Modeling the User for Education, Training, and Performance Aiding

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Summary

If we are to present instruction that is available anytime and anywhere, takes advantage of the substantial tutorial efficiencies of one teacher for every student, and is affordable, we must have recourse to technology, specifically computer technology. Such technology can be used in instructional applications that range from drill and practice and tutorial dialogues, to multiplayer simulations and games. It can be used in stand-alone modes or it can be used to supplement classroom instruction. It can be used by individuals or by groups. In all cases, however, it must take account of the current state of the learner, the eventual state of the learner that the instruction is intended to produce, and the instructional techniques that reliably effect transitions from one state to the other. Models of the learner that represent these current and objective states must to an appreciable extent be models of the learner's cognition, which produces the skills, performance, and competence needed for success in all military operations. These models may be implicit as found in intrinsically programmed instruction, or they may be explicit. Both types may be seen in technology-based instruction from its beginning. Early explicit models were largely quantitative, involving fairly simple instructional paradigms, but fairly elaborate mathematics, including instructional applications of optimal control theory. Current efforts are more concerned with qualitative models, 19 of which are briefly described and discussed. These models all contribute to some degree to the efficiency and effectiveness of technology-based instruction. However, new challenges have arisen from today's uncertain, asymmetric operational environment, which may require responses that cannot be foreseen nor well prepared for in advance. Instead we must prepare our military forces and personnel to expect the unexpected and be prepared for it with individual and collective agility, creativity, and adaptability. These qualities are fundamentally cognitive in nature and require more powerful and comprehensive cognitive models if they are to successfully serve our programs of education, training, and performance aiding.

Introduction

This paper concerns research on digital representations of human cognitive processes that may be used to develop computer-mediated learning and performance aiding systems. We refer to such representations as 'models' of human cognition. This topic turns out to be extensive in both breadth and depth, so we focused our discussion on the following three questions:

What is the military value of these models?

What is their current state of development?

What is their relationship to instructional systems development?

What research and development should be undertaken to advance their value and utility?

Paper presented at the RTO HFM Symposium on "Advanced Technologies for Military Training", held Genoa, Italy13 – 15 October 2003, and published in RTO-MP-HFM-101.

Report Documentation Page	*Form Approved* *OMB No. 0704-0188*

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
00 APR 2004	**N/A**	**-**

4. TITLE AND SUBTITLE	
Modeling the User for Education, Training, and Performance Aiding	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **BioSystems 3080 Defense, Pentagon Washington, DC 20301-3080; Institute for Defense Analyses 4850 Mark Center Drive Alexandria, VA 22311-1882**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR’S ACRONYM(S)
	11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited

13. SUPPLEMENTARY NOTES
See also ADM001667, NATO RTO-MP-HFM-101 Advanced Technologies for Military Training (Technologies avancées pour lentraînement militaire)., The original document contains color images.

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**	**UU**	**22**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

Many valuable contributions are being made by researchers who are modeling neurological activity at one end of the behavioral spectrum and by researchers who are modeling human physical activity and performance at the other. This paper is aimed somewhere in the middle of these efforts. It concerns models, or representations, of human cognitive processes such as perception, memory, learning, decision-making, and problem solving. These processes arise from "micro" neurological activity at one end of the spectrum and, in turn, produce "macro" physical activity and performance at the other. Eventually, research and development may yield models that unify the full spectrum of human behavior from neurons to psychomotor activity, but the current state of knowledge limits us to efforts to understand and model components of this spectrum, hence our focus in this paper on one such component – cognition – which seems an appropriate level of concern for learning and human performance.

Throughout the paper we refer to 'the user'. This is intended as a catchall term for students, decision makers, technicians, analysts, and anyone else who may be using computer technology for education, training, and decision and performance aiding. The paper focuses on digital representation of these users' cognitive processes.

The Military Value of Cognitive Modeling

It is a fact both obvious and frequently neglected that human competence, which is a product of human cognition, is essential to every military operation, across all echelons of command and activity. Its importance is perennially evident in the conduct of military operations. Even in the increasingly technology-saturated environments of modern operations, human competence is needed to launch and control systems in space, operate and maintain robotic vehicles, deploy remote sensors and systems in contested territory, and so forth. In short, there are no unmanned systems. Without competent people to operate, maintain, and deploy our materiel assets, investments in them will return little and may in effect be wasted. Given the wide availability of technology and the ease with which it can be obtained, human competence may increasingly account for the difference between success and failure in military operations. Its availability to commanders anytime and anywhere it is needed is a matter of first importance.

How might we ensure this availability? Training (and its performance aiding analog) provides one means to accomplish this objective, particularly if it can be delivered anytime and anywhere. For example, we might supply each user with an omnipresent tutor. Such tutoring is probably best done by a human who possesses expertise in the relevant subject matter, a comprehensive range of tutorial techniques, and sufficient knowledge of the user to identify, establish, and sustain in that individual the precise human competence needed. Research has shown such tutoring to be extremely effective, producing an often-noted two standard deviations of improvement over less accessible and less effective classroom instruction (Bloom, 1984). Such an approach has been called an instructional imperative and an economic impossibility. It would be maximally effective but remains unaffordable because, for many obvious reasons, we cannot supply every user with a human tutor. This situation creates a gap between what is needed and what we can afford. As in many other endeavors, we are attempting to apply technology to fill this gap.

