# AC 2008-180: USING COMPUTERS TO SUPPORT QUALITATIVE UNDERSTANDING OF CAUSAL REASONING IN ENGINEERING

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# Using Computers to Support Qualitative Understanding of Causal Reasoning in Engineering

As the Scottish philosopher David Hume claimed, causal reasoning is the "cement of the universe" [1]As intellectual cement, causality binds together reasoning processes that are common to all STEM disciplines, including making predictions, drawing implications, making inferences, and articulating explanations.

## Predictions

Reasoning from a description of a condition or set of conditions or states of an event to the possible effect(s) that may result from those states is called *prediction*. Prediction assumes a more or less probabilistic relationship between causal antecedent(s) and effect(s) because a potentially large number of causal relationships can participate in the occurrence of the effect. The two primary functions of prediction are forecasting an event (e.g., economic or meteorological forecasting) and testing of hypotheses to confirm or refute scientific assumptions. Predictions support experimentation; they are the hypotheses of experiments. Engineers regularly make predictions about the effects of interventions. Scientific predictions are empirically tested for their validity. Predictions assume a deterministic relationship between cause and effect, that is, that forces in the cause reliably determine an effect. In his Metaphysics, Aristotle argued that everything is determined by material causes, formal causes, efficient causes, and final causes (purpose of thing)[3].

## Implications

A less deterministic form of prediction is to draw implications from a set of conditions or states based upon plausible cause-effect relationships. To imply is to entail or entangle events or to involve an effect as a necessary consequence of some cause without necessarily knowing what the effect will be. Drawing implications involves identifying potential effects, anticipated or unanticipated consequences from a causal antecedent. Engineering interventions often entail unanticipated effects [3]. Therefore, implications of any event are often not known or could not have been hypothesized. As such, implications represent a conditional form of prediction that is less deterministic (teleological) than a prediction. Implications have received very little research or analysis in psychology or philosophy, so little is known about implicational reasoning.

## Inference

When an outcome or state exists for which the causal agent is unknown, then an inference is required. That is, reasoning backwards from effect to cause requires the process of inference. A primary function of inferences is diagnosis. Diagnostic causal reasoning is predominantly deterministic because only a determinable number of causes can be inferred to produce the effect. That is, the effect is already known with a fair amount of certainty and therefore only a limited number of causes can be inferred for the specific conditions in which it occurred. Diagnosis is the identification of a cause, an origin, or a reason for something that has occurred. In medicine, diagnosis seeks to identify the cause or origin of a disease or disorder as determined by medical diagnosis.

## Explanation

Causality is endemic to understanding any knowledge domain or discipline. Causality is essential for understanding all forms of scientific reasoning [4, 5, 6, 7]. Scientific explanations make very heavy use of what Aristotle called formal and efficient causes, which describe the essences of things and the forces that made those things. Reasoning in the social sciences and humanities addresses human goals, intentions, motives or purposes and is also subject to formal (teleological) causes that describe the goals or intentions of causal agents.

Explaining any entity requires more than an awareness of the parts of that entity. Explanations require functional knowledge of the entity or system being explained. Functional knowledge includes the comprehension of the function and structure of the interrelationships among the components in any system and the causal relationships between them [8].You cannot fully explain any entity or event without understanding it causally. For example, the process of diagnosing disease states requires that physicians' explanations of diseases include causal networks that depict the combination of inferences needed to reach a diagnosis [9]. Explanation of phenomena cannot occur without the abilities to predict, implicate, and infer.

## Attributes of Causal Propositions

Causality is the relationship that is ascribed between two or more entities where one incident, action, or the presence of certain conditions determines the occurrence or nonoccurrence of another entity, action, or condition. Hume was one of the first modern philosophers to explore causality. He identified the important attributes of causation [1, p. 116]:

"1. The cause and effect must be contiguous in space and time.
2. The cause must be prior to the effect.
3. There must be a constant union betwixt the cause and effect."

That is, causation arises from the empirical relations of contiguity, temporal succession, and constant conjunction. Spatiotemporal contiguity refers to the repeated and consistent associations among causes and effects in space or time. If kicking a ball always results in ball movement, humans induce a causal relationship. Temporal succession (AKA temporal priority) claims that causes always precede effects, not the other way around [10]. Constant conjunction means that they always appear together, that is, there is a subjectively perceived "necessary connection" between the cause and the effect. Balls do not move without being kicked.

Although causality is usually induced empirically, empirical descriptions are insufficient for understanding causality. Contemporary accounts of causality emphasize three main principles that validate a causal relationship, including covariation (co-occurrence) principle, priority principle, and mechanism principle [11]. Covariation is the degree or extent to which one element consistently affects another, which describes the empirical relationships between cause and effect. Covariation is expressed quantitatively in terms of probabilities and strength of relationship. The mechanism principle describes causal relationships qualitatively, in terms of the conceptual mechanisms that describe why a cause results in an effect.

