# Model Building for Conceptual Change: Using Computers as Cognitive Tools

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**SUMMARY**

Conceptual change is among the most popular, contemporary theories for describing meaningful learning. Different theories of conceptual change describe the reorganization of conceptual frameworks that results from different forms of activity. I argue that learners' mental models or personal theories resulting from conceptual change are most acutely affected by model-based reasoning. Further, model-based reasoning is fostered by learner construction of qualitative and quantitative models of the content or phenomena they are studying using technology-based modeling tools. Model building is a powerful strategy for engaging, supporting, and assessing conceptual change in learners because these models scaffold and externalize internal, mental models by providing multiple formalisms for representing conceptual understanding and change. Building models of domain content, problems, systems, experiences, or thinking processes using different representational formalisms represent different kinds of conceptual understanding that foster different kinds of conceptual change.

**KEYWORDS:** model-based reasoning, conceptual change, cognitive tools, knowledge representation

## INTRODUCTION

The cognitive-constructivist and situated learning movements of the previous decade have focused the attention of educators on sense making and other conceptions of meaningful learning. Among the myriad definitions of meaningful learning, different research communities (psychology, learning sciences, science and mathematics education) have recently focused attention on the role of conceptual change in meaningful learning (Limon & Mason, 2002; Schnotz, Vosniadou, & Carretero, 1999; Sinatra & Pintrich, 2003). Conceptual change has become one of the most common conceptions of meaningful learning, because it treats learning as an intentional, dynamic, and constructive process that encompasses developmental differences among learners. "Conceptual change is the mechanism underlying meaningful learning" (Mayer, 2002, p. 101). From an early age, humans naturally build simplified and intuitive personal theories to explain their world. Through experience and reflection, they reorganize and add conceptual complexity as they learn, manifesting strength, coherence, and commitment to their existing conceptions. Children and adults interact with new information to the degree that the information is comprehensible, coherent, plausible, and rhetorically compelling according to their existing conceptual models. The cognitive process of adapting and restructuring these theories is conceptual change (Vosniadou, 1999).

Conceptual change occurs when learners change their understanding of concepts they use and the conceptual frameworks that encompass them. However, those change processes vary with content and context, and so there are multiple theoretical perspectives on conceptual change. For some researchers (Smith, diSessa, & Resnick, 1993; Siegler, 1996), conceptual change is an evolutionary process of conceptual aggrandizement and gradual transformation of knowledge states. This model of conceptual change is Piagetian, where learners gradually accommodate existing knowledge into more coherent and well-organized knowledge structures. In this kind of evolutionary conceptual change, novices gradually shift toward experts (Carey, 1985).

In this paper, I argue that the most powerful method for engaging, fostering, and assessing conceptual change is the construction of qualitative and semi-quantitative models that represent their conceptual understanding of what learners are studying. The process of constructing and revising models mimics the cognitive processes described in the theories of conceptual change.

## WHY MODEL? MODEL-BASED REASONING

Science and mathematics educators (Confrey & Doerr, 1994; Frederiksen & White, 1998; Lehrer & Schauble, 2000, 2003; White, 1993) have long recognized the importance of modeling in understanding scientific and mathematical phenomena. Using and building models of phenomena is referred to as model-based reasoning (MBR).

What are models? Lesh and Doerr (2003) claim that models are conceptual systems consisting of elements, relations, operations, and rules governing interactions that are expressed using external notation systems and that are used to construct, describe, or explain the behavior of other systems. These models are in the minds of learners and also embodied in the equations diagrams, computer programs and other representational media used by learners to represent their understanding. There are models in the mind (mental models) and there are models in the world of the world. The relationship between internal and external models s not well understood. Our belief is that there is a dynamic and reciprocal relationship between internal mental models and the external models that students construct. The mental models provide the basis for external models. The external models in turn constrain and regulate internal models, providing the means for conceptual change. In this paper, we argue for the construction of models using different technology-based modeling tools, because each tool imposes a different set of structural or rhetorical constraints that enable student to tune their internal models. What kinds of models are used in MBR?

As with conceptual change, there are numerous conceptions. Harris (1999) describes three kinds of models: theoretical models, experimental models, and data models. Theoretical models are abstract representations, while experimental models are designed to test the theoretical models. They are more specific than theoretical, including directives for action; specifications of the size of sample populations; definitions of experimental variables and test statistics; and measures for comparing hypotheses and observed values. Their purpose is to predict or specify the kind of data that we are looking for and to specify analytical techniques for linking data to questions. Data models are sets of data manipulated by scientists so are different from raw data. Giere (1999) describes several kinds of models, including representational models (the central function of models used in science), abstract models (mathematical models), hypotheses, and theoretical models (abstract models constructed with theoretical principles, such as Newton's Laws). Lehrer and Schauble (2003) describe a continuum of model types including physical models, representational systems (grounded in resemblance between the model and the world), syntactic models (summarizing essential functioning of system), and hypothetical-deductive models (formal abstractions). Whatever they are, models must be qualitatively, functionally, or formally similar to the real objects under study (Yu, 2002).

Models can be used in a variety of ways. Hestenes (1986) proposed a modeling process for physics learning that includes four stages: describing the basic and derived variables in some diagrammatic form; formulating the relationships based on the laws of physics (writing equations; drawing ramifications of the model; and empirically validating the ramified model. For Hestenes, “the model is the message” (p. 446), that is, “mathematical modeling should be the central theme of physics instruction”(p. 453). In physics, the primary goal of modeling is the prediction of the performance of physical systems.

