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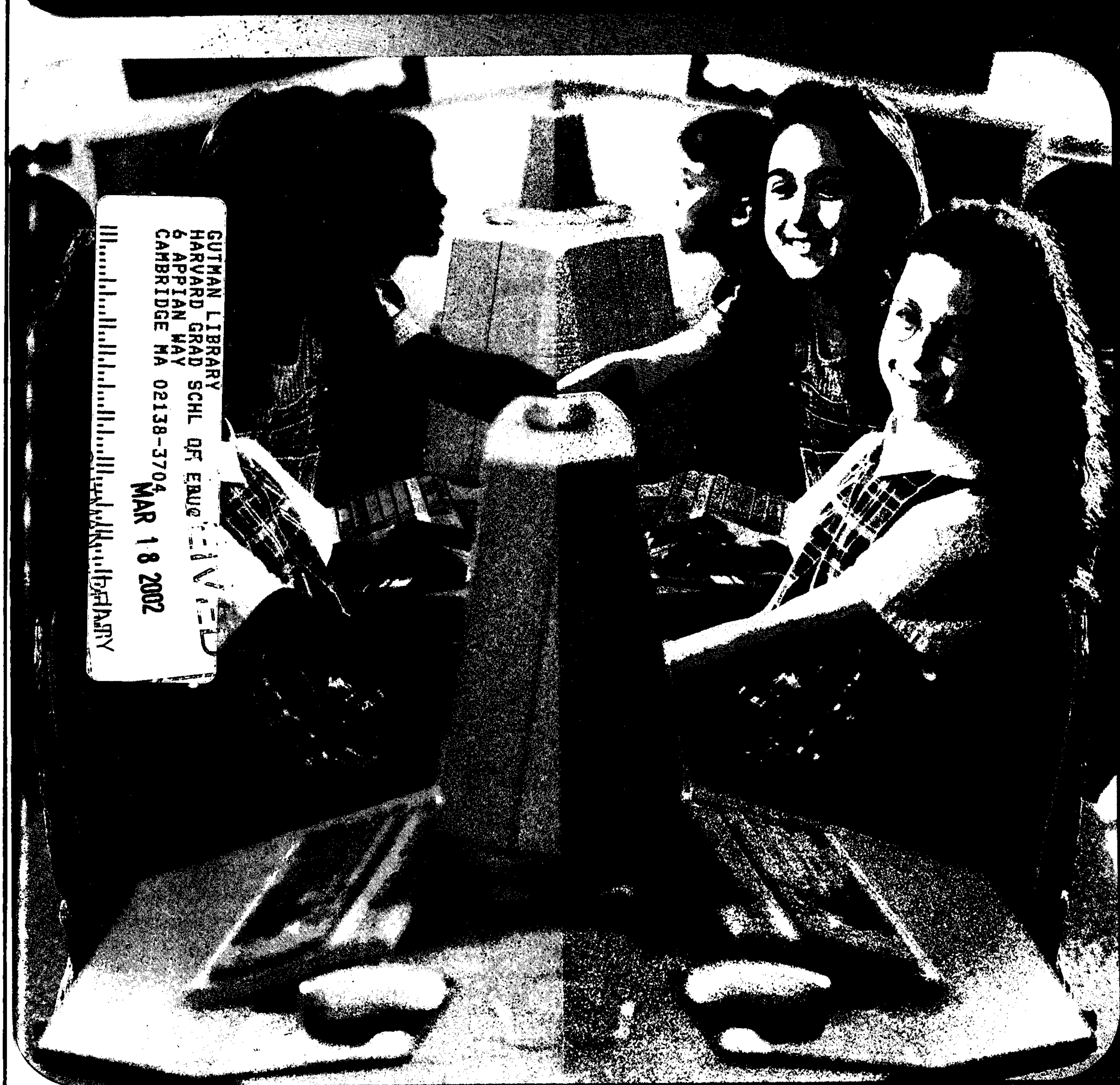

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Expanding Our Vision for Educational Technology: Procedural, Conceptual, and Structural Knowledge

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Introduction

Recall the early 1980s and the prevailing vision of the computer as an educational tool. Most applications aimed to teach *procedural knowledge* as narrowly defined by formulas and basic skills—for instance, how to multiply or divide with greater efficiency. Computer-aided instruction (CAI) was commonplace and typically sought ways to replace or augment the teacher in teaching basic skills. Soon the vision shifted towards using computers to teach *conceptual knowledge*. Computers could immerse students in scenarios to help them construct concepts in contexts simulating real life and offered inquiry-oriented activities, manipulable diagrams, and models. This shift towards conceptual knowledge radically expanded the variety of educational applications for computer technology.

