DOI: 10.2298/CSIS111226016S

A Model-based Approach for Assessment and Motivation

J. Michael Spector[1] and ChanMin Kim[2]

[1]University of North Texas
mike.spector@unt.edu
[2]University of Georgia
chanmin@uga.edu

Abstract. Representations support learning and instruction in many ways. Two key aspects of representations are discussed in this paper. First we briefly review the research literature about cognition and processing internal mental models. The emphasis is on the role that mental models play in critical reasoning and problem solving. We then present a theoretically-grounded rationale for taking internal mental representations into account when designing and implementing support for learning. The emphasis is on interaction with meaningful problems. Lastly, we present research that has led to a conceptual framework for integrating models into learning environments that includes technologies for formative assessment and motivation.

Keywords: assessment; complex problem solving; critcal reasoning; mental model; model-facilitated learning; motivation; problem conceptualization; problem representation

1. Introduction[1]

Cognition is both complex and multifaceted. Remembering and misremembering past events, recognizing family and friends, planning vacations, shopping for gifts, and solving puzzles are cognitive processes that are generally taken for granted yet surprisingly complex. It is when we become aware of an error that we are inclined to reflect on the relevant cognitive processes involved. “Why did I mistake that person for someone else? How can I avoid repeating that mistake?” Such thoughts about our

[1] Much of the work represented herein has been inspired by the work of David H. Jonassen. Several of his publications in this area are cited, but his influence extends far beyond his published work cited in this paper. See also the Spector & Park chapter in *The Role of Criticism in Understanding Problem Solving* by Fee & Belland (2012).

cognitive processes are not so uncommon and fall into the domain of metacognition – thinking about thinking, so to speak.

Most persons have a natural desire to be correct (most of the time, anyway). Those with a desire to understand such errors might investigate how knowledge is developed. Epistemologists have investigated such questions for centuries [99]. Psychologists have also investigated the nature of cognition, including critical reasoning and problem solving skill development. Many people engage in metacognitive activities and think about their own reasoning processes from time to time. Such self-reflection should be encouraged and scaffolded during learning. The focus here is on the role that externally created representations or models can play in support of formative assessment and motivation. The approach is naturalistic [98, 99] as we examine how individuals think and develop reasoning skills and expertise. A naturalistic approach takes into consideration both cognitive and non-cognitive aspects that occur in actual cases, including beliefs about the domain being investigated as well as beliefs about one's own ability to successfully solve problems. It is generally agreed that different kinds of problems require different kinds of reasoning and, as a consequence, different kinds of support for learning [45, 46, 47, 48, 106]. A deep understanding of reasoning and problem solving can provide the basis for personalized and meaningful feedback on specific problem solving activities, including support for motivational aspects that might affect performance [54].

2. Mental Models and Reasoning

To motivate the discussion let us consider a representative problem-solving situation that many have experienced – shopping for a gift. Here is a representative scenario:

Eli and Naomi recently received news from college friends, Sam and Lisa, whom they have not seen for several years, but who happens to be coming to town on their honeymoon. Upon hearing about the upcoming visit, Naomi says to Eli, "well, after more than five years together they finally got married!" and she suggests that they need to find a wedding gift. Eli and Naomi look at their bank account to see what they can afford, and then they start discussing what they might find within their price constraints. This discussion involves recalling many Sam and Lisa stories from their past and those stories begin to lead to gift possibilities.

The point of this scenario is to suggest that (a) there are both cognitive (e.g., planning) and non-cognitive (e.g., emotional) aspects to many problems and decisions, (b) many aspects of the situation are related and likely to be mutually influential (e.g., college memories and gift possibilities), (c) previous experience with similar problems is relevant (e.g., gifts they received when they got married and wedding gifts they have given to others), and, (d) alternative gift possibilities obviously exist.. These four kinds of considerations exist in many different problem solving situations and are likely to influence one's reasoning about a solution. Addressing such considerations often requires reflection on the nature of the problem and some deliberation about alternative means to resolve the situation.

2.1. The nature of reasoning

What is the nature of reasoning? Reasoning is a deliberative, goal-driven activity. A traditional definition of reasoning [25] includes such things as:

- Having an identifiable goal or purpose that one wants to attain; and,
- Being able to identify alternative means of achieving the goal and then analyzing which means might be more feasible or optimal in attaining the goal according to one or more criteria.

The second characteristic is often more challenging than the first. Goals arise frequently in every aspect of life. Some are short-term – "I want fish for dinner"– and some are longer-term – "When I grow up I want to be an educational researcher." Sometimes we decide on the means of attaining the goal without considering alternatives. Analyzing alternatives involves (a) identifying alternative ways of attaining a goal, (b) determining desirable and undesirable aspects among the alternatives, (c) prioritiziong alternatives, and (d) selecting the most desirable alternative using relevant criteria [97]. Reasoning typically involves deliberative thinking, including the consideration and evaluation of reasonable alternatives to reach the goal. Reasoning, being rational and becoming skilled in solving problems requires an ability to confront and embrace complexity, including the assumptions we make when conceptualizing the problem situation and the implicaitons we might associate with alternative solutions. The requirement to embrace complexity runs counter to a natural human tendency to simplify and avoid challenging problem-solving tasks [97].

One might characterize deliberation about assumptions and implications as a reflective process – reflecting on the quality of one's reasoning [18]. Deliberation and reflection are desirable aspects in solving complex problems, but they require time and effort. Devoting time and effort to an activity is an issue that also involves motivation (a desire to succeed) and volition (following through to achieve one's goal) [54, 55, 56]. Suppose that one decides to examine the consequences and implications of one way to reach a particular goal. For example, suppose that one really wants to become an educational researcher (goal), and, further, that understanding advanced statistical methodologies (means) is required to be successful. The volitional aspect involves active follow-through; the implication of accepting the goal is that one must take graduate courses in advanced statistical methodologies that require some mathematical abilility. One may believe that one is weak in mathematics and feel internal resistance to the goal of becoming a serious educational researcher. How might one overcome such internal resistance and succeed?

How might educational support be provided to help one overcome such internal feelings?

For now we simply want to suggest that the process of deliberation might be extended to include reflections about one's underlying assumptions as well as the consequences and implications of pursuing one course of action over another, including how one feels about those consequences and implications. We ought to recognize that emotions, habits and preferences established over a period of many years influence the processes of examining goals, assumptions, alternative solutions and consequences [59]. Perhaps we are only intermittently rational. Non-cognitive aspects of being who we are play a greater role in reasoning and problem solving than we may be inclined to believe. We proceed on the assumption that non-cognitive aspects influence decision making, problem solving and reasoning in general [54, 55, 56, 58]. Rather than consider these non-cognitive aspects of reasoning as limitations, a naturalistic approach accepts the influence of non-cognitive factors and attempts to take them into account when supporting learning. A virtual change agent to support motivation and volition is one means of implementing this naturalistic approach [55].

Reasoning has been analyzed in a number of ways by both philosophers and psychologists [6, 18, 38, 40, 85, 87, 91]. There are several traditional distinctions to consider. One is between formal and informal reasoning. A second is between deductive and inductive (non-deductive) reasoning, which is associated with logic. In order to create an instructional framework to improve critical reasoning skills, it is necessary to understand general reasoning processes, and argumentation is central to the reasoning process.

An argument can be defined as a collection of statements some of which are offered in support of another. The supporting statements are called premises and the statement being supported is called the conclusion. The landscape of logic is comprised of arguments, each of which consists of statements offered in support of another statement. Logic involves determining which kinds of arguments are good and in identifying deficiencies in specific arguments, which is needed in order to help improve reasoning skills [18, 23, 24, 25].