The research evidence suggests that such applications of technology can succeed. In nearly 300 studies comparing classroom (one teacher, many students) with computer-mediated, individualized instruction (one computer teacher, one student) across many different settings and subject matters, we find a 'rule of thirds' emerging. That is to say that, compared to classroom instruction, technology-based instruction costs about a third less and, additionally, either increases achievement by a third when instructional time is held constant, or decreases time to reach constant levels of achievement by about a third. More detailed discussions of these data have been presented by Fletcher (1997, 2002), Foster and Fletcher (2002), Kulik (1994), Niemiec, Sikorski, & Walberg (1989), and others. The primary payoff for military operations is, of course, the more rapid and reliable preparation of personnel to perform operational duties, producing significant payoffs for resource expenditures, readiness, and, most importantly, operational effectiveness.

Similar research evidence exists in support of technology used to aid performance and decision-making. For instance, technicians with only general training have been found to perform as well as specialists (who required time-consuming and expensive training) if they are provided hand-held or wearable performance aids (e.g., Fletcher and Johnston, 2002; Joyce, 2001; Wisher and Kinkaid, 1989). These aids contribute to military readiness and effectiveness not only by releasing individuals earlier for operational duty, but also, by enhancing human competence for maintaining, operating, and deploying materiel assets -- thereby significantly enhancing materiel readiness.

Costs also matter, of course. For instance, the United States military spends about $4 billion a year on specialized skill training. This is the training provided after "basic" or accession training to qualify personnel for the many technical jobs (e.g., wheeled vehicle mechanics, radar operators, avionics technicians, oceanographers, medical technicians) needed to perform military operations. It does not include aircraft pilot training, field training, or factory training, which are covered in separate cost categories. If the US were to reduce by 30 percent the time to train 20 percent of the personnel undergoing specialized skill training, it would save over $250 million per year. If it were to do so for 60 percent of the personnel undergoing specialized skill training, it would save over $700 million per year (Foster and Fletcher, 2002). These are appreciable savings by most standards.

What do these analyses and observations have to do with cognitive modeling? Effective education, and training must start with a dynamically updateable understanding, or model, of the current state of the user, a model of the knowledge, skills, and abilities the user should attain, and instructional techniques, strategies, and processes for getting from one to the other. This sort of modeling occurs in classroom learning where teachers continually assess what their students know, the level or degree to which they know it, and the most efficient ways to progress in achieving instructional goals. As discussed in the next section, this modeling is also found, both implicitly and explicitly in effective technology-based instruction.

Similar modeling processes are also required to support performance and decision aiding, even though the emphasis in these applications is on problem solution rather than learning. A model of the user is needed to provide advice that can be understood and carried out, as well as a model of the system or situation with which the user is interacting, and the ability to maintain something similar to an instructional dialogue to help the user identify correct solutions or decisions.

In both cases, concern with the knowledge, skills, and abilities that comprise human competence leads us to human cognition and the need to map current cognitive states onto goal cognitive states and determine what must be done next. This presents severe difficulties for classroom instruction (one teacher, many students). For instance, a problem arises from the degree to which students in a typical classroom vary in their prior knowledge, abilities, and learning progress. Research suggests variation by about a factor of five (e.g., Corno & Snow, 1986; Gettinger & White, 1980; Gustaffson & Undheim, 1996; Tobias, 1989). Especially notable for military applications is the observation that variability in prior knowledge increases with age and may be more important in determining progress in such post-secondary venues as military training than it is for students in their earlier years of schooling. Such variability suggests the importance, for both efficiency and effectiveness in military education, training, and performance aiding, of tailoring them to the specific needs of individual users.

Assessment of cognition in classroom instruction is necessarily both informal and imprecise. If we seek to achieve human performance outcomes reliably, anytime, anywhere, and affordably, we must have recourse to technology. If we are to use computer technology to achieve these ends we must be able to represent -- or model in digital form -- current cognitive states, goal states, and ongoing progress from one to the other. The empirical results discussed above, arising from technology-based education, training, and performance aiding, suggest that to some degree we have been successful in doing this. The question then naturally arises as to how well our ability to implement and use such models meets the need for them.

The Current State of Cognitive Modeling

Implicit Cognitive Models

Cognitive models are implemented both implicitly and explicitly in technology-based instruction. Consider the following sample instructional item, which is typical of much, perhaps most, computer-mediated instruction:

> In the multiplication 3 x 4 = 12, the number 12 is called a ________.
>
> | | | |
> |---|---|---|
> | A. | Factor | {Branch to remedial X1} |
> | B. | Quotient | {Branch to remedial X2} |
> | C. | Product | {Reinforce, go to next} |
> | D. | Power | {Branch to remedial X3} |

In this item, the system, the computer instructor, assumes that a student responding "A" misunderstands the meaning of 'Factor,' and lacks an understanding of 'Product', or both. The student will be branched to some instructional materials intended to correct one or the other of these cognitive states and then returned to this item or one similar to it. The same type of remedial approach is applied to responses of "B" and "D". A student responding with "C" may be rewarded, 'reinforced', with encouraging, or positive, feedback and is sent on to whatever item will continue progress toward the instructional goal(s), an action which may by itself constitute positive reinforcement.