In this article, I argue that a similar expansion of our vision for educational technology is on the horizon. We are beginning to harness the power of educational technology to teach *structural knowledge*—the very ways that knowledge is structured. In the paragraphs to follow, I review the earlier shift from procedural to conceptual knowledge. Then I explain what structural knowledge is, how it has been defined in the extant literature (e.g., Jonassen, Beissner, & Yacci, 1993; Rohrer-Murphy, 2000), and how the usage here builds upon and slightly departs from those definitions. Next, I explore the importance of structural knowledge for developing deep understanding through examples from our research on causality and science learning, and offer an illustrative example of how technology can help teach structural knowledge. Presently, structural knowledge is seldom addressed in school. The possibility of teaching structural knowledge in accessible and engaging ways holds profound implications for how educators and students will conceptualize the nature of learning and for what it means to engender deep understanding.

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An Early Focus on Procedural Knowledge

It makes sense that early computer applications focused on *procedural knowledge*. Traditionally, procedural knowledge referred to skills including understanding of symbols (such as the numerals 1, 2, 3...) and signs (such as +, –, x, ÷) as well as rules and algorithms for how to use the signs and symbols (Hiebert & Lefevre, 1986). Defined within these parameters, it is perhaps the most straightforward of the three knowledge types, and the computer held some obvious advantages for teaching it. The computer education literature of the time elaborated the benefits of using computers for teaching procedural knowledge. Computers provided immediate feedback, offered various types of reinforcement and simple strategies, and could even be programmed to track student progress. For instance, computers taught reading through drills followed by multiple-choice questions where students worked at their own level and progress was stored (Wells & Bell, 1980). According to Menis, Snyder, and Ben-Kohav (1980) computerized algebra drills made abstract concepts more concrete, offered encouragement through immediate feedback, prevented embarrassment by enabling privacy in learning, allowed students to work at their own pace, and gave individualized homework assignments. As these programs became more sophisticated, some sought to include various types of personalized tutoring.

There were notable exceptions to CAI packages, of course, such as Seymour Papert's *LOGO* (Papert, 1980), where the student programmed the computer with a simple programming language. According to De Laurentis (1980), while CAI was the most common use of computers in education, it was not necessarily the best. CAI took the control for learning away from students, whereas programs such as *LOGO* put students in control. Through the interactive programming in *LOGO*, students developed math and reasoning skills through problem-solving and application.

Procedural knowledge, in recent instantiations, has been more broadly and richly construed to include "science process skills" (e.g., Dunbar & Klahr, 1989; Kuhn, Amsel, & O'Loughlin, 1988), or the "epistemic rules" within a particular discipline (e.g., Collins & Ferguson, 1993; Morrison & Collins, 1995; Perkins & Simmons, 1988), for instance, knowledge about how to operationalize a question, how to isolate and control variables, and so forth. This richly construed type of procedural knowledge is at the heart of inquiry and developing deep understanding. However, the early computer applications focused on the more narrow construal.

An Expanded Focus on Conceptual Knowledge

It was not long before educators began to look beyond procedural knowledge as an educational objective and to seek ways to use the power of the computer to also teach *conceptual knowledge*. It is important to first clarify some terms. Here I intend conceptual knowledge to encompass declarative knowledge (knowing what) but to also encompass the connections between bits of information such that it results in a cohesive and meaningful mental model of what happens in relation to a given phenomenon, and why. Others have referred to the connections as structural knowledge (e.g., Diekhoff, 1983; Jonassen *et al.*, 1993) and so have argued that conceptual knowledge encompasses structural knowledge. I also argue that structural knowledge is an inherent (and yet distinct) part of conceptual knowledge. As such it can limit or enable the development of deep conceptual knowledge. However, as elaborated below, structural knowledge as defined here refers only to instances of very basic structuring of knowledge.