The primary purpose of modeling, from our perspective, is the construction and revision of conceptual understanding, that is, conceptual change. Building explicit models of conceptual understanding externalizes mental models and fosters conceptual change. The multiple formalisms afforded by different modeling tools enable learners to construct syntactically different models. Comparing and contrasting those models is an essential process in deeper understanding. Other essential characteristics of models include separation of model and its referent, assessment of the fit of the model to its referent, the conventionalization of the external representations used in the model, and the incorporation of models into disciplinary practice (Lehrer & Schauble, 2003). Perhaps the most important characteristic that Lehrer and Schauble cite is the evaluation of competing alternative models, that is, the comparison of two or more models for their relative fit to the world. Comparing and evaluating models requires understanding that alternative models are possible and that the activity of modeling can be used for testing rival models. That process is at the heart of conceptual change.

Historically, much of the modeling research has focused on mathematization as the primary modeling formalism. Representing phenomena in formulas is perhaps the most succinct and exact form of modeling. However, most contemporary researchers argue that qualitative models are just as important as quantitative. Qualitative representation is a missing link in novice problem solving (Chi, Feltovich, Glaser, 1981; Larkin, 1983). When students try to understand a problem in only one way, especially when that way conveys no conceptual information about the problem, students do not understand the underlying systems they are working in. So, it is necessary to help learners to construct a qualitative representation of the problem as well as a quantitative. Qualitative problem representations both constrain and facilitate the construction of quantitative representations (Ploetzner & Spada, 1998).

Modeling is fundamental to human cognition and scientific inquiry (Schwarz & White, in press). Modeling helps learners to express and externalize their thinking; visualize and test components of their theories; and make materials more interesting. Models function as epistemic resources (Morrison & Morgan, 1999). We must first understand what we can demonstrate in the model before we can ask questions about the real system. Modeling is an important method for engaging conceptual change (Nersessian, 1999).

**Model Construction vs. Model Use**

We learn from models (model-based reasoning) by building them and using them (Morgan, 1999). Learning from building models involves finding out what elements fit together in order to represent the theory or the world or both. Modeling requires making certain choices, and it is in these choices that the learning process lies. Morgan believes that we can also learn from using models, however, that depends on the extent to which we can transfer the things we learn from manipulating the model to our theory or the real world. “We do not learn much from looking at a model — we learn a lot more from building the model and from manipulating it.” (Morrison & Morgan, 1999, pp. 11-12). We learn from models by constructing models and from manipulating and experimenting with those models.

Despite the cognitive benefits from building models, technology-based learning environments more often exemplify model-using. Models are commonly used as the intellectual engine in so much software. Most intelligent tutoring systems possess learner models, expert or domain models, and tutoring models. Model-based reasoning focuses on an explicit model of the physical systems that is being learned (deKoning & Bredweg, 2001). Models also provide the intellectual engine in microworlds, such as Geometric Supposer, SimCalc, and others. In microworlds, the model is implicit in the exploratory options provided by the software, but the model is not explicitly demonstrated. More importantly, the model is immutable. Not only do learners have no access to the model, but also they cannot change it, except to manipulate a set of pre-selected variables within the model. Learners will interact with these black-box systems and infer the propositions embedded in the model in order to test hypotheses. Research shows that interacting with model-based environments does result in development and change of mental models (Frederiksen & White, 1998; Mellar, Bliss, Boohan, Ogborn, & Tompsett, 1994; White, 1993).

Why is model building so much more productive of learning and conceptual change than model using? When solving a problem or answering a complex conceptual question, learners must construct a mental model of the phenomena and use that model as the basis for prediction, inference, speculation, or experimentation. Constructing a physical, analogical, or computational model of the world reifies the learner's mental model. One reason that constructed models are so powerful is because of their intellectual autonomy. Models are autonomous because they are independent of theories and the world, which allows them to function as tools or instruments of investigation (a tool or instrument is independent of the thing it operates on) (Morrison & Morgan, 1999). Models mediate between theories and world, allowing us to learn about one or the other. Therefore, the form of model-based reasoning that I promote in this paper refers to student construction, manipulation, and testing of their own technology-mediated models. Rather than providing a black box model that learners manipulate in an attempt to induce the underlying model, the most effective way of engaging, supporting, and assessing conceptual change is by building and comparing models that represent incommensurate conceptual systems.

## WHAT CAN BE MODELED

If model building externalizes mental models, then learners should learn to use a variety of tools to model a variety of phenomena. Different models engage different formalisms for thinking (Jonassen, 2000). In this section, we describe the range of phenomena that can be modeled using different modeling tools. Most of these models are what Lehrer and Schauble (2000) refer to as syntactic models. These are formal models, each of which imposes a different syntax on the learner that conveys a relational correspondence between the model and the phenomena it is representing. The purpose of syntactic models is to summarize the essential function of the system being represented.

### Modeling Domain Knowledge

The primary use of modeling has been in the math and science domains. Middle school and high school students use computer-based modeling tools, such as semantic networking or concept mapping tools, systems modeling tools, or other qualitative modeling tools, to construct their models of domain knowledge. For example, Figure 1 illustrates a single frame of an extensive semantic network on plants. As students study domain content in a course, semantic networking tools provides them a semantic structure for representing their domain knowledge. Comparing your semantic network with others often results in conceptual change as students see how other models represent and structure the same ideas.

