# MODEL BUILDING FOR CONCEPTUAL CHANGE

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**Abstract**

Meaningful learning should be the *raison d'etre* of schools and universities. Assuming that, the goal of conferences such as this should be to decide how to best use technology to support meaningful learning, given the constraints that education imposes on learning. I first argue that the best conception of meaningful learning is conceptual change. I then argue that building computer-based models of the ideas and processes that students are studying is the most conceptually engaging technology-based activity possible with the greatest contribution to conceptual change. I demonstrate how a variety of computer-based tools can b used to build models of domain content, problems, systems, and the cognitive processes required to learn (i.e. cognitive simulations).

## Meaningful Learning

There are many conceptions of meaningful learning, including problem solving, critical thinking, collaborative learning, self-regulated learning, creativity, and many others. All of those conceptions assume that meaningful learning occurs when students are intentionally engaged in interacting with the world or representations of it for the purpose of individual knowledge construction and social co-construction of meaning. Unless and until learners willfully try to achieve some cognitive goal, they will not learn meaningfully. Meaningful learning requires engagement in meaningful tasks, those that emerge from, or at least simulate, some authentic context.

Because learning in educational contexts must be assessed, we need a more circumscribed conception of meaningful learning. Emergent learning in everyday and professional contexts often is not assessed or is assessed using only performance indicators (did the job get done, in time, under budget?). It is only in formal education contexts where we assess what learners know, not what they do. What happens to learners when they are willfully engaged in an authentic task? Their theories about the world change. So if we need to assess learning from authentic tasks, we need to be able to assess changes in personal or social theories about the task environment learners are working on.

From a cognitive perspective, I believe that the most powerful and assessable conception of meaningful learning is conceptual change. Conceptual change occurs when learners change their understanding of concepts or conceptual frameworks. Those conceptual frameworks change more rapidly when learners are engaged in some meaningful performance. There are many ways to assess those changes.

The process and pace of conceptual change varies, according to different researchers. For some (Chi, 1992; Thagard, 1992), conceptual change is a revolutionary process where the ways that concepts are understood is replaced by another hopefully better understanding. The change is a radical or dramatic reorganization of knowledge structures (Dole & Sinatra, 1998). Radical change involves a process of categorical reassignment. The learner's ontologies (ways of representing and making sense of the world) are revised, as are the learner's beliefs or theories about how the world works.

For other researchers (Smith, diSessa, & Resnick, 1993; Siegler, 1996), conceptual change is a more evolutionary process of aggrandizement and gradual transformation of knowledge states. This model of conceptual change is more Piagetian, where learners gradually accommodate existing knowledge into better knowledge structures. While it is obvious that learners undergo both kinds of conceptual change, the scope and timing of evolutionary makes it very problematic to assess. Therefore, I will focus on radical conceptual change, a process that occurs over a shorter period of time.

Dole and Sinatra (1998) have proposed a model of conceptual change as the cognitive reconstruction of knowledge. Learners manifest a certain strength, coherence, and commitment to their existing conceptions. They will interact with new information to the degree that the information is comprehensible, coherent, plausible and rhetorically compelling. The degree to which learners interact with new information lies on a continuum from low cognitive engagement to high metacognitive engagement. Low engagement refers to unregulated, surface level processing, while high engagement refers to self-regulated, effortful, analysis and synthesis (deep processing) of information. At the highest level of engagement, according to Dole and Sinatra (1998), learners think deeply about arguments and counterarguments related to the message, resulting in the strongest likelihood of conceptual change. Learners who process information at the highest level of engagement are more epistemically aware than other learners (Jonassen, Marra, & Palmer, in press).

Conceptual change is a function of the level of conceptual engagement. Conceptual engagement describes how enmeshed, enthralled, perturbed, or otherwise interested learners become in trying to figure something out. The harder learners work at a task, the more conceptually engaged they are. I argue that the most conceptually engaging way that computers can be used is to construct models of the phenomena being studied. Model building is engaging because the mental models that people have constructed of phenomena in the world (scientific, social, cultural, political, and even phenomenological) are often naive, uninformed, and often inconsistent with established theories. While developing personal theories and integrating them into mental models may be a natural human process, people are usually not very good at it. Personal theories and mental models are replete with misconceptions and inadequate conceptions. So, building models has the greatest likelihood to result in radical conceptual change, because while building models, learners represent their conceptions or theories about the world, and they can compare, contrast, and test those models relative to others. If learners see better models, or models that produce better results, they are compelled to change their conceptualization.

Science and mathematics educators (Confrey & Doerr, 1994; Frederiksen & White, 1998; Hestenes, 1987; Lehrer & Schauble, 2000; White, 1993) have long recognized the importance of modeling in understanding scientific and mathematical phenomena. I believe that modeling is an essential skill in all disciplines, that is, it is an essential cognitive skill for meaning making in all domains. I also argue that in addition to modeling domain knowledge (the primary focus of math and science education work to date), learners can also benefit from modeling problems (constructing problem spaces), modeling systems, and modeling thinking processes (i.e. cognitive simulations). Why is modeling so important?

What is model building? The conceptions vary with the tools and domains that people study. Most mathematicians and scientists tacitly believe that modeling phenomena is a mathematical process, that quantitative representations are the most explicit and informative. Defining the relationships among variables is the primary goal of modeling. 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).

Other researchers, however, believe 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).

## **Model Construction vs. Consumption**

As stated before, models are quite common in math and science education and are present to a lesser degree in other disciplines. Most science textbooks present a model of some phenomenon for students to comprehend. They follow-up the model with well-structured problems related to those models for learners to solve. This hypothetico-deductive approach to learning is the most common method used in formal education:

teach an abstract theory and maybe require learners to apply the theory in a story problem.

Models are also commonly used as the intellectual engine in many learning software programs. For example, 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). In addition to intelligent tutors, most of the microworlds and other immersive learning environments represent model-based phenomena for learners to manipulate and experiment with. The model is implicit in the system. However, 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.