Articles on computers in education appearing between 1980 and 1990 reveal this shift in focus from procedural to conceptual knowledge. Simic wrote, "No longer are computers seen as tutors or drillers. Instead, educators now are realizing that the computer is a tool for handling information" (1994, p. 2). Programs designed to help students learn particular concepts, such as frog dissection in *Operation Frog* (Goldhammer & Isenberg, 1984) or about ecosystems and whales in *The Voyage of the Mimi* (Bank Street College of Education, 1985), grew common. Some programs engaged students in inquiry-oriented quests to gain understanding of a particular phenomenon. Real-world problems could be easily transported to the classroom (Bransford, Brown, & Cocking, 1999) lending greater authenticity to school learning. In some cases (as in *The Voyage of the Mimi*), video and computer technology combined to present real-world problems. Students could discover knowledge through application, and feedback was given within a meaningful context (Keegan, 1993). Some simulations replaced real-world experience like lab experiments, as in *Operation Frog*, but were preferable to reading experiments in texts (Mace, 1984).

Some of the best of these conceptually focused programs, such as *The Voyage of the Mimi*, also engaged students in the epistemology of the discipline, thus encompassing the richer construal of procedural knowledge. For example, students collected and analyzed data along with the scientists. They were given the opportunity to examine data patterns, isolate and control for variables, and deal with ambiguity—all forms of thinking that are part of scientific inquiry.

Programs focused on conceptual knowledge and the more richly-construed version of procedural knowledge have continued to evolve into increasingly powerful educational tools. A number of these programs help students achieve understanding of concepts that are difficult to visualize either due to their abstractness or to dynamic processes that involve a heavy cognitive load. For instance, *Stark Design Molecular Dynamics* (Stark Design, 1999) simulates atoms in motion, and *GenScope* (Concord Consortium, 1997) enables students to visualize and manipulate processes of inheritance. Students can move between different levels (DNA, Chromosome, Cell, Organism, Pedigree, and Population) to design and examine the effects of different manipulations. Various processes are animated, for instance, the process of meiosis at the cell level. *ThinkerTools* allows students to perform experiments to explore Newtonian models of force and motion (e.g., White & Horwitz, 1987). It uses dots as stripped down analogs (Perkins & Unger, 1994) that simulate the physics principles minus situational variables. *Archimedes and Beyond* (Snir, Raz, Smith, Grosslight, & Unger, 1994) enables students to experiment with concepts of mass, volume, and density. Students use "dots per box" models to explore what leads to sinking, floating, or suspending.

Recent programs have sought to apply research on cognition, for instance, the literature on scientific misconceptions or alternative conceptions (e.g., Driver, Guesne, & Tiberghien, 1985). Developers have teased apart concepts that students have great difficulty with and provided ways for them to grapple with the inherent difficulties. For instance, researchers (Lewis, Stern, & Linn, 1993; Wiser & Kipman, 1988) have helped students gain a better understanding of thermodynamics through computer simulations that make thermal processes more apparent. Students could manipulate variables to observe the results. Other applications have used the diagnostic power of the computer to encourage and track the growth of students' conceptual knowledge. For instance, the DIAGNOSER Program (Levidow, Hunt, & McKee, 1991) is a HyperCard tool with physics questions written by researcher and educator Jim Minstrell, that allows teachers to track students' understanding around difficult science concepts. It enables intelligent tutoring and tracking of student progress.

Additional advances include networked opportunities to share ideas with other students, paralleling a shift from Piagetian notions of learning (with a greater emphasis on an individual's construction of knowledge) to Vygotskyian notions of the nature of learning (with a greater emphasis on the social construction of knowledge). Examples include Project GLOBE (Lawless & Coppola, 1996), CoVIS (Pea, 1993), and CSILE (Scardamalia *et al.*, 1989; Scardamalia, Bereiter, & Lamon, 1994). Project GLOBE (Global Learning and Observations to Benefit the Environment) involved thousands of K–12 students across the world in gathering and sharing data on their local environment (Lawless & Coppola, 1996). CoVis (Learning through Collaborative Visualization) gave students access to scientific visualization software to study atmospheric and environmental sciences and encouraged collaboration between students in 40 different schools. CSILE (Computer Supported Intentional Learning Environments) involves students in creating networked databases and generating knowledge through interacting with the data and other students around the data.