Students can use a wide range of tools to construct models. In each of these models, students are representing domain principles that they are studying. Figure 2 illustrates a simulation of the generation and growth of a pathogen, bacillus, produced using a spreadsheet program. The simulation model was produced by students in the context of a food product development course. Fresh food products are always susceptible pathogen growth, so it was necessary to understand the generation process and any impediments in order to determine the feasibility of introducing new fresh food products. Spreadsheets enable the explicit representation of mathematical models that are used to generate visualizations of the models.

### Modeling Problems

In order to transfer problem-solving skills, problems solvers need to construct some sort of internal representation (mental model) of a problem (problem space). These personal problem representations serve a number of functions (Savelsbergh, de Jong, & Ferguson-Hessler (1998):

- To guide further interpretation of information about the problem,
- To simulate the behavior of the system based on knowledge about the properties of the system, and
- To associate with and trigger a particular solution schema (procedure).

Problem spaces are mentally constructed by selecting and mapping specific relations of the problem (McGuinness, 1986). The underlying assumption of this paper is that using modeling tools to create physical, visual, or computational models externalizes learners' conceptual models. Related to problem solving, constructing visual and computational models of problems externalizes learners' internal problem spaces. Constructing models of problem spaces is important for all kinds of problems. As the complexity of the problem increases, producing efficient representations becomes more important; and efficiency of representations is a function of organization, integration, or coherence (McGuinness, 1986).

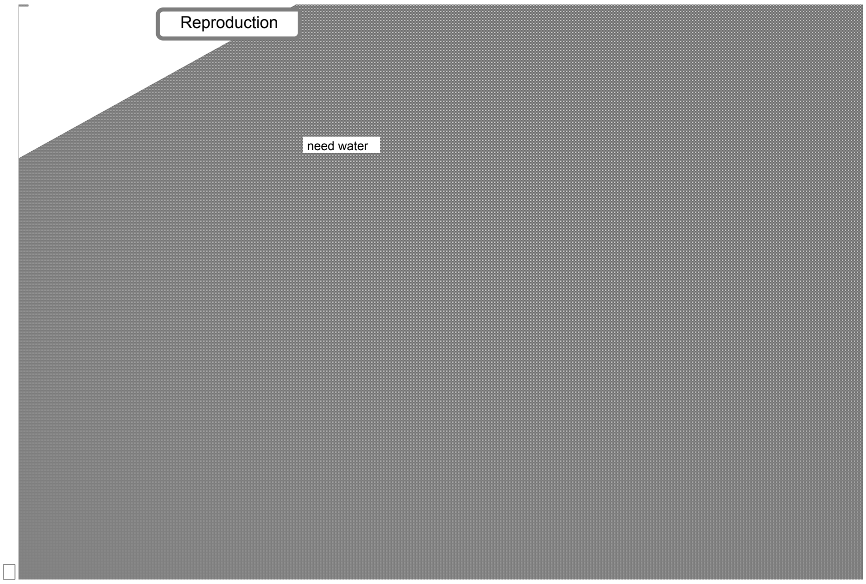


*Figure 1*. One frame of a semantic network on plants.

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*Figure 2*. Spreadsheet simulation of pathogen generation

Although many computer-based modeling tools support the construction of quantitative models of problems, constructing qualitative models of problems is equally, if not more, important. Qualitative representations assume many different forms and organizations. They may be spatial or verbal, and they may be organized in many different ways. Qualitative representations are more physical than numerical. Physical representations of problems consist of entities that are embedded in particular domains (e.g. physics), and the inferential rules that connect them and give them meaning are qualitative (Larkin, 1983).

In fact, Ploetzner, Fehse, Kneser, and Spada (1999) showed that when solving physics problems, qualitative problem representations are necessary prerequisites to learning quantitative representations. When students try to understand a problem in only one way, they do not understand the underlying systems they are working in. Qualitative representations support the solution of quantitative problems. The best problem solutions may result from the integration of qualitative and quantitative models. That integration is best supported in systems modeling tools, such as Stella, that provide quantitative representations of the relations between problem components expressed qualitatively. Figure 3 illustrates a Stella model of a stoichiometry problem, providing both quantitative and qualitative representations of the problem.

