Dimensions of Causal Understanding: the Role of Complex Causal Models in Students' Understanding of Science

DAVID N. PERKINS
TINA A. GROTZER
Harvard University, USA

SCIENCE IS MORE BAFFLING THAN MAGIC

A magician locks his 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 challenges the audience to explain how it was done.

Most people say: 'a trap door.' The magician invites people to tour the stage as active investigators. No trap door is apparent, but still they say, 'a trap door.' Surprised, the magician decides to reveal all. He explains that there are twin assistants. The first assistant is still in a hidden space inside the first cabinet; the second was already hidden in the second cabinet. He shows the audience the two assistants side by side. The audience members examine the cabinet. Most are convinced for the moment, but a week later, many are saying, 'you know, it was really a trap door.'

This story is not very plausible. People examining the stage carefully would probably be convinced that there was no trap door. People seeing the twins side by side would probably embrace that theory and stay with it.

However, the stubborn adherence to an initial theory we would not expect to encounter on the magician's stage we see all the time in science classrooms throughout the world. Students often develop tacit theories of their own about scientific phenomena, and in some settings science teaching uses an inquiry approach that encourages them to formulate explicit theories. So far so good, but students' theories usually diverge considerably from established scientific views, and yet students tend to cling to them in the face of apparent counter-evidence. Even when students go on to contrast their theories with the scientifically accepted view, examine further evidence in support of each, and appear persuaded, they typically relapse to their initial views when trying to explain phenomena, although often remembering the 'official story' for the test. What is not such a plausible scenario for the magician's audience occurs all the time in science learning. For many a learner, science is more baffling than magic.

Why does this happen? One source of the problem is certainly the specific difficulties posed by particular concepts and theories. However, more general factors may also 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, rules like Boyle's Law that govern the global behaviour of systems, and large-scale patterns of action emergent from small-scale interactions, as with the gas laws. They entail far greater complexity than everyday explanation.

This article argues that an important source of the difficulty is the narrow range of *types of causal models* with which most learners are familiar. We have in mind the contrast between, for example, simple causal chains (A affects B affects C) versus constraint system models, as with Ohm's Law, or with cyclic causal models, as in predator-prey interactions in an ecosystem, where prey provides food for predators while predators cull unhealthy prey and keep the prey population from exploding beyond the capacity of the environment. Most learners are only familiar with relatively simple styles of causal models, but many concepts and theories in science depend on styles substantially more complex in ways that we will define shortly.

It is important to acknowledge that modelling as an activity relevant to science learning has received considerable attention in recent years. The development of constructivist pedagogy in science education has done much to foster students' sophistication about inquiry, encouraging them to formulate theories, test hypotheses, seek consistency, and so on. Conceptual change theories of learning have encouraged a more reflective stance on students' initial and evolving conceptions (Posner, Strike, Hewson & Gertzog, 1982). In the past decade, science education has come to recognize the important role of modelling in how scientists develop and test explanations (e.g., Penner, Giles, Lehrer, & Schauble, 1997; Ost, 1987; Stewart, Hafner, Johnson & Finkel, 1992). Increasingly, students are encouraged to create and test models of concepts and to engage in the systematic revision of models as they trade up for models with the most explanatory power towards the scientifically accepted explanations. This emphasis on student modelling of concepts has been shown to result in deeper understanding (e.g., Gobert & Clement, 1999).

These are all positive developments. However, when we refer to styles of causal models, we have in mind more than just fostering the process of building models; we want to highlight learners' *repertoires* of various types of models. Despite an increased focus on modelling, and important work on how students reason about complex forms of causality by Chi (e.g., 2000; Chi & Slotta, 1993), Resnick (e.g., 1994, 1996; Wilensky & Resnick, 1999) and others, attention to students' repertoires has been quite limited.

We offer an analysis of four dimensions of complex causality and argue that the increasingly complex styles along the dimensions present challenges that help to explain students' difficulties in mastering science concepts. We present two kinds of evidence in support of this argument. First, we offer analyses of students' understanding of several challenging science concepts based on the extant literature and our research. Second, we report two intervention studies that we conducted, involving teaching interventions where cultivating greater complexity in students' causal models led to better understanding. The interventions do not involve the teaching of modelling styles in the abstract, but rather context-situated, inquiry-centered learning experiences that draw students' attention to how they are modelling the causality involved in particular phenomena and encourage more sophisticated causal modelling, embedded in their science learning.

A PERFORMANCE VIEW OF SCIENCE UNDERSTANDING

To introduce this perspective, it is useful to take a performance view of science understanding. What kinds of 'performances' are learners actually asked to attempt around science concepts that build their understanding? For instance, what sorts of problems do they solve, experiments do they conduct, and phenomena do they analyze? Such questions resonate 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). They also allude to a constructivist framework developed by the first author and colleagues called 'Teaching for Understanding' or 'TfU' (e.g., Perkins & Unger, 1999; Wiske, 1998). 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.

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

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 modelling systems.*** Some students learn general modelling 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 modelling system to build and perhaps test a model for a given system, for instance, a complex circuit that students have never seen before.

3. ***Learning and reusing modelling styles.*** Some students eventually become familiar with a range of modelling styles. For example, students who have seen circuits modelled with Ohm's Law, gases modelled with Boyle's Law, and dynamic systems modelled with Newton's laws and conservation of energy may come to recognize modelling 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 modelling 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.

Comparing the three levels, those 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 versions of the third type do occur, typically in the context of inquiry-based instruction, they usually foreground inquiry processes (look for logical inconsistencies, design tests, gather evidence), but rarely deal explicitly with different modelling styles. In general, science instruction hardly ever stands back to examine the general styles of modelling 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, is an important source of students' problems in understanding science. As students progress through the years, they encounter a wide range of science concepts involving modelling styles that are increasingly removed from common sense and everyday experience. Without specific help in understanding these modelling styles, students fail to grasp how particular modelling systems and models work. They resort to routines for familiar types of problems—level 1 above—their mastery of the routines masking their lack of real understanding. Some textbooks and teachers are complicit in this, foregrounding routines to secure an acceptable albeit shallow level of performance.

COMPLEX MODELLING STYLES AS A LEARNING BOTTLENECK

Naturally, some concepts confuse students only for lack of an opportunity to learn. For example, 4- to 7-year-olds hold less biological knowledge than older children and typically do not have adult-like concepts of living things (Piaget, 1929). However, by age 9 or 10 there is a marked increase in biological knowledge, and typically by age 11 (Carey, 1985) and perhaps earlier (Carey, 1995), children hold an adult-like conception of living things. This is not to imply that all confusions have vanished. However, with time, experience, and conventional schooling, youngsters do develop a concept of biological functioning.

More interesting from the present perspective are concepts that prove particularly resistant to 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 is even held by 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, a more scientifically acceptable 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; Shipstone, 1985).

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 many of these concepts characteristically involve complex (in ways to be defined below) causal modelling styles. Such styles do not simply extend but rather contradict simpler modelling styles. In the case of simple circuits, the circuit-filling model (e.g., Shipstone, 1985; Slotta & Chi, 1999) involves a kind of serial causality, like dominoes tipping over one after the other, whereas the bicycle-chain model involves a simultaneous causality, where everything happens at once (Grotzer & Sudbury, 2000). For other kinds of contradiction, scientific models sometimes 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 modelling systems, and the modelling systems at different levels contrast in their modelling styles, generating confusion (Frederiksen & White, 2000; Frederiksen, White, & Gutwill, 1999).

Support for the idea that students' causal modelling is less than adequate for learning complex science concepts can be found in the research literature. Driver and colleagues (Driver *et al.*, 1985) outlined characteristics of student thinking that impede students' ability to grasp scientific concepts. Some of these characteristics concern how students reason about causality. For instance, students tend to focus on changes as opposed to steady states, consequently failing to see a need to explain systems in equilibrium. Also, students tend toward linear causal reasoning, looking only for sequential chains of causes and effects when systemic patterns are in play.

Brown (1995) identifies core causal intuitions that can lead students astray when learning difficult science concepts. He points out several types of attributions of agency—initiating, initiated, reactive, and so on—that can be misapplied. 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 this and like notions play a role in difficulties students have in learning various science concepts.

Chi (1992, 2000) argues that students' struggles reflect misunderstandings about the ontological status of concepts: students mistakenly assign causal attributes to processes that have structures of emergence, which in her terminology are essentially non-causal. diSessa (1993) introduced the concept of phenomenological primitives (p-prims), small knowledge structures that people use to describe a system's behaviour. Though not necessarily generalizable beyond the particular contexts that elicit them, 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.

Complex modelling styles are all the more challenging because students are not adept at patterns of inquiry that reveal weaknesses in simpler models and drive toward models with greater explanatory power. In everyday argument, people commonly make convenient assumptions, neglect alternatives, excuse and patch favoured theories, and so on (e.g., Voss, Perkins, & Segal, 1991). Kuhn's (1991, 1993) research identifies a number of shortfalls in students' general and scientific reasoning, including difficulty in generating counter-evidence and persistence of a favoured theory despite blatant counter-evidence. Kuhn, Amsel, and O'Loughlin (1988) have shown that students' prior expectations make it hard for them to perceive co-variation evidence that contradicts their expectations. For instance, students have difficulty perceiving instances where a variable is non-operative or is operative but leads to a different outcome than students expect.

Sandoval (2003) found that for the most part, students sought plausible accounts of available data, understood the need for coherent explanations, and were able to develop them. However, they seemed more inclined to generate what they perceived as a right answer than to support their claims by using the data as evidence in support of a theory. 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 argue that the likelihood of changing one's theory is not particularly high and that it is much more common for individuals to patch their theories, or to ignore or reject the anomalous data, 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 present framework asserts that learners tend to assimilate scientific concepts to a limited repertoire of causal modelling styles that are relatively simple, as specified below. 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, not in the abstract but in the context of the science concepts to be learned.

We develop our argument as follows. The following section explicates four dimensions of complexity for causal models. After that, we report evidence from the literature and some studies of our own suggesting that learners' early models indeed fall at relatively low levels of complexity on the dimensions. This is not terribly surprising, but it does substantiate the notion that the levels defined as 'simpler' are indeed more accessible, illustrates how the dimensions apply to several topics, and helps to explain what makes them difficult.

Next, we report two intervention studies designed with the dimensions in mind. The studies sought to enrich students' causal modelling styles and thereby advance their understanding in two problematic areas of science learning, electrical circuits and density. The positive results offer evidence for our framework, but the case is not meant to stand on those alone. These studies are representative of a larger body of evidence (e.g., Basca & Grotzer, 2001; Grotzer & Basca, 2003; Grotzer & Sudbury, 2000; Houghton, Record, Bell & Grotzer, 2000), the trends of which will be discussed below.