Advances such as those outlined above show incredible promise for teaching conceptual knowledge and epistemic forms of procedural knowledge. While acknowledging the importance of procedural and conceptual knowledge, below I argue that a third type of knowledge is also needed—that of structural knowledge—and that technology offers special affordances for teaching it.

A Currently Expanding Vision to Include Structural Knowledge

The shift in focus from procedural to conceptual knowledge was profound in terms of how we use computers in education. This is not to imply that one focus completely replaced the other. Computers still hold great leverage for teaching procedural knowledge. However, our view of how computers should be used for educational purposes expanded considerably. In the paragraphs to follow, I elaborate the argument that another such expansive shift may be on the horizon, that of teaching structural knowledge in addition to procedural and conceptual knowledge. This shift parallels changes in how cognitive scientists and educators conceptualize the nature of learning and frame what education entails. As before, one focus certainly won't replace the other; rather, they may mutually enhance one another and at some point, we may see programs that attempt all three in integrated contexts.

Structural knowledge has been defined in a couple of different ways. According to Jonassen and colleagues (1993), it is the knowledge of how concepts within a domain are interrelated. They view it as mediating between procedural and declarative knowledge and offer the following example. "The dictum 'warm air rises' entails connections between air and its modifier, warm as opposed to cold. That warm air rises is predicated on a causal relationship between warm and rising, the basis of the principle of convection" (p. 4). Structural knowledge, then, is the understanding of these relationships and enables people to know more than what or how, but also why. Others (e.g., Preece, 1976; Rohrer-Murphy, 2000; Shavelson, 1972, and as reviewed by Jonassen *et al.*, 1993) define structural knowledge as cognitive structure or the way that concepts are organized in long-term memory. Still others have used it to refer to individuals' knowledge structures (e.g., Champagne, Klopfer, Deseña, & Squires, 1981).

Structural knowledge, as defined here, fits with the spirit of the earlier definitions; however it is a bit more restrictive—a subset of the cases defined by Jonassen and colleagues (1993). While I do intend for it to refer to interconnections between concepts, I reserve it to refer to connections at the level of very fundamental structuring. So rather than connections at the level of specific principles, such as convection, it refers here to connections at a more basic level for how we make sense of experience; for instance, the way that one categorizes, or how one attributes causality, or characterizes the nature of numerosity. In this way, it does refer to cognitive structures. Novices and experts frame causal forms, define what it means to categorize, and think about the nature of number in ways that impact what they perceive as causal, or related, or countable, for examples.

Presumably, there are structures in the world that impact the knowledge we must gain in order to create models with the greatest explanatory power. The pedagogical challenge of helping students develop structural knowledge involves enabling them to reflect upon and revise their current ways of structuring experience to more closely align with the ways that experts in a domain structure experience or information. For instance, an elementary student might use domino-like patterns to explain events in ecosystems (e.g., Grotzer, 1993), while an expert might also include re-entrant patterns and oscillations, among others. So teaching structural knowledge involves helping novices learn how experts structure, at a fundamental level, the phenomenon in question.

Cognitive scientists have studied and illuminated some of the ways in which we structure our experience. For instance, Ellen Markman has mapped processes of categorization (1989), Rochel Gelman and colleagues (e.g., Bullock, Gelman, & Baillargeon,1982) have contributed to our understanding of how we structure basic causal events, and Dehaene (1997) and others have studied how our minds create numerosity. Evidence suggests that we have certain default patterns for how we structure experience. For instance, according to Bullock *et al.* (1982), we use the principles of determinism, temporal priority, and contiguity to determine whether events are causal and ultimately to define what we view as causally linked. Similarly, we expect a correlated structure of categories based upon natural kinds; for instance, we expect feathers to go with wings (Markman, 1989; Rosch *et al.*,1976).

Without the necessary expert structural knowledge (which may depart from our typical defaults) and a reflective sense of where it applies, students risk imposing limiting structures on new information. This results in distorting understandings to fit a typically less complex structure (e.g., Grotzer & Sudbury, 2000; Slotta & Chi, 1999; Wilensky & Resnick, 1999). We have seen this in science learning. Students often impose simple linear causal structures as opposed to the more complex ones that scientists use to frame their explanations (e.g., Driver, Guesne, & Tiberghien, 1985; Grotzer & Bell, 1999; Perkins & Grotzer, 2000). So, for example, when learning about simple circuits, students typically create models where the "electricity goes through the wire to the bulb" in a consumer-source model (Grotzer & Sudbury, 2000; Shipstone, 1985). Students need opportunities to learn structural knowledge as they are learning procedural and conceptual knowledge to minimize the likelihood that they will impose limits that stem from novice patterns of thought and to encourage the development of structures that fit with expert understanding. They also need to develop a reflective stance on how they structure understanding so that they actively consider and revise the structures that they engage (Grotzer & Bell-Basca, 2001; Zohar, in press).

