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ABSTRACT

A cognitive demands analysis of a learning technology, a term that includes the hardware and the computer software products that form learning environments, attempts to describe the types of cognitive learning expected of the individual by the technology. This paper explores the context of cognitive learning, suggesting five families of cognitive learning. These families are: (1) content understanding; (2) collaboration; (3) communication; (4) problem solving; and (5) metacognition. Three technologies are analyzed with reference to these types of learning. The first technology, Algebra Tutor, is an intelligent tutoring system to help students learn algebra skills. "Hands-On Universe" is an astronomical research environment for high school students. "Function Machines" is an application for a visual programming language designed for mathematics and science education. Analyses of the types of learning expected for each of these technologies have resulted in the development of a suite of performance tasks (an integrated simulation) that includes individual and collaborative concept mapping tasks, a problem-solving search task, an explanation task, and a metacognitive questionnaire. This assessment environment is integrated across grade levels and within content areas to blend real-world tasks with a project-based scenario that captures many types of cognitive learning. (Contains 1 table and 79 references.) (SLD)

THE FIVE FAMILIES OF COGNITIVE LEARNING: A CONTEXT IN WHICH TO CONDUCT COGNITIVE DEMANDS ANALYSES OF INNOVATIVE TECHNOLOGIES

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The Five Families of Cognitive Learning: A Context in which to Conduct Cognitive Demands Analyses of Innovative Technologies

The purpose of this paper is two-fold: 1) provide an intellectual context of this type of learning that my colleagues today are assessing. We call this context the five families of cognitive learning; and 2) provide a context for the type of learning demanded by the specific technologies that we are assessing. As technology becomes more integrated into general classroom instruction and as assessment draws learning closer to instruction, it becomes increasingly important to find ways of evaluating what students are learning via these technologies. By "technologies" we refer not only to the actual machines, but also to the learning environments (e.g., software products), which afford students the opportunity to learn. We need to understand what a particular software product does and how students learn from using it. Whereas cognitive task analysis attempts to identify the cognitive skills an individual uses or needs to perform a *task* proficiently (Klein, 1995; Means & Gott, 1988; Roth & Mumaw, 1995), a cognitive demands analysis seeks to describe the types of cognitive learning expected of the individual by the *technology*. Clearly, this learning is dependent upon a number of factors, including both the context in which the technology is used and the individual characteristics of the learner. However, within a given learning situation, we can attempt to understand what is expected—or demanded—of the learner.

Information regarding the cognitive demands placed on students using the technology can simplify the assessment process by allowing the alignment of student assessments with the technology. Students are not expected merely to learn the *content* being presented to them; rather, learning demands may also include the types of activities and instructional opportunities in which students are expected to engage. By identifying these types of expected learning, we can create a suite of performance assessments integrated into a real-world, problem-solving environment that can assess varied student learning and understanding.

Context: The Five Families of Learning

In order to carry out a cognitive demands analysis, we must examine the types of learning that a particular technology targets. In the CRESST model of learning, Baker (1995) posits five families of cognitive learning: content understanding, collaboration, communication, problem solving, and metacognition (see Figure 1). These cognitive types of learning owe their intellectual history to Gagné (Gagné, Briggs, & Wager, 1992), Mayer (Mayer & Wittrock, 1996), Merrill (1983, 1993a,b), and Salas (Salas, Dickinson, Converse, & Tannenbaum, 1992). The five families describe the range of cognitive learning in which students engage; they are seen as working together to influence overall learning. Once we determine the types of learning in which students engage, we can create assessments to evaluate each learning family.