The above item appears in an article by Norman Crowder written for Automated Teaching, a book that was published in 1959. We may assume the use of cognitive models is a recent innovation in technology-based instruction, but there is a model of cognition and instructional progress evident in this approach. It covers transitions from unlearned to learned states and illustrates what Crowder called 'intrinsic' programming. This approach stands in contrast to the expensive and difficult-to-prepare 'extrinsic' programming advocated by B. F. Skinner (e.g., 1954), and for good reasons of economy and utility it is the dominant approach (still) in use today in technology-based instruction. It may be found covering many subject matters, posing questions following text paragraphs, graphic displays, simulations, audio presentations, video sequences, and/or other sources of instructional content, but the underlying logic remains the same as Crowder's original – display something, elicit a response, and branch to remedial or reinforcing material depending on the response.

In order to prepare an item such as the above, a developer must both anticipate and prepare responses for several discrete cognitive states, represented by the correct answer (response C) and the 'distractors' (responses A, B, and D) to the item. The cognitive model represented by these states is static, implicit, and limited, but it is there. The main difference between the cognitive modeling in Crowder's (and Skinner's) approaches and the cognitive modeling being developed today is that the earlier models for intrinsic (and extrinsic) programming were implicit, embodied in the program of instruction, whereas today we are attempting to use more explicit models of cognition that we can abstract, express, and validate separately from the systems in which they are used.

Explicit Cognitive Models: Quantitative

These more explicit cognitive models are being used for such applications as intelligent tutoring systems and the human behavior modeling we need to generate computer (automated) military forces for constructive and virtual simulation. Explicit models of cognition were also applied early-on, in the 1960s. They were simple and intended to account for rudimentary learning objectives that could be reduced to something like the substantial amounts of stimulus-response, associative pairing required to learn such material as arithmetic 'facts' (addition, subtraction, multiplication tables), second language vocabulary, and technical jargon (names and functions of biological or mechanical structures). Nonetheless, they led to sophisticated and effective instructional approaches, and the line of research needed to determine the full range of learning situations and objectives to which they could be applied was begun but left unfinished and is rarely found today.

As an example of this approach (and its use of cognitive models) consider the following model of learning (adapted from Paulson, 1973) which attempted to account for the probability that a particular item for a particular learner would transition from the unlearned state (U), to either a short-term learned state (S), i.e., present in working memory, or to a long-term learned state (L), i.e., stored in long-term memory:

		State on Trial n+1				
		L	**S**	**U**		**P(correct)**
State on Trial n	L	**1**	**0**	**0**		**1**
	S	**c**	**1-c**	**0**		**1**
	U	**a**	**b**	**1-a-b**		**g**

In words:

- If a learned item (state L) is presented, then:
- With probability = 1, it stays there.

- If an unlearned item (state U) is presented, then:
- With probability = a, it will transition to long term-memory and the learned state,
- With probability = b, it will transition to a short-term state (S) in working memory from which it can either be learned or forgotten, and finally,
- With probability = 1-a-b, it will remain unlearned.

- If an item is in short-term, working memory (state S), then:
- With probability = c, it will transition to long-term memory and the learned state, otherwise,
- With probability = 1-c, it will remain in the short-term state.

- An item in the short-term state will not slip back to the unlearned state.

This formulation, which is based on Paulson's (1973) discussion, accounts for guessing. As shown in the right-most column above, he assumed a probability = g (presumably for 'guessing') of a correct answer to an unlearned item, but a probability = 1 for a correct answer to an item in the learned or short-term state. The parameters are estimated for each item-student combination.

A key feature of this model is that it accounts for items that are not presented on a trial. In Paulson's formulation -- based on Rumelhart's General Forgetting Theory (1967) -- when an item is not presented, transitions between states are expected to occur in accord with the following transition matrix:

		State on Trial n+1		
		L	**S**	**U**
State on Trial n	L	**1**	**0**	**0**
	S	**0**	**1-f**	**f**
	U	**0**	**0**	**1**

In words, when an item is not presented:

• If it is in the learned or unlearned state, it stays there;

• If it is in the short-term state, it may regress to the unlearned state with probability f or remain in the short term state with probability 1-f.

Formulations such as this, which are based on explicit transition models of memory, led to an instructional strategy that has been proven optimal in maximizing the number of items learned in the total time set aside for instruction, T, and allowing for a predetermined number of items, N, to be presented in a single session (e.g., Atkinson and Paulson, 1972). The optimal solution determines which N items to present to a particular student so that the total number of items the student learns is maximized at time T. The solution is roughly the following:

1. Before each trial, identify the item or items in N that have received the fewest number of correct responses since the last error.
2. If only one item is identified, present that item.
3. If more than one item is identified, select from this group the item or items that have been presented the fewest number of times.
4. If only one item remains, present that item.
5. If more than one item remains, select one at random and present it.

This description does not describe how items that have reached criterion in the current pool of N items can be optimally replaced with new items. Such procedures have been discussed by Atkinson and Paulson (1972) and Chant and Atkinson (1973).