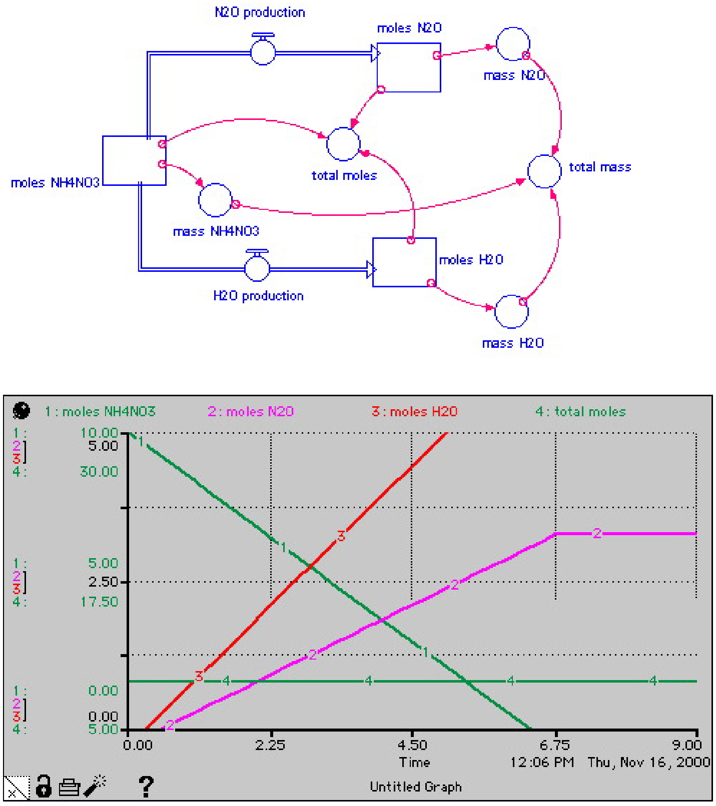


*Figure 3*. Systems dynamics model of stoichiometry problem in Stella.

Identifying the problem and discerning important and unimportant factors in order to solve problems are two key skills separating expert problem solvers from novices. Our mental models of the problem have two influences in problem solving. The first is determining what the problem is and determining possible solutions for the problem. Problem solvers often try to identify the single cause or the single problem in order to fix it. Good problem solving starts with the acceptance that there are not only multiple solutions to one problem, but that there is not one problem, and that most ill-structured problems consist of a multitude of interrelated problems that need better understanding before one can start talking about solutions.

The second is determining possible solutions for the problem. Conceptual understanding of ill-structured problems requires conceptual change. Problems tend to be different than how they appeared first and underlying assumptions need to be stated very clearly. In modeling the problem space information and assumptions are made explicit. In this process the problem space will go through a series of changes and the map of the space will have been changed. In this process, the discrepancies of the mental model get exploited. Extrapolating on a previous theme, we suggest that perhaps mental models are not built in the mind. Rather the mind assimilates what previously externalized in the construction of external models using culturally accepted modeling tools.

## Modeling Systems

Another way of thinking about subject matter content is as systems. Rather than focusing on discrete facts or characteristics of phenomena, when learners study content as systems, they develop a more integrated view of the world. There are several, related systemic conceptions of the world, including open systems thinking, human or social systems thinking,

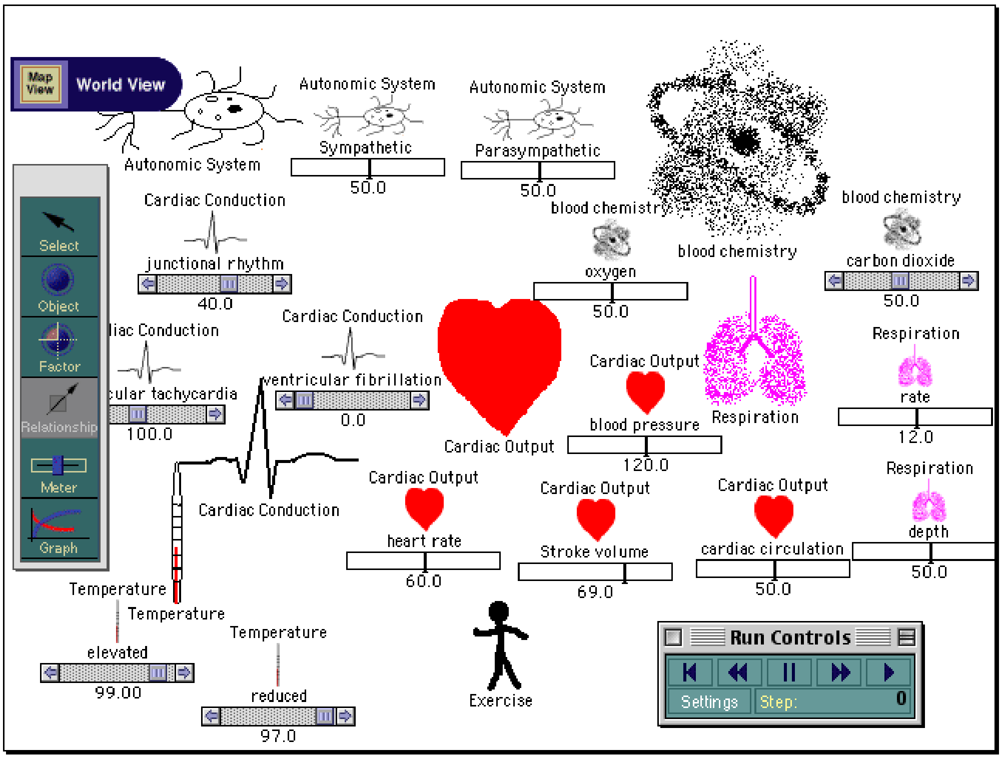


Figure 4. Modeling the circulatory system with Model-It.

process systems, feedback systems thinking, systems dynamics, control systems or cybernetics, activity theory, and the most common living systems. All of these conceptions share similar attributes, including irreducible wholes, self-
producing pattern of organization determined by dynamic interactions among components, interdependent parts, goal-driven, feedback controlled, self-maintaining, self- regulating, synergetic, and teleological. Requiring learners to organize what they are leaning into relevant systems that interact with each other provides learners with a much more holistic as well as integrated view of the world. Systems are representations in form of clusters (distinct sub-systems) that have their own features, attributes, and relationships. Systems and subsystems consist of causal relationships. Humans tend get overwhelmed even with less complex systems. To perceive, understand, and predict change of

conditions, inputs, and outcomes over time is very difficult and requires a lot of working memory. That can be one reason why our understanding of systems is often naïve and lead by many pre- and misconceptions. Computational models allow us to focus on facets of the model without loosing the picture.