The covariational and the mechanism principles are the two most common conceptual frameworks for studying causal reasoning [12, 13]. While significant differences can be seen between the two main theoretical directions related to scientific inquiry, recent work [14, 15, 16]

shows that instead of being separate descriptions of causal relationships, covariational and mechanistic explanations are reciprocal. Both are necessary for understanding; neither is sufficient. Although learners can induce a correlation (covariation) between two variables using statistical methods, failure to provide an explanatory mechanism that shows how and why the covariation occurs, the relationship will not be understood [16].

Covariation

Causes are usually inferred from observational data that people formally or informally assimilate or from interventional data where one or more variables are experimentally manipulated [17]. In order to be able to explain and apply causal relationships, learners must be able explicate the following covariational attributes for any causal relationships they are studying. As designers, we must design, develop, and implement tools for supporting those explanations.

Temporal Succession

According to the principle of temporal succession (temporal priority), a cause C must be present for an effect E to occur, that is, cause must precede effects. In order to understand and apply causal relationships, learners must be able to describe the temporal sequence of any causal relationship. For each cause that results in an effect, even if those causes are conjunctive, learners must be able to accurately describe the order of that relationship. In many situations, cause-effect relationships do not occur alone. They are usually part of more complex causal chains. An effect, for instance, can become a cause in another cause-effect relationship. In the end, learners must be able to distinguish a concept as cause or effect, depending on its position in a causal relationship.

Temporal succession alone is insufficient to establish causality because it does not necessarily imply a causal relationship. Many phenomena are temporally contiguous (they covary) but do not necessarily imply causality. For example, Monday always precedes Tuesday, but no causality exists.

Direction

The direction of a causal relationship describes the direction of the effect. Does the cause have a positive or negative effect? The directionality of cause-effect relationships should be described as “an increase in cause C results in an increase (decrease) of effect E” or “a decrease in cause C results in an increase (decrease) in effect E.” It is essential that learners be able to explain whether a causal relationship is positive or negative.

Valency (Strength)

In addition to the direction of causality, empirical descriptions of causality also describe the strength of the relationship between cause and effect. How large is the effect of the cause on the effect? An increase/decrease in the cause C will have a slight/small/significant/or great increase/decrease on effect E. Valency describes the strength or amount of effect of the causal relationship. The strength of that relationship may be expressed in terms of changes in variance

expressed in ANOVAs or structural equation modeling, the most common quantitative representation of valency.

Probability of Causality

Covariation usually represents the probability of the cause producing the effect, a quantitative representation of causal reasoning [9]. Therefore, the covariation index is most often expressed as the difference between the conditional probability of the target effect E, given the presence of the conditional factor C and the probability, given the absence of the factor ($p(E|C) - p(E|\sim C)$ [10, 18] which is represented as a directed graph (Ahn & Kalish, 2000). Also referred to as the regularity or consistency view, covariation is most often expressed as a probabilistic or contingency model [18] that considers the probability of an effect minus the probability of an effect occurring when cause is absent.

Duration

How long does the effect persist? Is it short-term, long-term, or constant? Different temporal units of analysis are necessary to describe the duration (nano-seconds to years). The duration of every causal relationship should be described by learners who are trying to solve problems or explain phenomena.

Immediacy/Delay

How readily does cause produce the effect? Another covariational indicator of causality includes the assumptions about temporal delays between causes and effects. Effects may be immediate or delayed. Different temporal assumptions about causal delays may lead to dramatically different causal judgments. Hagmayer and Waldmann [19] showed that temporal assumptions guide the choice of appropriate statistical indicators of causality, by selecting the potential causes among a set of competing candidates, and by influencing the level of aggregation of events.

Mechanisms

Many contemporary causal theorists argue that empirical inductions, while necessary, are insufficient for understanding causal relationships. In a series of studies, Ahn, Kalish, Medin, and Gelman [12] found that people do not spontaneously seek out covariational information between factors and effects, nor do they use such information when it's provided. "Patterns of association and covariation are interpreted in light of beliefs about mechanisms and causal powers that are fundamental elements of conceptions of causal relations" [14]. Mechanisms are conceptual descriptions of causal relationship. They specify the way that something works, answering "why" questions in order to specify "how" the event occurred. How does oxygen feed a fire? Causal-mechanism explanations attempt to fit the empirical findings into a causal structure in order to explain an event (Salmon, 1984). In order to understand and use causal relationships to make predictions, inferences, or explanations, learners must be able to describe different mechanistic attributes of causal relationships.