Quantitative models of this sort continue to be used in technology-based as particularly evidenced by efforts to apply Bayesian networking to assess the cognitive states of learners (e.g., Van Lehn & Niu, 2001). These models use Bayes' theorem to work backward from users' responses to determine the probabilities that they are using (perhaps have learned) specific cognitive processes. This approach can lead to quite sophisticated models of learners' knowledge and skills.

Three points may be worth making here: (1) Both implicit and explicit models of cognition and cognitive processes have been used in technology-based instruction from its beginning; (2) Fairly simple cognitive models for fairly simple instructional paradigms can lead to sophisticated and effective instructional strategies; and (3) This approach remains a promising line of quantitative research that deserves to be explored more fully.

Explicit Cognitive Models: Qualitative

A line of research and development in cognitive modeling that has been more vigorously pursued in recent years is less quantitative than the above models, but the range of cognition covered tends to be more comprehensive and can thereby be used to meet a wider range of learning objectives. This work typically comes under the heading of 'human behavior modeling' and is increasingly used in the development of simulations for training personnel and units, analyzing tactical, operational, and strategic alternatives, and designing, developing, and acquiring military materiel.

We are fortunate that a number of systematic and comprehensive analyses of these models have recently appeared such as those by Pew and Mavor (1998), who reviewed 11 such models, Ritter, et al. (2002), who reviewed 7 models not covered by Pew and Mavor, and Morrison (2003), who reviewed 19 such models.

The models selected for analysis in these reviews were intentionally devised to be implemented in digital form – in computer algorithms. Doing this for any model is a significant demonstration. If a model can be represented in an algorithm, it can be tested. Using its algorithmic representation to capture and test cognitive processes can significantly enhance both our knowledge of these processes and the effectiveness of our education, training, and performance aiding applications. Diagnostic information indicating where the model is correct, will demonstrate the validity of the model, and indicating where it is incorrect, will suggest where the model must be modified to account for the full range of human cognition. Significant scientific and technological advances can arise from information of this sort, as well as substantial improvements in our ability to educate, train, and assist military personnel.

As Morrison (2003) points out, most of these models are systems of if-then, condition-response ('production') rules that simulate cognitive structures and processes. The 19 models he reviewed, which provide a snapshot of the current state of human cognition and behavior representation, are summarized in Table 1.

Table 1. Summary Descriptions of Cognitive Aspects in Models Reviewed by Morrison (2003)

Model Name	**Summary Description**	**Reference(s)**
Atomic Components of Thought (ACT)	Intended to provide a unified theory of mind and a design basis for instructional environments (e.g., intelligent tutors, computer generated forces) and human interfaces. Distinguishes between declarative knowledge (represented with semantic networks) and procedural knowledge (represented using if-then rules).	(Lebriere, 2002) (Anderson, Bothell, Byrne, and Lebriere, 2002)
Adaptive Resonance Theory (ART)	Family of neural net models designed to explain sensory-cognitive processes (e.g., perception, recognition, attention, reinforcement, recall, and working memory). Postulates bottom up (e.g., perceptions) and top down (e.g., expectations, attention control) functions in working memory that interact to produce learning.	(Grossberg, 1976a; 1976b) (Krafft, 2002) (http://web.umr.edu/~tauritzd/art)
Architecture for Procedure Execution (APEX)	Intended to reduce time and effort needed to develop models of human performance in complex, dynamic environments such as simulations, explorations of human performance theories, and assessments of equipment design on human performance. Includes goal-directed action selection for tasks and procedures and resource allocation for perceptual (mostly visual), cognitive, and psychomotor functions.	(Freed, Dahlman, Dalal, and Harris, 2002) (http://www.andrew.cmu.edu/~bj07/apex)
Business Redesign Agent-Based Holistic Modeling System (Brahms)	Models social as well as man-machine interactions. Uses agents to model interactions among physically dispersed groups (e.g., teams), and if-then rules ("detectables" and "beliefs") to model decision making (via "thoughtframes") and behavior within the groups. Emphasizes ethnographic analyses and socio-technical work practices, activities shaped by socio-technical environment, and constructivist, situated cognition to model cognition and behavior.	(Sierhuis and Clancey, 1997) (Clancey, Sachs, Sierhuis, and van Hoof, 1998) (Acquisti, Clancey, van Hoof, Scott, and Sierhuis, 2001)
Cognition and Affect Project (CogAff) {with associated SimAgent toolkit}	Conceptual space for describing cognitive architectures. Integrates emotional with cognitive processes. Incorporates three layers of cognition (reactive, deliberative, and reflective or meta-cognitive), three layers of information processing (perception, central processing, and action), and three types of emotions (primary based on reaction, secondary based on deliberation, and tertiary based on reflection) all producing different perceptual, memory, and motor functions.	(Sloman, 2001; 2003) (http://www.cs.bham.ac.uk/~axs/cogaff.html)

