The International Conference on Education Research (ICER) 2009

Cognitive and Neuroscience Research on Learning and Instruction: Recent insights about the impact of non-conscious knowledge on problem solving, higher order thinking skills and interactive cyber-learning environments.[1][2]

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Abstract

There are as least three powerful insights from recent studies of the brain that support cognitive science research findings: First, our brains learn and process two very different types of knowledge; non conscious, automated knowledge and conscious, controllable, declarative knowledge. Evidence also suggests that we believe we control our own learning by conscious choice when in fact nearly all mental operations are highly automated, including learning and problem solving; Second, human beings have a very limited capacity to think during learning and problem solving and when that capacity is exceeded, thinking and learning stop without us being aware. Thus instruction and self managed learning must strive to avoid cognitive overload; and Third, nearly all of our instructional design and cyber learning theories and models fail to account for the influence of non-conscious

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[1] Some of the ideas and research reviews in this discussion have been described in previous papers and chapters by the author including "Not knowing what we don't know" presented at the EARLI conference in Leuven Belgium in 2006 and in discussions with researchers at the USC Center for Cognitive Technology such as Drs. Kenneth Yates and David Feldon. Any errors are the responsibility of the author.

cognitive processes and therefore are inadequate to deal with complex learning and performance. Evidence for these points will be described and their implications for instruction and the learning of problem solving and higher order thinking skills will be discussed.   Models of learning and instruction that appear to help overcome some of these biological and cognitive barriers will be described. In addition, suggestions for new research questions on interactive learning environments that take account of the three insights will also be described.

1. Introduction

Scientific progress results from new ideas and technologies but also from new ways of framing old problems. The purpose of this paper is to suggest that as educators, we would derive a huge benefit from reframing the importance of evidence gathered in the past two centuries about automated, non-conscious cognitive processes (also called procedural, implicit and tacit knowledge). This suggestion is based on the assumption that we do not yet fully appreciate the huge impact of automated processes on complex learning, thinking, goal pursuit, motivation, self-regulation and problem solving. This situation may have caused important gaps in the design of instructional research and practice and held back the development of instructional design theories and models intended for use in new technologies and cyber learning.

We seem tempted to view evidence about automated mental processes as an odd and unimportant sideline in the history of education and psychology. Perhaps we avoid the idea because it has been the basis for some very strange and unscientific theories in the past such as the magical "collective unconscious" theory proposed by the European Psychologist Carl Jung (1956) or Sigmund Freud's dark presentation of unconscious urges (MacIntyre, 1958). Whatever the reason, we have avoided overwhelming evidence that non-conscious processes control much of our learning and performance. Failing to account for these processes has 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.

1.1 Automated Non-Conscious 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 we are consciously aware of as little as 30 percent of our cognitive operations and automated procedural knowledge and thus as much as 70 percent of our learning and problem solving may be automated and unconscious (Bargh, 1999, Bargh & Chartrand, 1999). Clark, Feldon, VanMerrienboer, Yates and Early, (2008) review evidence from many studies providing evidence that when experts in many different subject matter areas teach or train they leave out approximately 70 percent of the knowledge required to perform adequately. This lack of complete descriptions of how to solve complex problems and perform important cognitive processes leads to major learning problems for most students (Clark, Yates, Early and Moulton, 2010).

In many regards, the problem is even more complicated than simply ignoring the huge impact of non-conscious knowledge processes in instruction and learning. It appears that most human beings are convinced that they make conscious and willful decisions to set and pursue goals including learning and performance goals. Yet strong evidence exists to support the claim that once people intend to set a goal, make a decision or act, unconscious processes are controlling a significant element of what our conscious minds attribute to our will (Bargh, Gollwitzer and Ottingen, 2010). For example, over twenty-five years ago we had solid evidence from brain scans that when subjects are asked to choose which one finger they will move on either hand, they report making the decision long (800 ms) after the brain indicates that muscles have already started to move a specific finger – the one that subjects later report having moved because they chose it. When interrupted before the choice but after the brain signals the finger to move, subjects deny they have made a choice (Libet, et al, 1983). More recently we have solid evidence that consciously unnoticed cues in an environment can cause us to invest more mental effort in a learning task (Bargh, Gollwitzer, Lee-chai, Barndollar and Trotschel, 2001), help others learn and perform even when

faced with difficult barriers (Custers, Maas, Wildenbeest and Aarts, 2008) or that people can be primed with very brief (250 ms) subconscious cue to express specific values in reference to novel objects or opinion statements even though the value they believe they have consciously decide to express takes 30 times longer to decide and express (Bargh, Gollwitzer, and Ottingen, 2010). These and many other experimental indicators of the influence of complex and important non-conscious cognitive processes that seem to be willful and deliberate have been repeated many times by many different researchers in different national laboratories (see Bargh et al, 2010 for a review).