## Causal Process

Salmon [20, 21] describes the "causal nexus", a vast network of interacting causal processes. In order to understand and apply causal relationships, learners must also be able to describe all of the cause-effect relationships that comprise more general cause-effect relationships. Causation is commonly conceived on a general level. For example, most of us attribute the contraction of a common cold to someone sneezing near us. While the sneeze may be the key causal agent, the process of viral transmission is much more complex than that. So students of medicine, microbiology, or other related fields must be able to explain the numerous casual relationships necessary to transmit germs and cause a cold. Germs are dispersed through the air by the sneeze, some of which attach to host cells. The virus injects its genetic material into the host cell. That genetic code is copied into the host cell, breaking out of it and invading other cells, all of which sets off complex immunological reactions, including the distribution or mast cells to the site of the infection, the release of histamines causing inflammation of the tissue causing more immune cells to be delivered to fight off the infection. If learners cannot adequately articulate these complex causal processes, their conceptual understanding is overly simplified.

## Conjunction/Disjunction

Most causal relationships result from a conjunction of different types of causes. Conjunctive plurality occurs when two or more causes, $C_1 \ldots C_x$ must be jointly present in order to produce the effect E and no subset of causes will produce the same effect E. For example, many people believe that terrorism results from overzealous adherence to religious dogma. However, effects are almost invariably produced by multiple factors that are individually necessary and jointly sufficient to produce the effect [22]. Even Hume[1] recognized the role of conjunctive causes: "…an object, which exists for any time in its full perfection without any effect, is not the sole cause of the effect, but requires to be assisted by some other principle, which may forward its influence and operation" (p. 117). Terrorism is caused by the conjunction of religious beliefs, poverty, repression, aggressive societal tendencies, and a host of other potential causes.

Disjunctions identify a combination of causes, any one of which may produce the effect, but do not pinpoint the actual cause that produced the effect in this case [23]. Identifying the cause of death for someone who is in very poor health may be impossible or irrelevant, given the plurality of factors that could have been the immediate cause. A disjunction of causes occurs when the effect may be produced by each of several factors alone, and joint occurrence of two or more do not alter the effect.

## Necessity/Sufficiency of Causes

In order to understand the role of different conjunctive causes, it is important that learners also be able to describe all causes as necessary or sufficient. In the previous section, we said that causes may have an influencing or enabling effect. Influencing effects in mechanistic explanations of causality must also include indications about the necessity and sufficiency of the causes. Cheng and Nisbett [24] proposed that causal relationships be represented in terms of whether the causal factor is a necessary or a sufficient condition for an effect to occur. Necessity/sufficiency is a difficult but essential attribute of causality. Necessity is a more

complex concept than sufficiency. For sufficiency, people only verify whether the cause is always followed by the effect, whereas for necessity, there are two possibilities that can be verified: does the cause always precede the effect, and can the effect occur without the cause. More importantly, both concepts have a different structure: necessity is considered as an all-or-none property whereas sufficiency is a more liberal characteristic [25].

## Supporting Causal Reasoning

Having explicated the processes of causal reasoning, learners must be able to completely describe those relationships covariationally in terms of direction, probability, valency, duration, and responsiveness and mechanistically in terms of causal explication, conjunctions/disjunctions, and necessity/sufficiency. In this next section, I describe instructional methods for supporting the learning of those causal attributes. There are three classes of methods that may be used to enhance causal learning: direct instruction that conveys causal relationships, exploring causal relationships in simulations, and learner modeling of causal relationships. No direct comparisons of these methods have been made.

### Conveying Causal Relationships

A potentially effective method for conveying information about causal relationships is through the use of influence diagrams. Influence diagrams are visual displays for depicting causal relationships among the variables in complex phenomena and simulating the underlying mechanism that governs the relations [26]. Influence diagrams are especially useful for representing causal reasoning processes because they offer a set of comprehensive directional (causal) relation indicators that enable learners to represent a problem space causally and conceptually [27]. Influence diagrams visualize the causal structure of the phenomena [28]. Hung and Jonassen [29] found that students who studied mechanistic models of causality in the form of influence diagrams (see Figure 1) while learning to solve rotational dynamics problems performed better on a test of conceptual physics than students who experimented with simulations (described next).

Influence diagrams diagrammatically represent temporal succession and direction but do not normally convey covariational attributes of valency, probability, duration, or immediacy. In order to explicate those attributes, verbal explanations or visual codes added to the diagram would be necessary. It is probable that the visual codes would add cognitive load to the interpretation of the diagram. Influence diagrams are especially effective for representing mechanistic attributes, including processes and conjunctions/disjunctions. Necessity and sufficiency would require verbal elaborations and/or visual codes added to the diagram.