Model Name	Summary Description	Reference(s)
Cognition as a Network Of Tasks (COGNET) {with associated GINA and iGEN™ toolkits)	Intended for cognitive task analysis and description of work domains in multi-task environments requiring contemplative, decision-oriented, open-ended responses. Uses three subsystems to represent information processing (sensory/perceptual, mental modeling, action/motor), four forms of if-then rule-based task knowledge (goal directed task hierarchies, perceptual demons to guide attention, blackboard for organizing declarative information, and possible actions linked to time and resource requirements), and meta-cognitive functions. Allows interfacing with other applications.	(Zachary, Campbell, Laughery, Glenn, and Cannon-Bowers, 2001) (http://www.chiinc.com/cognethome.shtml)
Cognitive Complexity Theory (CCT) {with associated GLEAN3 toolkit}	Focused on human interface design, human-computer interaction, and sequential task performance. Employs device models (transition networks), user models (sequentially executed if-then rules, the fundamental CCT units of cognition, retrieve from long-term memory), and mental operators to represent covert cognitive processes. Long-term memory	(Kieras and Polson, 1985) (Kieras, 1999)
Cognitive Objects within a Graphical EnviroNmentT (COGENT)	Intended solely to provide tools (via a visual programming environment that evolves with the model being built) for cognitive modeling, assuming functional modularity (cognition as interaction among semi-autonomous subsystems) and using low-level processing components.	(Cooper, Yule, and Sutton, 1998) (Yule and Cooper, 2000) (http://cogent.psyc.bbk.ac.uk)
Concurrent Activation-Based Production System (CAPS)	Hybrid model for central cognitive functions (e.g., reading comprehension). Primary focus is on modeling patterns of brain activation patterns in high-level cognition via if-then rules for specific areas of the brain and associative networks for cognitive subsystems. Total activation in working memory is capped, concerned exclusively with declarative knowledge (facts), but with different limits for different individuals. Long-term memory includes procedural and declarative knowledge.	(Just, Carpenter, and Varma, 1999) (http://coglab.psy.cmu.edu/projects_set.html)
Construction-Integration Theory (C-I Theory)	Uses a symbolic theory of sentence comprehension and propositions (actions and objects of the action) stressing goal formation to provide a general model of cognition. Comprehension progresses from approximations to verified integration through mutually reinforced associations and spreading activation in memory. Extended to cover comprehension of novel computer interfaces (LInked model) and new websites (CoLiDeS model) and to incorporate concepts from Latent Semantic	(Kintsch, 1998) (Landauer & Dumais, 1997) (Kitajima & Polson, 1997) (Kitajima, Blackmon, & Polson, 2000) (http://psych-www.colorado.edu/ics)

Model Name	Summary Description	Reference(s)
	Analysis (LSA) used to derive meaning from text.	
Distributed Cognition (DCOG)	Intended to model individuals' expert behavior with agents that use multiple strategies to respond to a complex environment (air-traffic control). Based on a two dimensional space: Abstraction with three levels (skill-based responses to signals, rule-based responses to signs, and knowledge-based responses to symbols) and Decomposition (ranging from individual component to total system processing). Processing within this space depends on level of expertise, workload environment, and an individual's preferred level of engagement.	(Eggleston, Young, & McCreight, 2000) (Eggleston, Young, and McCreight, 2001)
Executive Process/Interactive Control (EPIC)	Intended to model details of peripheral cognitive processes, input (perception) and output (psychomotor responses) to inform human-system interface design by predicting the order and timing of responses. Includes long-term storage of declarative and procedural knowledge and working memory for assessing their application. Capacity and retrieval limitations arise only from perceptual and/or psychomotor systems, not from central memory store.	(Kieras & Meyer, 1995) (http://www.eecs.umich.edu/~kieras/epic.html)
Human Operator Simulator (HOS)	Intended to inform human-system interface design by modeling human performance based on the sequence and timing of subtasks organized in networks. Uses simulation objects (configuration of displays and controls), task networks (if-then rules selecting verb-object pairs used to manipulate the objects), and micro-models (times to complete required subtasks involving perception, information processing, and psychomotor responses) to determine human response times.	(Wherry, 1976) (Harris, Iavecchia, & Dick, 1989) (Glenn, Schwartz, & Ross, 1992)
Man-machine Integrated Design and Analysis System (MIDAS)	Intended to inform human-system interface design by modeling individuals and interactions among individuals in performing multiple, concurrent tasks. Uses sensory input (operators and perceivable – detectable, recognizable, and identifiable – objects), memory (with declarative – beliefs in long-term memory, contexts in working memory – and procedural components), decision-making, attention (with limitations on processing resources), situation awareness (actual and perceived), and psychomotor output to model human operator limitations and capabilities.	(Corker & Smith, 1993) (Hart, Dahn, Atencio, & Dalal, 2001) (http://caffeine.arc.nasa.gov/midas/index.html)