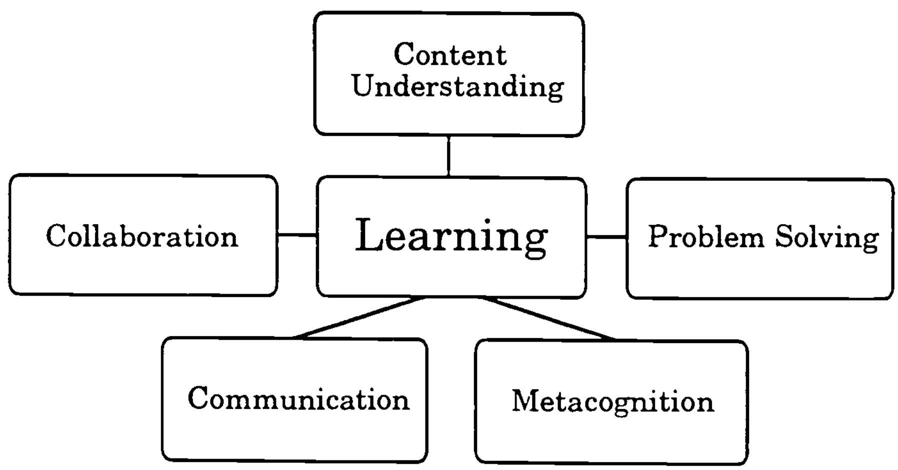

Figure 1. The CRESST model of learning.

Content understanding. The first type of learning is the understanding of subject matter content. Whereas the other types of learning involve relatively context-free material—that is, learning that could occur within any number of varied contexts—content understanding refers to the learning of domain-specific material. For instance, students engaged in learning astronomy via the use of an innovative technology will learn particular facts, concepts, procedures, and principles related to astronomy.

Assessment of content understanding should evaluate not only basic factual knowledge, but also a deeper level of understanding of the subject area (Herman, 1992; Linn, Baker, & Dunbar, 1991). There are many approaches to this assessment: explanations or essays, representational tasks (e.g., concept mapping), multiple-choice questions, and so on. The CRESST content understanding model (Baker, Aschbacher, Niemi, & Sato, 1992) uses student explanations to assess comprehension: this model has been used successfully for assessing deep understanding in history, geography, mathematics, science, and interdisciplinary tasks at the elementary, middle school, and high school levels (Aschbacher, 1995; Baker, 1994; Baker, Aschbacher, et al., 1992; Baker, Niemi, Herl, et al., 1995; Herl, Baker, & Niemi, 1996; Niemi, in press). This assessment model includes the following activities: stimulating prior content area knowledge, reading primary source documents containing new information, and writing an explanation of important issues that integrates new concepts with prior knowledge. Understanding is assessed by examining overall content quality, prior knowledge, principles, and use of resources.

Another approach to the assessment of content understanding is to evaluate students' underlying knowledge structures. Research on memory suggests that knowledge is organized in complex semantic networks (Jonassen, Beissner, & Yacci, 1993; Rumelhart & Ortony, 1977). Ausubel (1968) posited a hierarchical memory model in which new concepts are integrated hierarchically into existing cognitive structures and relationships generated accordingly. Rather than constraining cognitive structures in a hierarchical arrangement, Deese's associationist memory model (1965) allowed for various types of cognitive structures. Expert-novice research has provided additional information regarding individuals' knowledge structures, indicating that expert knowledge is organized in a qualitatively different way than is novice's knowledge (Chase & Simon, 1973; Chi, Feltovich, & Glaser, 1981; Chi, Glaser, & Farr, 1988; Gentner & Stevens, 1983). As novices become more expert, a restructuring of their knowledge occurs (Royer, Cisero, & Carlo, 1993). Whatever the exact nature of students' knowledge structures. by eliciting specific information from students we can attempt to assess these cognitive structures.

A *concept map* is a graphical representation of information consisting of nodes and links, or labeled links. Nodes correspond to concepts within a particular subject area or domain; links indicate relationships between pairs of concepts (or nodes), and labels on each link explain how two concepts are related (refer to Jonassen et al., 1993, for more in-depth coverage of concept mapping). Students create concept maps by identifying important concepts and generating and appropriately labeling the links between those concepts. This approach assumes that a deep understanding in a subject domain allows an individual to conceive a rich set of interrelationships among important concepts within that domain (Heinze-Fry & Novak, 1990; Novak & Gowin, 1984). Asking students to show relationships between important concepts by creating these maps, we can evaluate their content understanding (Baker, Niemi, Novak, & Herl, 1992; Herl et al., 1996; Jonassen et al., 1993; Ruiz-Primo & Shavelson, 1995). Concept mapping relies less on verbal ability and is less dependent upon language skills than an actual essay writing task, while still requiring other skills involved in such a task. Thus, using a concept mapping approach allows us to separate the assessment of content understanding from the assessment of communication skills.