### Exploring Causality

Students may also explore causal relationships through the use of simulations in microworlds. Simulations are environments where values for components of a system are manipulated by learners in order to test the effects of one or more variables on another. The manipulations that are available are determined by some underlying black-box model of the system that the learners must infer through experimentation. For example, Figure 2 illustrates a simple simulation of a

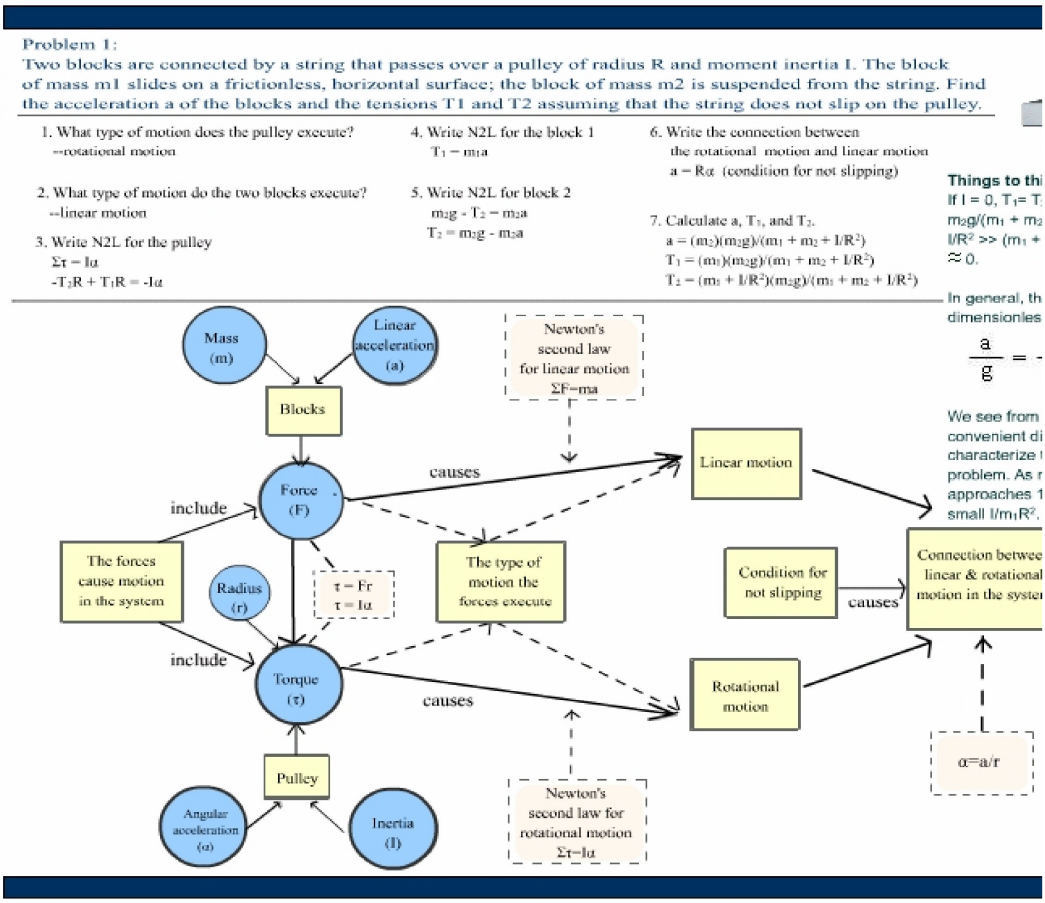


Figure 1. Influence diagram illustrating causal relationships in rotational dynamics.

circuit in which students can measure and change values in a simple circuit and observe the effects. When learners interact with the simulation, change values of (input) variables and observe the results on the values of other (output) variables, they are testing the covariational effects of factors. That is, they are exploring the extent of effects of causal agents on other factors. Because the learner seldom has access to the underlying model, learners must infer parts of the model through manipulating the environment. These are known as black box systems. Because of the limitations on learner interaction with the model, simulations can support learning only covariational attributes of direction, valency, and probability. It is difficult to convey duration and responsiveness in the simulation model, and mechanistic attributes are rarely conveyed in any coherent way in simulations.