FOUR DIMENSIONS OF COMPLEXITY IN CAUSAL MODELS

The central notion behind this framework is *complex causality*: some explanations are more complex than others in fundamental ways. But what do

we mean by 'complex?' We recruit the term from its natural language origins as an apt umbrella term. The science concepts examined are 'complex' in several different senses already illustrated—because of simultaneous models at different levels, more intricate causal relationships than simply 'A causes B,' models that conflict with typical expectations, and other senses are elaborated below. There is no implication that the label 'complex' suits each of these senses equally, only that it fits the overall tenor of the analysis well enough to provide a convenient label.

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 twins explanation for the magician's trick. As to Mechanism, the twins explanation depends on ordinary ideas about a familiar world, what Table 1 calls commonplace elements. As to Interaction Pattern, the twins explanation proposes a simple linear causal relationship: the similarity of twins causes people to think it's the same person. As to Probability, 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. As to Agency, there is a central agent: the magician, with the collusion of the twins, creates the illusion.

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 behaviour of electrons serve as illustrations for this introduction. Further examples appear 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. Often the deep explanation entails inferred or posited entities that are part of the scientifically accepted explanation, but not easily verifiable by non-scientists.

Table 1: Dimensions of Complexity in Models

Mechanism	*Interaction Pattern*	*Probability*	*Agency*
From a same-level generalization to an inferred underlying mechanism	From A causes B to complex reciprocal relations and constraint systems	From deterministic causality to chaotic and quantum systems	From a central and direct agent to highly distributed and emergent causality
Surface generalization: Simply describes the regularity under consideration in a generalized way (*'When it is hot and it rains, there is lightning'*) Often incorrect or confuses correlation with causation. (*'Heat and rain cause lightning'*)	*Simple linear causality:* A impinges on, pushes, influences B. A is seen as not affected. E.g., A pushes, pulls, initiates, resists, supports, stops B. A is typically seen as active as in pushing, but can be passive as in resisting.	*Deterministic systems:* Certain consequences, inevitable, and predictable outcomes (*e.g., as in* Ohm's Law, *law of gravitation).*	*Salient central agents:* One or a very small number of key factors fairly directly and conspicuously yield the result. May be interwoven with intentional causality (see mentions of intention in the mechanism category).
Token Explanation: Some entity or phenomenon, intentional or not, made things come out that way. Entity/phenomenon's behavior parallels outcome, no real differentiation. (*'Static electricity makes it happen.'*)	*Multiple linear causality:* Multiple uni-directional causes and/or effects: multiple immediate causes and/or multiple immediate effects. Domino causalities where effects in turn become causes as in simple causal chains like A causes B causes C or branching patterns. Necessary and sufficient causes, etc. Often includes previously neglected causes of lower saliency in the causal story.	*Noisy systems:* Basically deterministic systems perturbed by random or unanalyzed factors *(air friction, turbulence on thrown objects)*	*Nonobvious central agents:* With a passive role or delayed or spatially remote influence. *(e.g., spatially remote as in gravity or electrostatic forces).*
Function-centered: Explains in terms of form-fits-function but without any elaborated intentional or blind adaptive mechanism. Often teleological *('plants grow upward because they need the sun')*. May be insightful as far as it goes *('archeologists' explanations of the function of prehistoric tools')*.	*Mediating cause:* At least three causes 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.	*Chancy systems:* At certain junctures, things might go one way or another with a certain probability.	*Additive causes:* Causes with cumulative effects over time *(e.g., erosion).*
Commonplace elements: Constructs explanations with familiar elements of the system in question rather than those underlying it. *(Can 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.)*	*Interactive causality:* Two-Way Causality: Interactive causation with a mutual effect (*as in particle attraction*). Mutual cause with two outcomes (*as in symbiosis*). Relational causality where the outcome is due to the relationship between two variables (*as in pressure or density differentials*).	*Chaotic systems:* Fundamental unpredictability in long term due to 'butterfly effects' *(e.g., the weather)*	*Long causal chains, branching structures, cycles: (as in ripple effects of an ecological disaster).*
Analogical model: System explains target phenomenon by analogy and analogical mapping (*e.g., electricity as fluid flow*).	*Re-entrant causality:* Simple causal loops as in escalation and homeostasis.	*Order from chaos:* Averaging effects smooth out chaotic systems into highly orderly large-scale patterns *(e.g., gas laws).*	*Causal webs:* Complex webs of causes and effects, often involving reasoning at the population level *(as in ecologies).*
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.)* There are often two or three levels of underlying mechanism, each underlying the previous. Form-fits-function explanations that include an elaborated causal mechanism for the adaptive process, intentional or mechanistic, and thus are not solely function-centered.	*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).*	*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.	*Trigger effects.* A modest influence 'topples' a complex system into a new state or pattern of activity *(e.g., tipping points in epidemiology)*
			Self-organizing systems. Seemingly messy systems evolve into clear patterns over time without an external agent or an internal blueprint.
			Emergent entities and processes: Agency is distributed. The actions of many individual agents at a lower level converge to give rise to new, complex patterns that are not easily anticipated based on the lower order actions *(as with the emergence of new species, chemical compounds, etc.)*

- ***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 *relational causality* and *re-entrant causality*, as in the co-evolution of bees and flowers. Ohm's Law, a *constraint-based* system, addresses electrical circuits. Increased complexity along this dimension can also entail movement from sequentiality towards simultaneity between causes and effects and from linear towards non-linear patterns.

- ***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. Causal patterns can become harder to detect with increased complexity along this dimension because of increased noise and lack of reliable correspondence between causes and effects.

- ***Agency.*** This dimension refers to agency and to the compounding of agency in ways that lead to new and not easily anticipated outcomes. The simplest level involves central agents with immediate influence: the ducks needed webbed feet; the battery makes the current move. 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. Increased complexity along this dimension can also entail increasing spatial distance or temporal delay between causes and effects and forms of agency that are non-intentional or passive.

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. A fair amount of developmental research supports a general trend of younger children reasoning at less complex levels and older children at more complex levels of the dimensions. For example, research on reasoning about gears found that younger children tended to reason in functional terms (Metz, 1991) or in terms of surface level generalizations without an underlying mechanism, whereas older children included an underlying mechanism (Lehrer & Schauble, 1998). On the other hand, there is also evidence that relatively young children display some understanding of more complex concepts along the dimensions in the right contexts. For instance, analogical models are placed toward the complex end along the dimension of Mechanism and, while young children do not typically construct analogical explanations of science phenomena at the level of scientific experts, they do indeed have a developing understanding of analogy (e.g., Goswami, 1992). (An in-depth discussion of developmental issues can be found in Grotzer, 2003.) Moreover, 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, our general claim is simply that difficulty increases roughly with complexity along the dimensions.

With this emphasis on the challenges of complexity, the virtues of simplicity also need to be acknowledged. The simpler ends of the four complexity dimensions are not intrinsically 'wrong'. Explanations constructed out of them may suit very well the phenomenon or purpose 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 modelling styles make things harder for learners? One way is simply their lack of familiarity. Another, as noted earlier, is that some modelling styles of higher complexity do not simply elaborate but rather contradict other more familiar modelling styles of lower complexity. The more complex causal styles challenge basic assumptions about how the world works, such as that magnitude of effect correlates with magnitude of cause or temporal priority between causes and effects (Bullock, Gelman, & Baillargeon, 1982). 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 modelling 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 *et al.*, 1999). Students have a notoriously hard time coordinating different levels of explanation (Chi, 2000; Wilensky & Resnick, 1999).

Others have noted the importance of one or more aspects of these dimensions in students' scientific misconceptions. For instance, attention has been paid to difficulties with issues of agency, such as expecting centralized rather than decentralized control structures (Resnick, 1996), or not recognizing the phenomenon of emergence (Resnick, 1994; Chi, 2000), or focusing on linear interaction patterns (e.g., Driver *et al.*, 1985; Barbas & Psillos, 1997), or difficulties reasoning at and between different levels of mechanism (Chi, 2000; Frederiksen & White, 2000; Wilensky & Resnick, 1999). Our purpose in setting forth the dimensions of complex causality is to offer a broader framework that can serve as a tool for analyzing the full range of difficulties in understanding causal structure.

EVIDENCE FOR THE DIMENSIONS OF COMPLEX CAUSALITY FROM LEARNERS' INITIAL CONCEPTIONS

With the dimensions of complex causality 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 scientifically accepted theories. Rather, the framework predicts that there would be a strong trend for initial conceptions of scientific phenomena to be low on the dimensions of complexity.

We tested these implications by examining initial conceptions of several science topics, both in the literature and through classroom-based studies: electrical circuits, static electricity, density, ecosystems, and natural selection. The first and third are also the focus of intervention studies reported later. The results offer support for the framework. As acknowledged earlier, this is not terribly surprising, since we constructed the levels of complexity to be plausible. However, the results do affirm that that learners find more accessible the levels defined as 'simpler'. Also, the examples illustrate how the dimensions fit a range of topics and help to explain what makes them 'more baffling than magic'.

Electrical Circuits

As noted earlier, researchers have pointed to the difficulty that students have in conceiving of the circuit as a system (e.g., Dupin & Johsua, 1987; Shipstone, 1985) and in reasoning about the types of causality present in an electrical circuit (Andersson, 1986; Barbas & Psillos, 1997). Students typically try to analyze effects locally (Cohen, Eylon, & Ganiel, 1983; Shipstone, 1985) and following instruction, they commonly employ what can be called a 'cyclic sequential' causal pattern for how the current 'flows.' They envision the circuit as initially empty and filling with a 'substance-like material' (Slotta, 1997; Slotta & Chi, 1999) that eventually reaches the bulb and causes it to light. The current is seen as traveling from point to point and affecting each component in turn as it is encountered within the circuit (Closset, 1983; Shipstone, 1984).

Slotta and Chi (1999) and Slotta (1997) have found that a substance notion of the electrical current, as opposed to a process notion, creates a major stumbling block for students learning to think about electrical circuits. Heller and Finley (1992) found that of the many misconceptions that teachers hold about the nature of the circuit, the belief that 'the circuit is initially empty of the 'stuff' that flows through the conductors' (p.268) is seldom modified or compromised. This belief fits firmly with a cyclic sequential model. The cyclic sequential model has been found even in university physics (Picciarelli *et al.*, 1991).

In addition to the focus on substance versus process (Chi & Slotta, 1993; Slotta & Chi, 1999), students' difficulties appear to stem in part from elements of a persistent underlying linear causal model that students attempt to apply and from their lack of a repertoire of intermediate models of causality (Andersson, 1986; Grotzer & Sudbury, 2000; Rozier & Viennot, 1991). Numerous researchers have demonstrated that students tend to create uni-polar models that join one part of the battery to one part of the bulb and describe 'flow' of electricity as moving from the battery to the bulb (e.g., Andersson & Karrqvist, 1979; Fredette & Lochhead, 1980; Osborne & Gilbert, 1980; Tiberghien & Delacotte, 1976). These uni-polar models fit with a simple linear model of cause and effect in which one thing typically makes another thing happen in a domino-like pattern of effects. Turning to the dimensions, from the standpoint of Mechanism such learners are explaining electrical current with a *token cause*. 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 applies 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, the battery and in turn the electrons.