Modeling in this presentation refers to student representation, construction, manipulation, and testing of a model. I describe how computer-based modeling tools can be used by learners to represent their conceptions and theories of phenomena and to manipulate and test those theories. Constructing computational models of phenomena in the world using computer-based modeling tools can engage students in rapid conceptual change more effectively than any other application of technology.

## What is Being Modeled

If modeling can aid the construction of mental models, then learners should learn to model a variety of phenomena. In this section, I will briefly describe the range of phenomena that can be modeled using different tools. Later, I will briefly describe the nature of some of those 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.

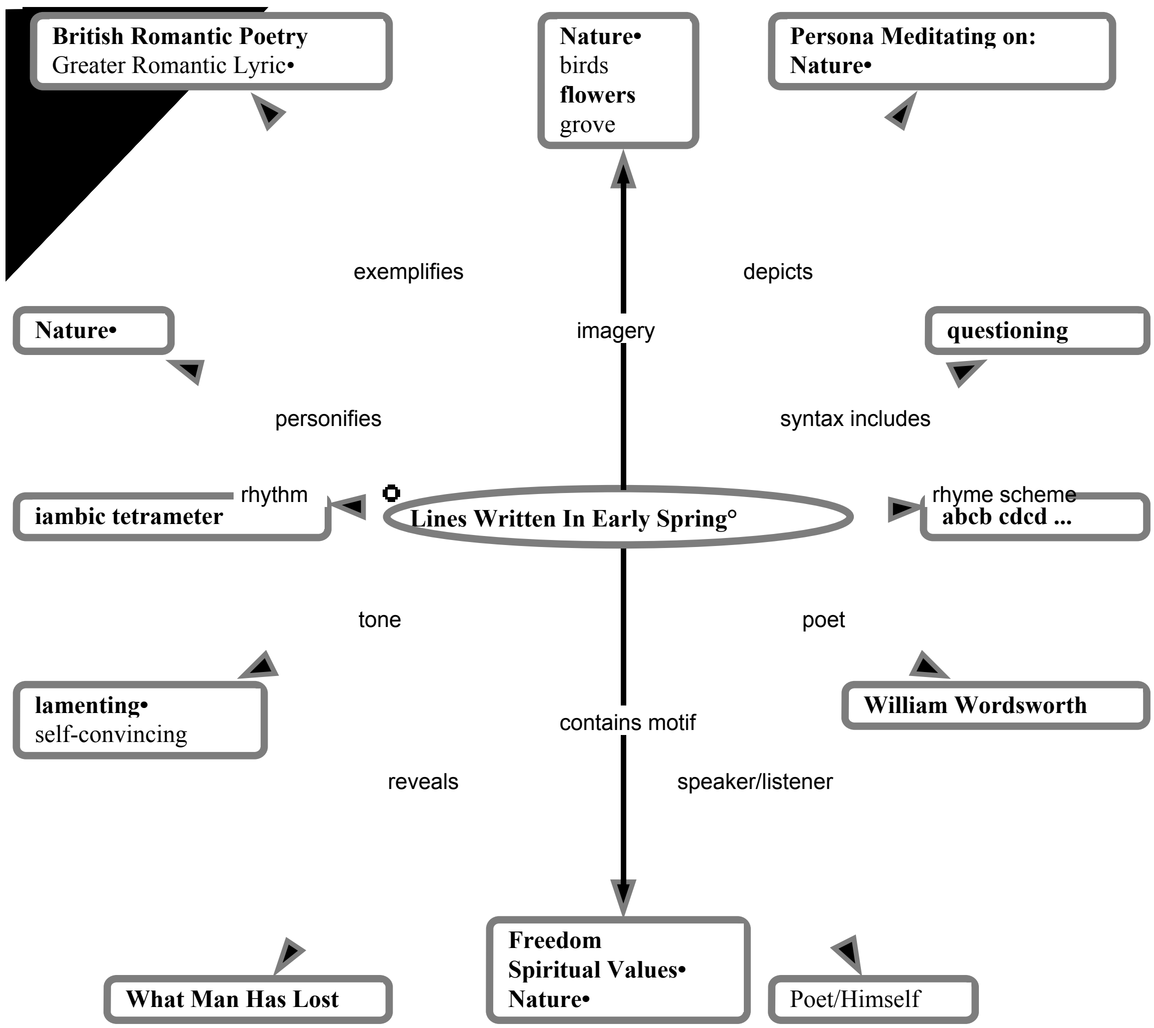


*Figure 1. Concept map or semantic network about a poem.*

## <u>Modeling Domain Knowledge</u>

It is generally accepted by psychologists that knowledge in long-term memory is organized in a variety of structures. These structures describe how concepts are interrelated. These organizations provide meaning to concepts and principles that are part of every domain of study. That is, the meaning for ideas is determined by the associations between them, and most educators believe that it I important for students to understand the language of the field. Understanding the language of a domain requires that learners build meaningful associations between the concepts in a domain. Building models of domain knowledge is one use for model-building tools.

Figure 1 shows a concept map that is part of a much larger map address British romantic poetry. The central concept is the title of a poem, which is linked to important characteristics of that poem. Clicking on any of the other concepts shows all of the associations to that concept. The aggregation of all pf these individual maps is someone's semantic network related to the domain. Understanding poetry requires that learners understand the associations between these concepts, such as rhyme, rhythm, motif, imagery, and so on.