Like other enterprises involving quality determinations, standards or criteria are needed. In order to develop appropriate standards, one needs to consider the different kinds of arguments that one wishes to sort. If one were sorting apples, for example, it would be relevant to know if both red delicious and golden delicious apples were in the batch to be sorted – knowing this allows appropriate color and other criteria to be used.

Since the nature of an argument is to offer statements intended to support another, one place to start is to determine the *kinds of support* that might be offered. Two kinds come to mind immediately: conclusive support and non-conclusive (suggestive) support. The nice thing about this distinction is that it is all inclusive and the two categories are mutually exclusive. Moreover, such a distinction allows for correction of the type of support offered – that is to say that the person presenting the argument may believe that he or she is offering conclusive support when only suggestive support has been provided. Before evaluating the adequacy of the support actually offered, one ought to be sure the argument is located in the proper category since the evaluation standards are different. An example of this problem can be found at the end of a correlation study in which the researcher claims that the study *proves* a certain point. Proof is a strong notion that is best reserved for the strongest types of argument, which are generally considered to be of the conclusive variety (deductive arguments). Correlation studies may *suggest* or *show* something, but they do not establish conclusions with certainty. Even rigorous controlled experimental studies aimed at establishing causality do not establish conclusions with certainty, although they may establish conclusions with very high degrees of probability.

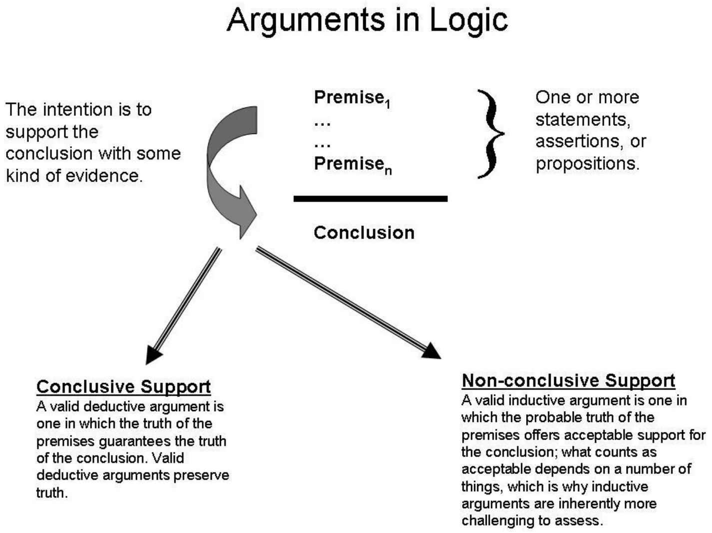

Fig. 1. The logical form of arguments.

Mathematical proofs are familiar examples of the deductive variety. Statistical studies are familiar examples of the inductive or non-deductive variety. What is worth carrying forward is that, when reflecting on one's reasoning, understanding the kind of argumentation involved (deductive or inductive) is important. Moreover, when deliberating on the quality of an argument, a critical factor is in determining whether or not adequate evidence has been developed to support the conclusion or decision to be taken.

Finally, we should not forget that non-cognitive aspects influence our reasoning, decision making and problem solving. In a model-based discussion of reasoning, there is a place to include these non-cognitive aspects of reasoning, and they can be given prominence in a formal deductive or inductive argument as well. For example, in a deductive argument, one can provide a statement representing an affective aspect of a problem, such as "If we want to celebrate when Sam and Lisa first met at that Bob Dylan concert, then we should find a gift related to that first date." Likewise, one can introduce perceptions and preferences and affective factors into an inductive argument based on survey and interview results, as frequently happens in educational research. This by no means is a claim that all aspects of non-cognitive factors can be given an appropriate representation in language; in fact, the process of representing affective aspects may well alter the underlying emotions and feelings and is a deviation from a completely naturalistic approach. However, some affective factors can and should be represented in language as they often have relevance for assessing how learners think about a problem; they may also be useful in providing learners with feedback to improve problem solving performance, enhance motivation, promote meaningful follow-through, or perhaps change epistemic beliefs relevant to learning progress.

There is another distinction to introduce – namely, the distinction between formal and informal reasoning. Both formal deductive and inductive logics have informal counterparts. Language influences thought. Language facilitates thinking. We make use of language to express and represent our deliberations, reflections and to explain our actions. While there are several kinds of deductive logic – multi-valued logic, first-order predicate calculus, modal logic, and so on – the simplicity of a two-valued propositional logic can also facilitate thinking and serve to improve the quality of deliberations and reflections. The purpose here is to clarify the relationships between reasoning and mental models, so we next turn to internal representations that are involved in our reasoning. These internal representations can be grouped together using the term 'mental models'.

2.2. Mental models and schemas

Our interest in mental models is driven by a concern to contribute to the improvement of human reasoning. It is clear that people do not generally reason in terms of formal logic [23, 24, 26, 27, 28]. We have also said that we believe that people are intermittently rational. We occasionally engage in deliberative and reflective processes – cognitive processes – in order to achieve a goal or fulfill a purpose. Those internal cognitive processes are hidden; they are not viewed directly and immediately by anyone; mental models are hypothetical entities. We make inferences about these hidden models based on external representations and observable entities and events, such as things that people say or write, diagrams that people create, actions that people take, and solutions to problems that people solve. It is generally believed that the quality of one's internal mental models influences the quality of one's ability to solve problems and reason critically. In the *Tracatus Logico-Philosophicus*, Wittgenstein said that *we picture facts to ourselves* (Remark 2.1) [110]. We naturally construct mental representations of the things we experience. When the things we experience are new or bewildering, we seem to struggle with those internal representations – we may begin to externalize them in our efforts to make sense of what is not immediately clear or easily understood. We often use language for this purpose – the ability to create internal representations of things we experience is truly amazing. Equally amazing is the ability to externalize those representations and talk about what we are thinking, occasionally even sensibly (see Wittgenstein's discussion of language games in *Philosophical Investigations*) [111].

We create internal representations and we interpret those internal representations by talking (or writing or drawing diagrams), creating new re-representations [16, 17, 20, 32, 36, 37, 42, 61, 63, 64, 65, 66, 68, 69, 72, 80]. Claims about internal mental processes and entities are inherently inferential – we do not observe any internal mental objects directly, not even our own. Conclusions about mental models and associated cognitive processes are, as a consequence, at best more or less probable. As a consequence, we ought to be modest in what we claim to know about mental models and cognitive processes (recall the discussion of inductive reasoning).

This word of caution does not mean that mental model research is not worthwhile or that one cannot investigate mental processes in a rigorous scientific manner. There can be and is a science of mental models, just as there can be and is a science called psychology. Indeed, one might argue that mental models are at the core of modern cognitive psychology. Just because that which is being investigated is a hypothetical entity or hypothetical process does not mean that those objects cannot be investigated. Indeed, mental models and cognitive processes are of interest precisely because of their potential to explain a great many human phenomena and behavior patterns of interest to psychologists, educators, instructional designers, parents, and people in general. We want to understand who we are, why we think and act the way we do, why we make the mistakes the way we do, why we are intermittently rational, and how we might become better decision makers and problem solvers.