Scientists, on the other hand, might envision the system at the particulate level as described by a 'cyclic simultaneous' kind of causality, where electrons already exist throughout the wire (Barbas & Psillos, 1997; Grotzer & Sudbury, 2000). Hooking the wire up to a battery causes flow, the excess negative charge in the battery repelling nearby electrons, which repel other electrons. As mentioned earlier, the net effect on the macro-scale is that current moves all at once, more like the movement of a bicycle chain (Shipstone, 1985). Scientists would characterize the overall system in terms of differentials between electrical potential or by a set of constraints. While there are electrons all along the wire, the battery creates an imbalance that results in flow as electrons move from areas of greater concentration towards areas of lesser concentration. Flow is a systems level effect.

The scientists' account involves an elaborated *underlying mechanism* (Mechanism dimension) and *relational, re-entrant (as the circuit reaches equilibrium)*, and *constraint-based (Ohm's Law) causality* (Interaction Pattern). Scientists would view the circuit's behaviour as deterministic at the macro-level (Probability). However, the circuit's behaviour reaches its steady state through a *self-organizing* process, the equilibration of the charges involved (Agency).

Static Electricity

From the standpoint of the scientifically accepted explanation, elementary electrostatics involves an *underlying mechanism* (Mechanism dimension) 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 (Interaction Pattern).

We investigated how 96 fourth graders structured their initial explanations of static electricity phenomena by scoring their journal explanations in response to a demonstration where a balloon was rubbed against a piece of wool and then was held near other objects (bits of paper, someone's hair, and another balloon that had also been rubbed by wool). Protocols were scored for the level of Mechanism and the Interaction pattern that they represented. Two raters scored the protocols and inter-rater reliability was assessed using a Pearson Product Moment Correlation ($\underline{r} = .97$).

Students' explanations tended to take very simple and efficient forms, for example: 'Electricity pulls your hair up' [Subject #15]. 'I think it happened because of the static electricity coming from the wool' [Subject #28]. 'I think it happened because the electricity from the wool gave it to the balloon' [Subject #2]. I think it happened because it had a static reaction to the electricity on the balloon' [Subject #34]. 'When you rub the cloth to the balloon, something happens to the balloon to make it stick' [Subject #4].

Such responses plainly involve *token causes* (Mechanism) and *simple linear causality* (Interaction Pattern). 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' [Subject #82]. The relational 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' [Subject #25]. 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.

Density

Density and the related phenomena of floating and sinking are matters we encounter in everyday life and are common parts of elementary science curricula. However, they pose considerable challenges to learners. The majority of students hold undifferentiated weight and density conceptions (Smith, Carey, & Wiser, 1985; Smith, Maclin, Grosslight, & Davis, 1997; Smith, Snir, & Grosslight, 1992). Children's earliest notion of density is 'heavy for size,' a concept which resides within their concept of weight (as in 'a heavy telephone') (Smith *et al.*, 1985). Smith and colleagues (1985) found that in the case of density, students tend to focus on one feature of an object (either weight, size, or shape), with one often having more salience for them than the other. Students also often attend to only one feature of a kind of material (a liquid is thin, thick, or loose). They argue that until children realize that the heaviness of the kind of material is a property of that material, they cannot be said to have distinguished the concepts of weight and density. Yet, the salience of the surface features (felt weight) attracts students' attention, making it unlikely that they will look beyond it to infer the existence of density.

This limited focus is also found when students begin to think about sinking and floating. Typically, students focus only on the object that they are testing to see if it sinks or floats (Kohn, 1993). In other words, they do not focus

relationally when attempting to describe the cause of sinking and floating. Raghavan, Sartoris, and Glaser (1998) found that prior to instruction only 2 students of 36 revealed some understanding of the significance of relative density. Most of the students in their study (28 of 36) focused on properties of helium or air to explain why a helium balloon rises.

The present analysis of complex causality helps in systematizing and understanding these shortfalls. Along the dimensions of complex causality, density and its role in sinking and floating is challenging both in terms of Mechanism and Interaction Pattern. On the dimension of Mechanism, density is an intensive quantity—its existence must be inferred by holding volume or mass constant and assessing the implications of the other variable (Inhelder & Piaget, 1958) and this gives students difficulty (e.g., Bliss, 1995; Rowell & Dawson, 1977). In explaining sinking and floating, differences in mass per unit volume, and so forth, density plays the role of an *underlying mechanism* that is not part of the surface situation. Everyday experience does not necessarily provide opportunities to hold volume or mass constant to make the existence of density obvious. Weight, on the other hand can immediately be perceived or felt as one lifts an object.

Considering the causes of differences in density in terms of atomic theory rather than in terms of the relationship between mass and volume is no less complex. The atomic mass, the atomic bonds, the spacing and arrangement of atoms and molecules, and so forth, are entities that are not part of the surface features available to students. Students need to accept the idea that there are atoms and that they have mass, without ever being able to witness it directly. This engages students in the highest levels of complexity along the Mechanism dimension.

In terms of Interaction Pattern, understanding density involves *relational causality*. Students need to reason about the relationship between mass and volume and understand that if the relationship between them changes, the density changes. Similarly, in understanding the role of density in sinking and floating, students need to reason about the relationship between the densities involved. This relational type of causality involves recognizing that an effect is caused by the relationship, often one of balance or imbalance, between elements of a system. Neither element is the cause by itself. Thinking about relational causality requires a departure from linear, unidirectional forms of causality where one entity acts as a causal agent on another affecting an outcome in one direction only—in a domino-like pattern (Grotzer, 1993; Perkins & Grotzer, 2000).

Ecosystems

Many teachers consider ecosystems concepts to be important, and relatively easy for students to learn (Barman & Mayer, 1994). 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; Grotzer & Basca, 2003; Webb & Boltt, 1990). For instance, Barmen, Griffiths, and Okabukola (1995) found that senior high school 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 beliefs in a study of grade 10 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 9- and 11-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 without scaffolding. 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 uncued, only 16% of 20-year-olds gave two-way causal accounts of predator-prey relationships. Further, only 9.5% used two-way causal models when explaining a three-level problem. 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 were to be 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 particularly notable because students in principle have enough basic familiarity with foxes, rabbits, and their everyday actions to construct a more complex story. There are no esoteric entities like electrons or viruses in play. Students' everyday knowledge creates ample opportunities for putting their simpler models at risk through common-sense reasoning that constructs disconfirmatory instances. However, students fail to think in terms of populations and see the systemic implications of what they know.

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 behaviours or how to give themselves new traits; *crossbreeding*, 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 four dimensions. Most responses were composed of *commonplace elements* (Mechanism dimension), 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 theory constructed of commonplace elements such as inheritance of traits (well-known from selective breeding), albeit one much more complete than the students offered. The explanations were mostly simple linear (Interaction Pattern), as with *environmentalism*, where the circumstances somehow cause the trait to develop. Concerning the Probability dimension, most accounts were deterministic: the adaptation would follow inevitably. Concerning the Agency dimension, 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.

It's notable that, as with the ecosystems topic, students surely often had enough knowledge to challenge their models. Their responses show failure to examine their models critically for gaps in the causal story. Students' *survival, crossbreeding*, and *dissemination* theories assume that the relevant trait conveniently appears or is already in the population. The *environmentalism* theory assumes that somehow the environment draws out the adaptation without explaining how. The training theory takes it for granted that the acquired traits are passed along without explaining how.

In summary, analyzing the students' thinking through the dimensions of complex causality helps to delineate the kinds of learning challenges particular students or groups of students are likely to face and does so with greater specificity than other qualitative lenses that focus on single aspects of dimensions (such as a tendency towards linear causal reasoning). The framework provides more than a sense of what is problematic with students' reasoning in a given instance; it offers a sense of what models would offer a better fit.

EVIDENCE FOR THE DIMENSIONS OF COMPLEX CAUSALITY FROM INTERVENTIONS

The present theory predicts that students tend toward very simple causal explanations, as gauged by the four dimensions. While the studies reviewed above support that prediction, one can still question whether the results reflect shortfalls in learners' repertoires of causal models or something else. 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 is that perhaps the former is the sole source of students' difficulties. That is, perhaps the strangeness or intricacy of particular topics such as electricity or evolution somehow masks or suppresses models that are part of students' repertoire, or are easily enough constructed by students when the content is less intricate and more familiar.

Teaching experiments provide a direct way to approach this puzzle. We have taught students more complex models in the context of learning science concepts, examining whether this expands their understanding, in contrast to teaching only the science concepts. Generally speaking, the studies we have conducted contrast control conditions, featuring what would be considered best practices in science instruction, with treatment conditions that add explicit attention to styles of causal modelling.

Great effort was invested in 'honest' control conditions that supported learning for understanding, without foregrounding complex causality. The control group instruction included Socratic discussion, computer simulations, grappling with discrepant events, and so forth. All of the students engaged in constructing models (on white boards, in journals, etc.), sharing and discussing those models, and critiquing the models in terms of which had the most explanatory power given the evidence that students were discovering. The teachers and researchers scaffolded these discussions to help students focus on bringing evidence and counter-evidence to bear on the process of critiquing the models. Sandoval (2003) recently suggested that public classroom discourse with teacher guidance of this type might be necessary to help students see what claims are warranted by the data. The instructional design assumed that students' models would evolve and change over the course of repeated explorations. However, the control instruction never focused directly on the causal complexities of the science concepts in question.

We turn now to treatment conditions. The interventions never involved merely providing students with generic accounts of complex modelling styles. Rather, we introduced what we call RECAST activities or 'activities designed to REveal the underlying CAusal STructure.' We also introduced discussions about the nature of causality—the specific causal rules and patterns in play—in the context of learning particular science topics. All this was subject to the same modelling, discussion, and critique for explanatory power as other ideas and simpler models that students advanced. In other words, the RECAST activities and discussion about causal structure were the added ingredients that marked the contrast between our treatment conditions and the generally good teaching and learning for understanding in the control conditions.

The full specifics for each topic are described in topic-focused sections that follow. However, to give a feel for RECAST activities, we describe one employed in the intervention on density to be detailed later. In exploring the role of density in sinking and floating, students see a demonstration that directs their attention from a linear causal interpretation to a relational causal interpretation. They are first shown a big piece of candle that sinks when it is placed in a clear liquid, and a small piece of candle that floats when it is placed in a clear liquid. This outcome fits with most students' expectations. Then the pieces of candle are switched. To the students' surprise, the big piece of candle floats and the small piece of candle sinks. The outcome pushes them beyond a linear, feature-based causal conception of 'the weight makes it sink' or 'the density makes it sink' to a relational causal conception. Students begin to focus on the liquid and the object and realize that the causal pattern is a relationship between greater and lesser density of objects and liquid (Liem, 1981). These causally-focused activities reveal, through results that are discrepant with students' expectations, that the structure of the causality involved is different than students anticipate and offer insights into the nature of that causality. Such activities were the basis of explicit discussion about the nature of causality in the causal treatment group described below.