When first reading Ellen Markman's (1989) work on categorization, I found it illuminating to consider the problem space of how we create categorical structures. I was struck by how those structures need to constantly evolve as the parameters of that which we are categorizing shifts and so do the sensible parsings. The unfinished nature of my filing cabinet suddenly became a necessarily evolving process rather than a failing of sorts. Of course, one's filing cabinet is a rather concrete instantiation of how one structures experience. Typically, the ways in which we structure experience are not so apparent either to ourselves or others. It is this invisibility of such a fundamental part of the learning process that makes it so important that we seek to understand the structures students impose upon their learning and to help them explicitly reflect upon and revise these structures. Indeed, we often don't recognize how we are structuring knowledge until it in some way is revealed through outcomes that are discrepant with our expectations. For example, imposing an additive structure as opposed to a multiplicative one when calculating exponential increases can result in startlingly larger outcomes than expected. Similarly, using class inclusion to systematize categories can lead to puzzles if one assumes categories to be mutually exclusive; thus for young children it is difficult to see how a doll can be both a doll and a toy (Markman, 1989).

Teaching Structural Knowledge Enables Deeper Understanding: An Example from Our Research on Causality

Teaching students to reason about the structure of knowledge while they are learning conceptual knowledge improves their ability to achieve deep understanding (e.g., Grotzer & Perkins, 2000). In the following paragraphs, I briefly review work that my colleagues and I have carried out on how students structure the nature of cause and effect and its impact on their subsequent understanding of certain science topics as an example of how teaching structural knowledge can impact conceptual knowledge.

A growing body of research suggests that students hold limited notions about the nature of cause and effect (e.g., Chi, 2000; Driver *et al.*, 1985; Perkins & Grotzer, 2000; Wilensky & Resnick, 1999). Here are some examples of how students from elementary through high school tend to structure causality (as reviewed in Grotzer & Bell, 1999). Students expect obvious causes and obvious effects, missing effects that involve systems in equilibrium or those that involve "passive" agents such as seatbelts. They detect local causes and local effects but fail to recognize action at a spatial or temporal distance (Spelke, Phillips, & Woodward, 1996). They assume simple linear, sequential causal patterns with temporal priority between causes and effects (Bullock *et al.*, 1982) but miss instances where an outcome is due to a relationship, such as in pressure (Bell-Basca & Grotzer, 2001) or density differentials or where there is no clear temporal priority as in a simple circuit in steady state (Grotzer & Sudbury, 2000). They focus on the current situation rather than on processes or patterns of effects (Dorner, 1989). They expect absolute correspondence between causes and effects as an indication that a causal relationship exists (Siegler & Liebert, 1974) and miss instances where the relationship is less reliable as in lightning strikes or germ transmission (Kalish, 1997).

As part of *The Understandings of Consequence Project*, we have sought to identify how these patterns for structuring knowledge impact students' science learning and how interventions designed to modify students' structural knowledge about causality affect their learning. I report briefly on those efforts here. Our work with students in a range of grades (third, fourth, eighth, tenth, and eleventh) strongly suggests that students need opportunities to learn structural knowledge in order to achieve deep understanding of certain science concepts. It also suggests that it may not be enough to simply teach new patterns, particularly when they depart significantly from students' default assumptions. Presumably, unless students become reflective about the ways in which they are structuring concepts, they may later lapse back to simpler structures.

We contrasted the performance of three groups of students: (1) students who learned science concepts as typically taught—with a focus solely on the conceptual knowledge; (2) students who learned science concepts with supporting activities designed to reveal the underlying structural knowledge (Activities Only or AO); (3) students who learned science concepts with supporting activities designed to reveal the underlying structural knowledge and with explicit discussion about the nature of the underlying causality (Activities and Discussion or AD). Students in the AO and AD groups engaged in the activities designed to REveal CAusal STructure or help students RECAST their understandings. Students in the AD group were asked to consider the differences between the CAusal STructure or CAST that they implicitly included in their own models in contrast to those of scientists. The context for all groups was a set of curriculum units incorporating best practices (Socratic discussion, inquiry-based activities, computer simulations, discrepant events, and starting with initial conceptions). Students participated in units on simple circuits, pressure, density, force and motion, and ecosystems.