Another tool for helping learners to articulate the semantic structure of ideas within a domain is the common database. Databases are used ubiquitously to organize information about every aspect of our lives. They can also be used by learners to organize information that they are studying. Figure 2 illustrates a database about cells created by biology students. This database, including fields about function, shape, location, tissue system, and other attributes of cells, provides a structure for interrelating these attributes. Students can compare and contrast cell types by searching and sorting the database.

| cell type | location | function | shape | related cell | specialization | tissue syst |
|---|---|---|---|---|---|---|
| Astocyte | CNS | Supply Nutrients | Radiating | Neurons, Capillaries | Half of Neural Tissue | Nervous |
| Basal | Stratum Basale | Produce New Cells | Cube, Columnar | Epithelial Cells | Mitotic | Epithelial |
| Basophils | Blood Plasma | Bind Imm.E | Lobed Nuclei,Gr | Neutrophil, Eosinoph | Basic,Possible Mast | Connective, I |
| Cardiac Muscle | Heart | Pump Blood | Branched | Endomysium | Intercalated discs | Muscle |
| Chondroblast | Cartilage | Produce Matrix | Round | | | Connective |
| Eosinophil | Blood Plasma | ?, Protozoans, Aller | Two Lobes, gran | Basophil, Neutrophil | Acid, Phagocytes (N | Connective, I |
| Ependymal | Line CNS | Form Cerebralspinal | Cube | | Cilia | Nervous |
| Erythrocytes | Blood Plasma | Transport O2, Remo | Disc | Hemocytoblast, Pros | Transport | Connective |
| Fibroblast | Connective Tissue | Fiber Production | Flat, Branched | | Mitotic | Connective |
| Goblet | Columnar Epithelia | Secretion | Columnar | Columnar | Mucus | Epithelial |
| Keratinocytes | Stratum Basal | Strengthen other Cel | Round | Melanocytes | | Epithelial |
| Melanocytes | Stratum Basale | U.V. Protection | Branched | Keratinocytes | Produce Melanin | Epithelial |
| Microglia | CNS | Protect | Ovoid | Neurons, Astrocytes | Macrophage | Nervous |
| Motor Neuron | CNS(Cell Body) | Impulse Away from | Long, Thin | Sensory Neuron, Ne | Multipolar, Neuromus | Nervous |
| Neutrophil | Blood Plasma | Inflammation, Bacter | Lobed Nuclei | Basophils, Eosinophil | Phagocytes, Neutral | Connective, I |
| Oligodendrocyte | CNS | Insulate | Long | Neurons | Produce Myeline She | Nervous |
| Osteoblast | Bone | Produce Organic Mat | Spider | Osteoclasts | Bone Salts | Connective |
| Osteoclast | Bone | Bone Restoration | Ruffled Boarder | Osteoblasts | Destroy Bone | Connective |
| Pseudostratified | Gland Ducts, Respi | Secretion | Varies | Goblet | Cilia | Epithelial |
| Satellite | PNS | Control | Cube | Schwann, Neurons | Chemical Env. | Nervous |
| Schwann | PNS | Insulate | Cube | Neurons, Satellite | Form Myelin Sheath, | Nervous |
| Sensory Neurons | PNS(Cell Body) | Impulse to CNS | Long, Thin | Motor Neuron, Neuro | Unipolar, Action Pot | Nervous |

*Figure 2. Database on cells.*

Domain knowledge building tools, such as databases, concept mapping, hypermedia construction, and others force students to use organize the knowledge that they are constructing. The organizational formalisms that are embedded in this software require students to explicitly signal the interrelationships between these ideas, forming the semantic foundation for understanding a domain.

## Modeling Problems

Another important but unresearched issue is the use of modeling tools for developing explicit models of problems that students are trying to solve. In these applications, students are representing the problem space (Jonassen, under review). It is generally accepted that problem solvers need to construct some sort of internal representation (mental model) of a problem (problem space) in order to solve a problem. 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).

The purpose f problem representation tools is the explicitly represent problem spaces.