EVIDENCE FROM AN INTERVENTION CONCERNING ELECTRICAL CIRCUITS

We discussed earlier how students learning about electrical circuits become entrenched in a linear causal pattern (*Interaction Pattern*): the electrons begin at the battery and fill up the circuit. Or sometimes after further instruction, they develop another model also resistant to change, a cyclic sequential pattern: the empty circuit fills sequentially and the electrons are then recycled. A better scientific account invokes a cyclic simultaneous causal pattern in which causes and effects co-occur, the electrons moving in the circuit like a bicycle chain (Shipstone, 1985). In terms of the Interaction Pattern dimension, this involves *re-entrant* or *cyclic causality* that occurs simultaneously rather than sequentially and necessitates attention to the whole system at once. At a slightly more complex level, an electrical potential model, it can be said to involve *relational causality*, electrons repelling and being repelled when electrical current is flowing in a steady state, a differential in the concentration of electrons that results in flow; and it can also be expressed through *constraint-based causality*, in the form of Ohm's law. The scientists' account also involves an elaborated underlying mechanism (Mechanism dimension). Scientists would view the circuit's behaviour as deterministic at the macro-level (Probability). However, regarding Agency, the circuit's behaviour reaches its steady state through a *self-organizing process*, the equilibration of the charges involved (Agency).

We designed an intervention unit using RECAST activities and discussion to shift students toward a cyclic simultaneous model of electrical circuits. Given the age of the subjects, the study did not attempt to move students beyond the cyclic simultaneous model to an electrical potential model, as we might have done with middle school students. Instead, it tested whether the intervention could move students beyond the resistant cyclic sequential model.

Method

Subjects

The subjects were students in three 4th grade classes (n=72). The students were from two elementary schools in the Boston area with an ethnically diverse and mixed SES population. As discussed later, the three classes proved to be equivalent in their pre-intervention performance on the assessments employed.

Procedure

All of the students participated in a three-week (two classes per week) mini-unit on static electricity followed by the Science and Technology for Children 'Electric Circuits' unit (NSRC, 1991), for approximately eight weeks (two classes per week). One class (C&D for causal plus discussion) participated in RECAST activities and explicit scaffolded discussions of the underlying causal modelling styles. The second class (CAU for causal only) participated in RECAST activities, and discussed the causal models they suggested, but without the explicit scaffolding around causal modelling styles. The third class (CTL for control) participated in the static and electricity units without the RECAST activities, discussing instead the activities they did do and their ideas about models for what was going on, but without scaffolding regarding causal modelling styles. More details on the instructional conditions are given below. The overall length of the units and total classroom time were the same for all conditions. All students were pre- and post-tested and the same nine students from each class (n=27) were pre- and post-interviewed in depth using questions to reveal the causal models that they used for analyzing electricity problems.

Pretest and Post Assessment

Students took a researcher-designed, group-administered, pre- and post-inventory consisting of 14 multiple-choice and 2 essay questions. The inventory answers were designed to fit with the types of models (and related misconceptions) that students typically hold for analyzing electrical circuits based on research by Shipstone (1985), Slotta and Chi (1999) and others. The inventory asked students to reason about simple circuits, series and parallel circuits, and to consider the relationship between voltage, resistance, and current. Nine students from each class (balanced to represent low- middle- and high-achievers) were interviewed beginning with open-ended questions and progressing to more targeted and scaffolded questions to see whether students would choose the scientifically accepted model if it was offered as a choice.

Intervention

Each class was taught by the classroom teacher and two researchers (who were former teachers, one a retired fourth grade teacher with a strong science background). All three classes used an inquiry-based, constructivist approach for both the static and electric circuits units. Opportunities were infused for all students to model and discuss what they thought was going on causally at different points in their experimentation and to revise their ideas as they discovered new information that contradicted their earlier models. Students kept journals and tested and discussed their models in light of the evidence that they found.

The mini-unit on static electricity preceded the unit on electrical circuits, to introduce the particle model of electrons and protons and attracting and repelling, and to give students a basis for understanding the behaviour of electrons in the circuit. It was based partly upon materials developed by AIMS (AIMS Education Foundation, 1991) for the intermediate grades and partly on activities developed by the researchers.

Then students participated in the Science and Technology for Children unit, 'Electric Circuits' (NSRC, 1991). It was modified in the following ways and as detailed in Appendix A. For the causal models (CAU) and causal models plus discussion (C&D) groups, RECAST activities were infused into the NSRC unit, using role-playing and physical models such as marbles and tubing. Students in both groups engaged in these activities to help them consider the implications of different causal explanations for why electrons move in a circuit. Students in the CAU group discussed the activities and the models for electrical circuits that the activities suggested, but without scaffolding to focus on modelling styles. In contrast, students in the C&D group engaged in scaffolded conversations that foregrounded causal modelling styles. These students explicitly discussed the idea that the circuit, after a transient delay, operates according to cyclic simultaneous causality, with flow sustained by the repelling of electrons (each electron playing the role of both cause and effect) along the circuit. They were invited to contrast this with cyclic sequential causality and linear causality. For instance, here is an excerpt of class discussion:

T: Let's compare how cause and effect works in these two different kinds of cyclic models. In the cyclic sequential one, what makes the electrons move?

S1: They want to get out of the battery because of all the electrons so they go onto the wire.

T: Okay, and then what happens?

S2: They go along the wire till they get to the bulb and that makes the bulb light up.

T: Why do the electrons move in the cyclic simultaneous model?

S1: The electrons push the one in front but at the same time they are pushed by the one before them. So everything moves at the same time.

T: Yes, in a sense, each electron repelling is the cause of the next one but it is the effect of the one behind it. It's both a cause and an effect at the same time. What you get is the whole thing turning like the chain on a bicycle. What causes the bulb to light?

S3: When the electrons start to flow.

They also discussed what was difficult about learning each type of causality. For instance, one student commented about cyclic simultaneous causality, 'It's kind of hard to think about. The way we have to learn it is like what's making what happen so you think of it in a line, so then it's really hard to think that it's happening all at once' [Subject #27]. The amount of discussion that each group (CTL, CAU, C&D) engaged in was the same, but the focus differed. As noted earlier, the classroom time and overall length of the units was the same for each intervention condition.

Scoring

Interview Data

The interview data from each subject were scored globally for model type based on a scoring scheme developed from the extant research (e.g., Shipstone, 1984, 1985) and to characterize the implicit causal assumptions. The models aimed to capture the 'why' behind current flow, rather than focus on 'how' as is prevalent in the available curriculum materials. The first few models overlap directly with those of Shipstone (1984, 1985) in that they begin where the students begin (with various forms of linear models). We did not introduce these to students; they brought these conceptions with them. Scores were attached to each model type, reflecting the level of complexity that it involved. When students had aspects of more than one model type, the scores were averaged.

No causal model (Level 0) was assigned when students gave background conditions, peripheral information or configurations only or no explanation. Simple Linear Causal Models (Level 1) were assigned to 'token causes,' linear consumer source models characterized by a single wire running from the battery to the bulb where 'stuff' from the battery travels to the bulb and is consumed (i.e., '*The battery gives energy to the bulb*') or passes through the bulb, but stops there with no mention of the recycling of electrons. Double Linear Causal Models (Level 1.5) were assigned to linear models where a second wire *passively* contributes to the lighting (i.e., '*The other wire has to be there or it won't work*'); or with active assistance or additive aspects where a second wire *actively* contributes to the lighting (makes it stronger, fuels it, etc.) (i.e., '*You need two wires to get enough power to make it light*'); and to 'clashing currents' or attraction models characterized by electricity traveling up from both terminals and attracting or clashing to fuel the bulb (i.e., '*The electrons travel up one side and the protons travel up the other and they clash together to make it light*'). Cyclic Sequential Causal Models (Level 2) were assigned to models characterized by electrons traveling around the circuit in a sequential manner where they start filling the circuit at the battery and travel to the bulb (i.e., '*The electricity goes along the wire in a circle and when it gets to the bulb, the bulb lights up. Then it keeps going back into the battery and goes around again.*'). Cyclic Simultaneous Causal Models (Level 2.5) were assigned to models characterized by electricity/electrons already existing in the circuit and simultaneously repelling each other as more electrons are repelled onto the wire by the battery (i.e., '*The electrons are pushed by the electrons behind it and that makes them all move at once and makes the bulb light*').

The interviews were transcribed and then scored by two independent raters. A Pearson Product Moment Correlation was conducted and initial agreement was assessed at ($\underline{r}$ = .92). The differences were discussed and resolved until there was 100% agreement.

Whole Class Electricity Inventory

Students were assigned a general score on the inventory. Multiple-choice questions were scored for the scientifically accepted explanation (for instance, in a series circuit, both bulbs light at the same time). A rubric was designed for each of the essay questions based on the underlying causal model they revealed. For instance, one question asked, 'If you increased the length of the wires in a pictured circuit, would it take longer or approximately the same amount of time for the bulb to light and why,' revealing either a sequential notion of electron flow or a simultaneous one. Sequential models were typified by the idea that the electricity or electrons have to reach the bulb, while simultaneous models were typified by the idea that the electrons are already along the wire and that the flow of electrons was responsible for the lighting of the bulb rather than the electrons reaching the bulb. (The possibility existed that some students would reason that there might be a transient delay even though the process is nearly a simultaneous one. This is a rather sophisticated line of reasoning, but one that better fits the scientific explanation than a purely simultaneous model.)

The following kinds of statements were scored as indicating a sequential model: 'It would take longer because the electrons need to flow through the wires to get to the bulb;' or 'It won't take longer because the electricity makes up the difference by traveling faster.' The following kinds of statements typified simultaneous models: 'It wouldn't take longer because the wire is made up of atoms and they get pushed as others get pushed out of the negative side of the battery and get pulled toward the protons on the positive side;' or 'It wouldn't take longer because there are atoms along the wire and as soon as you hook it up, it begins to flow. The flow makes it light up.' Other scoring categories included mixed models, other models, unclear, or unscoreable. Two scorers each scored 100% of the data. Initial agreement was assessed using a Pearson Product Moment Correlation ($\underline{r}$ = .87) on Essay 1 and ($\underline{r}$ = .91) on Essay 2. Differences were discussed until 100% agreement was reached.