Cognitive psychologists are in general agreement that people have the ability to process a variety of different information and act appropriately in many different situations. These abilities were mentioned earlier and include perception, pattern recognition, storing and retrieving different kinds of information, and acting on previously gained experience [2, 81, 85, 86, 87, 88, 89, 91, 92, 108, 109, 112]. Pattern matching is an ability at which humans excel [89]. Humans quickly and effortlessly recognize objects, as shown by the ability of most people to recognize a familiar face in a group of people. Pattern recognition is a critical cognitive process that involves perceiving, remembering, and interpreting, which are all essential in many decision-making and problem-solving situations [8, 11, 19, 29, 30, 34, 35, 36, 41, 52, 68, 76, 77, 78, 79, 82, 83, 85, 86].

Pattern matching and recognition are generally believed to be based on schema, which are well-established cognitive artifacts stored in long-term memory based on past experience [4, 88, 89]. Moreover, it is not simply patterns of familiar objects that people can recognize and match with prior experience to help select appropriate actions. People also recognize general situations that call for particular kinds of responses, such as the way that a restaurant is organized with a host who seats customers, with a different person taking orders, and possibly with others bringing drinks and clearing the table. Because such a situation has been experienced many times, one generally knows what to do in a restaurant even though it may be the first visit to that particular restaurant. Schank and Abelson [90] and others [1, 2, 3] refer to the ability to recognize such general situations and respond appropriately as involving *scripts* (a specific kind of internal mental strucrure). In what follows, the more general term ‘schema’ will be used to refer to specific cases involving previous experience in that situation as well as general cases involving unfamiliar objects set in a familiar kind of situation. Schemas involve somewhat complex but well-established internal representations that enable a person to respond imemdiately in a particular situation [1, 2, 3, 4, 5, 6, 7, 8, 11, 14]. It is often the case that a person may have difficulty in explaining why he or she acted automatically in a particular situation, which is evidence that the internal representation is so well established and so automated that little or no conscious thought is devoted to retrieving and activating the schema [9, 10]. With regard to reflecting on one’s assumptions in a deliberative reasoning process, when schemas are involved it is sometimes a challenge to bring all relevant assumptions into consideration. It should be obvious that a schema necessarily involves a simplification of the actual situation in which it is invoked [13, 14, 16, 17]. Only a few key aspects of the situation are needed to activate a schema, such as a host or hostess at the front of the restaurant for seating or a receipt left inside a holder on a tray for payment.

Many problems do not lend themselves to resolution based solely on schema and well-established prior experience. According to cognitive psychologists [33, 43, 44], humans have another way to resolve unfamiliar and puzzling problems – namely by creating internal models of the situation and using those internal representations to think through to a solution. These models are created just when needed and are typically called mental models [43, 44, 94]. Mental models are generated to represent the perceived structure of a puzzling or new phenomenon. These mental models are not and could not be replicas of the world. Like schema, a mental model is necessarily a simplification. Such simplifications are useful in helping a person understand an unfamiliar situation or puzzling phenomenon. Recognizing relevant aspects of the problematic situation are critical for the development of useful mental models; this will be taken up again in a subsequent section involving the implications of internal representations for the design of effective learning and problem-solving support.

Mental models and schemas are internal constructions that enable a person to confront a problem or situation and act in a reasonably appropriate manner [3, 93, 94, 95]. Neither mental models nor schema are directly observed. However, one can elicit a representation of a mental model, and with perhaps more effort, a representation of a schema. These re-representations are often useful in diagnosing miscues and misunderstandings and can be useful in helping a person develop expertise. Such re-representations form the basis for formative feedback and motivational/volitional support in a framework we call model-faclitated learning [75].

To conclude this section on mental models and schemas, it is worth noting that these two categories of internal representations are related and interact in many problem solving situations. A person confronts a problem or situation and creates one or more internal representations to respond to the situation. Domain-specific prior knowledge, established schemas and newly created mental models may all be brought to bear in this process of understanding the problem at hand. The main purpose of this process is to create a causal explanation of the puzzling problem or phenomenon. As Kant [51] noted *in The Critique of Pure Reason*, it is natural and unavoidable for people to think in terms of cause and effect, just as space and time are added to our experience of the world. The reasoning process of invoking schemas and integrating newly constructed mental models fits well with Piaget's [83] epistemology. When a schema is invoked and a newly constructed mental model can be fit easily within that schema, one might say that assimilation has occurred. When no existing schema is found to help resolve the situation, a newly constructed mental model might be said to lead to a process of accommodation, which involves a refinement of an existing schema. One might also introduce the notion of an internal cognitive structure which is akin to a repository of schemas. Humans are generally very good at modeling their experiences. We can anticipate new states of affairs and predict likely outcomes of existing states of affairs with relative ease, thanks to our ability to create and manipulate internal representations (mental models and schemas). Figure 2 is a representation of how mental models and schemas might interact over time as a person builds competence and expertise.

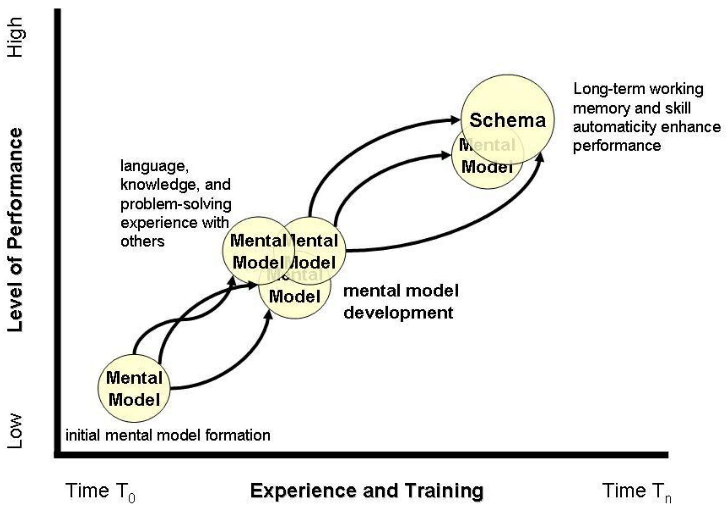

Fig. 2. Mental models, schemas, and expertise development

Figure 2 suggests that over time, mental models are constructed and become associated with other mental models and eventually with schemas, which may be modified in order to take into account what has been learned from activation of the mental models and schemas. Based on this view of human reasoning processes it is possible to discuss implicaitons for learning and instruction as the basis for a general model-based framework to integrate external models into learning, performance support, formative feedback, motivational support, and instruction. The general strategy is to elicit representations of internal models and then provide appropriate support, based in part on a comparison with models elicted from highly experienced problem solvers [84].

It is possible to distinguish two different kinds of mental models: *perceptual models* and *thought models* [102]. Glaser, Lesgold, and Lajoie [31] and Johnson-Laird [43] consider perceptual models to be *appearance* or *structural models* that are used to represent an external reality. This kind of model serves to mediate between internal visual images and external representations in the form of statements, whereas *thought models* also include qualitative processes and inductions which support the construction of artifacts to represent complexity and causal relationships. In any case, the point here is that there is an interaction between the construction of internal models and external representations of those models; that interaction will be taken up in the framework to be presented subsequently [29, 30, 33, 74, 75].

3. Implications for Learning and Instruction

Researchers are typically familiar with and concerned about ecological validity, which is the degree to which an experimental situation reflects a naturally occurring real-world situation. Instructional designers have a related principle that suggests that primary instruction and practice should involve problems and situations that closely resemble problems and situations that are likely to be encountered subsequent to instruction. Instruction itself as well as research designs should have a high degree of ecological validity. With regard to instruction, understanding how people process information and reason about problems is a critical aspect of instructional ecological validity. Instruction that ignores how people process information and reason about problems is less likely to be effective [2, 31, 48, 74]. Many examples can be cited to support this basic instructional design principle. The limitations of working memory are well established. When an instructional system or learning environment violates those limitations by presenting too much information all at once with too little learning support, cognitive overload results, learning outcomes become suboptimal, and many learners become frustrated [104] The major implication from the previous discussion for learning and instruction, therefore, is that mental models and schemas should be taken into account when designing instruction and implementing support for learning and performance.