There are a variety of computer-based tools for modeling systems. Based on systems dynamics, tools like Stella, PowerSim, and VenSim provide sophisticated tools for modeling systems. These tools enable learners to construct systems models of phenomena using hypothetical-deductive reasoning. Students must construct the models before testing them. Figure 4 illustrates a systemic view of the circulatory system constructed with Model-It, a simplified systems modeling tool developed by the HI-CE group at the University of Michigan for junior high school students. This tool scaffolds the identification of relationships among variables. Rather than entering formulae to describe relationships, students must identify the direction of the relationship and the potential effect of one variable on another.

Another class of tool enables learner to inductively construct models of systems. Microworlds such as StarLogo, AgentSheets, and Eco-Beaker enable learners to construct rules about the nature of the behavior in systems and to immediately test the effects of those rules.

These models can be examined, so they function as external sources for internal conceptual conflicts. System models represent our conceptions. Contradictions and unexplainable behavior of the system is directly related to our conceptions and less from external data.

## Modeling Experiences (Stories)

Stories are the oldest and most natural form of sense making. Stories are the "means [by] which human beings give meaning to their experience of temporality and personal actions" (Polkinghorne, 1988, p. 11). Cultures have been conveyed most often through different types of stories, including myths, fairy tales, documentaries, and histories. Humans appear to have an innate ability and predisposition to organize and represent their experiences in the form of stories. One reason for that proclivity is that stories require less cognitive effort because of the narrative form of framing experience (Bruner, 1990). To be part of a culture, it is necessary to be connected to the stories that abound in that culture (Bruner, 1990). Telling stories is a primary means for negotiating meanings (Bruner, 1990; Lodge, 1990; Witherell, 1995), and they assist us in understanding human action, intentionality and temporality (Bruner, 1990; Huberman, 1995). Perhaps more importantly, stories help us to articulate our identity (Polkinghorne, 1988; Schafer, 1981).

Stories can function as a substitute for direct experience. If we assume that we learn from experiences, then we should also be able to learn from stories of experiences. Some people believe that hearing stories is tantamount to experiencing the phenomenon oneself (Ferguson, Bareiss, Birnbaum, & Osgood, 1991). In other words, the memory structures used for understanding the story are the same as those used to carry out the task. Given the lack of previous experiences by novices, experiences available in a case library of stories augments their repertoire of experiences. Reasoning from stories or cases helps us to solve problems.

Stories are a primary medium for learning. Polkinghorne (1988) found that practitioners provide explanations to each other in narrative form. They work with case histories and use narrative explanations to understand why the people they work with behave the way they do" (p. x). Schön's (1993) studied architects, engineers and psychotherapists and found that they encoded their experiences in narrative form by using case histories and narrative explanations. These practitioners offered stories to explain and justify their thinking and actions For these practitioners "storytelling represents and substitutes for firsthand experience" (p. 160). Henning (1996) found that stories afforded technicians a means to form and express their identity as technicians and to assist others in their initiation. By being able to tell stories to their coworkers, technicians, particularly the newer ones, were able to form and strengthen the bonds that give cohesiveness to their community of practice.

The cognitive theory describing how stories are recalled and reused is case-based reasoning (CBR). An encountered problem (the new case) prompts the reasoner to retrieve cases from memory, to reuse the old case (i.e. interpret the new in terms of the old), which suggests a solution (Aamodt & Plaza, 1996). If the suggested solution will not work, then the old and or new cases are revised. When the effectiveness is confirmed, then the learned case is retained for later use. Cases or stories are reminded and retrieved by indexing them to previous cases, that is, what does the current situation have in common with previously stored cases. Stories can be collected in case libraries and indexed by the learners. Cases can be indexed by similarities in the features of the problem situation (goal or intentions to be achieved or constraints), features of the solutions chosen (activities involved, justifications, expectations), or features of the outcomes of the problem situation (successes, expectations violated, repair strategies used) (Kolodner (1993).

Students can support conceptual change by modeling people's experiences, that is, collecting stories about their experiences. Probably the easiest tool for capturing stories in order to model experiences is the database. The database in Figure 5 recounts one of many stories that were collected by students studying the conflict in Northern Ireland. The database contains many stories that have been indexed by topic, theme, context, goal, reasoning, religion, etc. When students analyze stories in order to understand the issues, they better understand the underlying complexity of an phenomenon in terms of the diverse social, cultural, political, and personal perspectives reflected in the stories. Encountering this diversity of beliefs provides anomalous data that entails the need to change ones conceptual models of the world. Learning, from a CBR perspective, is a process of indexing and filing experience-based lessons and re-using those in similar situations in the future. In this example, students learn about the horrors of religious conflict by examining others' experiences.

In order to build case libraries, you must identify cases or stories from practitioners or those with experiences relevant to the phenomenon being studied. Stories may be collected from personal interviews (the most powerful method), surveys, magazines, or news reports. Following their telling of the story, analyze their story with the practitioner to identify the problem goals and expectations, the solution and why it was chosen, the outcomes of the solution, and most importantly, what lessons were learned.