Results

How does students' understanding compare from pre- to post-measures depending upon intervention group? The interview data reveal whether students achieved a deep understanding of the cyclic simultaneous model and could apply it to analyzing simple circuits. A one-way analysis of variance (ANOVA) on students' pre-interview scores by group confirmed that there were no significant starting differences between the groups (F (2, 26) = .15, p = .86). However, the post-interview scores showed a significant main effect of intervention condition (F (2, 26) = 10.11, p = .0007). A Tukey Kramer HSD multiple comparisons t-test revealed that the C&D students held significantly different models on the post-interview than the CTL (Abs(Dif)-LSD = .34, p < .05) and CAU students (Abs(Dif)-LSD = .06, p < .05). No significant differences were found between the CTL and the CAU groups.

Table 2 shows the means and standard deviations for each group. While the numbers do not appear to be dramatically different, they signal deep differences in understanding. Students who hold a cyclic sequential model would receive a score of 2.0 and those students who hold a cyclic simultaneous model would receive a score of 2.5. Students with a cyclic sequential model are likely to focus on local effects in a simple circuit, to reason that the circuit is empty to begin with, and to make erroneous predictions about parallel and series circuits, Ohm's Law and so forth. Students with a cyclic simultaneous model reason at a systems level and make correct predictions about parallel and series circuits, Ohm's Law and so forth. Figure 1 shows that all but one of the students in the C&D group held cyclic simultaneous models on the post-interview. Notice the smaller standard deviation in the C&D group, suggesting that there is less variation in student performance when all students are given access to the underlying causality.

Table 2
Means and Standard Deviations for Post interviews by Intervention Condition

Intervention condition	Number	Mean	Standard deviation	Standard error of mean
1 = Control	9	1.67	.37	.12
2 = CAU	9	1.94	.51	.17
3 = C&D	9	2.44	.11	.04

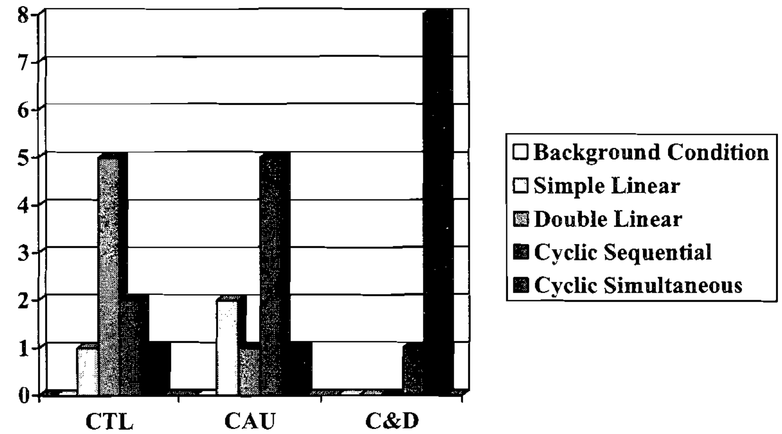

Figure 1. Number of students using each model type on post-interview by intervention condition (n= 27).

Note that learners were not just giving back what they were taught. The assessments asked students to apply what they had learned to situations not directly addressed in the instruction, novel circuits, and probed for typical misunderstandings not directly addressed in the instruction.

Related to the finding of less variance in the C&D group, it appears that the C&D 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 showed that intervention group (F (2, 27) = 11.2, p = .0004) was a significant predictor of post-interview performance, but that achievement level was not (F (2, 27) = 2.3, p = .1238). In the C&D group, nearly all of the low achievers reached the most sophisticated model.

The inventory data gave a measure of whether students applied the models that they learned to reasoning about the circuit to overcome typical misconceptions, such as the idea that the circuit is initially empty or that current is not conserved. A one-way analysis of variance (ANOVA) by intervention condition on the pre-inventory scores confirmed that there were no significant starting differences between the groups (F (2, 63) = .0356, p = .9651). Post-inventory scores revealed a significant main effect of intervention condition (F (2, 65) = 5.14, p = .008). C&D Students did significantly better than the CAU (Abs(Dif)-LSD = .11, p < .05) and CTL students (Abs(Dif)-LSD = .38, p < .05) as revealed by a Tukeys HSD. The C&D group outperformed the others by nearly one standard deviation. There were no significant differences between the CAU group and the CTL group. Students in the C&D group gained on average 5.6 points, one standard deviation above the CTL group at 2.9 points and close to one standard deviation above the CAU group at 3.3 points.

Table 3
Inventory Gain Scores by Intervention Condition

Intervention condition	Number	Mean	Standard deviation	Standard error of mean
1 = Control	21	2.88	1.81	.39
2 = CAU	22	3.34	2.70	.57
3 = C&D	23	5.59	2.41	.50

The overall results suggest that students who experienced RECAST activities and *explicit causal discussion made the greatest gains in the type of model that* they used to explain simple circuits and in overcoming typical misconceptions. It appears that the pattern of causal interactions was complex enough and counterintuitive enough to require explicit discussion of the RECAST activities for them to have impact.

EVIDENCE FROM AN INTERVENTION CONCERNING DENSITY

Earlier we discussed the complex causality involved in the concepts of density and sinking and floating. To summarize, under Mechanism, density is not a directly observable property and explanations of density in terms of atomic theory are even more removed from experience. Under Interaction Pattern, density depends on the interaction of weight and volume, whereas young learners tend to focus on one variable at a time. We designed an experiment using RECAST activities and causal discussion to introduce students to the underlying causal structure of density.

Method

Subjects

The subjects were eighth graders (n=91) from a middle school in a predominantly middle-class suburban community outside of Boston. The students were from four science classes taught by the same science teacher. The students had science class five days per week for approximately 45 minutes each day.

Procedure

All of the classes began the year with a unit on the nature of matter, after the teachers and researchers agreed that it was a useful prerequisite for understanding density. A unit on density and the role of density in sinking and floating followed. Prior to the Density Unit, we tested students' understanding with a pre-inventory of 10 assessment questions (6 open-ended assessment questions designed to elicit students' models of how causality behaves in density-related phenomena and 4 multiple choice questions focused on key misconceptions.).

Two classes were control classes (CTL). They were taught a unit called Basic Density. The unit was inquiry-based, involved a lot of modelling, Socratic discussion, and use of computer simulations. Two other classes participated in a causal activity plus discussion (C&D) intervention and were taught a unit called Causal Density. The Causal Density was essentially the same as the Basic Density unit except that it included RECAST activities and causal discussion while Basic Density did not. The units were designed to be the same length so when C&D classes had RECAST activities and causal discussion, the CTL classes participated in similar activities (without the causal focus) that are typically a part of density units. For instance, when C&D classes experimented with making soda cans sink or float by adjusting the density of the liquid that the cans were floating in, CTL classes created an object that would sink, float, or suspend in water by analyzing its density relative to water and figuring out what materials to add to it.

Following the density unit, students took a post-inventory of 10 questions as above. We also interviewed three students from each class (n = 12) (balanced groups chosen by the teachers to represent high, medium, and low achievers), collected relevant work samples throughout the unit, and videotaped classroom discussion for later analysis.

Pre and Post Assessment

Students were pre- and post-tested with an Open-Ended Inventory of 10 questions designed to assess understanding of density and its role in sinking and floating. Students had opportunities to reveal that they understood the relationship between mass and volume, the microscopic material causes of density, that as temperature and pressure change density is dynamic, and the relational causality involved in both the mass/volume relationship and the role of density differentials in sinking and floating. For instance, one question asked students to explain differences in felt weight between two objects of the same volume. Another question asked students to show the possible outcomes when an object is dropped into a liquid to see if it will float and to explain each. They were also asked to answer questions that students typically have misconceptions about, such as what happens to the density when you cut an object in half (Smith, Grosslight, Davis, Macklin, Unger, Snir, & Raz, 1994).

Intervention

The Basic Density and Causal Density Units each contained 15 lessons designed to teach about density and the role of density in sinking and floating. The units took five weeks to teach. Both units included work with Archimedes' Laboratory, a computer simulation program by Snir, Smith, Grosslight, Unger, and Raz (1989) designed to teach density as a 'dots per box' model. The lesson sequence for the units, specifying what was taught to each group in each lesson can be found in Appendix B. All four classes were taught by the same teacher and by a researcher, who was a former science teacher.

The Causal Density Unit included RECAST activities and discussion aimed at helping students achieve the following understanding goals about the nature of causality as it relates to the causes of density and the role of density in sinking and floating. One goal focused on the causal mechanism for differences in density, in particular, that density as a causal mechanism is non-obvious, and the causes of differences in density are non-obvious because they occur at the microscopic level (with the exception of some cases of mixed densities). Part

of this was some sense of what causes differences in density at the microscopic level (such as atomic mass, atomic bonds, etc.). We also wanted students to understand that density is dynamic because some of the causes of density are dynamic. While atomic mass is constant, the bonds between atoms and molecules are affected by variables such as temperature and pressure. Unfortunately, middle school textbooks often state 'density cannot change,' fostering the notion that we assign a number to the density of an element 'under standard conditions' and that the number doesn't change. The two ideas tend to be confused by both students and textbook writers, leaving students with the belief that density is static and making it difficult for them to understand a vast range of everyday phenomena.

The second understanding goal concerned the relational interaction patterns that characterize density as mass per unit volume and the role of density in sinking and floating. Typically, people assume a linear causal interaction pattern and say things like 'dense objects sink' or 'heavy objects sink.' However, the scientifically accurate model is a relational causal interaction pattern. Whether something sinks or floats depends on what it is sinking or floating in and the relationship of the densities.

Scoring

A rubric was designed to score each answer by the level of scientific correctness and the complex causality it represented. For instance, one question asked students to show the possible outcomes when an object is dropped into a liquid to see if it will float and to explain each. The following scores were assigned. No response was scored as Level 0. Repeating information given in the problem or giving examples of things that sink or float was scored as Level 1. Weight attributions, token uses of density, or merely stating that hollow things float and solids sink were scored as Level 2. Attributing sinking or floating to material kind or to air particles inside a material were scored as Level 3. A focus on the density or crowdedness of the material or on the density or crowdedness of the liquid was scored as a Level 4 (including mixed density where the density of air plus the density of the material gives a total density). A focus on the density or crowdedness of the material in relation to the density or crowdedness of the liquid was scored at Level 5.

One scorer scored 100% and a second scorer scored 25% of the data and inter-rater reliability was assessed using a Pearson Product Moment Correlation ($\underline{r}$ = .85). The scoring rubric was adjusted and clarified to account for categories of differences (without discussion of individual cases) resulting in an improved Pearson Product Moment Correlation ($\underline{r} = .91$). Differences were discussed until 100% agreement was reached.

Results

A one-way analysis of variance (ANOVA) on students' pre-interview scores by group confirmed that there were no significant starting differences between the groups ($\underline{t}$ (89) = -1.72, $\underline{p}$ = .09). However, given that numbers were approaching significance, pre-test scores were entered as a covariate in the regression analysis below.