Model Name	Summary Description	Reference(s)
Micro Systems Analysis Of Integrated Network Of Tasks (Micro Saint) {May include the Integrated Performance Modeling Environment (IPME), using HOS micro-models, and WinCrew for estimating workload}	Simulation tool that uses a detailed task analysis to decompose human performance into a networked hierarchy (with branching logic and sequential dependencies) of discrete tasks and subtasks for which performance estimates can be validated. Network consists of subtask nodes (with launching conditions, time to complete, and effects) and relationships (that may be probabilistic, tactical requiring a threshold value, or multiple initiating more than one subtask). Designed to communicate with other models and applications through middleware.	(Laughery & Corker, 1997)
Operator Model Architecture (OMAR) {Uses Developers Interface, a graphics toolkit, for developing performance models.}	Models human behavior as interactions among independent computational agents representing interacting individuals or cognitive processes within individuals. Allows both sequentially dependent and parallel task performance with order determined by activation levels of tasks – without an explicit executive process. Allows facile interface with other models.	(Deutsch, MacMillan, & Cramer, 1993) (Deutsch, 1998) (Cramer, 1998)
PSI (Not an acronym)	Attempts to integrate motivation with cognitive processes. Based on three levels of needs that interact to determine motive strength and specific goal behaviors: System needs (water and energy), Preservation level (pain avoidance), Information level (certainty, competence, affiliation). Action strategies first seek automatized skills, then knowledge-based behavior, then trial and error to satisfy goals.	(Bartl & Dörner, 1998) (Ritter, et al., 2002) (http://www.uni-bamberg.de/~ba2dp1/psi.html)
Situation Awareness Model for Pilot-in-the-Loop Evaluation (SAMPLE)	Generalized from original effort to model situation awareness of pilots and air crews in air combat. Uses cognitive task analyses, pattern recognition from Klein's Recognition-Primed Decision-Making, Endsley's three levels of awareness (detection, identification, and prediction), and Rasmussen's three tiers of action strategy (skill-based pattern recognition, standardized if-then rules, and knowledge-based problem solving) to provide three stages of processing: information processing (with a continuous state estimator and a discrete event detector), situation assessment (with the information fusion and reasoning required by multi-tasking), and decision-making (with a procedure selector and a procedure executor). Output includes information disparity, situation awareness disparity, and combat advantage index.	(Rasmussen, 1983) (Endsley, 1988) (Klein, 1989) (Mulgund, Harper, & Zacharias, 2002)

Model Name	Summary Description	Reference(s)
State, Operator, And Result (SOAR)	Intended as a comprehensive model of human cognition focused on operational task domains depicting all behavior as goal-driven movement through problem spaces that define states and operators for the task(s) at hand. Uses a four-cycle iterative process involving: Input (via human perception), Elaboration (matches if-then, condition-action rules in long term memory with those in working memory to issue proposals for decision making and direct commands for psychomotor actions), Output (psychomotor execution), Decision (either selects operators or identifies 'impasses' requiring a new subgoal until all impasses are resolved). Uses a single process for long-term memory, learning, task representation, and decision-making. All learning occurs through "chunking," which occurs through impasse subgoaling and resolution. Emotions arise from situation awareness clarity and confusion. Integrates individual and team knowledge and allows goals and plans to be shared among team members.	(Lewis, 2001) (http://ai.eecs.umich.edu/soar) (http://www-2.cs.cmu.edu/afs/cs/project/soar/public/www/home-page.html) (http://www.isi.edu/soar/soar-homepage.html) (http://www.nottingham.ac.uk/pub/soar/nottingham/soar-faq.html) (http://phoenix.herts.ac.uk/~rmy/cogarch.seminar/soar.html)

How might these models contribute to the development of computer-mediated learning and performance aiding environments? As suggested above, a model intended to support education and training needs either an implicit or explicit model of cognition if it is to assess the state of a learner's knowledge, skill, and abilities. To do this, it must represent memory and its interactions with other cognitive functions such as perception and attention. It may also represent such cognitive functions as decision-making and problem solving as well as cognitive responses to the environment such as social behavior and situation awareness and/or the extent of cognitive workload.

However, if a model is to support education and training, it is not enough for it just to represent the current state of cognitive processing. It must also represent and project its evolution and development. In short, it must include a model of human learning. Table 2, taken directly from Morrison, summarizes the cognitive functions covered by the models summarized in Table 1. It indicates which models explicitly represent one or more of the following cognitive processes: perception, psychomotor performance, attention, situation awareness, short-term memory, long-term memory, learning, decision-making, problem solving, cognitive workload, emotional behavior, and social behavior.

The table indicates that:

- All 19 models represent decision making – but it is largely the reactive form of decision making that is captured in if-then rules.
- All 19 models represent either short- or long-term memory.
- Perception and attention were well represented in 16 of the reviewed models.

- Although only 4 of the models explicitly represented situation awareness, the functions of situation awareness were present in those representing perception and attention.

- Social behavior was represented in only 5 of the models.

- Emotional behavior was represented in only 3 of the models.

- Learning was represented in only 5 of the models as was problem solving. Morrison suggests that this limited representation may be due to the nature of condition-response production models, which can react to the situations contained in anticipated if-states, but which may not adapt well, if at all, to the unanticipated states and conditions that must be accommodated in learning and problem solving.

