Models and Moves

The Role of Causal and Epistemic Complexity in Students' Understanding of Science

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Abstract

Extensive research on students' understanding of science has documented persistent shortfalls at all ages. One way to account for students' difficulties is to consider the particular challenges posed by individual science concepts. This article offers an alternative view. We argue that students' difficulties in large part reflect unfamiliarity with a small number of causal modeling styles characteristic of received scientific models. These include, for instance, explaining surface phenomena with an underlying mechanism, relying on constraint-system explanations as in Ohm's law, including probabilistic elements as in chaos theory, and acknowledging causal webs and self-organizing systems as in ecologies--in sum, aspects of "complex causality." A further barrier to understanding is students' unfamiliarity with epistemic moves that might challenge their initial explanations, such as looking for missing links in a causal story or putting a model at risk. The article offers a framework for classifying aspects of complex causality in modeling and for supporting epistemic moves. Empirical research both from the literature and our own work is presented in support of the framework, including evidence that instruction based on causal models and epistemic moves enhances students' understanding of science concepts.

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Science is More Baffling than Magic

A magician locks his comely assistant into a cabinet and waves a wand. When he opens the cabinet, the assistant has disappeared—only to reappear in a cabinet on the other side of the stage. Breaking tradition, the magician asks the audience to explain how it was done.

Most people say, “A trap door.” The magician invites people to tour the stage. No trap door is apparent, but still they say, “A trap door.” The magician decides to reveal all. He explains that there are twin assistants. The first assistant is still inside the first cabinet; the second was already hidden in the second cabinet. He shows the audience the two assistants side by side. Most are convinced for the moment. But a week later, many are saying, “You know, it was really a trap door.”

This story does not have a very plausible middle and end. People examining the stage would probably be convinced that there was no trap door. People seeing the twins side by side would probably not relapse to the trap door theory. It is not a plausible scenario for the magician’s audience. However, just such a tale unfolds again and again in science classrooms throughout the world. Students are invited to engage in inquiry. They make up their own initial theories—so far so good—but then they cling to those theories stubbornly in the face of apparent counterevidence. Students hear the received theory and examine supposedly persuasive evidence for it. For a while, they may be convinced, but next week or next month they relapse to their initial views. What is not such a plausible scenario for the magician's audience happens all the time in science learning. For many a learner, science is more baffling than magic.

Why is this the case? One possible answer points to the specific difficulties posed by particular concepts and theories. This certainly is part of the story. However, more general factors may figure in learners' troubles. In the story of the magician, notice how accessible the twin explanation is. It is no more exotic than the trap door explanation, making a shift from the trap door view to the twin view relatively easy. Both reflect the commonsense world of everyday things and actions. In contrast, most scientific models go well beyond causal explanations of ordinary events. They posit invisible entities like electrons, rule systems like Ohm's law that govern the global behavior of systems, and large scale patterns of action that are "emergent" from small-scale interactions, as with the gas laws.

This paper argues that the difficulty of scientific concepts can be explained in large part by two general factors. The first is the limited models of causality held by most learners. Their relatively simple styles of causal modeling contrast with the esoteric character of scientific models, what we refer to as *complex causality*. By causal models, we mean the nature of how causes and effects interact—types of causal structures. This is distinct from conceptual or explanatory models used to explain a certain phenomenon—an instance of causation—although conceptual models embed situated causal models. The second is the process of inquiry as understood by learners. They typically have little experience or comfort with *epistemic moves* such as remaining alert to gaps in a causal story or seeking disconfirmation for theories—moves that lead toward more complex models. With complex causal models and epistemic moves in mind, we call this theory *Models and Moves*.

A Performance View of Science Understanding

To introduce this perspective, it’s useful to take a performance view of science understanding. What kinds of “performances” are learners actually asked to attempt around science concepts that show as well as advance their understanding? Do they solve problems, undertake experiments, analyze phenomena? Such a question resonates with the general notion of learning as doing and with the constructivist emphasis on inquiry activities as an avenue to understanding (e.g. Duffy & Jonassen, 1992; Perkins, 1999; Phillips, 1995; Wilson, 1996). It also echoes a constructivist framework developed by the first author and colleagues (e.g. reference) called, "Teaching for Understanding" or "TFU." TFU foregrounds the role of “understanding performances” in learning for understanding—understanding performances being thought-demanding activities that display a learner’s present understanding as well as advancing it further (e.g. Perkins & Unger, 1999; Wiske, 1998).

Reflecting on typical science learning reveals three levels of performance. We argue that, the third, although found least often, offers the best prospects for preparing students to understand a range of science concepts readily.

1. ***Learning and applying specific models.*** Most students learn particular models for particular situations. For instance, they learn how to model the fall of released objects in a gravitational field. They can calculate how long an object will take to hit the ground or how fast it will be going.
2. ***Learning and applying modeling systems.*** Some students learn general modeling systems, for instance Ohm’s law and related rules for analyzing circuits that are sometimes quite complex, or Newtonian dynamics for analyzing a range of physical motions. Here the core performance is to use the modeling system to build and perhaps test a model for a given system, for instance, a complex circuit that students had never seen before.

3. ***Learning and reusing modeling styles.*** Some students eventually become familiar with a range of modeling styles. For example, students who have seen circuits modeled with Ohm's law, gases modeled with Boyle's law, and dynamic systems modeled with Newton's laws and conservation of energy may come to recognize modeling by constraint equations as a familiar "game." Faced with another set of scientific concepts in the same style, they may feel comfortable with the manner of thinking involved and proceed with some confidence and skill to learn and apply the concepts. There are many modeling styles, as will be seen. By way of preview, a couple of others are decentralized control systems, as in flocks of birds or schools of fish where there is no one leader, and large-scale effects due to small-scale statistical processes of equilibration, as in erosion or the gas laws or free-market economies.

Sometimes inquiry-oriented approaches to science learning engage students not just in applying models but in building them. Such approaches draw both upon students' repertoire of modeling styles and their repertoire of epistemic moves—testing and improving candidate models. The testing process often drives models toward more complex modeling styles.

Comparing the three levels, anyone familiar with patterns of science education will recognize that the first is the most common, the second less so, and the third rather rare. When something like three does occur, usually in a context of inquiry-based instruction, it mostly foregrounds the epistemic aspects of inquiry (look for logical inconsistencies, design tests, gather evidence) but rarely deals explicitly with different modeling styles. In general, science instruction hardly ever stands back to examine the general styles of modeling that figure in various particular theories. Students who catch on to such styles do so on their own, by and large.

This situation, we propose, lies at the heart of students' problems of understanding science. As students progress through the years, they encounter a wide range of science concepts involving styles of modeling increasingly removed from common sense and everyday experience. Without specific help in understanding these modeling styles and the epistemic moves that drive inquiry toward them, students fail to grasp how particular modeling systems and models work. They instead resort to routines for responding to familiar types of problems, routines that mask simplified conceptions.

Complex Modeling Styles as a Learning Bottleneck

Naturally, some concepts confuse students only for lack of an opportunity to learn. For example, four to seven year olds do not hold much biological knowledge and they typically do not have adult-like concepts of living things (Piaget, 1929). However, by age 9 and 10 there is a marked increase in biological knowledge and typically by age 11, children hold an adult-like conception of living things (Carey, 1985). This is not to imply that they do not still have a number of different kinds of confusions. However, they do develop a concept of biological functioning.

More interesting from the present perspective are concepts that prove particularly resistant to students' learning. For example, when students study electricity, many arrive at the idea that electrical current fills the circuit from point to point, affecting each component in turn within the circuit (Closset, 1983; Shipstone, 1984). This model has been found even in students who have taken university courses and passed university level exams in physics (Picciarelli, Gennaro, Stella, & Conte, 1991). In contrast to this circuit-filling model, the received model pictures the electrons in all parts of a simple circuit moving at the same time and with the same flow rate, rather like a bicycle chain, once the circuit achieves a steady state (e.g. Dupin & Johsua, 1984; Grotzer & Sudbury, 2000; Hartel, 1984).