Having collected stories, we must decide what the stories teach us, so the stories must be indexed. These indexes are used to retrieve stories when needed and to compare and contrast experiences and their conceptual frameworks. Databases facilitate this learning process by allowing teachers to search or sort on any field to locate similar cases or results. More powerful retrieval engines are needed for larger, instructive case libraries, however the complexities involved are not justified when learners are creating their own case libraries.

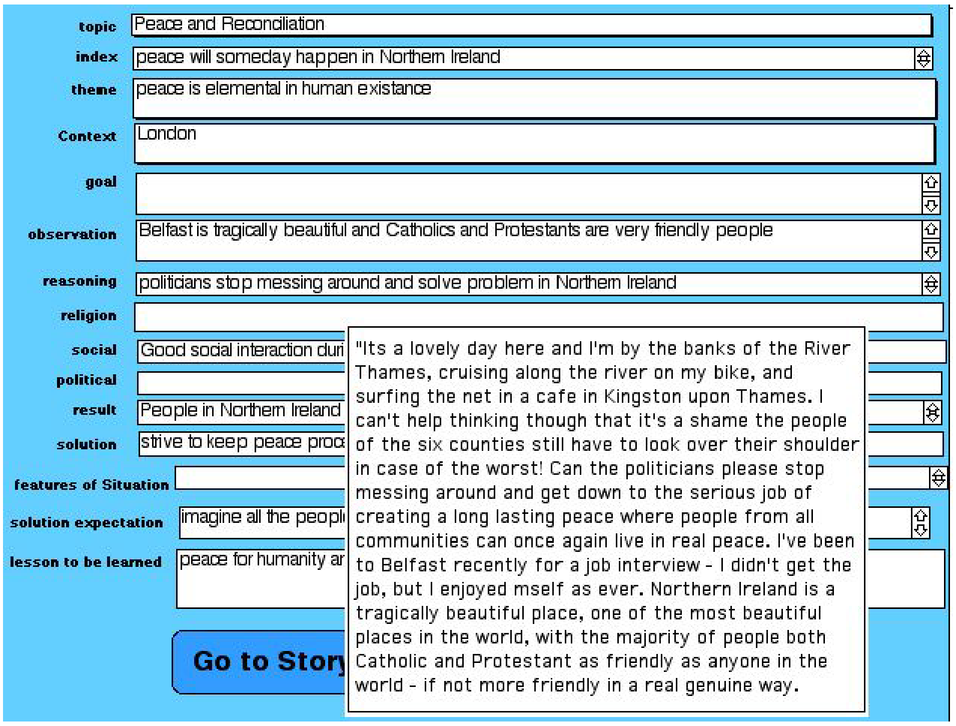


*Figure 5*. Entry in database on Northern Ireland stories.

## Modeling Thinking (Cognitive Simulations)

Another kind of modeling entails developing models of thinking processes. Rather than modeling content or systems, learners model the kind of thinking that they need to perform in order to solve a problem, make a decision, or complete some other task. That is, learners can use computer-based modeling tools to construct cognitive simulations. "Cognitive simulations are runable computer programs that represent models of human cognitive activities" (Roth, Woods, & People, 1992, p. 1163). They attempt to model mental structures and human cognitive processes. "The computer program contains explicit representations of proposed mental processes and knowledge structures" (Kieras, 1990, pp. 51-2). The primary purpose of cognitive simulations is the attempt to reify mental constructs for analysis and theory building, that is, to manifest theories and models of human mental functioning. Therefore, they have obvious implications for studying psychological processes. Rather than studying about cognitive phenomena, constructing simulation models of those phenomena necessarily better support reasoning with the theory rather than learning about the theory. Theories of cognition all rely on constructs that may or may not exist. Cognitive simulations provide a medium for testing those theories in a computational model.

Cognitive simulations were originated by Newell and Simon (1972) during the information processing revolution in psychology. Computers were first being used to represent the way that humans processed information, and developing a runable computer model of those operations seemed to be the most scientific way to operationalize them. Cognitive simulations have always represented the junction of psychology and computer science. They convert a set of vague ideas into a more specific and precise theory (Kieras, 1985). In so doing, simulations also provide detailed theoretical statements that summarize data on human mental functioning (Kieras, 1990).

Another rationale for building cognitive simulations is the metacognition that it engages. Building cognitive simulations is a systematic approach to reflection and introspection, requiring learners to reflect on the cognitive process they use to perform any activity. That reflection engages thinking about thinking, that is, metacognition (Weinstein, 1978). Learning in any domain engages cognition, which can be simulated to articulate the thinking processes involved. Jonassen and Wang (2003) describe the process of constructing a cognitive simulation of metacognitive reasoning using an expert system shell. Students were required to reflect on how they used executive control and comprehension monitoring activities while study for their seminar. Learning by building cognitive simulations is more meaningful because learners evaluate not only their own thinking processes but also the product of those processes.