While this implication for designing learning support may seem obvious to many, there is the subsequent challenge to be more specific about all that is implied in such a principle. How can learning designs take into account the hidden processes of constructing mental models, activating schemas, and developing ever more useful and productive internal representations? If one is only concerned about performance and learning outcomes, then perhaps such questions are not a pressing concern. However, if one believes that the development of robust and flexible internal representations is critical for the development of competence and expertise, then such questions become a foundation concern for instructional design, which is what is being proposed in this paper.

When learners are in an instructional situation, they will naturally be engaged in activating schemas and constructing mental models. Another way to think about the implications for the design of effective instruction is through the lens of cognitive efficiency, which can be defined as the optimal effort required to solve a problem correctly or perform a task in a satisfactory manner [39]. The notion of cognitive efficiency involves a tradeoff between time, resources and desired outcomes. There are three primary measures of cognitive efficiency: instructional efficiency, processing efficiency, and outcomes efficiency [39]. The first and third are already familiar to most instructional designers who are concerned that learners achieve acceptable performance in a reasonable amount of time. Processign efficiency is most directly related to the reasoning processes discussed previously and clearly influences both instructional and outcomes efficiency. Measures of cognitive efficiency and the means to enhance it are well known to instructional designers. There are two factors that have yet to be fully explored in the research literature on cognitive efficiency and instructional design research: (1) individual differences that impact internal cognitive processes, and (2) how cognitive efficiency improvements and other instructional design principles can be effectively applied to situations involving complex and ill-structured problem-solving tasks. These considerations are likely to be imporant challenges for future research (see the last section of this paper).

While there is much that is unknown and difficult to determine with regard to how individuals process information, solve problems, and develop competence in reasoning about challenging situations, some initial steps have been taken. First, instruction should be centered around meaningful and realistic problems [48, 67, 74]. Second, the analysis of problems and tasks reveal that there are different kinds, which require different kinds of learning support [45, 46, 47, 48]. Third, representations of internal mental models and schemas can be used explicitly to support learning [84, 98]. Fourth, when learners are struggling, there are often wrong-head beliefs (e.g., “I did not inherit the math gene”), motivational issues (e.g., “this lesson is terribly boring”), and volitional challenges (e.g., “while I would like to stay and understand this material, I would also like to take a break and go see a movie” [57]. Models play a central role in representing all of these aspects involved in a learning situation.

Before presenting a general framework to support model-based reasoning, a discussion of the different kinds of models that might be used in alignment with internal models is relevant. Just as there are different kinds of internal representations, there are a variety of different kinds of external representations or models. External models come in many forms. Some are mathematical in nature, such as a regression model. Some are graphical, such as a schematic drawing. Some are in the form of arguments with premises and a conclusion. Some models involve video or animation depicting how a device works. Some involve a combination of different forms of representation. Which are effective when, for whom, and why?

One temptation is to think at the level of learning styles and preferences based on a belief that those individual differences are key factors in learning effectiveness. Certainly learning styles and preferences are often relevant, but they do not reach a level that aligns easily with how a person processes information. Some learners may say that they are visual learners, for example. They may even have some evidence for such a claim. However, this does not resolve the issue of which visual models will be easily aligned with a particular learner's internal representations and, as a consequence, be likely to help that learner with particular content to be learned. On the other hand, visual learners are likely to respond well to visually oriented motivational and volitional messages [55].

An established approach to support learning in complex domains is to have a general sense of common problems encountered for different tasks. A cognitive task analysis can be a start along these lines, and cognitive task analysis has proven useful for the design of instruction. Those who have implemented intelligent tutoring systems have developed libraries of commonly encountered mistakes and misunderstandings that can be used to inform an instructional decision such as selecting an appropriate learning activity or providing targeted feedback [84, 100]. Dörner [21, 22] reports that those confronting complex and ill-structured problems experience a number of challenges: (a) a failure to grasp the full breadth of a problem situation with a tendency to focus on just one component or familiar aspect of the problem, (b) the inability to reason effectively about non-linear relationships among different aspects of the problem, and (c) difficulty in understanding and predicting delayed effects and the accumulation of effects over time.

In addition, one can elicit a learner's representation or conceptualization of the problem space (a re-representation of mental models and schemas) and use that to assess of progress of learning (e.g., indicate how well it matches an expert's representation), provide formative feedback (e.g., suggest missing factors or relationships among problem components), and support motivation and volition (e.g., display successful application in a situation likely to be meaningful to the learner) [57,75, 84, 100].

The question of whether and how designers and instructors can influence model-building activities in learners is a core educational concern [52]. According to Johnson-Laird [44] and other authors there are several sources of mental models: (1) the learner's ability to construct models in an inductive manner; (2) everyday observations of the outside world combined with the adaptation of familiar and generally recognized models; and (3) the explanations, representations and examples provided by others. All of these sources are relevant for model-based instruction. In the framework we propose, the learner should be encouraged to construct an initial model and reflect on that model based on his/her prior experience and with feedback from peers (#1). In addition, a reference model should be constructed based on an instructor's or an expert's knowledge and, along with models of other students, the reference model can be used to encourage targeted reflective analysis (#2 and #3).

According to Carlson [12], it is possible to design instruction to involve the learner in a process of inquiry in which facts are gathered from data sources, similarities and differences among facts are noted, and concepts developed. In this process, the instructional program serves as a facilitator of learning for students who are working to develop their own answers to questions. On the other hand, instructional programs can present clearly defined concepts followed by clear examples, including a generalized reference model. A designed conceptual model may be presented ahead of the learning tasks in order to direct the learner's comprehension of the learning material. More generally, we can distinguish between different paradigms of model-oriented instruction depending on whether they aim at (a) self-organized discovery and exploratory learning, (b) guided discovery learning, or (c) learning oriented toward the imitation of an expert's behavior or the adaptation of teachers' explanations.

In the next section, a framework that integrates aspects of all three of these approaches into a general framework will be presented. This framework should be considered provisional. Research to explore this and other possibilities will conclude the discussion.

4. A Framework for Integrating Models in Learning and Instruction

A well-established instructional design framework that has wide applicability is cognitive apprenticeship [15]. The cognitive apprenticeship model involves six different methods and the notion that learners new to a domain require more support than more experienced learners. The six methods are: (a) modeling (e.g., show how an experience person solves the problem), (b) coaching (e.g., observe performance and provide timely and constructive feedback), (c) scaffolding (e.g., implementing explicit support to facilitate learners' problem solving), (d) articulation (e.g., getting learners to talk about how they are thinking about solving a problem), (e) reflection (e.g., encouraging learners to compare their solution with that of others), and (f) exploration (e.g., allowing learners to investigate new problems and problem approaches on their own with little or no guidance).

The cognitive apprenticeship model is consistent with Gagné's nine events of instruction (a claim with which some will disagree) as well as with Merrill's

[74] first principles of instruction, just as the relatively new notion of cognitive efficiency is consistent with a great deal of traditional instructional design. Essentially, cognitive apprenticehship can be characterized as a significant and explicit cognitive extensive of earlier instructional design models. What is really new and only recently emerging is the recognition that it is important to take into account how individuals think and feel about complex problems and process information in the course of solving problems. In any case, there is a great deal of evidence that cognitive apprenticeship is a useful instructional design model [15]. The next step is to refine that model to explicitly account for internal reasoning processes.