Researchers have documented innumerable cases of science concepts that consistently and despite good teaching prove difficult for students (e.g. Clement, 1982; Driver, Guesne, & Tiberghien, 1985; McDermott, 1984; Novak, 1987). The present analysis proposes that these concepts characteristically involve complex (in ways to be defined) causal modeling styles that do not simply extend but contradict simpler modeling styles. In the case of simple circuits, the circuit-filling model involves a kind of serial causality (e.g. Shipstone, 1985), like dominoes tipping over one after the other, whereas the bicycle-chain model involves a simultaneous causality, where everything happens at once. For other kinds of contradiction, sometimes scientific models replace an earlier or intuitive deterministic view by a probabilistic one, or a central causal agent by a system with “emergent” effects (Resnick, 1994, 1996). Also, many scientific theories involve multiple layers of linked modeling systems, and the modeling systems at different levels contrast in their modeling styles, generating confusion (Frederiksen & White, 2000; Frederiksen, White, & Gutwill, 1999).

Support for the idea that students’ causal modeling and epistemic moves are less than adequate for learning complex science concepts can be found in the research literature. Driver, Guesne, and Tiberghien (1985) outlined characteristics of student thinking which they found impede students’ ability to grasp scientific concepts. A number of these concern how students reason about causality, for instance, focusing on changes as opposed to steady states and subsequently failing to see a need to explain systems in equilibrium, or, for instance, the tendency to engage in linear causal reasoning by looking only for sequential chains of causes and effects when systemic patterns are in play. diSessa (1993) introduced the concept of phenomenological primitives (p-prims), small knowledge structures that people use to describe a system’s behavior. These schemata come into play as ready explanations or components of explanations. While often considered to be self-explanatory and to need no justification, p-prims in their very accessibility can lure children and adults into mistaken explanations.

Similarly, Brown (1995) refers to core causal intuitions that he found can lead students astray regarding a variety of difficult science concepts. Brown focuses on core intuitions about how people attribute agency and how they assess responses to agency. He identifies a number of types—initiating, initiated, reactive, and so on. Andersson (1986) draws upon Lakoff and Johnson’s (1980) notion of an experiential gestalt of causation as a possible underlying element in scientific misconceptions. He considers how students extend the primitive notion, learned in infancy, of an agent that physically affects an object to a sense of “the nearer, the greater the effect.” Andersson outlines how such primitive notions play a role in difficulties students have in learning various science concepts.

Kuhn (1991, 1993) reports research that identifies a number of shortfalls in students’ general and scientific reasoning, including difficulty in generating counterevidence and perseveration in a favored theory despite blatant counterevidence. Kuhn, Amsel, and O’Loughlin (1988) have shown that students’ prior expectations make it difficult for them to perceive co-variation evidence that contradicts their expectations. For instance, they have difficulty perceiving instances where a variable is non-operative or is operative but leads to a different outcome than students expect. Chinn and Brewer (1993) review research and examples from the history of science in support of seven possible responses to anomalous data in the development and revision of theories. They illustrate that the likelihood of changing one’s theory is not particularly high and that it is much more likely for individuals to patch their theories, or to ignore or reject the anomalous data, and so on, than to take the data into account and revise one’s theory.

In summary, such research suggests that the manner in which we reason about causality influences how we analyze specific instances of causation in science class and beyond. The Models and Moves theory asserts that learners tend to assimilate scientific concepts to a limited repertoire of causal models that are relatively simple (in ways to be specified), and that learners lack a sophisticated repertoire of epistemic moves with which to challenge and perhaps improve their simple models. An important instructional implication follows: Learners will find whole ranges of complex science concepts more accessible when the instruction familiarizes them with the types of models involved and the types of moves that lead toward those models.

The following sections sketch the Models and Moves framework, offering four dimensions of complexity for causal models and four important phases of inquiry for epistemic moves, with associated pitfalls and remedies. Then, learners’ initial levels of modeling and reasoning when they first encounter a phenomenon are examined. Such observations provide one kind of evidence for the models and moves theory. For further evidence, interventions designed to introduce learners to more sophisticated models and moves are discussed.

The Models Framework

The central notion behind the models framework is *complex causality:* Some explanations are more complex than others in fundamental ways. In this framework, complex causality is simply the umbrella term for our area of interest. The science concepts examined are “complex” in several different senses to be discussed—because of simultaneous models at different levels, more intricate causal relationships than simply “a causes b,” models that conflict with typical expectations, and more.

Table 1 presents four proposed dimensions of complexity in models: *Mechanism, Interaction pattern, Probability,* and *Agency.* Relative to these dimensions, the causal explanations that people offer for everyday events are simple in several senses. Recall again the accessibility of the twin theory about the magic trick. The twin theory depends on a familiar *surface generalization:* twins are hard to tell apart. The twin theory proposes a *simple linear* causal relationship: The similarity of twins causes people to think it’s the same person. The causal relationship is close to *deterministic:* The perceptual similarity of the twins triggers a perception of the same person, unless an observer sees them side by side or knows that twins might be involved. A *central agent,* the magician with the collusion of the twins, brings about the effect.

In contrast, scientific models exhibit greater complexity, usually on more than one of the four dimensions. Evolution explained by natural selection and elementary electrical phenomena explained by Ohm’s law and the behavior of electrons offer apt illustrations for this introduction. Further examples will be introduced in the course of the article. Italics refer to categories in the framework:

- ***Mechanism.*** This dimension refers to the causal mechanisms invoked in an explanation. At their simplest, they take the form of (not necessarily correct) *surface generalizations* from experience, like “animals learn their necks need to be longer” or the token use of labels like “the balloon sticks to the wall because of static electricity.” Scientific explanation typically involves one or more levels of *underlying mechanism* involving properties, entities, and rules that are not part of the surface situation, as with DNA or electrons and the rule systems governing them.
- ***Interaction pattern.*** This dimension refers to the patterns of interaction between causes and effects. At their simplest, such patterns take the form “A causes B,” as in “They needed wings and grew them” or “Electricity makes the bulb light.” In contrast, natural selection offers an account of evolution that involves *interactive causality* and *re-entrant causality*, as in for example the co-evolution of bees and flowers. Ohm’s law, a *constraint-based* system, addresses electrical circuits.
- ***Probability.*** This dimension refers to expectations about the level of certainty in causal relationships. At their simplest, such relationships are deterministic, consequences inevitable. In contrast, contemporary natural selection recognizes evolution as a *chaotic system.* Ohm’s law treats electrical circuits as deterministic systems, but it is *order from chaos,* averaging effects smoothing out atomic-level events into large scale orderly patterns.
- ***Agency.*** This dimension refers to agency and to the compounding of causes and effects in ways that lead to new and not easily anticipated outcomes. The simplest level here involves central agents with immediate influence: The ducks needed webbed feet; the battery makes the current flow. In contrast, from the perspective of current science, species are *emergent entities* of evolution. Electrical circuits display *self-organizing* characteristics, where circuit configurations can yield unexpected (if you are not in the know) large-scale regularities, as in oscillations.

While each of the four dimensions ranges from a simple to a complex extreme, no claim is made about strict order of difficulty or of developmental stages. Indeed, each level of the four dimensions within itself allows simpler and more complex variations. For example, entirely within the *mediating cause* level of Interaction pattern, A causes M causes B seems a more accessible relationship than M catalyzes A causes B. Accordingly, the general claim here is, loosely, that difficulty increases roughly with complexity along the dimensions.