Table 2. Cognitive and Behavioral Functions Represented in Models Reviewed by Morrison (2003)

Acronym/ Abbreviation	**Cognitive Function Represented**											
	Perception	**Psychomotor Performance**	**Attention**	**Situation Awareness**	**Working Memory**	**Long-term Memory**	**Learning**	**Decision Making**	**Problem Solving**	**Cognitive Workload**	**Emotional Behavior**	**Social Behavior**
ACT	X	X	X		X	X	X	X	X			
ART	X		X		X	X	X	X				
APEX	X	X				X		X				
Brahms	X	X				X		X				X
CogAff	X	X			X	X		X			X	
COGNET	X	X	X	X	X			X	X	X		
CCT	X	X			X	X		X				
COGENT					X	X	X	X				
CAPS			X		X	X		X	X			
C-I Theory			X		X	X		X				
DCOG	X		X		X	X		X		X		
EPIC	X	X			X	X		X				
HOS	X	X	X		X			X				
MIDAS	X	X	X	X	X	X		X				X
Micro Saint	X		X			X		X		X		
OMAR	X		X			X		X				X
Psi	X	X	X		X	X	X	X	X		X	
SAMPLE	X		X	X		X		X				X
Soar	X	X	X	X	X	X	X	X	X		X	X

Note: An “X” entry indicates that the function is represented by the model.

The five models judged to represent learning are: ACT, COGENT, CAPS, PSI, and Soar. All five of these models also represent long-term memory, working memory, and decision-making. All except COGENT also represent perception, psychomotor performance, and attention.

A model of cognition that includes learning is necessary for education and training applications, but it is not sufficient. A model of learning is not a model of instruction. All 19 models, as good as many of them are, lack this component. This component is needed to suggest links between specific instructional interventions and specific learning outcomes – teaching strategies that reliably bring about transitions from the learner's current cognitive state to one capable of producing the intended instructional outcomes.

Instructional Systems Development

Attaining a "model of instruction" centered around models of human cognition would lead to what might be called "engineering of instruction" --instruction viewed as neither art nor science, but as a way to reliably and efficiently produce specified instructional outcomes. Such a capability for development of instructional and performance aiding systems should be based on empirically derived principles that can be realistically applied. Outcomes might consist of general objectives such as ability to transfer knowledge, long-term retention of knowledge and skill, motivation to continue learning, speed of response, accuracy of response, and so forth. The outcomes might be associated with more specific training objectives such as the ability to locate single component failures in the XYZ power supply, pack a reserve parachute, or devise tactical plans.

Fragments of such a capability for engineering instruction have been identified in research literature, data, and findings. Work is needed to organize, substantially expand, and include them as principles to be incorporated in our current models of cognition. In addition, engineering of instruction requires, as an essential foundational element, robust human cognitive models in order for the training, education or performance aiding system to "know" the user and to dynamically adapt to the user's state.

What Research and Development Do We Need?

This brief review of cognitive models applied to automated instructional and performance aiding systems suggests that much good progress has been made but that much remains to be done. We do not yet have the models we need to fully support the broad range of human behavior required for simulations we now use in training, analysis, and acquisition. More generally, we still lack the comprehensive models we need to represent subject matter expertise, levels of student learning, and most especially the links between specific instructional interventions and the development of specifically targeted cognitive abilities needed for competent performance. What research and development should we pursue to achieve short- mid- and long-term enhancements in the state of the art?

This issue was addressed in a workshop held in November 1999 to assess research and development needed to support the Department of Defense Advanced Distributed Learning initiative (Final Report, 1999), in a series of workshops sponsored in 2002-2003 by the Learning Federation (Learning Federation, 2003), and in another HFM Symposium(Foster and Fletcher, 2002). All three sources cover a wide range of issues and organize their results in different categories, but some common findings, specifically concerned with research necessary for the development of cognitive models, emerge from them. These findings, concerning cognitive modeling, are summarized in Table 3 as issues along with some specific research needed to meet these goals and fill gaps in our current capabilities.

Table 3. Issues and Research Requirements for the Development of Cognitive Modeling Summarized from Assessments of Learning Technology Needs

Issue	Research Requirements
Cognitive Theory	• Representation of 'higher order' cognitive capabilities (e.g., decision-making, problem-solving, meta-cognition, pattern recognition, critical thinking, situational awareness, teamwork). • New concepts and theories of cognition and cognitive workload based on new measurement capabilities. • Valid and verified representation of expertise and its development in complex, ill-structured environments. • Knowledge representations and ontologies that allow interoperability and logical operations within and across disciplines.
Human Behavior Representation	• Comprehensive and accurate representation of individual and crew, team, and unit expertise, capabilities, and performance. • Free, cognitively transparent exchange of virtual (avatar) and actual users in crew, group, team learning
Cognitive Model Authoring	• Automated development, verification, and validation of cognitive models. • Automated processes for performing cognitive analysis and cognitive readiness assessment. • Automated capture of expertise -- self-generating, self-modifying data bases built from cases and examples of successful problem solving and decision-making. • Principles for developing physically and cognitively realistic avatars.
User Assessment and Representation	• New forms of computer-administered assessment items using the full display, timing, and natural language understanding capabilities of technology. • Generation of valid, unobtrusive near real time assessment from interactions of individuals, teams, crews, and units with the learning or performance aiding environment. • Representation of subject matter misunderstandings and their sources. • Generation and use of questions to build cognitive profiles of users. • Assessment of cognitive workload.