Collaboration. The second type of learning, collaboration, involves learning how to cooperate with members of a team. Students learn to work together, each contributing to the group in his or her own way. Collaborative learning in the classroom can foster student learning and deeper understanding, as well as higher levels of self-esteem, attitudes towards others, and social skills (Webb, 1995; Webb & Palincsar, 1996). In addition, teamwork has been studied from a workplace readiness perspective: Interpersonal and teamwork skills are now recognized as essential for future job preparedness (O'Neil, Allred, & Baker, in press). Researchers in education, industry, and the military all recognize that collaboration can enhance learning, task performance, work productivity, and product quality. In a workplace environment in which teams are believed to offer the potential for greater competitiveness, employees are increasingly being asked to work in teams. For all these reason, organizations at the national, state, and local levels have begun calling for the use of collaborative group work in the classroom (for example, California State Department of Education, 1992b; Mathematical Sciences Education Board, National Research Council, 1989; National Council of Teachers of Mathematics, 1989; O'Neil, in press).

Teamwork is thought to be composed of two sets of skills: taskwork skills and teamwork skills (Morgan, Salas, & Glickman, 1993). *Taskwork skills* influence how well a team performs on a particular task. *Teamwork skills* influence how effective an individual member will be as part of a team. Further defining teamwork skills, O'Neil, Chung, and Brown (in press) identify six factors that affect collaboration. *Adaptability* refers to a team member's ability to recognize problems within the team and respond appropriately. *Communication* involves the clear and accurate exchange of information among team members. *Coordination* refers to how team members organize their activities to complete a task on time. *Decision making* involves using available information to make appropriate decisions for the team. *Interpersonal skills* affect the cooperative interaction of the individuals within a team. Finally, *leadership* is a team member's ability to provide direction and coordinate activities for the team. In combination, skill in these factors determines how well a student collaborates with his or her teammates.

One way to assess students' collaborative skills is through observation of group work; factors affecting collaboration can be thus be evaluated for each team member. Although observational methods are generally difficult and time-consuming, evaluation of collaborative activity becomes easier through the use of technology. If teammates communicate via computer, on-line messages sent back and forth between them can be saved for subsequent coding as process measures. Collaborative environments that present a set of constrained messages from which to choose (rather than allowing any message to be sent) can further simplify the coding process (O'Neil, Chung, & Brown, in press). By examining on-line messages, we can better understand the process by which a collaborative group arrived at its final product, as well as the contribution of each member of the group to that final product.

Communication. A third type of learning involves the communication of ideas. Communication is the ability to express oneself clearly and effectively—both orally and through writing—for various audiences and purposes. A more team-oriented definition sees communication as the process by which information is clearly and accurately exchanged between people, often in a prescribed manner using proper terminology (O'Neil, Chung, & Brown, in press). Throughout their lives, students will benefit from the ability to convey their beliefs. Whether by an oral presentation, through some form of writing, or by using some multimode approach, students must learn how to express themselves to others. This expression can take many forms, including persuasive, narrative, expository, explanatory, prose, and even questioning.

Much has been documented about the writing process, and scoring rubrics created to assess writing ability abound (e.g., Baker, Aschbacher, et al., 1992; California State Department of Education, 1992a; Koretz, Stecher, Klein, McCaffrey, & Deibert, 1994; Novak, Herman, & Gearhart, 1996; Wolf & Gearhart, 1993). Argumentation, organization, focus, development, mechanics, audience awareness, style, and tone are all part of good communication (Gearhart, Herman, Baker, & Whittaker, 1992; Wolf & Gearhart, 1993).

As with collaboration, communication skills are content-independent; if a student can communicate well, he or she should be able to do so across various content areas. However, prior knowledge plays heavily into this ability: It is difficult to write about something you know nothing about. Thus, we suggest assessing communication skills within a particular content area. By incorporating both a concept-mapping task (assessing content understanding) and an explanation essay task (assessing content understanding and communication skills—see Baker, Aschbacher, et al., 1992) in our performance assessment package, we can evaluate students' communication skills in conjunction with (and controlling for) content understanding. We have developed and validated a procedure for reliably scoring the essays students generate;

this manner of assessing content understanding implicitly includes within it an assessment of communication skills as well (i.e., mechanics and argumentation). That is, students who communicate well are better able to explain their content understanding.