The RECAST activities and discussion involved students in thinking about the structure of their knowledge—how their assumptions about the nature of causality influence their grasp of the conceptual knowledge. What are RECAST activities like? The following activity, designed to help students analyze pressure-related phenomena using interactive or relational causal patterns (Bell-Basca & Grotzer, 2001), provides an example. Typically, students interpret what happens when you suck on a straw in terms of simple linear causality, such as "sucking pulls the liquid up the straw," or they offer token explanations (Perkins & Grotzer, 2000) that they do not fully understand, such as "it happens because of a vacuum." In order to reveal that a pressure differential, a type of interactive causality, is in play, students are given three different flasks, each half-filled with liquid with a straw inserted, and are asked to see who can drink the liquid the fastest. Two of the flask/straw systems have various modifications that prevent the formation of a pressure differential. One has a hole in the straw above the height of the liquid that enables the lower pressure inside the straw to equalize with the outside air pressure, thus preventing the formation of a pressure differential so that the liquid will not rise up the straw when students suck on it. The other has a stopper at the top that is sealed tightly around the rim with a hole that exactly fits the size of the straw. When students try to drink from it, some liquid rises up the straw, lowering the air pressure inside the flask to match the lowered air pressure in the straw, making it nearly impossible to drink any more liquid. (This activity was adapted from one by Liem, 1992.) Activities such as these reveal, through results that are discrepant with students' expectations, that something other than linear causality is involved and offer insights into the nature of that causality.

Students in all three groups began with conceptions that fit those expected based upon the default assumptions outlined above. For instance, in a unit on simple circuits, the following explanations were common: "The electrons go to the bulb to make it light." "The protons go up one wire and the electrons up the other and they clash in the bulb" (Grotzer & Sudbury, 2000). Notice the underlying simple linear structure in comparison to an explanation, such as "Electrons are all along the wire. When you hook it up to the battery, each electron simultaneously repels the ones in front of it to cause flow. There is movement all at once around the circuit." The latter contains an underlying cyclic simultaneous causality that suspends temporal priority between causes and effects and allows for electrons to play the role of a cause and an effect at the same time. Similar simple linear models were used to describe the role of density in sinking and floating, for instance "The weight makes it sink." "It sinks or floats based upon how heavy it is" (Houghton, Record, Grotzer, & Bell, 2000). Contrast this to: "Whether it sinks or floats depends upon the density of the object in relation to the density of the liquid. Whichever is denser will sink." Notice that the latter explanation involves a relational or interactive type of causality where neither the object nor the liquid is solely responsible for the outcome, rather it is the relationship of densities to one another. We found similar types of conceptions in the other topics.

Across most topics, we found support for the value of engaging students in RECAST activities. On pressure (see Bell-Basca & Grotzer, 2001), we found significant gains in understanding in students who participated in RECAST activities. On ecosystems (see Grotzer & Bell-Basca, 2001), third-graders who participated in RECAST activities outperformed control students on the type of causal connections that students detected within food webs—noticing more direct, indirect, and multi-step links. For one topic, electrical circuits, RECAST activities alone were not enough to make a difference and there was significant benefit to adding explicit discussion of the structural puzzles (see Grotzer & Sudbury, 2000). An analysis of the topics suggests that the complexity of the causality to be learned may interact with the type of intervention needed to learn it, with RECAST activities being sufficient to learn less complex patterns and discussion of the causal patterns boosting performance when the patterns are more complex.

It is not the current state of educational practice for educators to teach structural knowledge. However, our research results suggest that structural knowledge is so linked to students' ability to grasp conceptual knowledge that it cannot be ignored in efforts to teach for deep understanding. Elsewhere (Perkins & Grotzer, 2000), we have outlined a taxonomy of the kinds of structural knowledge about causality that students are likely to encounter in their science learning and are designing ways to teach it.