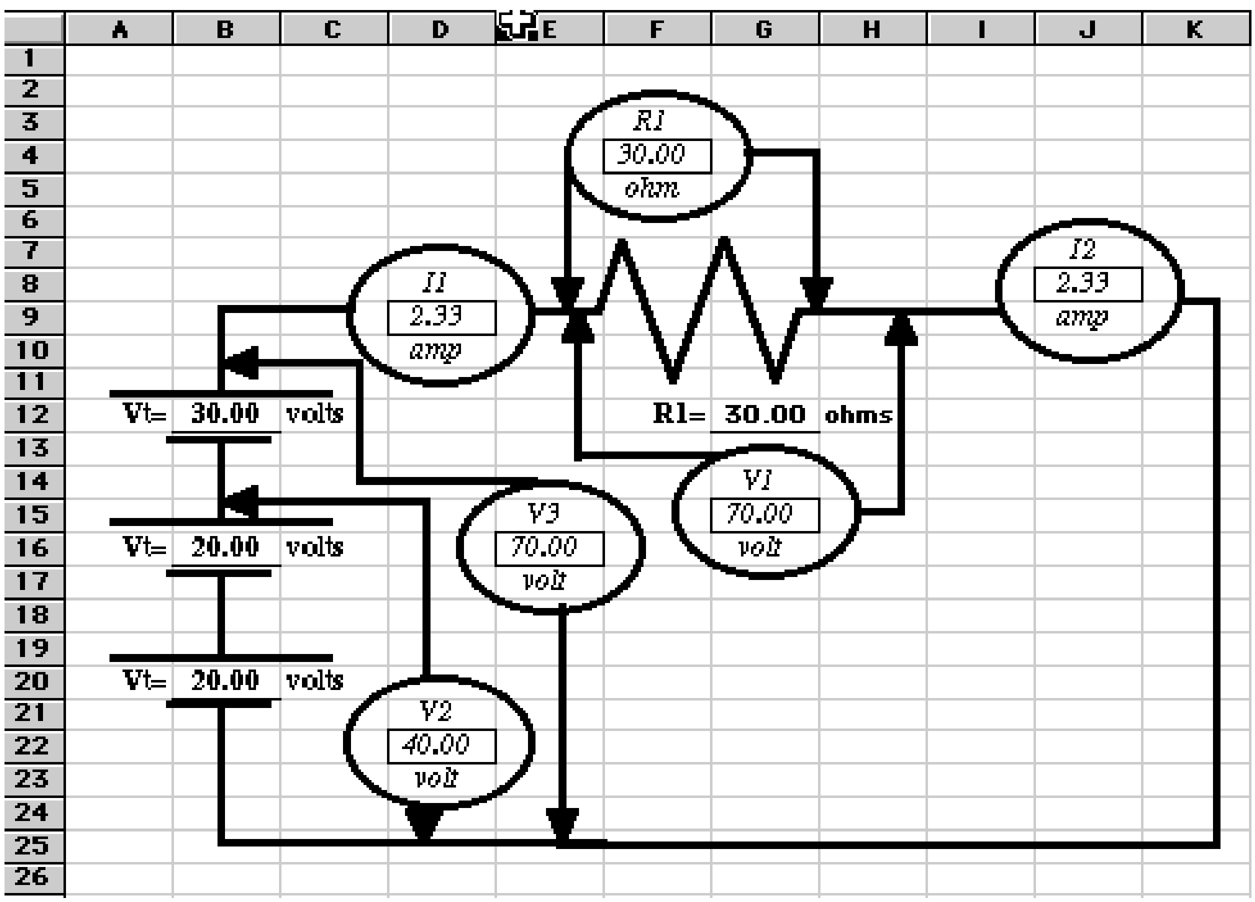


*Figure 3. Resistor series model built in a spreadsheet.*

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' mental 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).

Problem models can be built using spreadsheets. The model in Figure 3, for example, was built by students to test the effects of a series of resistors. The model is explicated in the formulae that are entered into each cell. If this model was built by the teacher for students to manipulate and test effects, it would function model using, not model building. Because students constructed the simulations themselves, they were model building.

Context 'This knowledge base is intended to simulate the processes of calculating molar conversions. '

D1: 'You know the mass of one mole of sample.'
D2: 'You need to determine molar (formula) mass.'
D3: 'Divide sample mass by molar mass.'
D4: 'Multiply number of moles by molar mass.'
D5: 'You know atomic mass units.'
D6: 'You know molar mass.'
D7: 'Divide mass of sample by molar mass and multiply by Avogadro's number.'
D8: 'Divide number of particles by Avogadro's number'
D9: 'Convert number of partcles to moles, then convert moles to mass'
D10: 'Convert mass to moles using molar mass, and then convert moles to molecules using Avogadro's number.'
D11: 'Convert from volume to moles (divide volume by volume/mole), and then convert moles to moles by multiplying by Avogadro's number.'

| | | |
|---|---|---|
| Q1: 'Do you know the number of molecules?' | A 1 'yes' | 2 'no' |
| Q2: 'Do you know the mass of the sample in grams?' | A 1 'yes' | 2 'no' |
| Q3: 'Do you know the molar mass of the element or compound?' | A 1 'yes' | 2 'no' |
| Q4: 'Do you know the number of moles of the sample?' | A 1 'yes' | 2 'no' |
| Q5: 'Do you want to know the number of molecules?' | A 1 'yes' | 2 'no' |
| Q6: 'Do you want to know the mass of the sample in grams?' | A 1 'yes' | 2 'no' |
| Q7: 'Do you want to know the molar mass of the compound?' | A 1 'yes' | 2 'no' |
| Q8: 'Do you want to know the number of moles of the sample? | 'A 1 'yes' | 2 'no' |
| Q9: 'Do you know atomic mass units?' | A 1 'yes' | 2 'no' |
| Q10: 'Do you know the volume of a gas?' | A 1 'yes' | 2 'no' |

Rule1: IF q2a1 AND q8a1 THEN D2
Rule2: IF (d1 OR q3a1) AND q2a1 AND q8a1 THEN D3
Rule3: IF q4a1 AND q3a1 AND q6a1 THEN D4
Rule4: IF q3a1 THEN D1
Rule5: IF q3a1 THEN D5
Rule6: IF q9a1 THEN D6
Rule7: IF qq3a1 AND q2a1 AND q5a1 THEN D7

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Rule8:   IF q1a1 AND q8a1 THEN D8
Rule9:   IF q1a1 AND q6a1 THEN D9
Rule10:IF q2a1 AND q5a1 THEN d10
Rule11:IF q10a1 AND q1a1 THEN d11
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*Figure 4. Excerpt from expert system rule base on stoichiometry*

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 inferencing rules that connect them and give them meaning are qualitative (Larkin, 1983).