Moreover, it is important to recognize that explanations falling low on the four complexity dimensions are not necessarily wrong. They may be entirely suited to the phenomenon at hand. The point, rather, is that typical scientific explanations routinely involve more complexity because the target phenomenon demands it, and often learners do not manage to get there.

How then do these more complex modeling styles make things harder for learners? One way is simply their newness, their lack of familiarity. Another, as noted earlier, is that some modeling styles of higher complexity that students encounter in their science instruction do not simply elaborate but contradict other more familiar modeling styles of lower complexity. The more complex causal styles challenge basic assumptions about how the world works, such as sizes of effects correlate with "sizes" of causes, temporal priority between causes and effects (Bullock, Gelman, & Baillargeon, 1982), correlation does not necessarily imply causation, and so on. For instance, often today's scientific models replace an intuitive deterministic view by a probabilistic one or a central causal agent by a system with "emergent" effects (Resnick, 1994, 1996). Moreover, a number of scientific theories include multiple layers of linked modeling systems with contrasting styles, as in the relation between the constraint system of Ohm's laws applied to a whole circuit and the forces that govern current flow at the micro-level, which involve interactive causality (Frederiksen & White, 2000; Frederiksen, White, & Gutwill, 1999).

With these problems in mind, we turn to another side of the matter: the moves framework.

The Moves Framework

The central notion behind the moves framework concerns the epistemic moves that serve scientific inquiry, and indeed inquiry in general. In everyday argument, people commonly make convenient assumptions, neglect alternatives, excuse and patch favored theories, and so on (e.g. Kuhn, 1993; Voss, Perkins, & Segal, 1991). For an informal illustration, let us bring back the story of the magician once more. Suppose an audience member simply assumes that the magician's trick uses trap doors. The audience member has not really elaborated a complete causal story: Two trap doors seem to be needed, and the assistant would have to get from one cabinet to the other quickly under the stage. Was there enough time? The audience member has only generated one hypothesis, where there could be others, such as the twins.

The moves framework identifies four broad aspects of inquiry, characterizing each in terms of typical trouble spots and specific moves that address those trouble spots: *seeking a gapless model, putting the model at risk, detecting flawed evidence,* and *building from counterevidence*. Table 2 gives the details. These four problems can readily come up in science inquiry, as illustrated again with evolution and Ohm's law.

- ***Seeking a gapless model.*** A plausible model does not leave gaps in the causal story it advances. The evolutionary explanation, "They needed wings and grew them" includes what Table 2 calls a *convenient assumption*—that they could know what they needed—and a *missing link*—how they might grow what they needed. Efforts to examine a model for gaps and to adjust or abandon the model are part of good inquiry.
- ***Putting the model at risk.*** Good inquiry also involves putting the model at risk. The explanation, "They needed wings and grew them" ignores the readily accessible counterevidence from everyday experience that ordinarily organisms cannot grow whatever features they want, a problem from Table 2 of *positively biased evidence.* Also, typically students

give one explanation rather than juxtaposing candidate explanations, a problem of *no rival model considered.*

- ***Detecting flawed evidence.*** Misleading evidence can lead both to the rejection of sound models and to the acceptance of unsound ones. Part of good inquiry is detecting flawed evidence, for instance a *very limited sample* that may accidentally mislead or *confounded variables* that do not discriminate which variable wields influence. Say a student exploring elementary series circuits observes, “When you rewire to leave out one bulb, the others get brighter.” But this is only true for series circuits, not for parallel circuits (assuming a battery with negligible internal resistance relative to the bulbs).
- ***Building from counterevidence.*** Genuinely sound counterevidence for a model does not necessarily imply rejecting the model altogether. Suppose, for instance, the above student now experiments with parallel circuits and discovers that removing a bulb does not change the brightness of the other bulbs. According to Table 2, this is a *blatant disconfirmation* of the student’s original idea that rewiring to remove a bulb makes the others brighter, regardless of the circuit’s structure. However, instead of discarding the generalization altogether, the student might seek ways to qualify it, for instance by distinguishing between serial and parallel circuits.

The moves of good inquiry often drive toward more complex models of the phenomenon being explained. In scientific inquiry, efforts to eliminate gaps, put the model at risk, detect flawed evidence, and build from counterevidence routinely lead to highly complex models of the sort that dominate contemporary science.

Evidence for Models and Moves: Learners' Initial Conceptions

With the Models and Moves framework outlined, questions of evidence invite attention. Notice that the issue is not whether learners' initial conceptions are mistaken by the measure of contemporary science; they almost always would be, given the sophisticated knowledge behind received theories. Rather, the Models and Moves framework predicts that initial conceptions of scientific phenomena would in strong trend be low on the dimensions of complexity. A secondary prediction (which we have not tested) is that if certain students, for whatever reason, have initial conceptions that are causally more complex in the direction of the standard scientific models, these students would learn the standard models more readily. Regarding Moves, the theory implies that initial conceptions are likely to display moves-related problems, the neglect of which allows learners to persist in those models despite shortfalls.

We tested these implications by examining initial conceptions of several science concepts, both in the literature and through classroom-based studies. The results, outlined below, support the Models and Moves theory.

Electrical Circuits

As noted earlier, when students learn about simple circuits, they typically find it hard to focus at the level of the system, instead analyzing effects locally (Shipstone, 1985). They commonly offer what might be called a "cyclic sequential" causal account for current flow. They envision the circuit as initially empty. The circuit fills with a "substance-like material" (Slotta & Chi, 1999) that eventually reaches the bulb and causes it to light. For instance, a typical student explanation sounds like this: "The electrons travel into the wire and they go to the bulb and then it lights. The electrons keep going until they are back in the battery and can travel around again. If the wire were longer, it would take longer for the bulb to light because it takes longer for the electrons to reach the bulb."

Turning to the Models framework, from the standpoint of Mechanism such learners are explaining electrical flow with a *token agent.* Even when they refer to electrons, the electrons simply fit into a story of flow, rather than the flow reflecting a set of rules that apply to electrons. From the standpoint of Interaction pattern, the students' accounts reflect *simple linear causality*: The battery pushes the electrons and the electrons in turn light the bulb. Regarding Probability, the system is seen as *deterministic.* Regarding Agency, there are *central agents,* the battery and in turn the electrons. Turning to the Moves framework, students' token agents implicate a serious shortfall in "Seeking a Gapless Model": a problem of *missing mechanism:* The students tell a story in which the electrons move and light a bulb, but without any account of why they move or how they light the bulb. It is difficult for them to "Put the Model at Risk" from such a point of departure since a token agent account makes virtually no predictions.

Scientists, on the other hand, might envision the system as described by a "cyclic simultaneous" kind of causality, where electrons already exist throughout the wire. Hooking the wire up to a battery causes flow, the excess negative charge in the battery repelling nearby electrons, which repel other electrons. The current flows all at once, more like the movement of a bicycle chain. The scientists' account involves an elaborated *underlying mechanism* and *interactive, re-entrant (as the circuit reaches equilibrium), and constraint-based (Ohm's law) causality.* Scientists would view the circuit's behavior as deterministic at the macro-level. However, regarding Agency, the circuit's behavior reaches its steady state through a *self-organizing* process, the equilibration of the charges involved.

Static Electricity

Our own investigations across a number of topics also support the claim that students bring impoverished causal models to their attempts to learn scientific concepts. For example, as well as confirming the above findings on circuit electricity, we interviewed students on static electricity. From the standpoint of received science, elementary electrostatics involves an *underlying mechanism* of electrons, electron displacement, repulsion of like charges, attraction of different charges, and so on. This mechanism implicates *interactive causality* and also *re-entrant* causality through the process of reaching equilibrium. In contrast, students' explanations in response to basic electrostatics demonstrations tended to take very simple and efficient forms, for example: "I think it happened because the electricity went to the paper to make it stay." "I think it happened because of static electricity." "I think it happened because the electricity from the wool gave it to the balloon." "I think it happened because when you rub the cloth to the balloon something happens to the balloon to make it stick."