Both groups of students showed significant improvement on the post-test as the result of instruction (across groups: $\underline{t}$ (86) = -8.69, $\underline{p}$ <.0001; within groups: CTL = $\underline{t}$ (45) = -4.80, $\underline{p}$ <.0001 and C&D = $\underline{t}$ (40) = -7.98, $\underline{p}$ < .001). This is not surprising because both units were designed around best practices. A multiple regression model plotting intervention condition and pre-test scores against pre- to post-test gains yielded an $\underline{R}^2 = .33$ and the Effect Test showed significant main effects of intervention condition (F (1, 87) = 12.73, $\underline{p}$ <.0006) and pre-test score ($\underline{F}$ (1, 87) = 34.99, $\underline{p}$ < .0001). The causal students outperformed the control students with respective least squares means of 11.23 and 5.56 ($\underline{SD}$ = 8.5).

From a developmental perspective, one might argue that students with lower starting scores are less ready to learn the more advanced models. However, the analysis also revealed a negative correlation between pre-test scores and gain scores ($\underline{r}$ = -.48) with lower pre-test scores correlating with higher gain scores. (See the prediction formula in Figure 2.) This makes sense in that there is a ceiling on how much one can gain, so those who start lower have more to gain. It also fits with our hypothesis that there are certain conceptual leaps that are hard for students to make, for instance moving from a linear to a relational model. Those who start lower can gain a greater amount before having to surmount the hurdle of those conceptual challenges.

For another way of looking at the data, we calculated the percentage of students in each intervention condition who ended up with a relational causal model. This measure focuses directly on the hurdle of leaving a linear causal model behind completely and adopting a fully relational model. Three questions on the assessment directly assessed whether students structured their explanation with a relational causal model. Students were assigned one point

for each relational model that they used. A multiple regression model plotting intervention condition and pre-test relational model use against pre- to post-test gains in relational model use yielded an $\underline{R}^2 = .35$ and the Effect Test showed significant main effects of intervention condition ($\underline{F}$ (1, 87) = 7.62, $\underline{p}$ < .0071) and pre-test score ($\underline{F}$ (1, 87) = 40.75, $\underline{p}$ < .0001). The causal students outperformed the control students with respective least squares means of 1.31 and .81 ($\underline{SD}$ = .99). Figure 3 illustrates the percentage of students in each condition who shifted from using linear to relational causal models on their pre- to post-test. Here 'use of relational causal model' was defined as employing relational causality on at least two of the three questions.

Intervention Condition

$$\text{Intercept} = 19.62 + \begin{cases} \text{match} & \text{when Control} \\ 5.66 & \text{when Causal} \end{cases} \quad \begin{cases} - 0.55 \times \text{total pretest} \end{cases}$$

Figure 2. Prediction formula detailing parameter estimates (intervention condition and interview version) to estimate density gain scores.

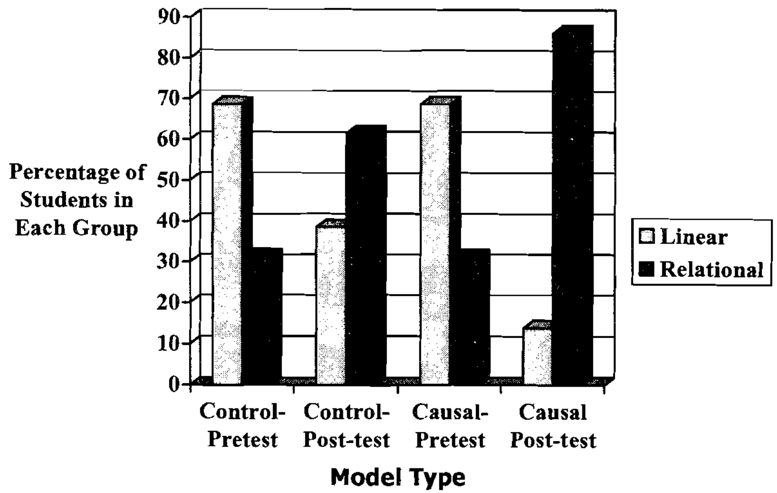

Figure 3. Percentage of students using each model type on pre- and post-test by intervention condition (n = 91).

The density results suggest that students significantly benefited from the infusion of RECAST activities and causal discussion into their science unit. However, the results are not as dramatic as in the electricity research: students in the control classes also saw significant gains and 61% of them (as compared to 86% of the causal group) used relational causal reasoning on the post-test. It appears that the pattern of relational causality may be less counterintuitive to students than those in electricity, some of them gleaning it from instruction that does not specifically focus on it.

Most of the assessment questions that we used were real-world type questions that blended the different dimensions of causality, so it was not possible to discern which dimensions were most impacted by the interventions. However, we found in both studies that students felt comfortable talking about interaction patterns and often spontaneously mentioned them and/or contrasted more complex forms to simple linear reasoning. Students also quickly picked up on the term 'token cause' and pushed not only themselves, but also their peers and sometimes their teachers, for more in-depth explanations when they asked a question and got back what they considered a token cause. Whether these aspects of the dimensions are inherently most easily fostered or the intervention was in some way more effective addressing these is an open question that warrants further study.

In summary, the foregoing studies offer support for the hypothesis that teaching students about more complex causal structures improves their ability to reason about topics for which they typically have misconceptions. This is corroborated by findings in our research on other topics such as ecosystems, pressure, and heat and temperature (e.g., Basca & Grotzer, 2001; Grotzer, 2004; Grotzer & Basca, 2003). Across the topics studied, students in the causal interventions demonstrated deeper understanding and fewer misconceptions. They analyzed problems at a more systemic level, made reference to causal models, and contrasted and critiqued the relevance of different causal forms to specific concepts. For example, in the study of students' understanding of ecosystems, students in the causal interventions detected significantly more connectedness in the ecosystem relationships and demonstrated a stronger grasp of decomposition and the non-obvious mechanisms that cause it (Grotzer, 1993; Grotzer & Basca, 2003). In air pressure, students who engaged in causal discussion plus a systemically-focused air pressure curriculum experienced greater conceptual change towards relational causal models than students who engaged in only the systemically-focused curriculum (Basca & Grotzer, 2001). In heat and temperature, students in causal intervention groups made substantive gains on understanding the interaction patterns involved in heat and temperature (domino, re-entrant, and linear causal structures) (Grotzer, 2004).

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 standard circuit), and, next to that, (2) learning and applying modelling systems (for example, Ohm's Law for any circuit), but rarely (3) learning and reusing modelling styles (constraint-system models in general for instance). Unfamiliar and uncomfortable with complex styles of causal modelling, learners often find themselves baffled and frequently backslide after a little progress.

Our tests of the complex causality framework found support from studies of students' initial conceptions, both prior to and after conventional instruction. The causal models implicit in students' explanations tend to be quite simple by the measure of the four dimensions of complex causality. Moreover, interventions designed to teach characteristically troublesome science concepts in a way that brought out complex causality yield considerable gains in students' understanding, compared with control groups receiving 'best practices' inquiry-oriented instruction without attention to complex causality.

At the beginning of this article, we asked: what makes some science concepts particularly hard to understand, not just requiring 'a little more instruction'? The following conclusions, all related to modelling styles, 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 elaborate.

One source of difficulty lies in concept-specific contrary intuitions such as those identified by diSessa (1993). We certainly acknowledge concept-specific intuitions are a problem. However, we do suggest that learners are in a better position to challenge such intuitions with a good sense of complex causality. Indeed some of these concept-specific intuitions can pull against students' ability to grasp the underlying causal structure. For instance, we have found that some students who reveal an underlying relational causal model in most of their reasoning about air pressure still lapse back to a linear model when they reason about hurricanes and the powerful winds involved (Ritscher, Lincoln, & Grotzer, 2003).

A further and serious source of challenge, we propose, is unfamiliarity with modelling styles toward the complex ends of the dimensions introduced above. 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.

The challenge is even greater when more complex modelling styles contradict rather than extend simpler ones. This generates particular resistance, because students have to abandon their initial thinking styles, styles that are fluent and comfortable because everyday explanations typically employ them.

Many scientific theories call for what Frederiksen and White (2000) have called 'multimodel thinking'—coordinating multiple levels or explanatory perspectives that may involve different modelling styles. Students find moving between and coordinating levels to be very difficult (Chi, 2000; Wilensky & Resnick, 1999).

Awareness and appreciation of complex modelling styles benefit from inquiry skills that are themselves often underdeveloped, and gain from ways of teaching and learning that give inquiry a significant place. As noted earlier, in at least some cases learners in principle could easily challenge their own overly simple models, if only they looked for gaps in the causal story or considered readily constructed counter-examples; yet they do not. Inquiry-oriented instruction fosters treating particular

models as provisional, under test, and subject to revision or replacement, an attitude quite removed from students' tendency to want to know the facts (e.g., Clement, 1993; Collins & Ferguson, 1993; Frederiksen & White, 2000; Perkins, 1997).

7. However, good inquiry-oriented instruction by itself is not sufficient to fully develop particular complex causal understandings and students' general sense of complex causality. As demonstrated in the teaching experiments reviewed earlier, it needs to be coupled with direct attention to complex causality, in the context of the particular target concepts.

While the research reviewed here supports the dimensions of complex causality, further important questions remain part of our ongoing research. For example, when students get acquainted with more complex modelling styles in the context of one science topic, can they transfer their repertoire to other science topics that seem quite different on the surface? Transfer of learning across different surface situations is one of the abiding challenges of pedagogy (see e.g., Bransford & Schwartz, 1999; Detterman & Sternberg, 1992; Salomon & Perkins, 1989). Anecdotal evidence from our intervention studies suggests that students do show some transfer, particularly when the instruction fosters reflective abstraction, and we are pursuing research in this area. However, even if transfer turns out to be limited, the modelling styles still would be important for deepening students' understanding, albeit on a case-by-case basis as in the studies of electrical circuits and density.

If the dimensions of complex causality hold up, even in considerable part, they offer significant insight into the difficulties learners encounter. Moreover, remember how in the opening anecdote learners find science more baffling than magic. It doesn't have to stay that way. Helping learners to achieve a better understanding of causal modelling styles as they study a range of concepts and topics in science could work a little magic in the classroom!

ACKNOWLEDGEMENTS

An earlier version of this paper was presented at the American Educational Research Association annual conference, New Orleans, April 24- 28, 2000.

This paper is based upon the work of Understandings of Consequence Project, which is supported by the National Science Foundation, Grant No. REC-

9725502 and REC-0106988 to Tina Grotzer and David Perkins, Co-Principal Investigators. Any opinions, findings, conclusions or recommendations expressed here are those of the authors and do not necessarily reflect the views of the National Science Foundation.

REFERENCES

AIMS EDUCATION FOUNDATION (1991). Electrical connections: AIMS activities, Fresno, CA: Author.