## ASSESSING CONCEPTUAL CHANGE WITH STUDENT-CONSTRUCTED MODELS

Although the theoretical accounts of conceptual change are replete (Limon & Mason, 2002; Schnotz, Vosniadou, & Carreter, 1999; Sinatra & Pintrich, 2003), there is very little literature that addresses how to effectively assess conceptual change. The dominant methods that are used include analyzing student protocols while engaged in problem solving activities (Hogan & Fisherkeller, 2000), structured interviews (Southerland, Smith, & Cummins, 2000), and the use of concept maps (Edmundson, 2000). The analysis of interview and conversation protocols is very difficult and time-consuming and is plagued with reliability problems. Throughout this paper, we have argued that the models that students construct while representing domain knowledge, systems, problems, experiences, and thought processes can be used to assess conceptual change. So, how do these models reflect conceptual change.

Thagard (1992) provides perhaps the best rubrics for assessing conceptual change in models in the form of explanatory coherence. Different kinds of explanatory coherence can be used to analyze models, including deductive coherence (logical consistency and entailment among members of set of propositions), probabilistic coherence (probability assignments), and semantic (similar meanings among propositions). Within models, assessors would look for symmetry, explanatory value, appropriate analogies, contradictions, competition among propositions, and acceptability of propositions. Extensive work is needed to operationalize these or any other criteria for assessing conceptual change in models.

## REFERENCES

Aamodt, A. & Plaza, E. (1996). Case-based reasoning: Foundational issues, methodological variations, and system approaches. *Artificial Intelligence Communications, 7* (1).

Bruner, J. (1990). *Acts of Meaning*. Cambridge: Harvard University Press.

Carey, S. (1985). *Conceptual change in childhood*. Cambridge, MA: MIT Press.

Chi, M.T.H., Feltovich, P.J., & Glaser,R. (1981). Categorization and representation of physics problems y experts and novices. *Cognitive Science, 5*, 121-152.

Confrey, J., & Doerr, H. M. (1994). Student modelers. *Interactive Learning Environments, 4* (3), 199-217.

DeKonig, K., & Bredwg, B. (2001). Exploting model-based reasoning in educational systems: illuminating the learer modeling problem. In K.D. Forbus & P.J. Feltovich (Eds.), *Smart machines in education* (pp. 299-3330). Menlo Park, CA: AAAI Press.

Edmundson, K.M. (2000). Assessing science understanding through concept maps. In J.J. Mintzes, J.H. Wandersee, J.D. Novak (Eds.), *Assessing science understanding: A human constructivist view* (pp. 19-40). San Diego: Academic Press.

Frederiksen, J. R., White, B. Y. (1998). Teaching and learning generic modeling and reasoning skills. *Journal of Interactive Learning Environments, 55,* 33-51.

Giere, R.N. (1999). Using models to represent reality. In L. Magnani, N.J. Nersessian, & P. Thagard (Eds.), *Model-based reasoning in scientific discovery*. New York: Kluwer Academic/Plenum Publishers.

Harris, T (1999). A hierarchy of model and electron microscopy. In L. Magnani, N.J. Nersessian, & P. Thagard (Eds.), *Models are used to represent reality.* . New York: Kluwer Academic/Plenum Publishers.

Hogan, K., & Fisherkeller, J. (2000). Dialogue as data: Assessing students' scientific reasoning with interactive protocols. In J.J. Mintzes, J.H. Wandersee, J.D. Novak (Eds.), *Assessing science understanding: A human constructivist view* (pp. 96-129). San Diego: Academic Press.

Huberman, M. (1995). Working with Life-History Narratives. In H. McEwan & K. Egan. (Eds.) *Narrative in Teaching, Learning, and Research*. NY:Teachers College Press.

Jonassen, D.H. (2000). *Computers as Mindtools for schools: Engaging critical thinking*. Columbus, OH: Merrill/Prentice-Hall.

Jonassen, D.H., & Wang, S. (2003) Using expert systems to build cognitive simulations. *Journal of Educational Computing Research*.

Kieras, D. (1985). The why, when, and how of cognitive simulation: A tutorial. *Behavior Research Methods, Instruments, & Computers, 17*(2), 279-285.

Kieras, D. (1990). The role of cognitive simulation models in the development of advanced training and testing systems. In N. Frederickson, R. Glaser, A. Lesgold, & M. G. Shafto (Eds.), *Diagnostic monitoring of skill and knowledge acquisition*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Kolodner, J. (1993). *Case-based reasoning*. New York: Morgan Kaufman.

Larkin, J.H. (1983). The role of problem representation in physics. In D. Gentner & A.L. Stevens (Eds.). *Mental models* (pp. 75-98). Hillsdale, NJ: Lawrence Erlbaum Associates.

Lehrer, R., & Schauble, L. (2000). Modeling in mathematics and science. In R. Glaser (Ed.) *Advances in instructional psychology: volume 5. Educational design and cognitive science* (pp. 101-159). New Jersey: Lawrence Erlbaum.

Lehrer, R., & Schauble, L. (2003). Origins and evolution of model-based reasoning in mathematics and science. In R. Lesh & H.M. Doerr (Eds.), *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, teaching, and learning* (pp. 59- 70). Mahwah, NJ: Lawrence Erlbaum Associates.

Lesh, R. Doerr, H.M. (2003). Foundations of a models and modeling perspective on mathematics teaching, learning, and problem solving. In R. Lesh & H.M. Doerr (Eds.), *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, teaching, and learning* (pp. 3- 33). Mahwah, NJ: Lawrence Erlbaum Associates.

Limon, M., & Mason, L. (2002). Reconsidering conceptual change: Issues in theory and practice. Amsterdam: Kluwer.