Such responses plainly involve *token agents* and *simple linear causality.* Once in a while, students made comments that referred to *interactive causality,* for instance, "There is an attraction between the wall and the balloon. Something about the wall and something about the balloon have been changed and it makes them attract." The interactive causal explanations that students offered were not necessarily scientifically accurate. For example, one student described air pressure as "pushing" the balloon to the wall while the wall "sucks" the balloon towards it using static cling. However, even though the student has not learned the information relevant to the scientifically accepted explanation, he does hold a causal form that will fit the information rather than distort it. Concerning the Moves framework, the *token agents* students employed brought along problems of *missing mechanism* and, in general, little opportunity to "Put the Model at Risk" for lack of predictions from the essentially empty account via a *token agent*.

Natural Selection

Ohlsson (n.d.) offers an interesting set of findings about initial conceptions of evolution. He conducted interviews of a number of college students, collecting their explanations for adaptive changes in species over time. Responses recounting Darwinian natural selection were rare. Ohlsson classified the responses into seven categories as follows: *environmentalism,* traits develop when the circumstances present a demand or opportunity; *survival,* the relevant trait and its opposite are in the population, and members without the trait die; *creationism,* God creates the trait; *training,* organisms learn or adapt during their lifetime and pass on traits (Lamarckian); *mutationism,* the trait suddenly appears in small numbers and spreads in the population; *mentalism,* animals decide, discover, learn, or are taught new behaviors or how to give themselves new traits; *cross-breeding,* traits arise via interbreeding between species; *dissemination,* organisms with the trait gradually increase in numbers generation by generation, displacing those lacking it.

We analyzed these categories from the perspective of the models dimensions. Concerning Mechanism, most responses were *composite explanations,* accounting for evolution by piecing together phenomena at the same level as adaptations themselves, rather than at an underlying level, as with genetics. It should be noted that Darwin’s own theory of natural selection was a composite theory, albeit one much more complete than the students offered. Darwin's work predated the theory of genetics. Concerning Interaction pattern, the explanations were mostly *simple linear,* as with *environmentalism,* where the circumstances somehow cause the trait to develop. Concerning Probability, most accounts were deterministic: The adaptation would follow inevitably. Concerning Agency, there was some recognition of *aggregate effects,* adaptations dominating in a population over time, but also sometimes *central agents with immediate influence,* again as with *environmentalism* where the environment causes the adaptation.

Concerning Moves, various Gap and Risk shortfalls appeared, reflecting the very partial nature of the explanations students offered. One was the Gap problem of *convenient assumption.* In *survival, crossbreeding,* and *dissemination,* the relevant trait conveniently appears or is already in the population. Both *environmentalism* and *training* suffer from *missing mechanism.* In the first case, somehow the environment draws out the adaptation; in the second, somehow the acquired traits are passed along. In summary then, these initial conceptions of evolution fall at the simple ends of the causal models dimensions and implicate moves problems as well.

Ecosystems

Research suggests that most teachers consider ecosystems and the related concepts of food webs and food chains to be important topics for students to learn (Barman & Mayer, 1994). However, this research also found that teachers consider these topics to be relatively easy for students. The wealth of investigations examining students' misconceptions about ecosystems contradicts this belief. A full scientific account of ecosystems is a formidable construct, involving *underlying mechanisms* such as bacteria (Mechanism dimension), *interactive causality and re-entrant causality* (Interaction pattern), *chancy* and *chaotic systems* (Probability), and *causal webs, trigger effects*, and *self-organizing systems* (Agency). However, students' typical accounts capture little of this complexity.

Research shows that when reasoning about effects in ecosystems, students usually miss the connectedness within the system and the implicit complex causal relationships (e.g. Griffiths & Grant, 1985; Webb & Boltt, 1990). For instance, Barmen, Griffiths, and Okabukola (1995) interviewed 32 students from senior high schools in the USA, Australia, and Canada. Students were asked to respond to hypothetical situations regarding populations influencing other populations and the overall impact on the food web by manipulating "cut-outs." They found that students believed that a change in one population will not be passed along several different pathways of a food web and that a change in one population will only affect another population if the two have a predator-prey relationship. Previously, Griffiths and Grant (1985) found similar misconceptions in a study of grade ten biology students. Grotzer (1989, 1993) found that the tendency to ignore indirect effects was, in part, age-related. Seven year olds were less likely than nine and eleven year olds to detect indirect effects on their own. However, instances where indirect effects were ignored or explicitly rejected occurred with fairly high frequencies across the age groups.

Students do not easily recognize interactive causal relations on their own. Most students break these patterns apart and miss their reciprocal aspects. According to Green (1997), although many systems in our world (economic, human relationships) involve complex chains of cause and effect encompassing two-way causal processes, people tend to construct one-way linear chains when explaining them. He found that when twenty-year olds were cued to think in terms of predator-prey relationships, sixty percent gave two-way causal accounts. Uncued, only sixteen percent gave two-way causal accounts. Similarly, forty percent of his subjects used two-way causal models when explaining a two-level problem. However, only nine and a half percent used two-way causal models when explaining a three-level problem. Such data suggest that more complex problems elicit fewer two-way causal models. Barman and Mayer (1994) found that students defined a food web as a more realistic representation of feeding relationships; however, when probed as to what would happen to an ecosystem if the fox population was reduced or the rabbit population doubled, the students revealed a lack of understanding of the mutual relationships within a food web. The students tended to believe that a change in the size of a prey population has no influence on its predator's population, and that a change in the population of a first-order consumer will not affect one or more producer populations.

Such shortfalls are striking. Better accounts of these food web situations can be given in terms of *commonplace elements* (Mechanism) such as foxes and rabbits and their familiar actions. Recalling the Moves framework, this creates ample opportunities for "Putting the Model at Risk" through common-sense reasoning that constructs disconfirmatory instances, challenging *positive bias.* Yet students generally do not make such moves.

Evidence for Models and Moves: Impact of Intervention

The Models and Moves theory predicts that students tend toward very simple causal explanations as gauged by the Models framework, with few sophisticated moves as gauged by the Moves framework. While the studies reviewed support that prediction, one can still question whether the results reflect shortfalls in learners' repertoire of causal models and epistemic moves. Indeed, a distinction can be drawn between instances of causation and the rules of causality (Murayama, 1994; Pazzani, 1991). Causation refers to explanations of cause and effect in specific instances—the particular mechanism in play and so forth—while causality refers to the rules of cause and effect relationships. A challenge to the hypothesis set forth here is that perhaps the former and not the latter creates students' difficulties. That is, perhaps the strangeness or intricacy of particular topics such as electricity or evolution somehow masks or suppresses models and moves that are actually already in students' repertoire or easily enough constructed by students when the content is less intricate and more familiar.

Accordingly, one way to test the Models and Moves theory further is to try to teach students models and moves, examining whether this expands their understanding. Therefore, we conducted intervention studies contrasting three conditions: 1) a Causal Activities Only (CAO) condition in which students engaged in activities designed to reveal the underlying causal structure of a topic; 2) a Causal Activities plus explicit Discussion (CAD) condition where, in addition to the activities, students heard introductions to, and explicitly discussed, the nature of causality—the specific causal rules and patterns in play—in the context of particular science topics; and 3) usually, a control group, which received what would generally be considered good science instruction, not just facts and exercises, including such best practices as Socratic discussion, computer simulations, grappling with discrepant events, modeling one's ideas, and so forth. However, the control instruction never focused on the causal complexities of the science concepts in question. The CAO and CAD treatment groups extended the style of treatment in the control groups, adding causally-focused activities and, for CAD groups, discussion of causality. Most of the studies addressed the role of models. We also report a preliminary study and some early findings on the role of moves.