Prompting with Questions

Questioning is one of the most fundamental cognitive components that guide human reasoning [30]. Answering deep-reasoning questions articulates causal processes; goals, plans, and actions; and logical justification [30]. The question-answer rhetorical structure is the most common dialogue pattern in naturalistic conversation [31] Question-driven explanatory reasoning predicts that learning improves to the extent that learners generate and answer questions requiring

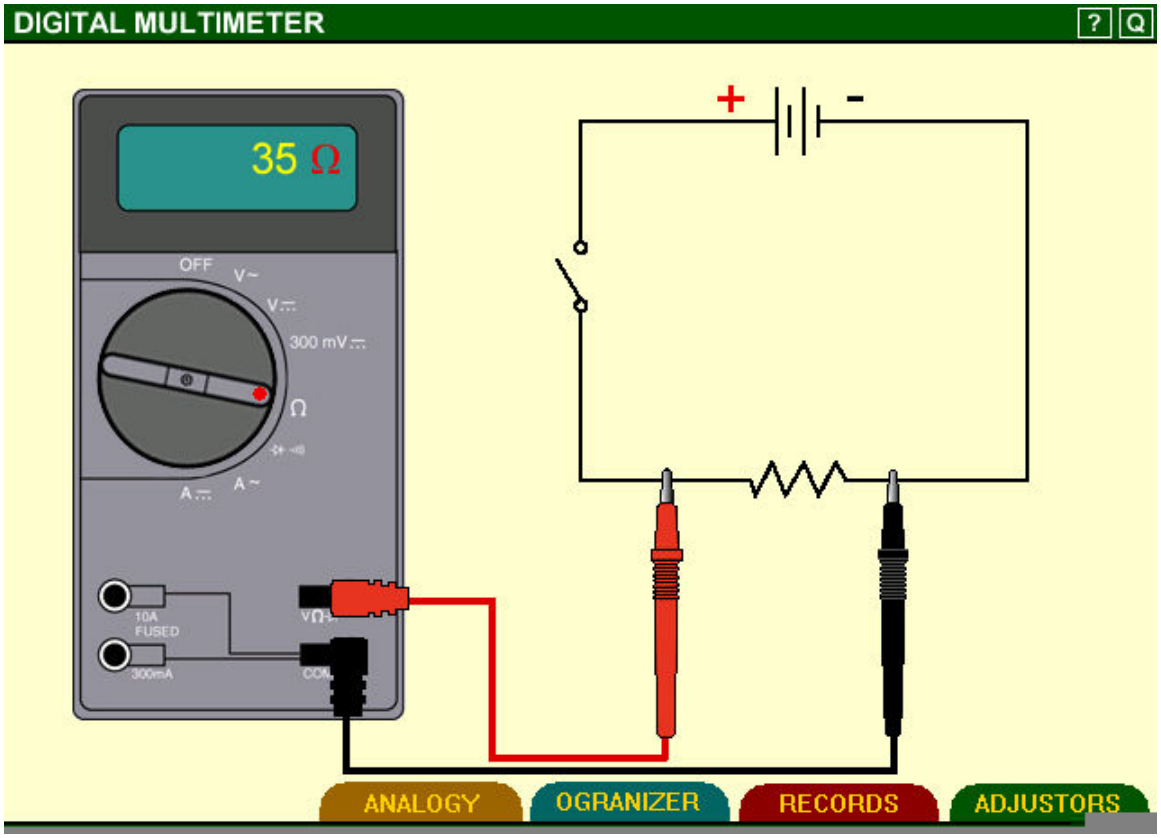


Figure 2. Simulation of simple circuit.