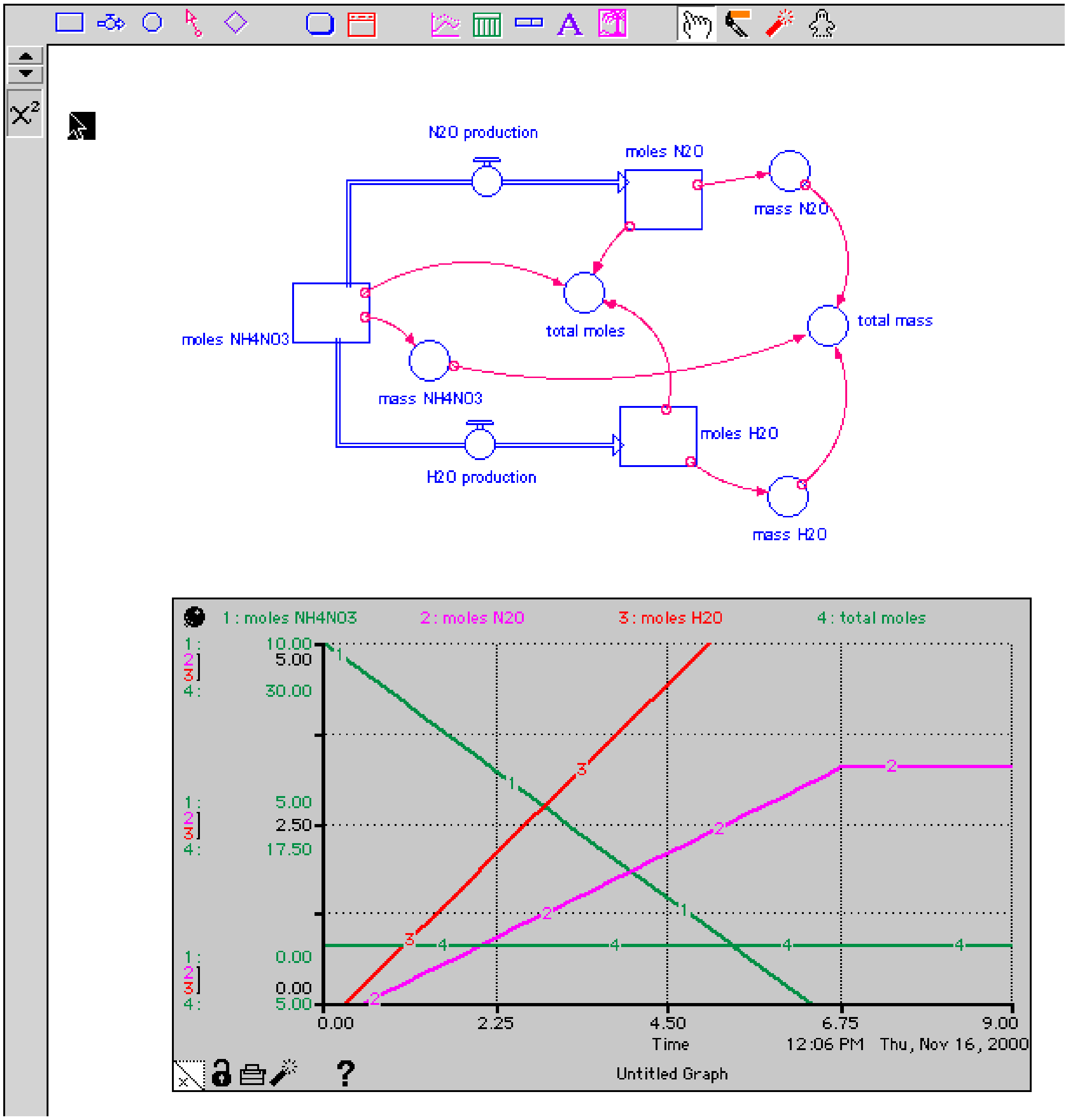


*Figure 5. Systems dynamics model of stoichiometry problem in Stella.*

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. Figure 4 illustrates a qualitative model of a simple stoichiometry (molar conversion) problem in chemistry using an expert system. That is, the learners constructed a production rule system that describes the logic needed to solve the problem. 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 5 illustrates a Stella model of a stoichiometry problem, providing both quantitative and qualitative representations of the problem. Qualitative representations function to:

- explicate information that is stated only implicitly in problem descriptions but is important to problem solution
- provide preconditions on which quantitative knowledge can be applied
- qualitative reasoning supports construction of quantitative knowledge not available initially, and yield a set of constraints that provide guidelines for quantitative reasoning (Ploetzner & Spada, 1993).

## 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 much more integrated view of the world. There are several, related systemic conceptions of the word, including open systems thinking, human or social systems thinking, process systems,

