van Merriënboer, 1997). Methods to facilitate understanding in such complex contexts include presenting multiple representations of problem situations (Spiro, Feltovich, Jacobson, & Coulson, 1991), interactions with simulations of complex systems (Milrad et al., 2002), and partially worked examples (van Merriënboer, 1997). Learner-constructed problem representations of the type to be described below have implications for instruction as well as for assessment.

The integration of technology in teaching and learning can be closely linked to systems-based approaches making use of such technologies as powerful and affordable computers, broadband networks, wireless technologies, more powerful and accessible software systems, distributed learning environments, and so on. Educational technologies provide many valuable affordances for problem-centered instructional approaches. The learning technology paradigm has appropriately shifted from structured learning from computers to one better characterized as learning linked with instructional uses of technology, or learning with computers (Lowyck & Elen, 2004). The emphasis is on (a) viewing technology as an ongoing part of change and innovation, and, (b) using technology to support higher-order learning in more complex and less well-defined domains (Jonassen, 2006; Spector & Anderson, 2000). The latter is a concern for many educational researchers (see, for example, Project Zero at Harvard University; <http://pzweb.harvard.edu/>).

Learning environments and instructional systems are properly viewed as parts of larger systems rather than as isolated places where learning might occur. Moreover, learning takes place in more dynamic ways than was true in the teacher-led

paradigm of earlier generations. Many more learning activities are made possible by technology and this further complicates instructional design – that is to say, determining how, when, which, and why particular learning activities promote improved understanding. Lessons learned in previous generations of educational technology should be taken into account. For example, simply putting sophisticated technologies into a learning environment is not likely to be either efficient or effective. Previous studies have focused on the effects of a particular technology on attitudes, motivation, and simple knowledge tests. Such studies perpetuate a wrongheaded debate about the educational efficacy of media (Clark, 1994; Kozma, 1994). What should be studied is the impact on learning in terms of improvements in student inquiry processes and other higher order aspects of learning directly relevant to understanding challenging and complex subject matter (Lowyck, et al., 2003; Spector & Anderson, 2000).

To demonstrate that specific instructional approaches and educational technologies are effective in improving complex problem-solving skills, a methodology to determine higher-order learning outcomes appropriate for such problems is required. A pilot test of such a methodology was demonstrated and discussed at the 2000 International System Dynamics Conference in Bergen, Norway (Christensen, Spector, Siuntine, & McCormach, 2000). A similar methodology developed in Germany has shown promise (Seel, Al-Diban, & Blumschein, 2000). General findings of a one-year National Science Foundation (NSF) study involving this modeling assessment methodology are discussed next.

The NSF project entitled “The DEEP Methodology for Assessing Learning in Complex Domains” (see Spector & Koszalka, 2004 for detailed findings; only high-level summaries are reported here) examined the use of annotated problem representations to determine relative levels of expertise in biology, engineering and medicine. Complementary studies with similar results have been reported in the literature (Seel et al., 2000; Stoyanova & Kommers, 2002; Taricani & Clariana, 2006). The DEEP study involved the selection of two representative problem scenarios for each of three complex problem-solving domains (biology, engineering and medicine). Subjects included both expert and non-expert respondents; they were provided with a problem scenario and asked to indicate what they thought would be relevant to a solution. Subjects were asked to document these items, providing a short description of each item along with a brief explanation of how and why it was relevant. Subjects were asked to indicate and document assumptions about the problem situation that they were making (initially and again at the end of the activity). Subjects were asked to develop the representation of a solution approach – but not a solution. Required parts of this representation included: (a) key facts and factors influencing the problem situation; (b) documentation of each factor – for example, how it influences the problem; (c) a graphical representation of the problem situation that linked key factors (see <http://deep.lsi.fsu.edu/DMVS/jsp/index.htm> for online access to the DEEP tool); (d) annotations on the graphical representation (descriptions of each link and each factor); (e) a solution approach based on the representation already provided, including additional information that would be required to fully specify a solution,

and (f) an indication of other possible solution approaches (very few of the respondents provided this last item).

Findings suggest that the DEEP method can be used to predict performance and relative levels of expertise in some cases (Spector & Koszalka, 2004; Spector, Dennen, & Koszalka, 2005). Expert representations were noticeably different from those of non-experts, although there were also differences among expert responses. There was much variation in non-expert responses. Differences occurred at three levels of analysis (surface, structure, semantic). In general, experts tended to identify more relationships among factors and generally said more about factors and links. In most cases, experts tended to identify more causal relationships as opposed to other types of relationships, although this was not the case with expert medical diagnosticians. As it happens, expert medical diagnosticians are very familiar with standard diagnostic procedures and used that knowledge to quickly develop a representation reflecting the standard diagnostic procedure; non-experts (medical school interns in this case) had extensive knowledge of the human body from recent coursework, and they used that knowledge to reason through a sequence likely to be result in a successful diagnosis. In other words, expert diagnosticians made use of a schema when reacting to the problem situation, whereas non-expert diagnosticians had to construct a causal mental representation of the problem. In the other domains, experts tended to reason more in terms of causal relationships than did novices. This variation across problem domains indicates that the DEEP methodology is sensitive to and useful in identifying such differences

In all three problem domains, experts and non-experts exhibited noticeable differences in identifying key or critical nodes identified. Experts identified similar critical nodes (the most inter-connected nodes), whereas the critical nodes identified by non-experts differed significantly from those experts and also from each other. For example, in response to one of the medical scenarios, none of the experts cited stress as a critical factor yet some non-experts did. Expert medical diagnosis was driven by evidence based on tests as the most critical factor; experts also mentioned follow-up visits and tests, while non-experts did not mention these things. In short, differences in the responses of experts and non-experts were evident at the surface and structural level (critical nodes) and also at the semantic level (what they said about specific nodes).