Problem solving. A fourth type of learning involves problem-solving skills. Whether termed problem solving or critical thinking, it is clear that—since schools cannot possibly teach students *everything* they will need to know for the future—problem-solving skills fill the gap by allowing students to use what they *have* learned to successfully solve new problems or learn new skills. Industry has complained that high school graduates are unable to function well in the workplace because they lack the problem-solving skills necessary for success (O'Neil, in press). Moreover, conditions of employment are now likely to change several times during one's life (Resnick, 1987; Resnick & Resnick, 1992). In such environments, it is clear that problem-solving skills can significantly affect an individual's likelihood of success in the workforce.

Problem solving is defined as "cognitive processing directed at achieving a goal when no solution method is obvious to the problem solver" (Mayer & Wittrock, 1996, p. 3). The CRESST model of problem solving is adapted from the problem-solving models of Glaser, Raghavan, and Baxter (1992) and Sugrue (1995). It includes four scored elements: (a) content understanding, (b) metacognition, (c) motivation (self-efficacy and effort), and (d) domain-specific problem-solving strategies. The elements are scored separately and are reported as a profile of problem solving. CRESST has created several feasible measures for all of these constructs except problem-solving strategies. To assess content understanding, CRESST has used both essay-based explanation tasks (e.g., Baker et al., 1995) and paper-and-pencil concept mapping tasks (Herl et al., 1996). We have also created measures of metacognition (O'Neil & Abedi, 1996) and motivation (Malpass, 1994, measuring self-efficacy; Huang, 1996, measuring effort). In our case, the CRESST domain-specific problem-solving strategies are measured on a search task by looking at search behavior and the use of the information found. We believe that content understanding and problem-solving strategies are best assessed domain-specifically whereas metacognition and motivation are best assessed as domain-independent constructs. However, we realize that all domain-independent constructs need to be instantiated in a particular domain.

One way to assess students' problem-solving skills is by having them search for information on concepts about which they are uncertain. This uncertainty principle for information seeking is described by Kuhlthau (1993) as bringing a person's knowledge of a content domain from an affective state of uncertainty (a.k.a. "anomalous state of knowledge" or ASK; Belkin, Oddy, & Brooks, 1982) to one of understanding. Searching involves determining the information need; choosing topics to pursue; exploring and finding general information to increase overall understanding; formulating a search based on the information found during exploration; collecting and gathering relevant information; and, finally, presenting and resolving the problem (that is, finding answers or solutions to meet the initial information need). The search process involves the affective, cognitive, and physical realms of humans' experience and is often iterative; the search queries are reformulated repeatedly as the information need changes (Marchionini, 1995).

Once relevant information is found, students must integrate this newly learned material into their existing knowledge base. Thus, assessment of problem solving in the context of searching can include both evaluation of the search itself and evaluation of this knowledge integration. For instance, we can assess student search behavior by giving students the task of improving their existing representational maps (i.e., concept maps). By monitoring their on-line search, we can determine whether (a) students search well enough to access rich information sources to support the "weak" concept areas in their maps (as determined from initial concept maps), and (b) students understand enough to define the problem well through their search behavior. This approach allows us to examine both the searching process (through analysis of student search strategies) and the final integrated product (the updated concept map). Thus, in our technical approach, we have created both process and outcome measures of problem-solving strategies.

Metacognition. The fifth and final type of cognitive learning is metacognition. Metacognition is defined as "knowledge or cognition that takes as its object or regulates any aspect of any cognitive endeavor" (Flavell, 1981, p. 37) or as knowledge about, awareness of, and control over one's thoughts, motivations, and feelings (Wittrock, in press). Thus, students who think about their thought processes, or monitor their progress, or are aware of the cognitive strategies they use to solve a problem are engaging in metacognitive activity.

In our work, we characterize metacognition as consisting of four components: (a) awareness, (b) knowledge of cognitive strategies, (c) planning, and (d) self-monitoring or self-checking (O'Neil & Abedi, 1996). The second component, knowledge of cognitive strategies, falls into the category of metacognitive knowledge; awareness, planning, and self-checking are considered metacognitive activities. Metacognitive activities are assumed to be resident in working memory or consciousness (Dembo, 1994).