Issue	Research Requirements
	• Assessment of high-level cognitive skills needed to deal with unanticipated and unexpected situations.
Management of Progress	• Ability to match instructional or problem solving goals with current state of the user and generate or select optimal tutorial and/or problem solving strategies. • Automated principles of design and presentation needed to ensure reliable achievement of targeted cognitive state(s) by individuals, crews, teams, and units. • Automated principles for the development of higher-level cognitive skills such as creativity, adaptability, problem solving, and situation awareness. • Comprehensive understanding of meta-cognition and its development. • Comprehensive understanding of incentive management and its interaction with cognitive development. • Technology-based tools allowing distributed users to manage their own progress and problem solving. • Predictions of learning rate and success from user profile information.
User Interface	• Management of user dialogue based on model of user cognitive abilities, style, and progress toward objective(s)

The efforts suggested by Table 3 are realistic in that that they are amenable to research that can be performed with approaches available from our current state of knowledge. They suggest goals that can be achieved to an appreciable degree in the next 3-5 years. Doing so will be worth the effort and will return much more to the success of our operational capabilities than it will cost.

The value of cognitive models has another, increasingly important dimension. The current world environment presents significant challenges to our capabilities for preparing military personnel to meet them, and thereby to our capabilities for providing military education and training. We have responded in ways that have proven successful in the past, with task lists, essential task lists, mission essential task lists, and even joint mission essential task lists. These task lists suggest education and training objectives that we know how to meet.

However, the current asymmetric, unpredictable operational environment now facing our military personnel will inevitably present situations that are unexpected and for which they may be little prepared. Our people and their allies will have to respond to these situations with agility, flexibility, creativity, and skillful leadership. Their readiness to acquire the additional capabilities needed to meet these unexpected, unforeseen challenges will contribute substantially to the success of their operations. How, then, can we best prepare our people to expect the unexpected and deal with it successfully? Such an aspect of readiness is a cognitive capability. It places special demands on our ability to model cognition and to train both individuals and units. It is an essential component of what we have called cognitive readiness (Etter, Foster, & Steele, 2000), and a combination of technology-based education, training, and performance aiding is expected to help our forces achieve it.

The components of cognitive readiness cover issues that include the following:

Situation awareness, which is generally defined as the ability to perceive oneself in relation to the enemy and the environment. Situation awareness has been shown to improve with practice and instructional feedback.

Memory, which is described as an active, reconstructive process supported by two underlying theoretical mechanisms: encoding specificity, which stresses the importance of external and internal cues, and transfer-appropriate processing, which stresses actions performed during encoding and retrieval. Trade-offs exist between instruction used to enhance retention and speed of initial acquisition. Conditions of learning, particularly those providing overlearning, can be designed to enhance retention.

Transfer of training, which is described as the ability to apply what is learned in one performance context to another. Massive amounts of practice with feedback will enhance "low-road" transfer requiring little cognitive mediation. Training in forming mindful, conscious abstraction will enhance "high road" transfer, which requires cognitive mediation.

Metacognition, which refers to the executive functions of thought, particularly those pertaining to knowledge and regulation of one's cognitive processes and progress toward accepted goals. Metacognitive skills can be enhanced by exercises designed to increase awareness of self-regulatory processes.

Automaticity, which refers to processes that are performed rapidly, requiring few attentional resources. Practice with feedback and overlearning can produce automatic processing in many tasks.

Problem Solving, which transforms goals and subgoals into a plan of action by processes such as trial-and-error, proximity, fractionation, and knowledge-based referrals. Techniques for problem solving matched to goal and situation categories can be successfully taught, as can the information base needed for "strong" problem solving methods, which depend on acquired knowledge.

Decision-Making, which is described as the selection of tactical and strategic plans, which are frequently primed by the recognition of learned patterns. Formal instruction in decision-making techniques may improve the quality of decisions, but some aspects of successful decision-making are determined by individual dispositions.

Mental Flexibility and Creativity, which may be cast as problem-solving, applying "strong" methods based on acquired knowledge and skills, and "weak" methods, used for poorly defined, ill-structured, chaotic tasks. Creativity may be more closely associated with the latter "weak" methods. The research is unclear whether these weak methods can be trained directly. It seems more likely that the facility with which people apply appropriate weak methods (i.e., achieve "creative solutions") to novel situations is determined by native abilities.

Leadership, appears to consist of motivational patterns and a combination of technical, conceptual, and interpersonal skills, the last being the most difficult to acquire and measure. However, technical and conceptual skills that are needed by leaders can, to an appreciable extent, be taught. Interpersonal skills and patterns of motivation required for leadership appear to be more dependent on native abilities and are thus more difficult to teach.

Emotion, must be channeled and controlled if military personnel are to perform complex tasks under the stress and confusion that accompany modern military operations. Deeply engaging, sensory immersing simulations provide promise for training warfighters to retain critical pieces of information and to perform under highly stressful conditions.

These issues have been discussed extensively in research literature and their specific relevance to cognitive readiness have been discussed by Morrison and Fletcher (2002). The points to be emphasized here are that (a) assessment and development of the capabilities suggested by these issues will key on the adequacy of the cognitive models on which our education, training, and performance aiding are based and (b) the adequacy of our cognitive modeling is a matter of first importance in the current unpredictable operational environment.

The modeling efforts reviewed in this paper along with similar efforts involving human cognition represent significant opportunities for cooperative research by the NATO community concerned with the human competence that is an essential component of every military operation. We may wish to rise to the opportunities they present.

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