Lodge, D. (1990). Narration With Words. In H. Barlow, C. Blakemore & M. Weston-Smith. (Eds.) *Images and Understanding*. Cambridge, UL: Cambridge University Press.

Mayer, R.E. (2002). Understanding conceptual change: A commentary. In M. Limon & L. Mason (Eds.), *Reconsidering conceptual change: Issues in theory and practice* (pp. 101-111). Dordrecht: Kluwer Acadmic Publisher.

McGuinness, C. (1986). Problem representation: The effects of spatial arrays. *Memory & Cognition, 14*(3), 270-280.

Mellar, H., Bliss, J., Boohan, R., Ogborn, J., & Tompsett, C. (1994). *Learning with artificial worlds: Computer-based modeling in the curriculum*. London: Falmer Press.

Morgan, M.S. (1999). Learning from models. In M.S. Morgan & M . Morrison (Eds.), *Models as mediators: Perspectives on natural and social science* (pp. 347-388). Cambridge: Cambridge University Press.

Morrison, M., & Morgan, M.S. (1999). Models as mediating instruments. In M.S. Morgan & M . Morrison (Eds.), *Models as mediators: Perspectives on natural and social science* (pp. 10-37). Cambridge: Cambridge University Press.

Nersessian, N.J. (1999). Model-based reasoning in conceptual change. In L. Magnani, N.J. Nersessian, & P. Thagard (Eds.), *Models are used to represent reality.* New York: Kluwer Academic/Plenum Publishers.

Newell, A. & Simon, H. A. (1972). *Human problem-solving*. Englewood Cliffs, NJ: Prentice-Hall.

Ploetzner, R., & Spada, H. (1998). Constructing quantitative problem representations on the basis of qualitative reasoning. *Interactive Learning Environments, 5*, 95-107.

Ploetzner, R., Fehse, E., Kneser, C., & Spada, H. (1999). Learning to relate qualitative and quantitative problem representations in a model-based setting for collaborative problem solving. *Journal of the Learning Sciences, 8*(2), 177-214.

Polkinghorne, D. (1988). *Narrative Knowing and the Human Sciences*. Albany: State University of New York Press.

Polson, M.C. & Richardson, J.J. (1988). *Foundations of intelligent tutoring systems.* Hillsdale, NJ: Lawrence

Raghavan, K., & Glaser, R. (1995). Model-Based analysis and reasoning in science: The MARS curriculum. *Science Education, 79* (1), 37-61.

Rips, L.J. (1986). Mental muddles. In M. Brand & R.M. Harnish (Eds.), *The representation of knowledge and beliefs* (pp. 258-286). Tuscon, AZ: University of Arizona Press.

Roth, E. M., Woods, D. D., & People, H. E. (1992). Cognitive simulation as a tools for cognitive task analysis. *Ergonomics, 35*(10), 1163-1198.

Schafer, R. (1981). Narration in the Psychoanalytic Dialogue. In W. J. T. Mitchell. (Ed.) *On Narrative*. Chicago: University of Chicago Press.

Schnotz, W., Vosniadou, S. & Carretero (1999). New perspectives in conceptual change. Amsterdam: Pergamom.

Schwarz, C.V., & White, B.Y. (in press). Developing a model-centered approach to science education. *Journal of Research in Science Teaching*.

Schön, D.A. (1993). *The Reflective Practitioner – How Professionals Think in Action*. New York: Basic Books.

Siegler, R.S. (1996). *Emerging minds: The process of change in children's thinking*. New York: Oxford University Press.

Sinatra, G.M, & Pintrich, P.R. (2003). The role of intentions in conceptual change learning. In G.M. Sinatra, & P.R. Pintrich (Eds.), *Intentional conceptual change*. Mahwah, NJ: Lawrence Erlbaum Associates.

Smith, J.P., di Sessa, A.A., Roschelle, J. (193). Misconceptions reconceived: A constructivist analysis of knowledge in transition. *Journal of Learning Sciences, 3*, 115-163.

Southerland, S.A., Smith, M.U., & Cummins, C.L. (200). "What do you mean by that?": Using structured interviews to assess science understanding. In J.J. Mintzes, J.H. Wandersee, J.D. Novak (Eds.), *Assessing science understanding: A human constructivist view* (pp. 72-95). San Diego: Academic Press.

Thagard, P. (1992). *Conceptual revolutions*. Princeton, NJ: Princeton University Press.

Vosniadou, S. (1994). Capturing and modeling the process of conceptual change. *Learning and Instruction, 4* (1), 45-70.

Vosniadou, S. (1999). Conceptual change research: The state of the art and future directions In W. Schnotz, S. Vosniadou, & M. Carretero (Eds.), *New perspectives on conceptual change* (pp. 1-13). Amsterdam: Pergamon.

White, B., & Frederiksen, J. (1990). Causal Model Progressions as a Foundation for Intelligent Learning Environments. *Artificial Intelligence, 24,* 99-157.

Witherell, C. S. (1995). Narrative Landscapes and the Moral Imagination. In H. McEwan & K. Egan. (Eds.) *Narrative in Teaching, Learning, and Research*. NY: Teachers College Press.

Yu, Q. (2002). Model-based reasoning and similarity in the world. In L. Magnani & N.J. Nersessian (Eds.), *Model-based reasoning: Science, technology, and values*. New York: Kluwer Academic/Plenum Publishers.