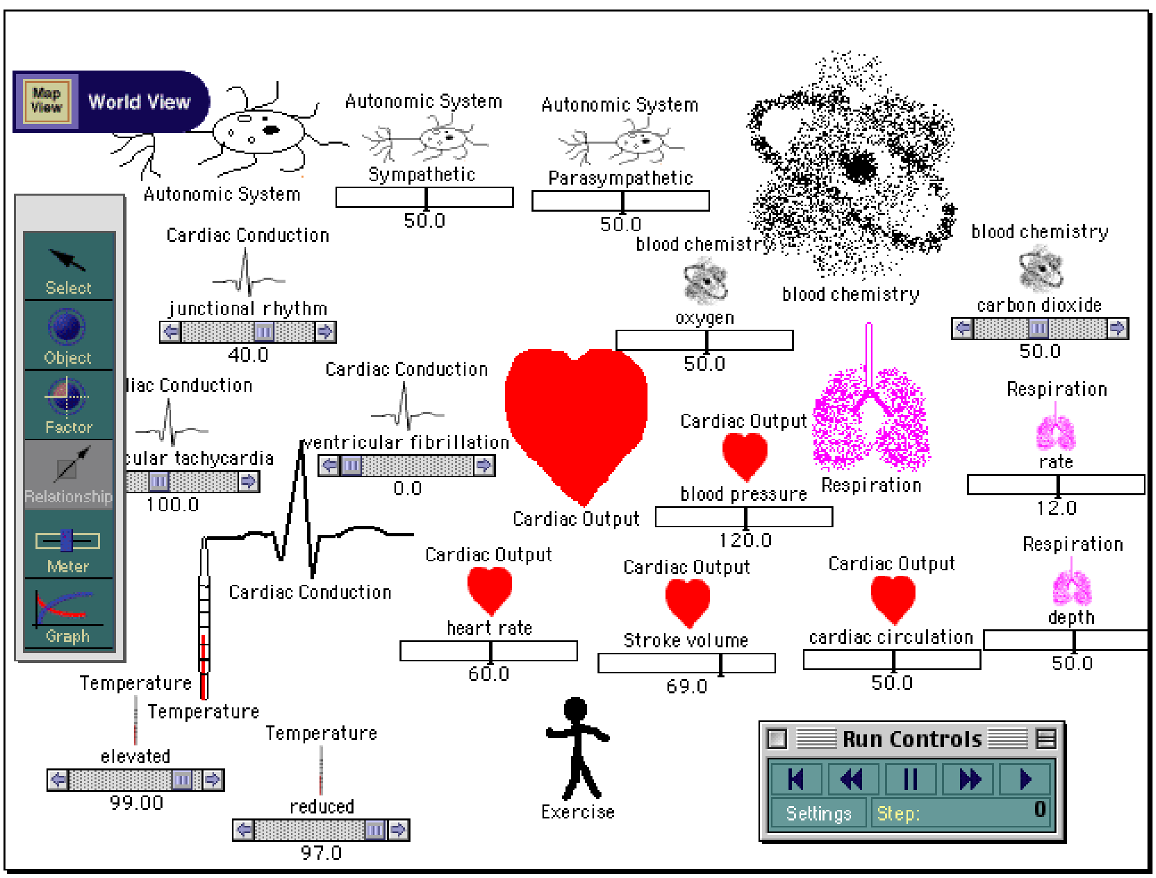

Figure 6. Modeling the circulatory system with Model-It.

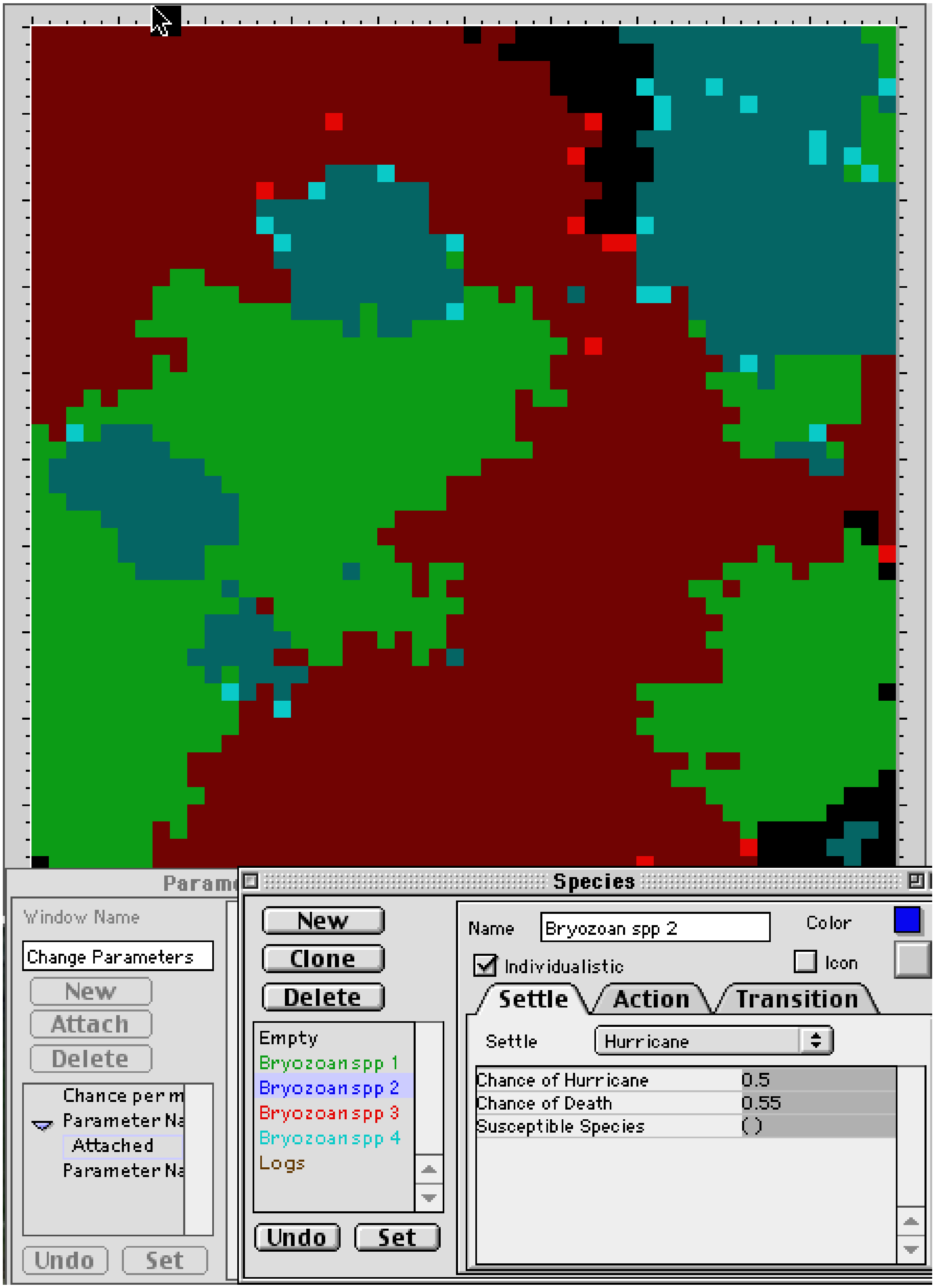


*Figure 7. Modeling the effect of a hurricane on Bryzoan using EcoBeaker.*

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. There are a variety of computer-based tools for supporting systemic thinking. 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 6 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