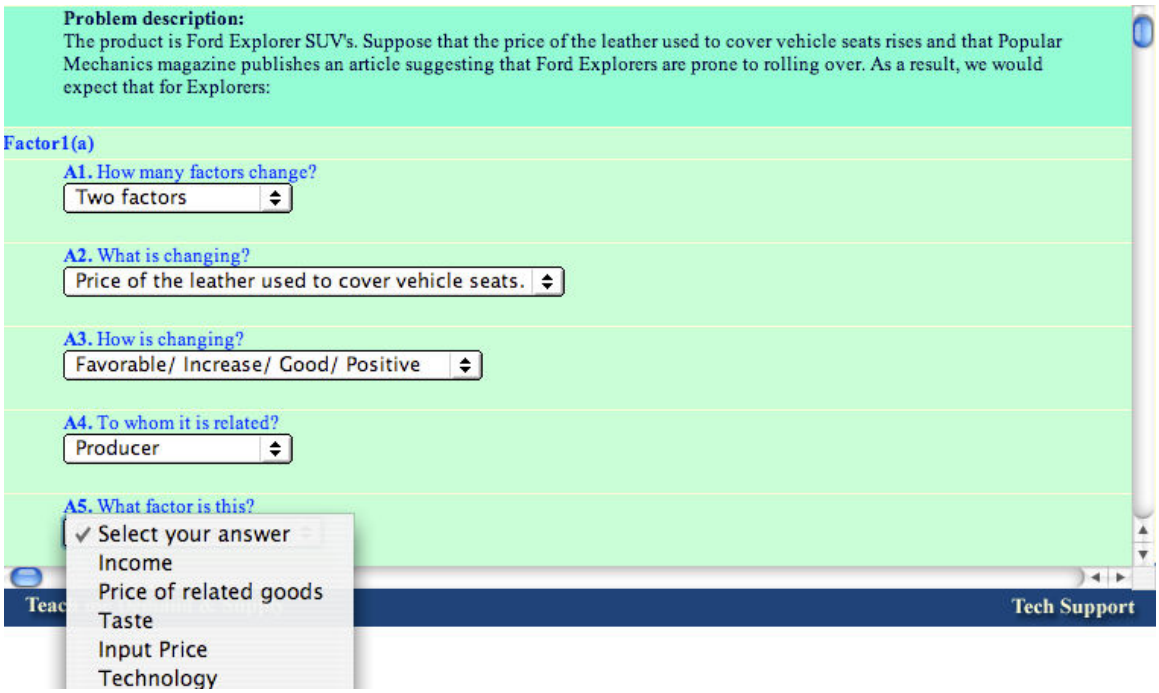


Figure 3. Questioning about causal relationships.

explanatory reasoning [31]. We recommend questioning learners about causal relationships using a point-and-query system for selecting questions relevant to a problem, similar to the system described by Graesser, Langston, and Lang [32] Learners select answers to causally oriented questions from a menu of questions (similar to the environment in Figure 3, enabling data collection relating question types to performance as well as modeling question-asking behaviors.

Questioning works by focusing the learner's attention to attributes of the relationship. Questions may be used to focus attention on any covariational attributes, including direction, valency, probability, duration, responsiveness as well as mechanistic attributes of process, conjunctions/disjunctions, and necessity/sufficiency. Being able to effectively answer those questions require prerequisite understanding of how each of those attributes relate to any causal relationship, making this a more difficult way to support learning.

Modeling Causality

Rather than using direct instruction to convey the meaning of causal relationships or questions to coach understanding, a number of tools and environments may be used by students to construct models of content or problems. These models convey the student's understanding of causal relationships.

Expert Systems

An expert system is a computer program that attempts to simulate the way human experts solve problems—an artificial decision maker. Expert systems include a knowledge base of facts about objects and IF-THEN rules about the relationships among those objects that can qualitatively represent covariational and mechanistic information about causal relationships. The rules are searched by the inference engine to provide advice that may be rendered by a human expert in order to reach a decision. Rules state that IF a set of conditions exists, THEN some conclusion is reached. For example, IF temperature increases, THEN pressure increases. Conditions can be combined using conjunctions (condition 1 AND condition 2 must exist), disjunctions (condition 1 OR condition 2 must exist), and negations (condition 1 but NOT condition 2 must exist) in order to reach a conclusion about a set or causal relationships. That conclusion may be an action or it may state another condition, which is then combined with other conditions to reach another decision.

Expert systems may be used by students as a powerful learning strategy where the students construct a rule base that represents some level of expertise. For example, Figure 4 illustrates a single rule from an expert system rule base in a meteorology course. The expert system predicts Lake Effect snow and identifies the factors that must be considered in making such a prediction. Building expert systems is an example of building a causal model. They are most easily constructed using an expert system shell that provides rule editors and an inference engine for testing the rule base. These shells enable learners to construct and test a predictive or inferential model of a set of causal relationships. Building expert systems better supports mechanistic representations of causal relationships, especially complex, conjunctive, and disjunctive relationships. Necessity and sufficiency are also effectively represented by rules. Articulating

covariational attributes, including such as succession and direction is easy. However, verbally conveying valency, duration, and immediacy lacks the exactitude of quantitative methods and so is not as effectively supported by constructing expert systems.