Research on metacognitive processes suggests that students who plan and monitor their learning and are aware of when to use which strategies often become more active in their own information processing; create more complex, efficient representations; and abstract information better than do students who do not engage in self-monitoring activities. These types of results in turn lead to greater transfer (Belmont, Butterfield, & Ferretti, 1982; Berardi-Coletta, Buyer, Dominowski, & Rellinger, 1995; Wittrock, in press). Research has also shown that students can be taught metacognitive techniques which in turn can enhance their performance and foster transfer (Berardi-Coletta et al., 1995; Brown, Campione, & Day, 1981; Lodico, Ghatala, Levin, Pressley, & Bell, 1983; Salomon, Globerson, & Guterman, 1989).

Assessment of metacognition in empirical work can be categorized as *domain-dependent* or *domain-independent* (O'Neil & Abedi, 1996). Many domain-dependent studies use think-aloud protocols in order to elicit insights into students' underlying thought processes (see Royer et al., 1993 for a review of mainly domain-dependent metacognitive assessments).

Domain-independent studies generally gather information about students' metacognition via self-report measures (see, for example, O'Neil & Abedi. 1996; O'Neil & Brown, in press; Pintrich & DeGroot. 1990; Weinstein. Palmer. & Schultz. 1987; Zimmerman & Martinez-Pons. 1990). These self-report measures have been found to be reliable with some promising validity information; in addition. they are clearly a much more efficient way to collect data than are think-aloud interviews. Including a measure of metacognition in our assessment package allows us not only to assess student learning of metacognitive techniques. but also to directly address a possible benefit of alternative assessment.

Analyses of Innovative Technologies

The cognitive demands analyses described below began with a large list of possible innovative technologies to be explored. As was discussed earlier, we are using CRESST assessment measures to assess government sponsored innovative educational technologies. Thus, we collected information on these technologies, using Web descriptions, technical reports (as available), information requested directly from the developers, and face-to-face interviews. Our decision of which innovative technologies to include for analysis was driven by which technologies would be in place for testing in the Fall, and by our desire to focus on student-level (rather than teacher-level) assessment. After reviewing all the information and investigating the current state of each technology, the following three technologies were selected for inclusion: Algebra Tutor, Hands-On Universe (HOU), and Function Machines.

For each technology, we then requested further information from the developers, as available. Not only did we want access to the software itself, but we needed to gain a better understanding of how the software was being used. Because many of the technologies are relatively context-free or domain-independent (that is, they can be used in a variety different contexts with varied student populations), how precisely a technology is integrated into the classroom curriculum will affect its impact on students. Thus, we asked developers to supply us with specific information regarding the expected student population using their product, the content area in which the product was to be used, and as much curriculum material as was currently available. Equipped with all this information, we then reviewed each technology or learning environment again, in order to analyze the types of learning afforded by each technology to its users. This matching of technologies with the five types of learning is shown in Table 1. The distinction of primary versus secondary goals was derived from the cognitive demands analysis.

For each technology listed in Table 1. the next section first includes a brief explanation of the technology's purpose, intended audience, and intended use withinthe assessment phase. This information is essential to the analysis of these innovative technologies because, as explained above, many of the products are usable in a variety of ways, in a variety of content domains. Following these descriptions, a cognitive demands analysis is presented for each technology.

Table 1

Matching Technologies With the Five Types of Learning: The Cognitive Demands of Five Technologies

Technologies	Content knowledge	Collabo-ration	Communi-cation	Problem solving	Metacog-nition
Algebra Tutor	XX	X		XX	
Hands-On Universe	XX			XX	
Function Machines	XX	X		XX	

XX= primary goals. X= secondary goals.

Algebra Tutor

Purpose. The stated purpose of this technology is to "help students to develop algebraic skills which they can use in the context of real-life problem situations" (Anderson, Mark, Pelletier, et al., 1992). This intelligent tutoring system encourages a hands-on, learning-by-doing approach in which students—individually and in groups—attempt to solve real-world problems on-line, rather than through the use of a textbook in the classroom. Algebra Tutor focuses on multiple representations of information, teaching students how to use, understand, and interpret various types of representations (e.g., text, tables, graphs) in order to solve real-world algebraic problems.