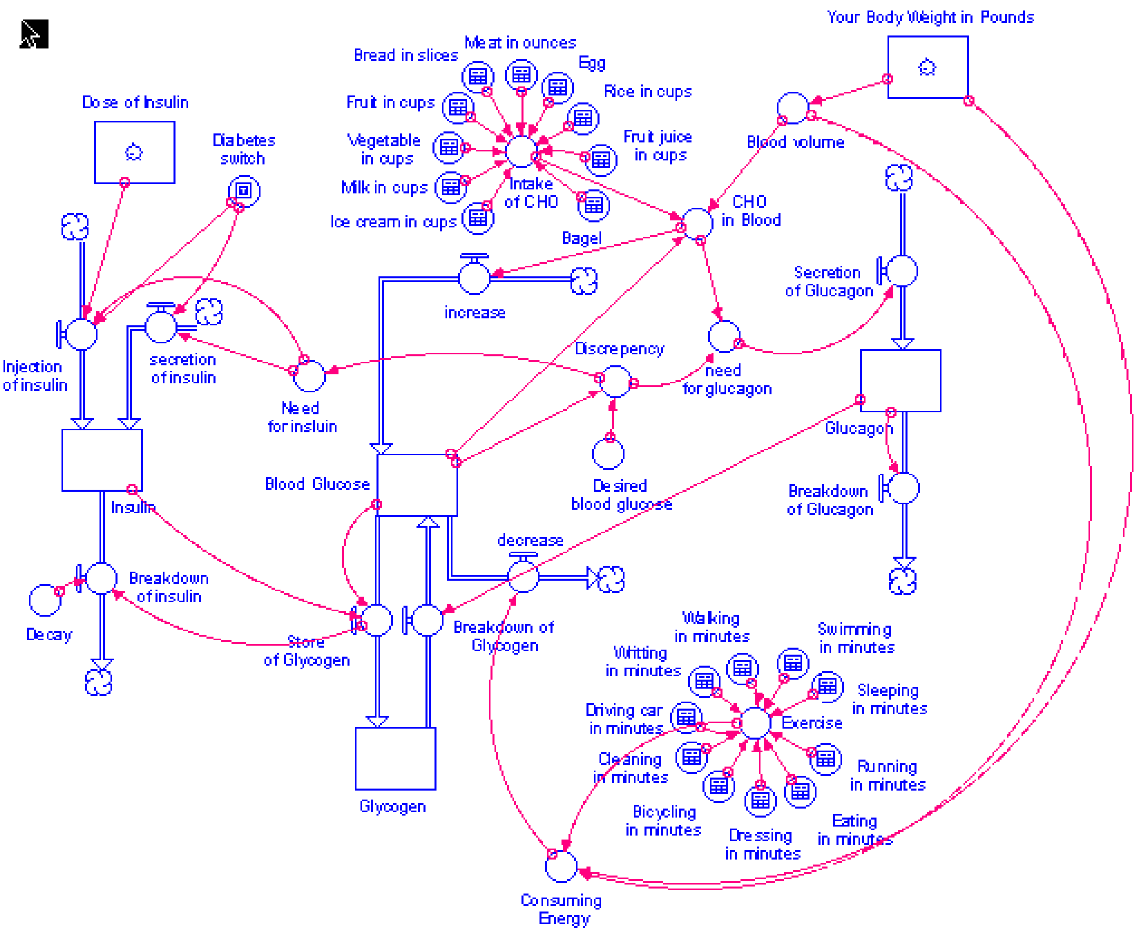


*Figure 8. Model of blood glucose using Stella.*

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.

## Modeling Thinking

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 runnable 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 to attempt to externalize mental processes for analysis and theory building. Most often used by knowledge engineers to construct elaborate tutoring systems, I have found that even young learners can reflect on their thinking in order to build these simulations. Jonassen (in press) describes the process of constructing a cognitive simulation of metacognitive reasoning using an expert system shell.

Figure 9 shows selected factors from that knowledge base. Students were required to reflect on how they used executive control and comprehension monitoring activities while study for their seminar. Lippert (1988) argued that having students construct small knowledge bases is a valuable method for teaching problem solving and knowledge structuring for students from sixth

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ASK:"Why am I studying this material?
Assigned = Material was assigned by professor
Related = Material is useful to related research or studies
Personal = Material is of personal interest"

ASK: "How well do I need to know this material?
Gist = I just need to comprehend the main ideas.
Discuss =  We will discuss and interrelate the issues.
Evaluate = I have to judge the importance or accuracy of these
ideas.
Generate = I have to think up issues, new ideas, hypotheses about the material."

ASK: "How fast of a reader am I?"
CHOICES:slow, normal, fast

ASK: "How many hours do I have to study?
None = Less than an hour
Few = 1 - 3 hours
Several = 4 - 8 hours"

ASK: "How many days until class?"
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CHOICES Days: more_than_7, 2_to_6,less_than_2

ASK:"How do I compare with the other students in the class?
Superior = I think that I am better able than my classmates to comprehend the material.
Equal = I am equivalent to the rest of the class in ability.
Worse = I am no as knowledgeable or intelligent as the rest of
the class."

*Figure 9. Metacognitive factors in cognitive simulation*

grade to adults. Learning is more meaningful because learners evaluate not only their own thinking processes but also the product of those processes

We have also been experimenting with systems dynamics tools for constructing cognitive simulations. Figure 10 illustrates a Stella model of memory (thanks to Ran-Young Hong). Stella is a systems dynamics tool for representing the dynamic relationships between systems phenomena. Both expert systems and systems dynamics tools enable the learners to construct and test the assumptions and functioning their models.