Model-facilitated learning (MFL) is an instructional design approach aimed explicitly at promoting model-based reasoning. MFL builds on cognitive apprenticeship [15] and Merrill's [74] first principles. MFL is centered around and facilitated by models in the form of expert and student representations of a problem or problem space, a solution approach, and/or a solution. The models may or may not be created by learners, but learner interaction with models is generally an integral aspect of learning activities.

The particular area for which model facilitated learning was designed involves complex and challenging learning tasks and problem-solving situations. Complex learning tasks tend to have many interacting components, some of which may be incompletely defined, and with some non-linear relationships and delayed interactions among the various components [21, 22, 103]. Such problems occur in economic forecasting, engineering design, environmental planning, management decision making and in many other every day problem-solving situations. Using models of complex phenomena to help learners gain a holistic and meaningful sense of the problem is one aspect of model facilitated learning. Having learners engage in modeling activities to gain insight into the complexity of a problem situation is a second aspect of MFL. MFL assumes three stages of learning development and has associated instructional guidelines for each stage [75]. The first stage is problem orientation in which problems or related sets of problems are presented to learners and learners are asked to solve relatively simple versions. The second stage of learner development involves inquiry exploration in which learners are challenged to explore a complex task domain and asked to identify and elaborate the relationships among the various components of the problem. The third stage of learner development involves policy development in which learners are asked to reason in a more global and holistic with regard to rules and heuristics to guide decision making with regard to various problem situations that may arise in that task domain. Principles to guide the elaboration of learning activities and instructional sequences within these stages include such notions as (a) situating the learning experience in the context of meaningful and realistic problems [74], (b) presenting problems of increasing complexity, involving learners in a sequence of related tasks involving the initial problem scenario [106], (c) involving learning in an increasingly set of complex inquiries and explorations with regard to the problem situation, and (d) challenging learners to develop rules and guidelines to guide decision making in anticipated problematic situations.

The foundations for model facilitated learning are derived from system dynamics [103], educational and learning psychology [67, 101], and from instructional design [74]. In addition, MFL adopts the principle of graduated complexity [75] in the form of guidance for the elaboration of instructional sequences. Graduated complexity in MFL is implemented consistent with cognitive apprenticeship methods [15]. According to the principle of graduated complexity, instructional sequences should progressively challenge learners to:

1. Characterize the representative behavior of a complex system, indicating how it behaves over time – guided discovery learning.
2. Identify a desired outcome and key variables and points of leverage with respect attaining that outcome – exploratory learning.
3. Identify and explain alternative causes for observed phenomena – deliberation in the context of problem solving.
4. Reflect on how the system and associated variables seem to change over time and through interventions; this challenge requires perceptual processing but the critical aspect is the ability to focus on key problem components and how they change over time and with intervention; this is also consistent with the reflection method in cognitive apprenticeship – reflective reasoning.
5. Develop a rationale to explain complex phenomena in terms of an underlying system stucture, including decision-making and policy formulation guidelines; this challenge is aligned with both articulation and reflection in the cognitive apprenticeship model – a high level of reflective reasoning.
6. Broaden understanding through diverse and new problem situations; this challenge addresses near and far transfer of learning, is consistent with Gagné's (1985) ninth event of instruction as well as with the exploration method in cognitive apprenticeship – more experiential learning.

In addition to making use of elicited representations of problems to support graduated complexity with an MFL context, models are also useful in designing and implementing virtual change agents [57]. Specifically, elicited models, combined with an analysis of the problem as perceived by experienced and successfuol problem solvers, can indicate particular meanings and causes introduced into the problem situation by the learner that may not be productive in finding a solution and that may well lead a learner to lose interest or quit working on the problem. For example, an elicited student's model may reveal a feeling of confusion due to having encountered a problem far beyond that student's perceived capacity (e.g., "I am embarrased to say that do not see how to perform the steps to reach the goal"), or a student may reveal in the course of creating an external model frustration or other distractors (e.g., "I wish the system would just tell me what to do next"), or perhaps a student's model may include emotional descriptors for some factors revealing feelings that could impede progress (e.g., "the stupid bureaucracy makes it difficult to see how to get from point A to point B in this problem"). In summary, the ability to identify relevant motivational and volitional factors is just as important as identifying problem missteps and miscues in the course of providing timely, informative, and meaningful feedback to students.

5. Further Research

The ability to solve complex problems depends in large part on the ability of individuals to overcome motivational and emotional resistance to explore a challenging problem situation and then construct productive mental models and activate relevant schemas. Mental models are useful in identifying individual resistance to problems and explaining puzzling phenomena and complex systems, especially in terms of cause and effect [35, 93]. Those who are confronting challenging problems are likely to avoid the problem (which can be detected and addressed through the use of external representations) or else construct mental models in order to provide explanations for the new or unusual phenomena. Greeno [33] suggested that productive mental models should be encouraged along with the significant properties of external situations and appropriate interactions; this principle has strong implicaitons for the design of learning and instruction. Moreover, such a principle is consistent with a constructivist approach to learning that suggests that the learning environment should serve as an information resource which can be used by a learner to focus on relevant aspects of a problem and activate relevant schemas and prior knowledge. Learning activities are, consequently, required that enable learners to explore and interact with the learning environment in a meaningful, problem-centered context. Consistent with cognitive apprenticeship and model-facilitated learning, support and scaffolding should be provided to help problem solvers to be successful and develop both competence and confidence [53, 59]. This general approach can also be found in what is currently being called *learning by design* [50, 62]. Additionally, Kirschner and colleagues [60] and Mayer [73] have argued that minimal guidance during instruction, especially with learners new to a problem-solving domain, is not effective. Consistent with cognitive apprenticeship and model-facilitated learning, explicit coaching and overt learning support should be provided to those inexperienced in the domain.

What is not known or well established is how best to support the development of expertise and insight with regard to complex, problem solving activities in specific problem domains. How well instruction created in accordance with the principles of MFL works in terms of developing competence and expdertise, especially in comparison with other instructional methodologies, has not been established. Which kinds of models (student-created, expert-created, partially complete, etc.) are effective with different learners and learning tasks is also not well known, nor is it well known how external models align with internal models in specific problem solving situations. In addition, the efficacy of using model representations to identify and address motivational, volitional and emotional issues has not been sufficiently explored in the research literature.

While versions of MFL have been implemented and evaluated in the first two stages indicated above (problem orientation and inquiry exploration), very few MFL environments exist to promote learning at the last stage of learner development (policy development). As a result, research on effective MFL techniques to promote policy development knowledge remains very open for further research and development, and additional research is needed in the first two stages as well. Additionally, effective MFL instructional sequences for complex problem task domains is not very well established. A central underlying problem concerns the need for well-developed means to assess the progressive development of student understanding in complex task domains. This requires validated means to elicit and evaluate student generated models in response to a wide variety of problem types and scenarios, yet those means are still in the early stages of development. Finally, integrating external models of various kinds and aligned those with individually generated internal models remains an important area open for further exploration.