A New Role for Educational Technology: Helping Students Build Structural Knowledge

Even if educators wish to offer opportunities, building more complex forms of structural knowledge is not a trivial challenge. To begin with, students need to deal with difficulties that are associated with greater complexity in general, for instance, increased levels of abstraction, inferred entities, and greater cognitive load. Beyond that students need to learn to handle the complexities inherent in the particular structural knowledge, such as suspending the notion of temporal priority in order to understand the circuit in steady state. As has been suggested by successful computer programs that aim to teach conceptual knowledge, technology holds promise for scaffolding students' ability to manage both types of complexity. Computers make dynamic and interactive representations possible (Nickerson, 1995). Jonassen (2000) has argued that computers can play the role of "mindtools"—intellectual partners that engage students in and facilitate higher-order thinking.

So educational technology may offer a promising avenue for helping students revise their structural knowledge. What might such programs look like? How can one teach structural knowledge in ways that are accessible and engaging to students? Next, I consider *StarLogo*, a program that exemplifies how technology can help in the aim to teach structural knowledge.

StarLogo (Resnick, 1994) is a computer modeling environment designed for exploring systems with multiple interacting components. It was developed by Mitch Resnick of the MIT Media Lab. It extends the concept of *LOGO* in which there is one programmable "turtle." *StarLogo* involves hundreds or thousands of turtles. The turtles represent different agents and can be used to model a variety of phenomena. Users are able to program the behavior of the turtles through the use of simple commands and the environment where the turtles interact through the use of "patches" that are computationally active and follow a set of rules programmed by the user (Wilensky & Resnick, 1999).

How does *StarLogo* teach structural knowledge? Simple rules of behavior at the lowest levels of a system can often lead to complex outcomes. For example, in a traffic jam, individual drivers behave according to certain rules (move into the fastest moving lane; try to minimize starting and stopping). These actions lead in non-linear fashion to complex emergent effects and a new level at which to analyze the system—at the level of a new "object"—the traffic jam. Interestingly, if you change the rules a very little bit at the lowest levels, the emergent effects can be radically altered. By experimenting with *StarLogo*, students learn about the nature of emergent causality. It is also possible for students to simulate actual rules that particular organisms or objects follow and to then learn how emergent causality structures the particular conceptual knowledge of the topic. However, students can just as easily experiment with a variety of rules that don't necessarily represent reality such that the primary lesson is about the nature of emergence in complex systems.

StarLogo is a promising example because it engages students in inquiry-based explorations, builds upon their ideas and interests, and enables them to see the dynamic emergent effects of the simple rules that they program. It often produces outcomes that are discrepant with students' expectations and therefore reveals the mismatch between the causal structures they are assuming and those reflected in the phenomenon being modeled. *StarLogo* also integrates other forms of knowledge. Students learn to specify the inputs in terms of specific sets of procedures and can certainly input rules that fit the available information in a domain to help them conceptualize patterns that might fit with scientifically accepted explanations. While *StarLogo* is, in my opinion, one of the best examples of technology that holds the potential to teach structural knowledge, it is not necessarily the only example. According to Jonassen (2000), programs such as *Stella* (High Performance Systems, 1987) and *Model-it* (HI-C, 1995) enable students to create run-able models to test dynamic systems concepts, potentially revealing certain kinds of structural knowledge.

Concluding Remarks

Whether such a shift in educational technology is on the horizon remains to be seen. If it is, it will most certainly be accompanied by a corresponding shift in how we view the nature of knowing and subsequently, teaching and learning. Structural knowledge is perhaps the most invisible of the three knowledge types and yet, perhaps, also the most pervasive. While this is a relatively new area of inquiry, the results of our research suggest that it definitely is an area for further investigation, even if definitive statements are premature. It is likely that we won't learn the power of teaching structural knowledge until we develop educational technologies like *StarLogo* that enable us to teach it well. When we do, structural knowledge may take its place with conceptual and procedural knowledge and a triadic focus with attention to the dynamics between the three types of knowledge may prove most effective in helping students develop deep understanding. □

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Forthcoming Articles

Among the articles scheduled to appear in the pages of this magazine during this year are the following:

- The Evolution of Authoring Tools and Hypermedia Learning Systems: Current and Future Applications.
- What Hardware and Software Are Most Critical for Learning Effectively with Technology?
- Can a Community of Practice Exist Online?
- Laptops and University Students: A Review and Survey.