In the DEEP study, there was no opportunity to examine changes in problem representations over time or through a sequence of instructional sequence or period of sustained practice. The goals were to determine (a) if the annotated problem representation methodology was suitable for use in multiple domains, (b) if it would show differences in expert and non-expert responses, and (c) whether or not it could provide a basis for assessing relative level of expertise. These goals were achieved. The next steps are to investigate the utility of DEEP in assessing changes in how individuals and groups represent problems and to integrate the method into personalized feedback for problem solving activities (Spector, Dennen, & Koszalka, 2005). This implies using the method with both individuals and small groups before, during and after instructional sequences and periods of deliberate

practice. It is our hope that the DEEP method can be used to assess team problem solving and predict team performance on complex cognitive tasks as this is a much under-explored area of research with significant societal implications. DEEP has the potential to become the basis for personalized and high-level feedback to individuals and groups, and may improve the development of metacognitive skills and self-regulation.

The DEEP methodology has the potential to scale up for use in educational and performance settings involving many individuals, whereas the more traditional think-aloud protocol analysis methodology is suitable only for examining a small number of individuals in order to investigate particular hypotheses with regard to learning and performance. The DEEP methodology has the additional advantage of being easy to learn and implement, which makes it potentially suitable for classroom and workplace use. Further refinements of the methodology and the associated tool, including extensions for use with small groups and problem-solving teams, are required. Moreover, investigations of more problems in more domains with persons at different levels of knowledge and skill are required in order to develop more precise and reliable assessment metrics. Finally, the DEEP tool is useful in revealing differences in types of problems and how they are perceived by different problem solvers. Such knowledge is relevant to understanding the development of problem solving skills in individuals and teams.

Variations and precursors of this methodology have been effectively demonstrated in other domains (see, for example, Dummer & Ifenthaler, 2005; Herl et al., 1999; Novak, 1998; Schvaneveldt, 1990). In addition to measures associated with DEEP and other assessment tools, it is possible to collect relatively reliable data, such as quantitative measures of measures of similarity to expert responses (e.g., presence/absence of salient features and their location in a concept map). By themselves, these do not provide insight into the progressive development of expertise or improvement in higher-order reasoning, especially in complex, ill-structured problem-solving domains, but they may predict performance on many types of complex problems. It is also possible to collect and analyze qualitative data, including responses to problem scenarios and think-aloud protocols. However, these are time-intensive and costly and, as a consequence, they are hardly ever used when a laboratory effort scales up to full-scale implementation; such qualitative measures are simply not useful for assessing large numbers of individuals or evaluating programs. The promise of DEEP (Spector & Koszalka, 2004) and other automated tools (Dummer & Ifenthaler, 2005) is that changes in individuals and teams can be assessed in real-time and through a sequence of instruction or period of practice.

In DEEP, the learner or group is asked to construct an annotated problem representation to determine how that learner or learning group is thinking about a particular problem situation. Once the learner or group constructs the diagram, it can be compared with one created by an expert practitioner and immediate feedback provided to the learner that is specific to that learner's representation. As these problem scenarios are accumulated, it is possible to determine if learner responses increasingly reflect expert-like conceptualizations (factors, complexity

of interactions among factors, and explanations of relationships). In sum, it is possible to use the DEEP methodology to predict how problem representations will develop and change in individuals and groups. This is consistent with other researchers who have studied the progressive development of mental models (Dummer & Ifenthaler, 2005; Seel, 2003).

TO GO WHERE NONE HAVE GONE

The goal of instruction is to facilitate learning – to help people. The goal of learning, especially that associated with schools, colleges and formal training, is to help people by helping them to improve performance and understanding. The goal of improving performance and understanding is to enjoy better lives in some way. As Suppes (1978) noted, there has been some concern that the links in this chain have not been well connected. Indeed, one could conclude that things have not changed much since 1978 nor from that beginning in which there was so much chaos and confusion. We have wandered about in the wilderness of new technologies and paradigms for learning and instruction for more than a generation. We have had some interesting and wonderful adventures. However, the real work of systematically and systemically improving learning and instruction – of learning to use technology effectively to improve learning and instruction – has only just begun. Perhaps our students will be able to go where we and others have failed to go – into the hearts and minds of people who need to learn to share limited resources, tolerate different perspectives, and become better neighbors. Perhaps our students will turn our adventures into advances.

NOTES

ⁱ The work reported in this section began at the University of Bergen and was continued at Syracuse University as part of a National Science Foundation Project entitled “The DEEP Methodology for Assessing Learning in Complex Domains.”

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