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). Molndal, Sweden: Gotesberg University.

BARBAS, A. & PSILLOS, D. (1997). Causal reasoning as a base for advancing a systemic approach to simple electrical circuits. *Research in Science Education*, 27(3), 445-459.

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, April). *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, Seattle.

BLISS, J. (1995). Piaget and after: the case of learning in science. *Studies in Science Education*, 25, 139-172.

BRANSFORD, J.D. & SCHWARTZ, D.L. (1999). Rethinking transfer: a simple proposal with multiple implications. *Review of Research in Education*, 24, 61-100.

BROWN, D. (1995, April). *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.

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.

CAREY, S. (1995). On the origin of causal understanding. In D. Sperber, D. Premack & A.J. Premack (Eds.), *Causal cognition: A multidisciplinary debate* (pp. 268-302). Oxford: Clarendon Press.

CHI, M.T.H. (1992). Conceptual change within and across ontological categories: Examples from learning and discovery in science. In R. Giere (Ed.) *Cognitive Models of Science: Minnesota studies in the Philosophy of Science* (pp.129-186). Minneapolis, MN: University of Minnesota Press.

CHI, M.T.H (2000, April). *Misunderstanding emergent processes as causal*. Paper presented at the Annual Conference of the American Educational Research Association, New Orleans.

CHI, M.T.H. & SLOTTA, J. (1993). The ontological coherence of intuitive physics. Commentary on A. diSessa's 'Toward an epistemology of physics.' *Cognition and Instruction*, 10, 249-260.

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* (pp. 313-19). Paris: Editions du Centre National de Recherche Scientifique.

COHEN, R., EYLON, B. & GANIEL, U. (1983). Potential difference and current in simple electrical circuits: A study of students' concepts. *American Journal of Physics*, 51(5), 407-412.

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

DETTERMAN, D. & STERNBERG, R. (Eds.) (1992). *Transfer on trial*. Norwood, NJ: Ablex.

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. In R. Driver, E. Guesne & A. Tiberghien (Eds.), *Children's ideas in science* (pp. 193-201). Philadelphia: Open University Press.

DUFFY, T.M. & JONASSEN, D.H. (Eds.) (1992). *Constructivism and the technology of instruction: a conversation*. Hillsdale, NJ: Erlbaum.

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*. Ludwigsburg.

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

FREDERIKSEN, J.R. & WHITE, B.Y. (2000, April). *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.

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 Teacher*, 18, 194-198.

GOBERT, J. & CLEMENT, J. (1999). The effects of student-generated diagrams versus student-generated summaries on conceptual understanding of spatial, causal, and dynamic knowledge in plate tectonics. *Journal of Research in Science Teaching*, 36(1), 39-53.

GOSWAMI, U. (1992). *Analogical reasoning in children*. Hillsdale, NJ: Erlbaum.

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, Harvard University, Cambridge.

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

GROTZER, T.A. (2003). Learning to understand the forms of causality implicit in scientifically

accepted explanations. *Studies in Science Education*, 39, 1-74.
GROTZER, T.A. (2004). *The Understandings of Consequence Project Report #5: Technical Paper.* Unpublished paper, Harvard University, Cambridge.
GROTZER, T.A. & BASCA, B.B. (2003). Helping students to grasp the underlying causal structures when learning about ecosystems: how does it impact understanding? *Journal of Biological Education,* 38(1), 16-29.
GROTZER, T. A. & SUDBURY, M (2000, April). *Moving beyond underlying linear causal models of electrical circuits.* Paper presented at the Annual Conference of the National Association for Research in Science Teaching, New Orleans.
HARTEL, H. (1984). The electrical circuit as a system. In R. Duit, W. Jung & C. von Rhoneck (Eds.), *Aspects of understanding electricity.* Ludwigsburg.
HELLER, P.M. & FINLEY, F. N. (1992). Variable uses of alternative conceptions: a case study in current electricity. *Journal of Research in Science Training,* 29(3), 259-275.
HOUGHTON, C., RECORD, K., BELL, B. & GROTZER, T.A. (2000, April). *Conceptualizing density with a relational systemic model.* Paper presented at the Annual Conference of the National Association for Research in Science Teaching (NARST), New Orleans, LA..
INHELDER, B. & PIAGET, J. (1958). *The growth of logical thinking from childhood to adolescence.* London: Routledge & Kegan Paul.
KOHN, A. S. (1993). Preschooler's reasoning about density: Will it float? *Child Development* 64(6), 1637-50.
INTERACTIVE PHYSICS [COMPUTER SOFTWARE]. (1996). Knowledge Revolution, Available: http://www.krev.com/products/ip.html.
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, CA: Academic Press.
LAKOFF, G. & JOHNSON, M. (1980). *Metaphors we live by.* Chicago: University of Chicago Press.
LEHRER, R. & SCHAUBLE, L. (1998). Reasoning about structure and function: Children's conception s of gears. *Journal of Research in Science Teaching,* 35(1), 3-25.
LIEM, T. L. (1981). *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.
METZ, K. E. (1991). Development of explanation: Incremental and fundamental change in children's physics knowledge. *Journal of Research in Science Teaching,* 28(9), 785-797.
MURAYAMA, I. (1994). Role of agency in causal understanding of natural phenomena. *Human Development,* 37, 198-206.
NATIONAL SCIENCE RESOURCES CENTER (1991). *Electrical circuits: Science and technology for children.* Washington D.C.: National Academy of Sciences.
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 Education*, 2(3), 311-321.
OST, D.H. (1987). Models, modeling, and the teaching of science and mathematics. *School Science and Mathematics*, 87, 363-370.
PAZZANI, M. (1991). A computational theory of learning causal relationships. *Cognitive Science*, 15, 401-424.

PENNER, D.E., GILES, N.D., LEHRER, R. & SCHAUBLE, L. (1997). Building functional models: Designing an elbow. *Journal of Research in Science Teaching*, 34, 1-20.
PERKINS, D.N. (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: Vol. II* (pp. 91-114). Hillsdale, NJ: Erlbaum.
PERKINS, D.N. & GROTZER, T.A. (2000, April). *Models and moves: focusing on dimensions of causal complexity to achieve deeper scientific understanding.* Paper presented at the annual conference of the American Educational Research Association, New Orleans.
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.* London: Routledge & Kegan Paul.
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 Education*, 16(1), 41-56.
POSNER, G.J., STRIKE, K.A., HEWSON, P.W. & GERTZOG, W.A. (1982). Accommodation of a scientific conception: toward a theory of conceptual change. *Science Education*, 66(2), 211-227.
RAGHAVAN, K., SARTORIS, M. & GLASER, R. (1998). Why does it go up?: The impact of the MARS curriculum as revealed through changes in student explanations of a helium balloon. *Journal of Research in Science Teaching*, 35(5), 547-567.
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.
RITSCHER, R., LINCOLN, R. & GROTZER, T. A. (2003, March). *Understanding density and pressure: How students' meaning-making impacts their transfer of causal models.* Paper presented at the National Association of Research in Science Teaching Conference, Philadelphia.
ROWELL, J.A. & DAWSON, C.J. (1977). Teaching about floating and sinking: an attempt to link cognitive psychology with classroom practice. *Science Education*, 61(2), 245-253.
ROZIER, S. & VIENNOT, L. (1991). Students' reasoning in thermodynamics. *International Journal of Science Education*, 13(2), 159-170.
SALOMON, G. & PERKINS, D.N. (1989). Rocky roads to transfer: Rethinking mechanisms of a neglected phenomenon. *Educational Psychologist*, 24(2), 113-142.
SANDOVAL, W.A. (2003). Conceptual and epistemic aspects of students' scientific explanations. *The Journal of the Learning Sciences*, 12(1), 5-52.
SHIPSTONE, D.M. (1984). A study of children's understanding of electricity in simple DC circuits. *European Journal of Science Education*, 6(2), 185-198.
SHIPSTONE, D. (1985). Electricity in simple circuits. In R. Driver, E. Guesne & A. Tiberghien (Eds.), *Children's ideas in science* (pp. 33-51). Philadelphia: Open University Press.
SLOTTA, J.D. & CHI, M. T.H. (1999, March). Overcoming robust misconceptions through ontology training. Paper presented at the Annual Conference of the American Educational Research Association, Montreal.
SLOTTA, J.D. (1997). Understanding constraint-based processes: A precursor to conceptual change in physics. Unpublished doctoral dissertation. University of Pittsburgh, Philadelpia.
SMITH, C., CAREY, S. 7 WISER, M. (1985) On differentiation: A case study of the concepts of size, weight, and density. *Cognition*, 21, 177-237.
SMITH, C., GROSSLIGHT, L., DAVIS, H., MACLIN, D., UNGER, C., SNIR, J. & RAZ, G.

(1994) *Archimedes and beyond: Helping students to construct an understanding of density and matter.* Cambridge, M.A: Educational Technology Center, Harvard Graduate School of Education.

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.

SMITH, C., SNIR, J. & GROSSLIGHT, L. (1992). Using conceptual models to facilitate conceptual change: The case of weight-density differentiation. *Cognition and Instruction*, 9(3), 221-283.

SNIR, J., SMITH, C., GROSSLIGHT, L., UNGER, C. & RAZ, G. (1989). Archimedes' Laboratory. [Computer software] Cambridge, MA: Educational Technology Center, Harvard Graduate School of Education.

STEWART, J., HAFNER, R., JOHNSON, S. & FINKEL, E. (1992). Science as model building: Computers and high school genetics. *Educational Psychologist*, 27, 317-336.

TIBERGHIEN, A. & DELACOTTE, G. (1976). Manipulations et representations de circuits electrique simples chez les infants de 7 a 12 ans. *Revue Francais de Pedagogie*, 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.

WILENSKY, U. & RESNICK, M. (1999). Thinking in levels: a dynamic systems approach to making sense of the world. *Journal of Science Education and Technology*, 8(1) 3-19.

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

WISKE, M.S. (Ed.). (1998). . San Francisco: Jossey-Bass.

Appendix A: Lesson Descriptions for Simple Circuits Units:

Lesson 1: Thinking About Electricity
Students in all three groups discussed what they already know about the nature of electricity, how it is used, safety issues to consider, and how their lives would be different without it.

Lesson 2: What Configurations Work to Light a Bulb?
Students in all three groups experimented with different battery and bulb configurations to see which ones would work. They found four different configurations that worked. They also found that it is possible to light the bulb with just a wire, battery, and bulb. They discovered that linear arrangements do not work to light the bulb.

Lesson 3: What is the Inside of a Light bulb?
Students in all three groups examined light bulbs that had been taken apart by the teachers and researchers. They observed how the wire that runs through the bulb goes in at one side of the base and comes out at the bottom of the base. They diagramed the parts of the bulb and considered how the places where the wire entered and exited corresponded to their findings in lesson two. They examined different types of light bulbs at school and in their homes.