References

1. Al-Diban, S., & Seel, N. M. (1999). Evaluation als Forschungsaufgabe von Instruktionsdesign – Dargestellt am Beispiel eines multimedialen Lehrprogramms. *Unterrichtswissenschaft*, *27* (1), 29-60.
2. Anderson, J. R. (1983). *The architecture of cognition*. Cambridge, MA: Harvard University Press.
3. Anzai, Y., & Yokoyama, T. (1984). Internal models in physics problem solving. *Cognition and Instruction*, *1*, 397-450.
4. Bartlett, F. C. (1932). *Remembering: A study in experimental and social psychology*. Cambridge, UK: Cambridge University Press.
5. Bhatta, S. R., & Goel, A. (1997). Learning generic mechanisms for innovative strategies in adaptive design. *The Journal of the Learning Sciences*, *6* (4), 367-396.
6. Braine, M. D. S. (1990). The natural logic approach to reasoning. In W.Overton (Ed.), Reasoning, necessity, and logic: Developmental perspectives (pp. 133-157). Hillsdale, NJ. Lawrence Erlbaum Assoc.
7. Braine, M. D. S., & O'Brien, D. P. (Eds.) (1998). *Mental logic*. Mahwah, NJ: Lawrence Erlbaum Assoc.
8. Briggs, P. (1990). The role of the user model in learning as an internally and externally directed activity. In D. Ackermann, & M.J. Tauber (Eds.), *Mental models and human-computer interaction 1* (pp. 195-208). Amsterdam: Elsevier Publ.
9. Brown, D. E., & Clement, J. (1989). Overcoming misconceptions via analogical reasoning: abstract transfer versus explanatory model construction. *Instructional Science*, *18*, 237-261.
10. Bruner, J. S. (1966). *Toward a theory of instruction*. Cambridge, MA: Harvard University Press.
11. Buckley, B. C., & Boulter, C. J. (1999). Analysis of representation in model-based teaching and learning in science. In R. Paton & I. Neilsen (Eds.), *Visual representations and interpretations*. (pp. 289-294). London: Springer.
12. Carlson, H. L. (1991). Learning style and program design in interactive multimedia. *Educational Technology Research and Development*, *39* (3), 41-48.
13. Casey, C. (1996). Incorporating cognitive apprenticeship in multi-media. *Educational Technology Research and Development*, *44* (1), 71-84.
14. Cheng, P. W., & Holyoak, K.J. (1985). Pragmatic reasoning schemas. *Cognitive Psychology, 17*, 391-426.

15.Collins, A., Brown, J.S. & Newman, S.E. (1989). Cognitive apprenticeship: Teaching the crafts of reading, writing, and mathematics. In L.B. Resnick (Ed.) (1989), *Knowing, learning, and instruction* (pp. 453-494). Hillsdale, NJ: Erlbaum.
*16.*Cornelissen, J. P. (2006). Making Sense of Theory Construction: Metaphor and Disciplined Imagination *Organization Studies, 27, 1579 - 1597.*
17.Darabi, A.A., Nelson, D.W., & Seel, N.M. (i.pr.). A dynamic mental model approach to examine schema development of a troubleshooting skill: Delayed retention of mental models as a test of schema development. *Technology, Instruction, Cognition, and Learning*.
18.Dewey, J. (1910). How we think. New York: D. C. Heath.
19.Doerr, H.M. (1996). Integrating the study of trigonometry, vectors, and force through modeling. *School Science and Mathematics*, *96* (8), 407-418.
20.Dole, J.A., & Sinatra, G.M. (1998). Reconceptualizing change in the cognitive construction of knowledge. *Educational Psychologist*, *33* (2/3), 109-128.
21.Dörner, D. (1976). *Problemlösen als Informationsverarbeitung*. Stuttgart: Kohlhammer.
22.Dörner, D., & Wearing, A. (1995). Complex problem solving: Toward a (computer-simulated) theory. In P. A. Frensch & J. Funke (Eds.), *Complex problem solving: The European Perspective* (pp. 65-99). Hillsdale, NJ: Lawrence Erlbaum Associates.
23.Evans, J.St.B.T. (1982). *The psychology of deductive reasoning*. London: Routledge.
24.Farnham-Diggory, S. (1972). Cognitive processes in education: A psychological preparation for teaching and curriculum development. New York: Harper & Row.
25.Friedman, M. (2002). Kuhn, and the rationality of scienc. *Philosophy of Science*, *69*, 171-190.
26.Funke, J. & Frensch, P. A. (1995). Complex problem solving research in North America and Europe: An integrative review. *Foreign Psychology, 5*, 42-47.
27.Funke, J. (1991). Solving complex problems: Exploration and control of complex systems. In R.J. Sternberg & P.A. Frensch (Eds.), *Complex problem solving: Principles and mechanisms* (pp.185-222). Hillsdale, NJ: Lawrence Erlbaum.
28.Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. Cognitive Science, 7, 155-170.
29.Gibbons, A.S. (2001). Model-centered instruction. *Journal of Structural Learning and Intelligent Systems*, *14* (4), 511-540.
30.Gibbons, A.S. (2003). Model-centered learning and instruction: Comments on Seel (2003). *Technology, Instruction, Cognition and Learning*, *1* (3), 291-299.
31.Glaser, R., Lesgold, A., & Lajoie, S. (1987). Toward a cognitive theory for the measurement of achievement. In R.R. Ronning, J. Glover, J.C. Conoley, & J.C. Witt (Eds.), *The influence of cognitive psychology on testing and measurement* (pp. 41-85). Hillsdale, NJ: Lawrence Erlbaum.
32.Gravemeijer, K., Cobb, P., Bowers, J., & Whitenack, J. (2000). Symbolizing, modeling, and instructional design. In P. Cobb, E. Yackel & K. McClain (Eds.), *Symbolizing and communicating in mathematics classrooms. Perspectices on discourse, tools, and instructional design* (pp. 225-273). Mahwah, NJ: Erlbaum.
33.Greeno, J. G. (1989). Situations, mental models, and generative knowledge. In D. Klahr & K. Kotovsky (Eds.), *Complex information processing* (pp. 285-318). Hillsdale, NJ: Lawrence Erlbaum.
34.Haberlant, K. (1999), *Human memory.,* Boston: Allyn & Bacon.
35.Hale, C.R., & Barsalou, L.W. (1995). Explanation content and construction during system learning and troubleshooting. *The Journal of the Learning Sciences*, *4* (4), 385-436.