What do we mean by "activities designed to reveal the underlying causal structure?" For instance, the following activity was designed to help students analyze pressure-related phenomena using interactive causal patterns (Basca & Grotzer, 2001). 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 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 were given three different flasks, each half-filled with liquid with a straw inserted, and were asked to see who could drink the liquid the fastest. Two of the flask/straw systems had various modifications that prevented the formation of a pressure differential. One had a hole in the straw above the height of the liquid that enabled the lower pressure inside the straw to be equalized with the outside air pressure, thus preventing the formation of a pressure differential so that the liquid would not rise up the straw when the student sucked on it. The other had a stopper at the top that was sealed tightly around the rim with a hole that exactly fit the size of the straw. When the student tried to drink from it, some liquid rose 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.)) These causally-focused activities revealed, through results that were discrepant with students’ expectations, that there was something other than linear causality involved and offered insights into the nature of that causality. These activities were the basis of explicit discussion about the nature of causality in the CAD group.

Insert Figure 1 about here

Pressure

In most of the topics we studied, engaging students in activities designed to reveal the underlying causal structure provided significant benefits. For instance, Basca and Grotzer (2001) found that involving eighth graders in causally-focused activities significantly improved their ability to learn about pressure and pressure-related concepts, phenomena for which students typically hold robust misconceptions. Specifically, we compared a pressure curriculum designed to incorporate systems concepts with the same curriculum plus explicit causal discussion. For this particular topic, we did not include a traditional control group because an extensive search turned up no comprehensive pressure curriculums that would have constituted a reasonable comparison. We knew from extant research that students' misconceptions about the nature of pressure are typically robust and persist after teaching. Therefore, in lieu of a control group, we looked for pre- to post-test gains and significant conceptual changes in the models that students held at the end of the unit. We found significant pre- to post-test gains in understanding in both groups. A paired t-test of students pre- to post-totals for causal model type on an open-ended inventory showed a significant difference (t (42) = 6.93, $p < .0001$) between students' pre- and post-test scores (a mean gain of 3.14 points). Forty-six percent of students reasoned relationally about pressure on the post-test as compared to 19% on the pre-test.

On some but not all measures, explicit discussion made a significant difference between the groups. On the measure of conceptual change (the extent to which subjects' models for thinking about pressure shifted in terms of the level of sophistication), students in the CAD group revealed greater change on the open-ended inventory than students in the CAO group (F (1, 42) = 5.19, p = .03). In sum, the causally-focused activities benefited both groups of students; by some measures there was slightly more change in the causal discussion group.

Ecosystems

Research on third graders' understanding of ecosystems (Grotzer & Basca, 2001; Basca, Grotzer, Donis, & Shaw, 2000) echoed these findings. Students who participated in causally-focused activities and causal discussion outperformed control students on two measures: 1) an overall point score corresponding to sophistication level of students' responses; and 2) the type of causal connections that students detected within the food web—whether these were direct or indirect and the number of links involved. There was a significant main effect of group (F (2, 26) = 3.95, p = .03) on the measure of total point scores. Students who participated in causally-focused activities and causal discussion significantly outperformed the control group (t (26) = 2.75, p = .01). CAD students had a base gain of 40 points, compared to CAO students with 19.8 points and controls with 10.2 points.

Regarding causal connections, the CAD group detected significantly more multi-step connections than the control group (t (26) = 2.08, p = .04). Mean gain scores for multi-step connections in each intervention condition were CON = 1.2; CAO = 2.7; CAD = 7.5. In sum, in the case of ecosystems, the causally-focused activities in combination with causal discussion made a significant difference.

In understanding the causality involved in matter recycling and decay, CAD students significantly outperformed control students (t (26) = 2.42, p = .0231). The performance of CAO students was better than those of control students at a level approaching significance (t (26) = 1.90, p = .0690).

Electrical Circuits

Grotzer and Sudbury (2000) found that on simple electrical circuits, fourth graders in the CAD group made the greatest gains. There was a significant main effect of intervention condition (F (2, 26) = 10.11, $p = .0007$) on post-interview scores, a measure of whether students underwent conceptual change in the models that they brought to analyzing simple circuits. CAD students significantly outperformed the control (Abs(Dif)-LSD = .34, $p < .05$) and CAO group (Abs(Dif)-LSD = .06, $p < .05$) as revealed by Tukey Kramer Multiple Comparisons t-test (HSD.) No significant differences were found between the control and the CAO groups.

There was also a significant main effect of intervention condition on post-inventory scores (F (2, 65) = 5.14, $p = .008$), a measure of whether or not students still held typical misconceptions that they brought to the unit. These included, for instance, the idea that the circuit is initially empty or that current is not conserved and that bulbs in a series will get progressively dimmer the further away from the battery they are. CAD Students did significantly better than the CAO (Abs(Dif)-LSD = .11, $p < .05$) and control students (Abs(Dif)-LSD = .38, $p < .05$) as revealed by a Tukeys HSD. The CAD group outperformed the others by nearly one standard deviation. There were no significant differences between the CAO group and the control group. Similar patterns were found with eighth graders. At least for the topic of electricity, causally-focused activities alone were not effective. Explicit discussion was needed to make a significant difference in students' performance.

Further, it appears that the CAD intervention benefited all of the students in the group regardless of achievement level. Regression analyses plotting pre-interview scores against achievement level showed that achievement level was a significant predictor of students’ pre-interview scores (F (2, 27) = 6.23, $p = .007$), with the lowest level students doing the least well, as would be expected. However, a regression plotting group and achievement level against post-interview scores shows that intervention group (F (2, 27) = 11.2, $p = .0004$) is a significant predictor of post-interview performance but that achievement level is not (F (2, 27) = 2.3, $p = .1238$). Figure 1 shows students' post-interview models by achievement level. Note that in the CAD group all of the low achievers reached the most sophisticated model.

Insert Figure 2 about here

Electrical Circuits with Both Models and Moves

We also have preliminary data on the effects of including epistemic moves in addition to models. The study contrasted the performance of three eighth grade classes studying simple circuits. One group was taught causal models using both activities and discussion as in the CAD conditions above. Another group received the same instruction, plus introduction to a set of three causal moves: *checking for gaps, testing the model*, and *comparing rival models* (slightly modified from those listed in Table 2). A third class functioned as a control group. The models and moves were incorporated into the curriculum design and homework assignments. The intervention was shorter in length and less intensive than the one reported above for fourth graders. Additionally, it was taught by the classroom teacher as his first attempt to teach the causal concepts. No differences were found between groups on students' post-test inventory scores (a total score which combines scores for multiple choice and essay questions) (F (2, 54) = .08, p = .91). However, when one looks at the essays only, there were differences in how students performed on explaining simple circuits. The main effect of total gain score across the essays approached significance (F (2, 53) = 2.81, p = .06) and was in the predicted direction (Models and Moves = 4.02 > Models Only = 3.46

> Control Group = 2.52). The essay asking students to draw a circuit that lights the bulb and to explain why it works revealed a significant main effect of intervention (F (2, 54) = 3.10, $p = .05$) based on gain scores. However, here there was no difference between the Models and Moves and the Models Only Group: Both gained significantly more than the control group (Models and Moves = 2.0 = Models Only = 2.0 > Control = 1.17), thus underscoring the efficacy of teaching models.

In summary, the foregoing studies offer considerable support for the hypothesis that teaching students about the structure of the nature of causality improves their ability to reason about topics for which they typically have misconceptions. Across topics, we found strong support for the value of engaging students in causally-focused activities. On some measures and for some topics, the casual discussion added value. For one study of electricity, activities alone were not effective; explicit discussion was needed to make a significant difference in students' performance. An analysis of the topics suggests that the complexity of the causal pattern to be learned may interact with the type of intervention needed to learn it, with causally-focused activities being sufficient to learn less complex patterns and causal discussion boosting performance when the patterns are more complex. The findings are inconclusive about whether moves may offer some additional benefit. The data reported here on moves is preliminary in the sense that it represents our first effort at designing an effective intervention and we expect that we might learn more about the effectiveness of moves as we discover the most effective pedagogy for teaching them.