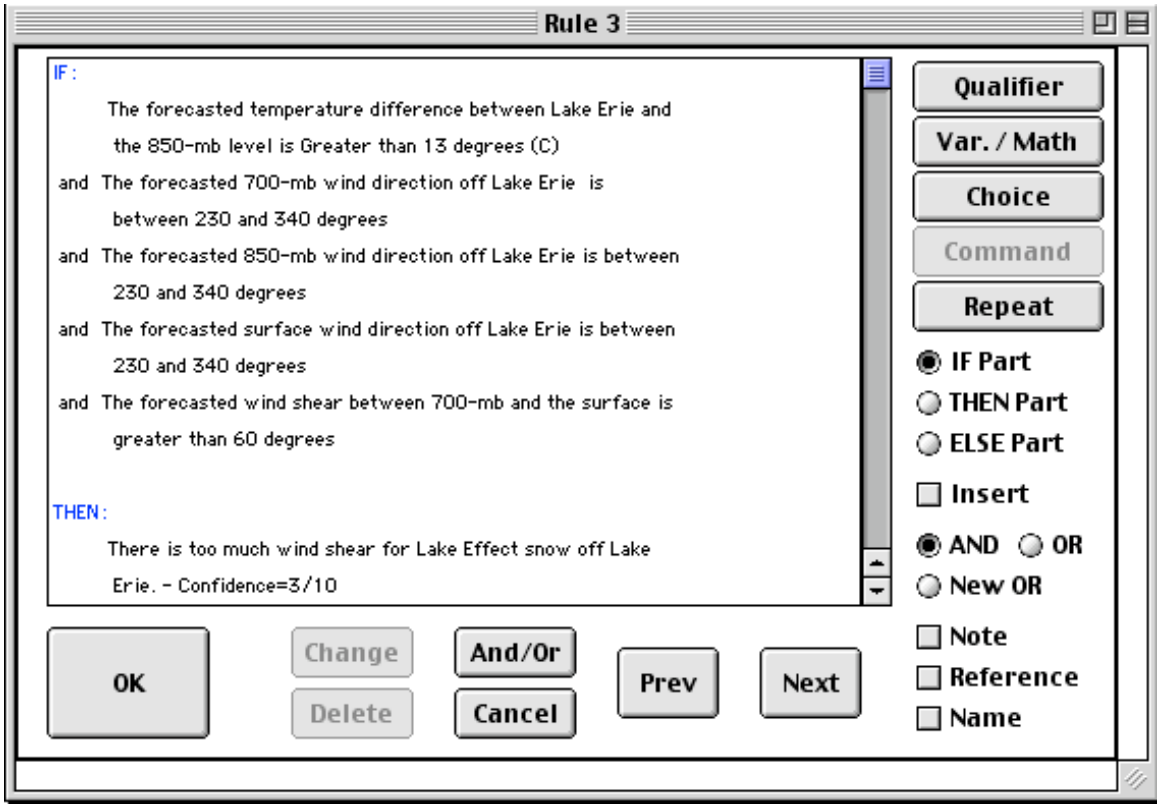

Figure 4. Rule from expert system rule base in meteorology.

Causal Modeling Tools

A few student-centered modeling tools are available or in development for mapping causal relationships. These tools support the construction of concept maps by learners that visually depict causal relationships. For example, Causal Mapper was developed by Marcia Linn as part of the Web-based Science Inquiry Environment. A similar tool is used by students to teach a computer agent, Betty, in Betty's Brain [33]. Students create a concept map in which the links convey a constrained set of causal relationships (increase or decrease) or dependency relationships, where one entity in the concept map needs another but does not change it.

These tools support the learning of only a few of the attributes of causal relationships, including temporal succession, direction, and conjunction. The existing tools do not afford the representation of other attributes. They are useful tools for introducing concepts of causality but cannot support detailed representations. We have submitted funding proposal to construct an elaborate causal modeling tool called the Causalometer.

Systems Modeling Tools

Systems modeling tools (e.g., Stella, Ven Sim, PowerSim) is the only class of tools that integrate covariational and mechanistic attributes. These tools enable learners to model both covariational and mechanistic attributes of causal relationships. These tools also enable learners to convey cyclical relationships as loops, where a cause changes an effect, which in turn changes (regulates) the causal state (see Figure 5).