In spite of the overwhelming evidence of non-conscious cognitive processes, most of our instructional research and indeed most of educational "science" emphasizes the learning of conscious, declarative knowledge and more or less ignores automated unconscious knowledge (Sun et al., 2005). Is it possible that we have developed an educational science that emphasizes only 30 percent of our self-regulatory and learning processes? If so, what are the consequences for learning problem-solving, higher order thinking skills and self-regulatory processes?

1.2 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; Anderson, 1983, 1993, 1996). 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 (Clark and Clark, 2010). 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 (1983, 1993; 1996) 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.

1.3 Non-Conscious Cognitive Processes Cause Learning 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 (2000) argues persuasively that a range of both physical and automated mental mechanisms that are largely automated and only occasionally influenced by will and intention cause our behavior. 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.

1.4 Teachers May Not Be Able to Describe Most of 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 non-conscious 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

1.5 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 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 et al. (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.

Finally, 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 and non-conscious 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.

With the weight of evidence about the pervasive and influential impact

of non-conscious cognitive processes it seems reasonable to ask about their function in learning and performance. The discussion turns next to theories and research that have attempted to explain why we have dual (conscious and non-conscious) knowledge systems and what part they play in learning and performance.

1.6 Explanations for the Benefits and Costs of Automated Cognitive Processes

Cognitive psychologists concerned with learning and problem solving (e.g. Anderson, 1983; 1993; Anderson and Lebiere, 1998; Clark, et. al., 2010: 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 learning and changes in our behavior. 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 (Anderson, 1996)

John Anderson's ACT-R (e.g. Anderson and Libiere, 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 Merrienboer, 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.

2.0 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.

2.1 Examine problems encountered in currently popular research topics that might be solved by including hypotheses related to the automatization of cognitive processes and/or non-conscious 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 used in e-learning and cyber learning contexts (for example, Mayer, 2001, 2006).

a. 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?

b. 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?

c. 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, et al., 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. Kayluga et al., 2001).

d. Cyber-Learning, Serious Games and Online Education

Another recent insight from extensive research on cognitive load theory (Mayer, 2004; Sweller, 2006) concerns the destructive power of common features of multi-media instruction and raises an even larger cause for concern about automated processes. Mayer (2001; 2005; 2006) has identified and studied the most common cyber learning instructional design strategies that overload learners mentally and cause learning problems. In most 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. In other instances, cyber learning presentations tend to provide rich visual and sound contexts for instructional messages that overload student's working memory. 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, 2005; 2006) identifies a number of multimedia and cyber learning design principles that if implemented, tend to help us avoid cognitive overload and help learning (see Table 1). Mayer's principles apply to what is commonly called screen design (for computer or cyber learning), or graphic design for the printed page. Each principle is based on many different studies and all are intended to focus student's attention on only relevant portions of instruction and not to distract them with irrelevant and dysfunctional depictions of information even if the distractions are interesting or entertaining.

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.

In addition to the evidence about the cyber-learning design strategies, we also have distressing results from research on the use of electronic games as motivational features in cyber learning courses. A number of studies and reviews of studies that examined the benefits of games have been conducted

(for example, Chen & O'Neil, 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.

e. 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 et. al. 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 (Wheatley & Wegner, 2001; Feldon, In Press). The more promising Cognitive Task Analysis strategy (e.g. Clark & Estes, 1997; Schraagen et al., 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; Clark et al, 2008).

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.

2.2. 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 even impossible to modify when it is no longer functional and may be interfering with performance (Sasaki, 2004; Clark, 2008). While automated routines are difficult to learn and require many

hours of application to speed and automate (Anderson, 1990), once automated they appear to be very difficult or impossible to modify, eliminate or "unlearn".

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). In a chapter that reviewed the research on personal and organizational change, Clark (2008) stresses three points: 1) Adults are largely unaware of many of the goals they are pursuing and the strategies they are using. The consequence of this situation is that we are largely unable to accurately report our attempts to change; 2) When change strategies fail, one of the important but largely unexamined causes is the interference caused by the automated and dysfunctional cognitive behaviors we wish to change, and; 3) We know very little about how to unlearn dysfunctional automated and unconscious knowledge to clear the way for new covert and overt behavior. His review of the research on changing automated knowledge is similar to the conclusion reached by Sasaki (2004) with one exception, he stresses the use of social support in the form of peer assessment and feedback on change efforts.

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 and 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 et al., 1992) are

exploring the use of powerful psychological interventions used in the treatment of drug addictions to change many individual and organizational behaviors.

2.3 *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 most 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 and Lebiere, 1998). His research, extending over a quarter century, makes a very compelling case that all knowledge we intend to apply (as opposed to knowledge we intend only to be able to consciously remember) 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 (van Merriënboer, 1977; Paas, Renkl and Sweller, 2003; van Merriënboer, Kirschner and 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, 2004; Flad, 2004) and neurological (Feldon, 2004) measures.

3.0 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.

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