Conclusion

We began with a puzzle: Magic was easier to understand than science. A likely reason was not hard to find. The baffling accomplishments of a master magician, once explained and demonstrated, occupy the everyday world of commonsense causality. Even if a trick is complicated, each element has a comforting familiarity. In contrast, a scientific explanation that might even have fewer principal elements would often be more complicated in other senses—invoking an underlying mechanism; interactive, cyclic, or constraint-like relations among factors; probabilistic elements; and emergence of various kinds.

Typical science instruction does little to prepare learners for this complexity. As noted earlier, science instruction characteristically foregrounds (1) learning and applying specific models (for instance, Ohm’s law for a simple circuit), and, next to that, (2) learning and applying modeling systems (for example, Ohm’s law for any circuit), but rarely (3) learning and reusing modeling styles (constraint-system models in general for instance). Unfamiliar and uncomfortable with complex styles of causal modeling, and not well equipped with the epistemic moves needed to reason their way toward them, learners would often find themselves baffled and frequently backslide after a little progress.

We tested our Models and Moves theory and found significant confirmation from studies of students’ initial conceptions and conceptions after conventional instruction. The causal models implicit in students’ explanations tend to be quite simple by the measure of the four dimensions of the Models framework. Also, students rarely appear to deploy the moves of Seeking a Gapless Model and Putting the Model at Risk that would take them beyond these simple models. Moreover, efforts to help students learn more complex models through activities and explicit discussion in the course of teaching particular science topics yield considerable gains in their understanding, in comparison with control groups that received "best practices" instruction without the causal interventions.

At the outset we asked where the resistance lies. What made some science concepts particularly hard, not just a matter of a little more instruction? The following conclusions, all related to modeling styles and epistemic moves, seem warranted.

1. What is *not* so challenging is complexity of scientific theories in the sense of daunting intricacy—at least not scientific theories usually found in the K-12 curriculum. Compare, for

example, the intricacy of a foreign language with its many rules, many exceptions, and huge vocabulary with the intricacy of most scientific theories. The foreign language is far more complex in the sense of intricacy.

2. A more serious source of challenge, we propose, is unfamiliarity with modeling styles at the complex ends of the dimensions introduced earlier. Causal reasoning about the everyday world does little to prepare students for dealing with underlying mechanisms, constraint-system models, highly probabilistic phenomena, or emergent effects.
3. Unfamiliarity with the kinds of epistemic moves that lead toward more complex models compounds students' problems. These moves motivate the more complex modeling styles. They also call for sustaining an attitude toward particular models as provisional, under test, and part of an inquiry process, an attitude quite removed from students' tendency to want to know the facts (e.g. Clement, 1993; Collins & Ferguson, 1993; Frederickson & White, 2000; Perkins, 1997).
4. The challenge is even greater when modeling styles toward the more complex ends of the dimensions contradict modeling styles toward the simpler ends. This generates particular resistance to learning, because students cannot simply extend their thinking but have to abandon their initial thinking styles.
5. Many scientific theories call for what Frederickson and White (2000) have called "multi-model thinking"—coordinating multiple levels or perspectives of explanation that may involve different modeling styles.

These conclusions imply that students need opportunities to learn how to structure causal relationships in the various ways defined by the four dimensions and to map these structures to fitting instances of causation. These opportunities can fit naturally within inquiry based classrooms where students are discussing the merits of different explanatory models and grappling with what particular models help to explain and what puzzles they present. However, these are not ways of thinking that teachers have necessarily had the opportunity to learn or if they have, to realize the value of explicitly discussing them with students. Thus the pedagogical challenges are not trivial.

While the research reviewed here supports the Models and Moves theory, other important questions remain part of our ongoing research. For one, do Epistemic Moves make a contribution to students' science understanding and scientific reasoning independent of model repertoire? Although many of the activities we investigated have included epistemic moves, we have not varied epistemic moves independently of attention to models. We conjecture that acquaintance with more complex models will have a greater impact on students' science understanding than incorporation of stronger epistemic moves—we believe that models are more of a bottleneck than moves—but that remains to be demonstrated empirically.

For another question, when students appear to become acquainted with more complex models in the context of one science topic, can they transfer this to other science topics that may be quite different on the surface? We conjecture that the answer is affirmative, and that therefore one of the most important things science instruction can do to empower students as science learners is to acquaint students with several key complex modeling styles through particular cases and reflective abstraction.

However, there is a natural rival to this hypothesis. The principal barriers to understanding a science concept might lie not in familiarity with the relevant complex modeling style but in the particularities of how that style applies to the science concept question. In that case, attention to modeling styles would be important, but on a case-by-case basis with little carry-over. Carefully designed empirical study is needed to provide insight into this question.

At this point, the current findings are encouraging. If the Models and Moves theory is valid, even in considerable part, it promises much toward explaining more deeply the difficulties learners encounter with many topics in science, and toward educating them more effectively.

References

Andersson, B. (1986). The experiential gestalt of causation: A common core to pupils’ preconceptions in science. *European Journal of Science Education*, 8(2), 155-171.

Andersson, B., & Karrqvist, C., (1979). Electric Circuits, EKNA Report No. 2, Gotesberg University, Molndal, Sweden.

Barman, C.R., & Mayer, D.A. (1994). An analysis of high school students' concepts & textbook presentations of food chains & food webs. *The American Biology Teacher*. 56(3): 160-163.

Barman, C.R., Griffiths, A.K., & Okebukola, P.A.O. (1995). High school students' concepts regarding food chains and food webs: A multinational study. *International Journal of Science Education*. 17(6): 775-782.

Basca, B.B. & Grotzer, T.A. (2001). *Teaching about the nature of causality in a unit on pressure: How does it impact student understanding?* Paper presented at the Annual Conference of the National Association for Research in Science Teaching (NARST), Seattle, April 9-14.

Bell-Basca, B., Grotzer, T.A, Donis, K. & Shaw, S. (2000). *Using Domino and Relational Causality to Analyze Ecosystems: Realizing What Goes Around Comes Around.* Paper presented at the Annual Conference of the National Association for Research in Science Teaching (NARST), New Orleans, April 28- May 1.

Brown, D. (1995). *Concrete focusing and refocusing: A cross-domain perspective on conceptual change in mechanics and electricity*. Paper presented at the Annual Meeting of the American Educational Research Association, San Francisco, April 18-22.

Bullock, M., Gelman, R., & Baillargeon, R. (1982). The development of causal reasoning. In W.J. Friedman (Ed.), *The developmental psychology of time* (pp. 209-254). New York: Academic Press.

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

Chinn, C.A., & Brewer, W.F. (1993). The role of anomalous data in knowledge acquisition: A theoretical framework and implications for science instruction. *Review of Educational Research 63*(1) 1-49.

Clement, J. (1982). Students' preconceptions in introductory mechanics. *American Journal of Physics*, *50*, 66-71.

Clement, J. (1993). Using bridging analogies and anchoring intuitions to deal with students' preconceptions in physics. *Journal of Research in Science Teaching*, *30*(10), 1241-1257.

Closset, J.L. (1983). *Sequential reasoning in electricity*. In Research on Physics Education. Proceedings of the First International Workshop. June 26 to July 13, La Londes Les Maures, France, Editions du Centre National de Recherche Scientifique, Paris, (1984) p. 313-19.

Collins, A., & Ferguson, W. (1993). Epistemic forms and epistemic games: Structures and strategies to guide inquiry. *Educational Psychologist*, *28*(1), 25-42.

diSessa, A. (1993). Toward an epistemology of physics. *Cognition and Instruction* 10(2 & 3), 105-226.