36.Hambrick, D., & Engle, R. (2003). The role of working memory in problem solving. In J. Davidson & R. Sternberg (Eds.), *The psychology of problem solving* (pp. 176-206). NY: Cambridge University Press.
37.Hammer, D. (1997). Discovery learning and discovery teaching. *Cognition and Instruction*, *15* (4), 485-529.
38.Heidegger, M. (1968). *What is called thinking?* [Tr. J. G. Gray]. New York: Harper & Row.
39.Hoffman, B., & Schraw, G. (2010). Conceptions of efficiency: Applications in learning and problem solving. *Educational Psychologist*, *45*, 1-10.
40.Hofstadter, D., & Sander, E. (2010). The essence of thought, New York: Basic Books.
41.Ifenthaler, D., & Seel, N.M. (2005). The measurement of change: Learning-dependent progression of mental models. *Technology, Instruction, Cognition, and Learning*, *2* (4), 321-340.
42.Jacobson, M.J. (2000). Problem solving about complex Systems: differences between experts and novices. In B. Fishman & S. O'Connor-Divelbiss (Eds.), *Fourth International Conference of the Learning Sciences* (pp. 14-21). Mahwah, NJ: Erlbaum.
43.Johnson-Laird, P.N. (1983). Mental models. Towards a cognitive science of language, inference, and consciousness. Cambridge: Cambridge University Press.
44.Johnson-Laird, P.N. (1989). Mental models. In M.I. Posner (Ed.), *Foundations of cognitive science* (pp. 469-499). Cambridge, MA:The MIT Press.
45.Jonassen, D. H. (2004). *Learning to solve problems: An instructional design guide*. San Francisco, CA: Jossey-Bass.
46.Jonassen, D. H. (2006). *Modeling with technology: Mindtools for conceptual change*. Columbus, OH: Merrill/Prentice-Hall.
47.Jonassen, D. H. (2007). *Learning to solve complex, scientific problems*. Mahway, NJ: Erlbaum.
48.Jonassen, D. H. (2011). Learning to solve problems: A handbook for designing problem-solving learning environments. New York: Routledge.
49.Jonassen, D. H., & Kim, B. (2010). Arguing to learn and learning to argue: Design justifications and guidelines. *Educational Technology Research & Development, 58*(4), 439-457.
50.Kafai, Y.B., & Ching, C.C. (2004). Children as instructional designers: Apprenticing, questioning, and evaluating ine the Learning Science by Design project. In N.M. Seel & S. Dijkstra, S. (Eds.). *Curriculum, Plans and Processes of Instructional Design: International Perspectives* (pp. 115-130). Mahwah, NJ: Lawrence Erlbaum.
51.Kant, I. (1781, 2009). *The critique of pure reason* [Tr. J. M. D. Meiklejohn]. Adelaide, Australia: The University of Adelaide eBooks.
52.Karplus, R. (1969). *Introductory physics: A model approach*. New York: Benjamins.
53.Keller, J. M. (2010). Motivational design for learning and performance: The ARCS model approach. New York: Springer.
54.Kim, C. (2012a). Beliefs about learning. In N. M. Seel (Ed.), *Encyclopedia of the sciences of learning* (pp.450-452). Dordrecht: Springer.
55.Kim, C. (2012b. Virtual change agents. In N. M. Seel (Ed.), *Encyclopedia of the sciences of learning* (pp. 3405-3407). Dordrecht: Springer.
56.Kim, C. (2012c). Motivational variables in learning. In N. M. Seel (Ed.), *Encyclopedia of the sciences of learning* (2347-2348). Dordrecht: Springer.
57.Kim C. (in press). The role of affective and motivational factors in designing personalized learning environments. *Eduational Technology Research & Development*.

58.Kim, C., & Balaam, M. (2011). Monitoring affective and motivational aspects of learning experience with the Subtle Stone. *Proceedings of the 11th IEEE International Conference on Advanced Learning Technologies (ICALT)* (pp.640-641). Athens, GA: IEEE Computer Society Publications.
59.Kim, C., Keller, J. M., & Baylor, A. L. (2007, December). Effects of motivational and volitional messages on attitudes toward engineering: Comparing text messages with animated messages delivered by a pedagogical agent. Proceedings of the IADIS International Conference CELDA, Algarve, Portugal.
60.Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, and problem-based, experiential, and inquiry-based teaching. *Educational Psychologist*, *41*, 75-86.
61.Kluwe, R.H., & Haider, H. (1990). Modelle zur internen Repräsentation komplexer technischer Systeme. *Sprache & Kognition*, *9* (4), 173-192.
62.Kolodner, J.L., Camp, P.J., Crismond, D., Fasse, B., Gray, J., Holbrook, J., & Ryan, M. (2004). Promoting deep science learning through case-based reasoning: Rituals and practices in Learning by Design classrooms. In N.M. Seel & S. Dijkstra, S. (Eds.). *Curriculum, Plans and Processes of Instructional Design: International Perspectives* (pp. 89-114). Mahwah, NJ: Lawrence Erlbaum.
63.Krems, J. F. (1995). Cognitive flexibility and complex problem solving. In P.A. Frensch & J. Funke (Eds.), *Complex problem solving. The European perspective* (pp. 201-218). Hillsdale, NJ: Lawrence Erlbaum.
64.Kurtz, K. J., Miao, C. H., & Gentner, D. (2001). Learning by analogical bootstrapping. *Journal of the Learning Sciences, 10*, 417-446.
65.Lakoff, G., & M. Johnson (1980). *Metaphors we live by*. Chicago: University of Chicago Press.
66.Lakoff, G., a& M. Johnson (1999). Philosophy in the flesh: The embodied mind and its challenge to western thought. New York: Basic Books.
67.Lave, J., & Wenger, E. (1990). *Situated learning: Legitimate peripheral participation*, Cambridge, UK: Cambridge University Press.
68.Lesh, R., & Doerr, H.M. (Eds.) (2003). Beyond constructivism. Models and modelling perspectives on mathematics problem solving, learning, and teaching. Mahwah, NJ: Lawrence Erlbaum.
69.Markman, A.B. (1998). *Knowledge representation*. Mahwah, NJ: Erlbaum.
70.Mayer, R. E., & Wittrock, M. C. (2006). Problem solving. *In* P. A. Alexander & P. Winne (Eds.), Handbook of educational psychology (2nd ed., *pp. 287-304).* Mahwah, NJ: Lawrence Erlbaum Associates Publishers.
71.Mayer, R. E., Mathias, A., & Wetzell, K. (2002). Fostering understanding of multimedia messages through pre-training: Evidence for a two-stage theory of mental model construction. *Journal of Experimental Psychology: Applied*, *8*, 147-154.
72.Mayer, R.E. (1989). Models for understanding. *Review of Educational Research*, *59* (1), 43-64.
73.Mayer, R.E. (2004). Should there be a three-strikes rule against pure discovery learning? The case for guided methods of instruction. *American Psychologist, 59* (1), 14-19.
74.Merrill, M. D, (2002). First principles of instructional design. *Educational Technology Research & Development, 50*(3), 43-59.
75.Milrad, M., Spector, J. M., & Davidsen, P. I. (2003). Model Facilitated Learning. In S. Naidu (Ed.), *Learning and teaching with technology: Principles and practices* (pp. 13-27). London: Kogan Page.