Intended audience and use. The intended audience is ninth-grade algebra students, both individually and in groups. Although some of the innovative technologies being reviewed here are relatively context-free, the Algebra Tutor is very domain-specific: This product tutors high school students in mathematics and algebra. Curriculum materials include problems in real-world mathematical applications, stressing the relevance of mathematics—and algebra in particular—to everyday life.

Analysis. Students using Algebra Tutor go through a series of steps in solving each problem. For example, students fill in tables by identifying important aspects of the problem and labeling table columns. select appropriate units of measurement. create graphs. solve equations, and write formulas. Algebra Tutor encourages students to become actively involved in the learning process. Whether used individually, in student pairs. or in collaborative groups, this intelligent tutor fosters learning and deep understanding of its algebra content via its interactive nature. Discussion (between team members), interaction (both between team members and between individual students and the tutor). and individualized feedback (from the tutor to the team or the individual student) are the key components of this system. Problem-solving and reasoning skills are fostered by the technology's emphasis on representations of real-world problems. and—in particular—its use of word problems.

Three types of learning are expected of students using Algebra Tutor. First, students are clearly expected to gain an understanding of the algebra content presented by the program. Second, it is anticipated that students will improve their problem-solving skills by using this technology. Finally, when used in a collaborative environment, collaborative skills as well as enhanced understanding of the content domain should be fostered.

Hands-On Universe

Purposes. Hands-On Universe's primary goal is to enable high school students to perform genuine, real-world astronomical research in their classrooms. so as to facilitate a deeper understanding of astronomy and to make clear to students how mathematics and science are applied to real-life scientific investigations.

Intended audience and use. The intended audience is high school science students.

Analysis. Hands-On Universe includes four components: the HOU Telescopes (which capture the actual images), the HOU Telecommunications Interface (World-Wide Web pages used to request and retrieve images, obtain weather information, etc.), the HOU Image Processing Software (PC- or Macintosh-based software used for data analysis), and the HOU Curriculum (which includes real-world applications of math and science). Students use information available on the Web and in the curriculum materials to request images from one of several participating telescopes. They can then use the image processing software to analyze their images. All four HOU components are considered research tools to facilitate scientific investigations, which in turn foster content understanding and problem-solving skills.

In summary, students learn about astronomy while using the same types of tools that real scientists and engineers are currently using in the field. Learning expected from students using this technology can be found in the five families of learning. First, students are expected to gain a deeper understanding of the astronomy content being studied. This will include both an understanding of the content itself and an awareness of the importance and relevance of this material to real-world science. Second, by using these three technologies as research tools to answer pertinent scientific questions, students will enhance their problem solving skills.

Function Machines

Purpose. Function Machines is an application for a visual programming language expressly designed for mathematics and science education. This product's intended outcomes are to engage students in mathematical investigations and to foster mathematical thinking and scientific inquiry.

Intended audience and use. Function Machines can be used in a variety of ways, with a broad class of students, to study a wide range of topics. The intended audience is fifth-grade students; the content area to be explored is mathematics and, in particular, *MathLand* curriculum. Developers plan to have students use Function Machines in collaborative teams.

Analysis. Function Machines uses graphical representations, which makes learning how to program easier and more straightforward. Using a simple metaphor of a mathematical function as a "machine" that takes something as input and produces something as output, Function Machines simplifies the mathematics it teaches by making everything visual. Students can literally *see* how functions work, by watching the machines in action, either step-by-step ("step" command) or in one uninterrupted sequence ("go" command). Creating machines (i.e., programming) in Function Machines is also visual; students construct machines using a tools palette, connecting machines together with drawn lines, called "pipes."

Machines (or programs) in Function Machines are actually sets of simpler machines, the lowest level machines being predefined as primitive functions (e.g., arithmetic functions, graphics, logic). Students can construct machines that are either primitives or composites; composite machines are made up of primitives and/or other composite machines. A machine can also be defined in terms of itself, as can its input, which can come from any machine, including itself. Thus, iteration and the complex concept of recursion are both seen more clearly through the use of this visual programming language. The program's beauty and flexibility lies in its allowing students to create anything from a very simple adding machine (e.g., input1 + input2 ==> output) to a complex series (and/or encapsulated package) of machines to solve complex real-life mathematical problems (e.g., planning a school dance). During the construction and running of these programs, students can always see what is really going on by "x-raying" a composite machine to reveal its interior contents.