Driver, R., Guesne, E., & Tiberghien, A. (1985). Some features of children's ideas and their implications for teaching (pp. 193-201). In R. Driver, E. Guesne, & A. Tiberghien (Eds.), *Children's ideas in science*. Philadelphia: Open University Press.

Duffy, T. M., & Jonassen, D. H. (1992) (Eds.). *Constructivism and the technology of instruction: A conversation.* Hillsdale, New Jersey: Lawrence Erlbaum Associates.

Dupin, J.J. & Johsua, S. (1984). Teaching electricity: Interactive evolution of representations, models, and experiments in a class situation. In R. Duit, W. Jung, & C. von Rhoneck (Eds.). *Aspects of understanding electricity*. Proceedings of the International Workshop, Ludwigsburg, September 10-14.

Dupin, J.J. & Johsua, S. (1987). Conceptions of French pupils concerning electric circuits: Structure and evolution. *Journal of Research in Science Teachin*g, 24(9), 791-806.

Frederiksen, J. R., & White, Barbara Y. (2000). *Sources of difficulty in students' understanding causal models for physics systems*. Paper presented at the Symposium on Complex Causality and Conceptual Change, Annual meeting of the American Educational Research Association, New Orleans, April 26, 2000.

Frederiksen, J. R., White, B. Y., & Gutwill, J. (1999). Dynamic mental models in learning science: The importance of constructing derivational linkages among models. *Journal of Research in Science Teaching, 36*(7), 806-836.

Fredette, N. & Lochhead, J. (1980). Student conceptions of simple circuits. *The Physics Teache*r, 18, 194-198.

Green, D.W. (1997). Explaining and envisaging an ecological phenomenon. *British Journal of Psychology, 88,* 199-217.

Griffiths, A. K., & Grant, B.A., (1985). 'High school students' understanding of food webs: Identification of a learning hierarchy and related misconceptions'. *Journal of Research in Science Teaching.* 22(5): 421-436.

Grotzer, T. A. (1989). *Can children learn to understand complex causal relationships?: A pilot study*. Unpublished qualifying paper. Cambridge, MA; Harvard University.

Grotzer, T. A. (1993). *Children's understanding of complex causal relationships in natural systems*. Unpublished doctoral dissertation. Cambridge, MA: Harvard University.

Grotzer, T.A. & Basca, B.B. (2001, January). *Helping students to grasp the underlying causal structures when learning about ecosystems: How does it impact understanding?* Unpublished paper. Harvard Project Zero, Cambridge, MA.

Grotzer, T.A. & Sudbury, M (2000). *Moving Beyond Underlying Linear Causal Models of Electrical Circuits*. Paper presented at the Annual Conference of the National Association for Research in Science Teaching (NARST), New Orleans, April 28-May 1.

Hartel, H. (1984). The electrical circuit as a system. In R. Duit, W. Jung, & C. von Rhoneck (Eds.). *Aspects of understanding electricity*. Proceedings of the International Workshop, Ludwigsburg, September 10-14.

Kuhn, D. (1991). *The skills of argument.* New York: Cambridge University Press.

Kuhn, D. (1993). Connecting scientific and informal reasoning. *Merrill-Palmer Quarterly, 39*(1), 74-103.

Kuhn, D., Amsel, E., & O'Loughlin, M. (1988). *The development of scientific thinking skills*. San Diego: Academic Press.

Lakoff, G. & Johnson, M. (1980). *Metaphors we live by*. University of Chicago Press: Chicago.

Liem, T.L. (1992). *Invitations to science inquiry*. Chino Hills, CA: Science Inquiry Enterprises.

McDermott, L. C. (1984). Research on conceptual understanding in mechanics. *Physics Today 37*, 24-32.

Murayama, I. (1994). Role of agency in causal understanding of natural phenomena. *Human Development, 37*, 198-206.

Novak, J. D. (Ed.) (1987). *The proceedings of the 2nd misconceptions in science and mathematics conference.* Ithaca, NY: Cornell University.

Ohlsson, S. (n.d.). Acquiring an explanatory schema: A preliminary model and related data. Unpublished paper.

Osborne, R. & Gilbert, J.K. (1980). A method for investigating concept understanding in science. *European Journal of Science Educatio*n, 2(3), 311-321.

Pazzani, M. (1991). A computational theory of learning causal relationships. *Cognitive Science, 15*, 401-424.

Perkins, D. (1997). Epistemic games. *International Journal of Educational Research, 27*(1), 49-61.

Perkins, D. N. (1999). The many faces of constructivism. *Educational Leadership, 57*(3), 6-11.

Perkins, D. N., & Unger, C. (1999). Teaching and learning for understanding. In C. Reigeluth (Ed.), *Instructional design theories and models: Volume II* (pp. 91-114). Hillsdale, New Jersey: Erlbaum.

Phillips, D. C. (1995). The good, the bad, and the ugly: The many faces of constructivism. *Educational Researcher, 24*(7), 5-12.

Piaget, J. (1929). *The child's conception of the world*. Routledge & Kegan Paul: London.

Picciarelli, V., Di Gennaro, M., Stella, R., & Conte, E. (1991). A Study of University Students' Understanding of Simple Electric Circuits:Part 1: Current in d.c. Circuits. *European Journal of Engineering Educatio*n, Vol. 16, No. 1, pp. 41-56.

Resnick, M. (1994). *Turtles, termites, and traffic jams: Explorations in massively parallel microworlds.* Cambridge, MA: MIT Press.

Resnick, M. (1996). Beyond the Centralized Mindset. *Journal of the Learning Sciences, 5*(1), 1-22.

Shipstone, D. M. (1984). A study of children’s understanding of electricity in simple DC circuits. *European Journal of Science Educatio*n, Vol. 6, No. 2, pp. 185-198.

Shipstone, D. (1985). Electricity in simple circuits (pp. 33-51). In R. Driver, E. Guesne, & A. Tiberghien (Eds.), *Children's ideas in science*. Philadelphia: Open University Press.

Slotta, J. D. & Chi, M. T. (1999, March). *Overcoming robust misconceptions through ontology training*. Unpublished paper.

Smith, C., Maclin, D., Grosslight, L., & Davis, H. (1997). Teaching for understanding: A study of students' pre-instruction theories of matter and a comparison of the effectiveness of two approaches to teaching about matter and density. *Cognition and Instruction, 15*(3) 317-393.

Tiberghien, A. & Delacotte, G. (1976). Manipulations et representations de circuits electrique simples chez les infants de 7 a 12 ans. *Revue Francais de Pedagogi*e, 34.

Voss, J. F., Perkins, D. N., & Segal, J. W. (1991). *Informal reasoning and education.* Hillsdale, NJ: Erlbaum.

Webb, P. & Boltt, G. (1990). Food chain to food web: A natural progression? *Journal of Biological Education, 24*(3), 187-190.

Wilson, B. G. (Ed.) (1996). *Constructivist learning environments: Case studies in instructional design.* Englewood Cliffs, NJ: Educational Technology Publications.

Wiske, M. S. (Ed.). (1998). *Teaching for understanding: Linking research with practice.* San Francisco, CA: Jossey-Bass.