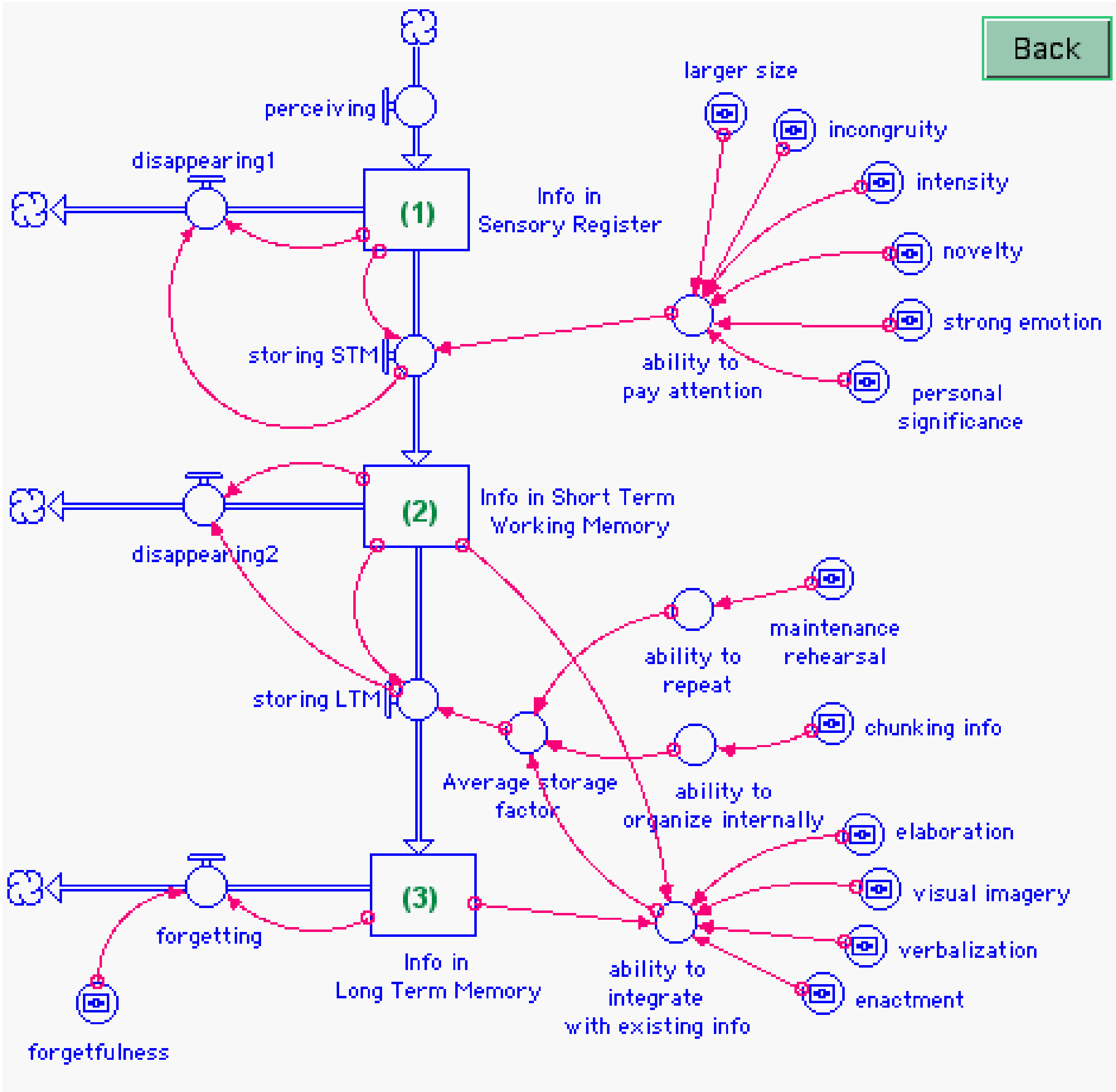


*Figure 10. Stella model of memory.*

## Rationales for Model Construction

Schwarz and White (in press) argue that modeling is fundamental to human cognition and scientific inquiry. They believe that modeling helps learners to express and externalize their thinking; visualize and test components of their theories; and make materials more interesting. I briefly summarize some of the reasons for constructing models to support meaningful learning and mental model construction.

- Model building is a natural cognitive phenomenon. When encountering unknown phenomena, humans naturally begin to construct theories about those phenomena as an essential part of the understanding process.

- Modeling supports hypothesis testing, conjecturing, inferring, and a host of other important cognitive skills.
- Modeling requires learners to articulate causal reasoning, the basis for most models of conceptual change.
- Modeling provides a high level of conceptual engagement, which is a strong predictor of conceptual change (Dole & Sinatra, 1998).
- Modeling results in the construction of cognitive artifacts (mental models) by constructing physical artifacts.
- When student construct models, they own the knowledge. Student ownership is important to meaning making and knowledge construction. When ideas are owned, students are willing to exert more effort, defend their positions, and reason more effectively.
- Modeling supports the development of epistemic beliefs. At the very root of learning are people's beliefs about what knowledge and truth are and how we come to develop these beliefs. From a biological perspective, we accept that humans are marvelously adapted to learning because of the size of their cortex. But what drives people to learn? Sociologists and psychologist talk about fulfilling needs, which supplies a solid conative reason for learning. But epistemologically, what motivates our efforts to make sense of the world. According to Wittgenstein, what we know is predicated on the possibility of doubt. We know many things, but we can never be certain that we know it. That uncertainty can only be mollified by efforts to know more about the world. Modeling tools enable learners to externalize and test their epistemological beliefs about the meaning of epistemological constructs, such as knowledge and truth and how those beliefs change over time
- Modeling provides shared workspaces provide a strong reason to collaborate.

## Limitations of Model Building

Although I have made a strong case for using technologies as model-building tools, I would be remiss if we did not acknowledge any limitations. Model building is a powerful way to use technology, but we must be aware of these limitations when assessing and evaluating their effectiveness.

- All models are incomplete; they are merely models of reality (identity theory inaccurate).
- Cognitive engagement equals effortful learning. Building models is hard work.
- Skill, time, effort must be expended learning the affordances of the different formalisms. Although Jonassen (2000) has argued that most of these tools can be learned with an hour or so, others require more time. And facility with the tools will require extensive use.
- Allowing learners to construct models will result in very different models. Teachers must accept that every student's model won't be correct. That requires that the teacher abdicate some intellectual authority. However, when student models contain misconceptions, the teacher can use them as important lessons.

- Barab, Barnett, Yamagata-Lynch, Squire, and Keating (in press) used activity theory as an analytical lens for understanding the transactions and pervasive tensions that characterized course activities. Reflecting on their analyses, they interpreted course tensions and contradictions in the framework of the overall course activity system, especially between learning to use the technology tools and learning the content. While model building can help students to learn content, it is necessary to expect some contradictions between those activities.

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