Three types of learning are expected of students using Function Machines. First, students will better comprehend the specific mathematical topics (i.e., content understanding) presented to them while using Function Machines. Because of its visual nature, Function Machines is also expected to foster an inquiry-based mathematical environment in which students can engage in explorations and investigations. Thus, we expect students' problem-solving skills to be enhanced via this software. Lastly, since Function Machines lends itself to use in collaborative environments (e.g., groups of students working together to solve multiple-step, complex mathematical problems), students using the program in this manner should gain collaborative skills.

Assessment Specifications for Our Integrated Simulation

Since we can map the types of learning we expect from students onto specific assessment tasks, we have assembled a suite of performance assessment tasks (our integrated simulation) that includes both individual and collaborative concept mapping tasks, a problem-solving search task, an explanation task, and a metacognitive questionnaire. The next section documents the domain specifications for our integrated simulation.

Explanation task. Using the CRESST model, students complete a short, paper-and-pencil prior knowledge measure, in order to activate relevant prior knowledge. Then, students will be presented with the paper-and-pencil explanation task. An interesting, relevant context will help to frame students' written responses, and the explanation prompt will require students to demonstrate deep understanding of the content area. These data will not be discussed today.

Individual concept mapping task. Students are also asked to construct a concept map using an on-line mapping tool. The specific concepts and link labels for this task are provided to the students, and students work alone during this task. The individual student concept maps are scored on-line, by comparing them to a criterion (i.e., expert-constructed) map.

Problem-solving task. Once students receive feedback on their concept maps, they are directed to use a constrained subset of Netscape to search for information that will justify improving their maps. Students are instructed to "bookmark" Web pages that they believe support the modifications they make to their concept maps, and to send those bookmarks to specific terms on the concept map. For instance, a student who finds a page with relevant new information about photosynthesis would bookmark the page and send that bookmark to the "photosynthesis" concept on his or her map.

The information space being searched by students has been designed specifically for the concept mapping content area. This information space is a series of Web pages that have been gathered from the Internet, edited, and re-purposed for assessment use. The information space includes a glossary of important terms, a search engine interface, and an index. In addition, each page has been coded on various dimensions of relevance such that we can evaluate each student's information seeking behavior as a problem-solving strategy aimed at improving an existing concept map.

Collaborative concept mapping task. In this portion of the integrated assessment, a three-member team collaborates on constructing a concept map. One member is initially cast as the leader; however, each member of a group has an opportunity to assume this pivotal role.

The leader is the only team member that has the ability to actually change the group concept map; the other two members have only visual access to the map. Any changes made by the current leader to the group map are automatically updated to the screens of all members in a group. Communication between group members takes place on-line, using either predefined messages or an open messaging system. As in O'Neil, Chung, and Brown (in press), type of message usage is utilized as an index of specific group processes. The product of each group—a collaborative concept map—reflects the shared mental model of the group with respect to the relevant and important connections between and among the concepts given. Using the individual and group maps combined, we can gauge each student's relative contribution to the group map.

Metacognitive questionnaire. A Likert-scale trait questionnaire queried students on their general metacognitive activities during the integrated simulation tasks. Items targeted the four aspects of metacognition described above: awareness (e.g., "I am aware of my own thinking"), knowledge of cognitive strategies (e.g., "I select and organize relevant information to solve a task"), planning (e.g., "I try to determine what the task requires"), and self-monitoring (e.g., "I check my work while I am doing it").

Conclusion

By combining all of the tasks described in the previous section, we create an integrated simulation based on our family of cognitive learning for students and use it for assessment of innovative technologies. This assessment environment is integrated both across grade levels and within content areas. In addition, we refer to this as an integrated assessment because it blends real-world, meaningful tasks with a project-based scenario that captures the many types of cognitive learning. The assessment is simulated in the sense that we have incorporated real-world activities, collaborative environments, and an Internet-like information space within a closed assessment. Also, the environment simulates the types of learning activities that innovative technologies afford in a controlled environment, which allows us to make inferences regarding student learning. The following papers will provide feasibility, reliability, and some validity data in our approach.

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