Table 1: Dimensions of Complexity in Models

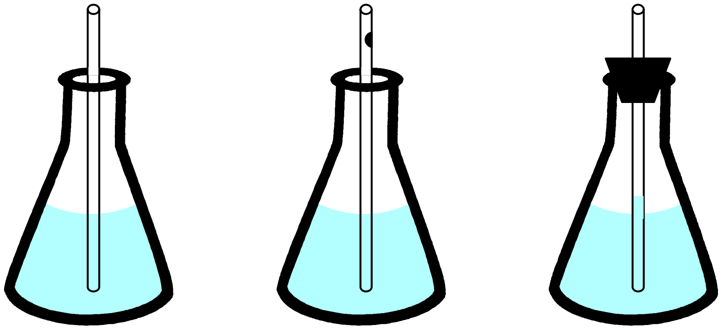
Mechanism From a same-level account of a phenomenon to an inferred underlying mechanism	*Interaction pattern* From A causes B to complex reciprocal relations and constraint systems	*Probability* From deterministic causality to chaotic and quantum systems	*Agency* From a central and direct agent to highly emergent causality
Surface generalization: Simply describes the regularity under consideration in a generalized way (often incorrect). Often variants of “More’s law”—more of this means more of that. ***Token agent:*** Some agent, intentional or not, made things come out that way. Agent’s behavior parallels phenomenon, no real differentiation. ***Commonplace elements:*** Constructs explanations with familiar elements of the system in question rather than those underlying it. (Such theories can sometimes be illuminating. Darwin’s theory of natural selection explains not at the genetic level but in terms of observable adaptive traits, the everyday notion of inheritance, etc.) ***Analogical model:*** System explains target phenomenon by analogy and analogical mapping (e.g. electricity as fluid flow). ***Underlying mechanism:*** Properties, entities and rules introduced that are not part of the surface situation but account for it (e.g. Ohm’s law; and underneath that electrons and their rules of conduct. *Note: There are often two or three levels of underlying mechanism, each underlying the previous*).	***Simple linear causality:*** A impinges on, pushes, influences B. A typically seen as not affected. (e.g. A pushes, pulls, initiates, resists, supports, stops B. A may be active as in pushing or passive as in resisting). Also simple causal changes like A causes B causes C. ***Multiple linear causality:*** Multiple immediate causes, multiple immediate effects, necessary and sufficient causes, etc. This often adds previously neglected agents of lower saliency to the causal story. ***Mediating cause:*** At least three agents in play, M mediates the effect of A on B but not simply in the sense of A causes M causes B (e.g. M is a barrier to A affecting B, or a catalyst, or an enabling condition). ***Interactive causality:*** Mutual interaction of two or more agents (e.g. mutual attraction, net effects as in lift) ***Re-entrant causality:*** Simple causal loops as in escalation and homeostasis. ***Constraint-based causality:*** Behavior of system reflects a set of constraints that the system “obeys”—constancy, conservation, and covariation rules (e.g. conservation of energy, Ohm’s law, law of gravitation)	***Deterministic systems:*** As in Ohm’s law, law of gravitation. ***Noisy systems:*** Basically deterministic systems perturbed by random or unanalyzed factors (air friction, turbulence on thrown objects) ***Chancy systems:*** At certain junctures, things might go one way or another with a certain probability. ***Chaotic systems:*** Fundamental unpredictability in long term due to “butterfly effects” (e.g. the weather) ***Order from chaos:*** Averaging effects smooth out chaotic systems into highly orderly large-scale patterns (e.g. gas laws). ***Fundamentally uncertain systems:*** As in quantum theory, uncertainty built into the nature of objects and events, even for very small systems in the very short term.	***Central agents with immediate influence:*** One or a very small number of key factors fairly directly yield the result. ***Long causal chains, branching structures, cycles:*** E.g. as in ripple effects of an ecological disaster. ***Aggregate effects:*** Cumulative effects over time (e.g. erosion). ***Causal webs:*** Complex web of interactions, often involving reasoning at the population level as in ecologies. ***Trigger effects.*** A modest influence “topples” a complex system into a new state or pattern of activity. (“Tipping points.”) ***Self-organizing systems.*** Seemingly messy systems evolve into clear patterns over time without an external agent or an internal blueprint. ***Emergent entities and processes:*** As with the emergence of new species, chemical compounds, etc.

Table 2: Epistemic Moves toward Better Models, with their Cues (Moves marked by ">" lead to more complex models)

Seeking a Gapless Model	*Putting the Model at Risk*	*Detecting Flawed Evidence*	*Building from Counterevidence*
Missing mechanism within a surface generalization or token agent. Moves: >Articulate a composite or analogical explanation or an underlying mechanism. >Elaborate token agent with an underlying mechanism. ***Centrist model without an obvious central agent.*** Moves: >Clearly identify the control mechanism and how it works. >"Decentralize" the model, looking for emergent effects. ***Convenient assumption*** begs the question. Moves: Abandon the model. >Add an explanation of the presence of the lucky element. ***Missing link in causal story.*** Moves: Reject model. Seek compelling empirical evidence, even if link not understood. >Elaborate link. ***Effects at a distance, or much delayed.*** Moves: Reject model. >Elaborate with mechanisms of propagation, persistence. ***Instantaneous effects.*** Moves: Accept as within paradigm. >View as brief unanalyzed transient. >Elaborate model to describe what happens in a brief interval.	***Counterevidence not possible.*** As formulated, nondisconfirmable in principle. Moves: Reject model. Revise model and/or expectations to make disconfirmable. ***Positive bias.*** Moves: Seek disconfirmatory instances. Formulate rival model and compare evidence. Look at extreme cases, simplified cases. Test against alternative physical or imagistic intuitions, experience. ***No rival model considered.*** Moves: Formulate rival model, define contrasting implications, check the evidence. ***Excusing and patching,*** excusing through dismissal of counterevidence or patching to accommodate counterevidence, often because model is so intuitively appealing or alternatives unappealing. Moves: Formulate rival model. Resist excuses, evaluate based on evidence and close reasoning, use of extreme cases, etc. Seek completely new model. >Seek reorganized, rather than patched, model. ***Same account of contrasting cases.*** The similarity may be suspect. Moves: Critique the similarity, look for crucial differences, revise model. ***Different accounts of similar cases,*** e.g. cases that are continuous variants of one another or that simply involve a change of frame of reference. Moves: Discard one model and extend the scope of the other. Try to unify the models.	***Apparent sources of noise in observations.*** Moves: Improve instrumentation, observation conditions. Use many observations, averaging, to filter out random error. >Extend model to include the "noise" as part of the system. ***Apparent sources of bias, including human bias.*** Moves: Use ways of detecting bias, filtering out biased data, correcting for it. Hedge claim. Strengthen claim when bias would seem to be *against* it. >Extend model to include bias as part of system. ***Very limited sample.*** Moves: Larger or repeated samples. Wider, deliberately disparate range of cases. Statistical methods to test adequacy of sample, reliability of conclusions. ***Confounded variables.*** Moves: Control of variables. Using "natural" experiments. Statistical methods to unconfound. ***Questionable whether observation was predicted by model.*** Moves: Check logic of prediction and simplifying assumptions. Check that observation falls within scope of model. ***Correlation taken for causation (post hoc, propter hoc).*** Moves: Consider coincidence, different direction of causal arrow. >Elaborate strong persuasive mechanism. >Consider more elaborate models, e.g. a common cause for two correlated effects.	***Blatant disconfirmation on central cases.*** Moves: Abandon model. >Elaborate to accommodate additional factors. ***Minor discrepancies on central cases.*** Abandon model. Reframe as approximation. >Elaborate model to accommodate additional factors. ***Central core of cases okay, disconfirmation on other cases.*** Move: Abandon model. >Narrow scope of model by a systematic criterion. >Elaborate to accommodate problematic cases. ***Erratic performance in "same" circumstances.*** Moves: Abandon model. >Develop a systematic criterion for when model applies. >Elaborate model to accommodate previously unrecognized differences in circumstances. >Elaborate model to include probabilistic elements.

Figure 1.

Illustration of Flasks for Causally-Focused Pressure Activity



1. Flask with Straw

2. Modification with Hole in Straw

3. Modification with Stopper in Flask

Figure 2.

Models on Post-Interview by Group within Achievement Level