76.Motah , M. (2006), *The Ontogeny of Memory and* Learning. In Proceedings of 2006 IS Conference. p.p 221-231.
77.Motah, M. (2007), *Learning, Types of Learning, Traditional Learning Styles.* In Proceedings of the 2007 CSITEd Conference.
78.Nair, K.U., & Ramnarayan, S. (2000). Individual differences in need for cognition and complex problem solving. *Journal of Research in Personality, 34* (3), 305-328.
79.Neubauer, A. C. & Fink, A. (2009). Intelligence and neural efficiency. *Neuroscience and Biobehavioral Reviews*, *33*, 1004-1023.
80.Norman, D.A. (1983). Some observations on mental models. In D. Gentner & A.L. Stevens (Eds.), *Mental models* (pp. 7-14). Hillsdale, NJ: Erlbaum.
81.Oaksford, M., & Chater, N. (1996). Rational explanation of the selection task. *Psychological Review, 103* (2), 381-391.
82.Penner, D. E. (2001). Cognition, computers, and synthetic science: Building knowledge and meaning through modeling. *Review of Research in Education*, *25*, 1-35.
83.Piaget, J. (1951). *The psychology of intelligence*. London: Routledge and Kegan Paul.
84.Pirnay-Dummer, P., Ifenthaler, D., & Spector, J. M. (2010). Highly integrated model assessment technology and tools*. Educational Technology Research & Development, 58*(1), 3-18.
85.Quine, W. V. O., & Ullian, J. S. (1978). *The web of belief* (2nd ed.). New York, NY: Random House.
86.Resnick, M., & Wilensky, U. (1998). Diving into complexity: Developing probabilistic decentralized thinking through role-playing activities. *The Journal of Learning Sciences*, *7*(2), 153-172.
87.Rips, L. J. (1984). Reasoning as a central ability. In R. J. Sternberg (Ed.), Advances in the psychology of human intelligence (Vol. 2, pp. 105-147). Hillsdale, NJ. Erlbaum.
88.Rumelhart, D. D. (1980). Schemata: The building bloack of cognition. In R. J. Spiro, B. C. Bruce, & W. F. Brewer (Eds.), *Theoretical issues in reading comprehension* (pp. 33-58). Hillsdale, NJ: Erlbaum.
89.Rumelhart, D. E., Smolensky, P., McClelland, J. L., & Hinton, G. E. (1986). Schemata and sequential thought processes in PDP models. In J. L. McClelland, D. E. Rumelhart, & The PDP research group (Eds.), *Parallel distributed processing. Explorations in the microstructure of cognition. Volume 2: Psychological and biological models* (pp. 7-57). Cambridge, MA: MIT Press.
90.Schank, R. C., & Abelson, R. (1977). *Scripts, plans, goals, and understanding*. Hillsdale, NJ: Earlbaum Assoc.
91.Schauble, L. (1996). The development of scientific reasoning in knowledge-rich contexts. *Developmental Psychology*, *32* (1), 102-119.
92.Schraw, G. (2006). Knowledge: Structures and processes. In P. A. Alexander & P. Winne (Eds.), *Handbook of Educational Psychology* (2nd ed.), (pp. 245-264). Mahwah, NJ: Erlbaum.
93.Seel, N. M. (1999). Educational diagnosis of mental models: Assessment problems and technology-based solutions. *Journal of Structural Learning and Intelligent Systems*, *14* (2), 153-185.
94.Seel, N. M. (2003). Model-centered Learning and Instruction. *Technology, Instruction, Cognition, and Learning*, *1* (1), 59-85.
95.Seel, N. M. (2005). Designing Model-Centered Learning Environments: Hocus-pocus – Or the Focus Must Strictly Be on Locus. In J.M. Spector, C. Ohrazda, A. Van Schaak & D.A. Wiley (Eds.), *Innovations in Instructional Technology: Essays in Honor of M. David Merrill* (pp. 65-90). Mahwah, NJ: Lawrence Erlbaum.

96.Seel, N. M., Al-Diban, S., & Blumschein, P. (2000). Mental models and instructional planning. In M. Spector & T.M. Anderson (Eds.), *Integrated and holistic perspectives on learning, instruction and technology: Understanding complexity* (pp. 129-158). Dordrecht, NL: Kluwer Academic Publishers.
97.Spector, J. M. (2001). A philosophy of instructional design for the 21st century? *Journal of Structural learning and Intelligent Systems, 14*(4), 307-318.
98.Spector, J. M. (2010). Mental representations and their analysis: An epistemological perspective. In D. Ifenthaler, P. Pirnay-dummer, & N. M. Seel (Eds.), *Computer-based diagnostics and systematic analysis of knowledge* (17-40). New York, NY: Springer.
99.Spector, J. M. (2012). Naturalistic epistemology. In N. M. Seel (Ed.) *The encyclopedia of the sciences of learning* (pp. 2433-2435). New York. Springer.
100.Spector, J. M., & Koszalka, T. A. (2004). *The DEEP methodology for assessing learning in complex domains* (Final report to the National Science Foundation Evaluative Research and Evaluation Capacity Building). Syracuse, NY: Syracuse University.
101.Spiro, R. J., Coulson, R. L., Feltovich, P. J., & Anderson, D. (1988). Cognitive flexibility theory: Advanced knowledge acquisition in ill-structured domains. In V. Patel (Ed.), *Proceedings of the 10th Annual Conference of the Cognitive Science Society* (pp. 375-383). Mahwah, NJ: Erlbaum.
102.Stachowiak, H. (1973). *Allgemeine Modelltheorie*. Wien: Springer.
103.Sterman, J. D. (1994). Learning in and about complex systems. *Systems Dynamics Review 10*, (2-3), 291-330.
104.Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12,* 257-285.
105.Turner, R.M. (1994). *Adaptive reasoning for real-world problems: A schema-based approach*. Hillsdale, NJ: Lawrence Erlbaum Associates.
106.van Merriënboer, J. J. G., & Kirschner P. (2007). Ten steps to complex learning: A systematic approach to four-component instructional design theory. New York: Routledge.
107.Volet, S. E. (1991). Modelling and coaching of relevant, metacognitive strategies for enhancing university students´ learning. *Learning and Instruction*, *1* (4), 319-336.
108.Wertheimer, M. (1959). *Productive thinking* (Enlarged ed.). New York: Harper & Row.
109.White, B. (1993). ThinkerTools: Causal models, conceptual change, and science education. *Cognition and Instruction*, *10* (1), 1-100.
110.Wittgenstein, L. (1922). *Tractatus logico-philosophicus* (translated by C. K. Ogden). London, UK: Routledge & Kegan Paul.
111.Wittgenstein, L. (1953). *Philosophical investigations* (translated by G. E. M. Anscombe). Oxford, UK: Blackwell.
112.Young, R. (1983). Surrogates and mappings: Two kinds of conceptual models for interactive devices. In D. Gentner & A.L. Stevens (Eds.), *Mental models* (pp. 35-52). Hillsdale, NJ: Erlbaum.

J. Michael Spector is Professor and Chair of Learning Technologies in the College of Information at the University of North Texas. He was previously Professor of Educational Psychology and Instructional Technology, Doctoral Program Coordinator for the Learning, Design, and Technology Program, and a Research Scientist at the Learning and Performance Support Laboratory at

the University of Georgia (2009-2011). Previously, he was Associate Director of the Learning Systems Institute, Professor of Instructional Systems, and Principal Investigator for the International Center for Learning, Education and Performance Systems at Florida State University (2004-2008). He served as Chair of Instructional Design, Development and Evaluation at Syracuse University (2000-2004) and Director of the Educational Information Science and Technology Research Program at the University of Bergen (1996-1999). He is a distinguished graduate of the United States Air Force Academy and earned a Ph.D. in Philosophy from The University of Texas at Austin (1978). His recent research is in the areas of intelligent support for instructional design, system dynamics based learning environments, assessing learning in complex domains, distance learning, and technology integration in education. Dr. Spector served on the International Board of Standards for Training, Performance and Instruction (ibstpi) as Executive Vice President; he is on the Executive Committee of the IEEE Learning Technology Technical Committee, is a Past President of the Association for Educational and Communications Technology (AECT) as well as a Past Chair of the Technology, Instruction, Cognition and Learning Special Interest Group of the American Educational Research Association. He is the editor (10th year as editor) of the Development Section of Educational Technology Research & Development, and he serves on numerous other editorial boards. He co-edited the third edition of the Handbook of Research on Educational Communications and Technology, is again lead editor on the fourth edition, and has more than 100 journal articles, book chapters and books to his credit. Dr. Spector is active in international educational technology developments and was the Conference Co-Chair and Local Organizer for the 2011 IEEE International Conference on Advanced Learning Technologies held at UGA 6-8 July.

Dr. ChanMin Kim is an Assistant Professor of Educational Psychology and Instructional Technology at the University of Georgia, in the United States. Her research agenda involves promoting learners' motivation and volition throughout the implementation of a virtual change agent in online learning environments.

Received: December 26, 2011; Accepted: January 23, 2012.