Lesson 4: What is the Underlying Causality of a Simple Circuit?
All of the students shared, discussed, and critiqued their models for why the simple circuit works. They considered what the circuits that worked had in common. The NSRC (1991) unit focuses on having students detect the configurations that work but not the underlying models for 'why.' The unit was modified so that students in all groups shared their ideas for why they thought certain configurations worked and engaged in simulations to illustrate the models that students presented where they pretended to be electrons and protons along the circuit. Students in the CAU and C&D groups were introduced (though activities or activities and causal discussion) to a cyclic simultaneous model for explaining electrical flow at the particle level as one of the possible models to consider. Some points of discussion in all three groups included that electrons are conserved in a circuit; that the bulb lights when electrons flow in the circuit and that flow requires a continuous 'push.'

Lesson 5: What Does the Battery Do?
A lesson was added for all students to the NSRC unit to consider the role of the battery in a simple circuit (without capacitors). Students observed that one side is positive and one is negative. The teacher took a battery apart. They discussed the role of the battery as separating electrons and protons (and accumulating 'charge' at the ends of the battery). The students in the causal groups did activities (and the C&D group engaged in discussion) to help them think about it in terms of the 'push' (though some students saw it as pull toward the protons at the positive end of the battery) that sustains flow in the cyclic simultaneous model.

Lesson 6: Building and Testing Circuits
All students experimented with building a circuit using a bulb holder and a battery holder, considered which parts of the circuit were important, and engaged in trouble-shooting circuits that didn't work for various reasons as per NSRC lessons five and six. Students engaged in conversation to relate what they were finding to their models for

why circuits work. Students in the causal discussion group explicitly discussed these in terms of a cyclic simultaneous model.

Lesson 7: What are Conductors and Insulators?

All students experimented with objects and tried to include them in the circuits to consider different levels of conductivity in their circuits. They then discussed conductors and insulators and related it back to what they learned about conduction and insulation in a unit of static electricity. The goal was to prepare students to think about resistance.

Lesson 7: What are Conductors and Insulators?

All students experimented with objects and tried to include them in the circuits to consider different levels of conductivity in their circuits. They then discussed conductors and insulators and related it back to what they learned about conduction and insulation in a unit of static electricity. The goal was to prepare students to think about resistance.

Lesson 8: Experimenting with Filaments: Why Does the Bulb Light When There is Flow?

Students in all groups experimented with different types of filaments and varied width, material type and length to observe the outcomes. Students were taught to think about resistance as being on a continuum between conductivity and insulation. Students in the C&D group discussed it in terms of a passive type of causality.

Lesson 9: Hidden Circuits

All students engaged in the NSRC lesson nine on hidden circuits where they had to use a circuit tester to test where there was a complete circuit and where there was not.

Lesson 10: Deciphering a Secret Language

Students in all groups were taught to decipher electrical circuit diagrams and created drawings of circuits that they built as per lesson ten in the NSRC unit.

Lesson 11: What Happens When Bulbs or Batteries are in Series or Parallel?

Students in all groups experimented with building series and parallel circuits with multiple bulbs or batteries. They made predictions about what they expected would occur and then observed what actually happened when they created each circuit. Students were asked to draw models of what they thought was going on and why. The students shared, discussed, and critiqued their models for explaining what happens in the case of parallel and series circuits. Students in the causal groups critiqued the cyclic simultaneous model along with other models put forth by the students.

Lesson 12: What do Switches do?

Students in all groups experimented with adding switches to their circuits and predicting and testing what happens. Students drew models of what they thought was going on and why. They discussed what the switch did in terms of their models for how a circuit works. The causal discussion group also considered the role of a switch in the cyclic simultaneous model.

Lesson 13: Constructing a Flashlight or Wiring a Miniature House

Students in all groups chose to either create a flashlight or wire a miniature house to use what they had learned about circuit configurations that work.

Appendix B: Lesson Descriptions for the Density Units:

Lesson 1: What are Volume, Mass, and Weight? How Do We Distinguish Each One?

Students in both groups were taught how to distinguish the concepts of volume, mass, and weight. They explored why it was difficult to distinguish between these concepts. Computer simulations created in Interactive Physics allowed them to explore the differences between mass and weight on different planets.

Lesson 2: How Can We Measure Mass and Weight?

Students in both groups were taught how and why mass is to measured with a spring scale. Mass is a measurement independent of gravity, it always involves a comparison. Students were taught that they find the mass of an object by finding out how many grams it takes to balance the object on a pan balance.

Lesson 3: How Can We Measure Volume?

Students in both groups deduced how to measure the volume of regular and irregular objects and practiced measuring them. They learned how to use the displacement method.

Lesson 4: Why Do Some Objects of the Same Volume Differ in Mass?

Students in both groups considered the problem of how objects made of different materials that have the same volume could have different masses. They compared different objects with the same shape and volume with different masses and drew models of what they thought might be going on.

Lesson 5: How Do We Calculate Density?

Students in both groups graphed out the relationship between mass and volume of different objects to find out that density can be deduced by knowing the relationship between mass and volume. They were taught that density is measured in units; g/cm3 [grams per cubic centimeter] or g/ml [grams per milliliter] and that of density, mass, and volume, if you know two of the variables, you can figure out the others. Students in the Causal Group were taught to think about density as a relational causality as compared to a linear causality. They were taught that in relational causality, the relationship between two variables accounts for the outcome, not one variable or the other. Changing the relationship in anyway changes the outcome.

Lesson 6: How Do We Calculate Density?: A Reinforcement Lesson

Students in both groups used a computer simulation called Archimedes Laboratory to learn how calculations of density relate to visual models. They also discussed the statement in their book, 'The density of a liquid can be measured...' and whether the word 'measured' is a good or bad choice. They debated whether density can be directly measured or has to be inferred.

Lesson 7: Why Do We Say Density is a Property of a Particular Kind of Matter?

Students in both groups made predictions about how certain transformations to matter (such as cutting or changing shape) might affect density and then calculated the density to realize that density is not affected by the size or shape of the object. They learned that specific densities are assigned to specific elements and that the density of a substance can be used to help identify that substance.

Lesson 8: Do Liquids and Gases have Density Just as Solids Do?

Students in both groups learned that liquids and gases also have density—that all matter has density. They figured out how to calculate the density of liquids and gases. They found the density of water and a number of other liquids.

Lesson 9: What are Some Useful Models of What More or Less Dense Might Look Like?

Students in both groups analyzed a set of different models for visualizing density and generated a number of their own. They were taught that one way to think about density that students often find helpful is to think about how crowded or packed a material is. Many models use various forms of crowdedness (or more or less packed in) as a way of conveying density.

Lesson 10: What Causes Differences in Density?: The Role of Atomic Mass

Students in the causal intervention were taught about the micro causes of density as an underlying causal mechanism and a way to conceptualize it despite its non-obvious nature. They learned that density has multiple contributing causes and that one cause of differences in density is the masses of the atoms (the number of protons, neutrons and electrons that the atoms are made up of). This cause applies equally to all states of matter. Students in the control condition continued to generate, explore and critique different models for helping them to visualize density as begun in the previous lesson. This included discussion of how the particles or molecules might be more crowded.

Lesson 11: What Else Causes Differences in Density?: The Crowdedness of Atoms and Molecules due to Structure, States, and Conditions

Students in the causal intervention were taught that another contributing cause to density at the micro-level (an underlying causal mechanism that is non-obvious) is the spacing between atoms due to the strength and structure of atomic bonds between the atoms and the spacing between atoms, molecules, and compounds due to states, structure, or conditions: how far apart the atoms, individual molecules, or molecular compounds are spread with other molecules (such as air or water) or vacuum in between due to various states, structure and/or conditions. Students in the control condition engaged in an activity called 'The Penny Lab' designed to help students realize that density is one means of figuring out the composition of an object and they considered pennies that had differences in density and what that implied for their composition.

Lesson 12: What Does it Mean for Density to have Multiple Contributing Causes?

Students in the causal intervention were taught that density has multiple contributing causes. Not every cause is involved in every situation where density is in play and that you can't compare objects by using just one of the causes alone. You also can't assume that every cause contributes to every situation. They explored situations where this was so both in science and social content. Students in the control condition completed 'The Penny Lab' activity from the previous lesson.

Lesson 13: Can the Density of a Solid Change?/ How does Density Change in Liquids and Gases?

Students in the causal condition heated a ball and ring to see that density is not static; it can change and analyzed what happened using the micro-causes of density and the relationship between mass and volume. They were taught that changing the temperature (and pressure) can change the density of a substance and that solids (and liquids) expand a little when heated. Gases expand a lot when heated. Students in the control condition were taught that numbers are assigned to elements that represent 'standard density' but that this applies only to standard conditions. Each group considered the density of sets of elements, with a relational focus in the causal group ('Which element is denser than the other?') and a typical, definitional focus in the other ('What is the density of gold at standard temperature and pressure?')

Lesson 14: How Does Density Affect Sinking and Floating?

Students in the causal group did a RECAST activity to help them realize that when considering whether an object will sink or float in a liquid, you have to compare the density of the object to the density of the liquid. They discussed linear and relational causal models and they layered liquids to see the relational density. Students in the control condition did an activity to learn that an object made of a substance with a density greater than 1.0 will sink in water, an object made of a substance with a density less than 1.0 will float in water, and an object with a density of 1.0 will suspend in water, controlling for other variables.

Lesson 15: How Does Density Affect Sinking and Floating?: A Reinforcement Lesson

Students in both conditions used Archimedes Laboratory to experiment with sinking and floating. Students in the causal condition had their experimentation guided and supported by a sheet that helped them to interpret what was happening through the lens of relational causality while students in the control condition used an unmodified version of the program (but also had a written guide sheet for their work).

Lesson 16: Manipulating Variables: What is Going on to Explain Sinking or Floating?

Students in the causal condition manipulated the variables in the relationship that determines what sinks or floats to modify the outcomes. Students found that Diet Pepsi floats while regular Pepsi sinks and they discussed why. Then they generated ideas for and modified the liquid it was floating in to make both sink. Students considered the exploration and the models that they generated to explain it through the lens of relational causality and the dynamic nature of density. Students in the control condition experimented with objects to see which would sink and which would float in water including some that are counterintuitive. They then deduced information about the object's density.

Lesson 17: What Happens When You Mix Densities?

Students planned and created objects that would suspend by using mixed density. Students in the causal condition analyzed and planned their objects through the lens of relational causality. Students in the control condition analyzed and planned their object to have a density similar to that of water (1 g/ml)

Contact address
Tina Grotzer,
Harvard Graduate School of Education,
Project Zero,
124 Mt. Auburn Street,
Cambridge, MA 02138.

e-mail: tina_grotzer@harvard.edu.