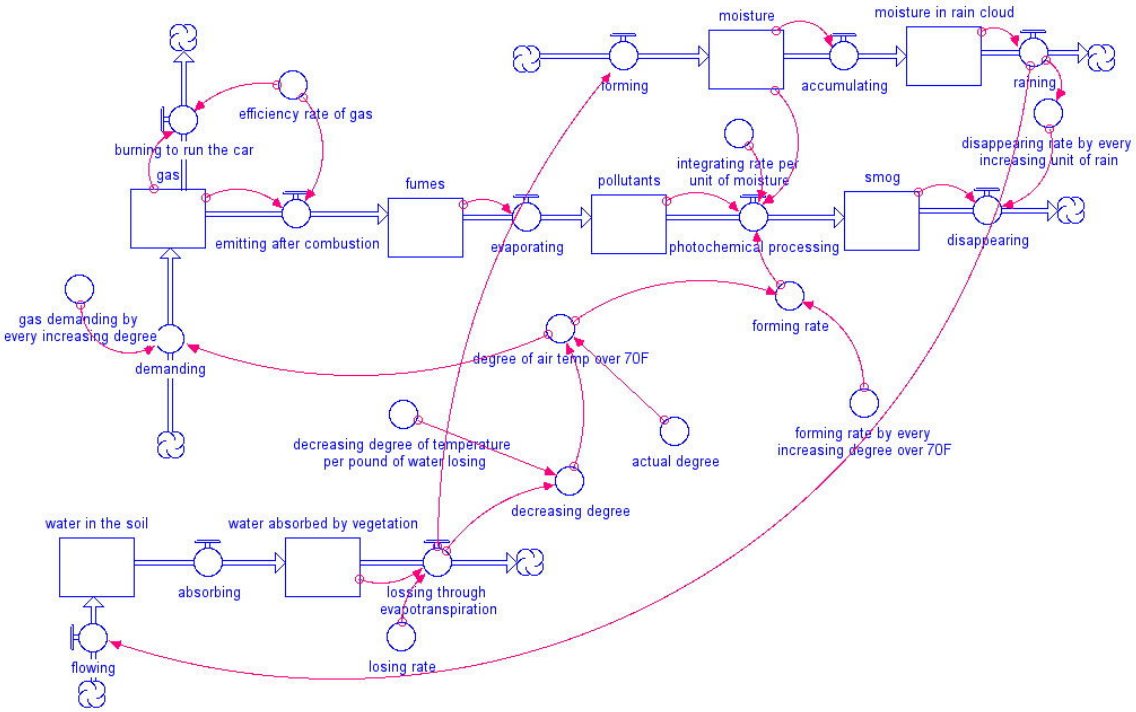


Figure 5. A systems dynamics model illustrating causal relationships.

When using aggregate systems modeling tools such as these, learners use a simple set of building block icons to construct a map of a process: stocks, flows, converters, and connectors (see Figure 5). Stocks illustrate the level of causal agents in the simulation. In Figure 5, *moisture, fumes, pollutants*, and *gas* are mechanistic descriptions of causes and/or effects. Flows convey the effects of these agents on the others. *Emitting after combustion, evaporating, absorbing,* and *demanding* are flows that represent the mechanisms of effects. The causal agent, *emitting after combustion,* has a positive influence on *fumes*, which causes a positive influence on *pollutants*. Converters are coefficients or ratios that influence flows. *Efficiency rate of gas* is a converter that controls both *emitting after combustion* and *burning to run car*. Converters are used to add complexity to the models to better represent the complexity in the real world. Finally, connectors are the lines that show the directional effect of factors on each other by the use of arrows. Students produce simple equations in the stocks and flows to convey the amount of covariation among the elements. Once a model has been built, Stella enables learners to run the model that they have created and observe the output in graphs, tables, or animations in order to test the

assumptions and relationships. The iterative testing and revising of the model to insure that it predicts theoretically viable outcomes is to date one of the complete methods for modeling causality that is available. Hogan and Thomas [34] found that the best systems modelers focused on the whole picture of model, modeling outputs and interactions rather than inputs and individual relationships while building and testing models. No empirical research has examined the effects of systems modeling on causal reasoning. Most research has employed case studies. For example, Steed [35] showed how Stella modeling portrayed diverse dimensions of information and helped high school students shift their thinking by allowing them to compare different representations (different models).

Systems modeling tools are the most powerful and effective means for modeling complex causal relationships. Temporal succession and direction are conveyed as connectors. Valency and probability are represented as simple formulae in the flows, and durations and immediacy are conveyed by different kinds of stocks that regulate the inflow or outflow. Using loops, learners can easily convey reciprocity in their models. The model in Figure 5 also shows the complexity of conjunctive causes that produce smog and pollution. Necessity and sufficiency may also be conveyed using logic formulae (if-then-else) to describe the flows. Although systems models are the most powerful way to represent complex causal relationships, the learning curve required for these tools is steep.

## Summary

In order to explain phenomena and solve problems, it is essential that we be able to induce and model the causal relationships that exist among the ideas in those domains or problems. Understanding causal relationships requires that learners comprehend the covariational (empirical) attributes of any relationship, including direction, probability, valency, duration, and immediacy. Complete understanding of causal relationships requires that learners also be able to analytically describe the mechanisms of each relation, including an explication of causal chains, causal conjunction, and necessity/sufficiency of the relationships.

Causal reasoning may be supported by direct instruction using influence diagrams, coaching of understanding using questions, exploring simulations, or student construction of expert systems, models using causal modeling tools, or systems dynamic models. Very little empirical research exists on causal reasoning, especially on instructional methods for supporting it. Research is needed to validate and contrast the effectiveness of each of these methods or other methods for engaging and supporting causal reasoning among learners. We are continuing our research on using causal reasoning tools in physics and electrical engineering.

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