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Fostering the Development of Domain-General, Nonlinear Mental Models: A Foundation for Systemic Thinking

Jeffrey S. Sinn
Old Dominion University

FOSTERING THE DEVELOPMENT OF DOMAIN-GENERAL, NONLINEAR MENTAL MODELS: A FOUNDATION FOR SYSTEMIC THINKING

by

Jeffrey S. Sinn
B.A. May 1991, Gustavus Adolphus College
M.S. December 1993, Old Dominion University

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Approved by:

Dr. Mark Scerbo (Director)

Dr. Barry Clemson (Member)

Dr. Glynn Coates (Member)

Dr. Danielle McNamara (Member)

ABSTRACT

FOSTERING THE DEVELOPMENT OF DOMAIN-GENERAL, NONLINEAR MENTAL MODELS: A FOUNDATION FOR SYSTEMIC THINKING.

Jeffrey S. Sinn
Old Dominion University, 1997
Director: Dr. Mark Scerbo

Two experiments examined whether people can develop a domain-general, nonlinear mental model when provided with an appropriate conceptual model. Both experiments presented causal loop models (i.e., variables connected in a circle by arrows representing causal relationships) as a conceptual model for positive feedback. Study 1 found that participants trained in causal loop modeling could accurately represent scenarios of low but not high complexity. Study 2 expanded on the design of Study 1 by varying the type of training and type of aid presented during testing. Participants received training with modeling instruction, training with cue-utilization instruction (i.e., participants were trained to represent scenarios as a list of bivariate relationships), general training, or no training. For a subset of testing scenarios, participants received either a modeling aid (i.e., a causal loop model) or a cueing aid (i.e., a list of bivariate relationships). Participants trained in modeling predicted the behavior of variables more accurately and quickly than those trained in cue utilization. In addition, participants provided with modeling aids during testing predicted system behavior more accurately and more quickly than those provided with cueing aids. In addition, spatial ability was found to correlate positively with accuracy scores. Overall, the results offer strong evidence that people can develop and successfully utilize a domain-general, nonlinear mental model.

To the memory of my father, Benjamin Sinn.

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INTRODUCTION

The Study of Mental Models within Psychology

Concept and Terminology

Mental models have become a popular construct for explaining how humans interact with complex systems. For instance, in examining the interaction between a person and a software program we can distinguish between the target system, the mental model, and a conceptual model (Norman, 1983). The target system is the actual phenomenon (i.e., how the software actually works), the mental model is the user's understanding of how the software works, and the conceptual model is an expert's understanding of the actual phenomenon presented to the user to foster development of an appropriate mental model. The mental model construct is formally grounded in the cybernetics principle that effective control of a system requires a model of that system (Conant & Ashby, 1970). In complex systems, the mental model is more likely to be a homomorph (i.e., a partial, many-to-one mapping) rather than an isomorph (i.e., a complete, one-to-one mapping) to the target system (Moray, 1987) and operator error may result when the mental model is not accurate for particular states of the system. This relationship between mental model accuracy and performance is a subject of intense interest in diverse arenas, from process control (Wickens, 1992) to corporate management (Senge, 1990).

Formal Definition

Despite widespread use, formal definitions of mental models vary. Rouse and Morris (1986) attempt to synthesize various points of view by defining mental models as

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mechanisms humans use to describe, explain, and predict the functioning of a system and the different states of a system. The concept of computation or runnability is often appended to this definition in order to distinguish mental models from schemas (Wilson & Rutherford, 1989). For example, researchers argue that mental models of simple physical systems consist of a set of autonomous objects in a specific typology that can be run through qualitative inferences (Williams, Hollan, & Stevens, 1983). Mental models of such dynamic systems must thus represent both the configuration of the system (i.e., the components and their arrangement) and the kinematics of the system (i.e., how the components interact over time; Hegarty, 1992; Hegarty & Just, 1993).

For the present paper, a mental model shall mean a set of autonomous objects, arrayed in a specific topology and runnable through qualitative inferences, that humans use to describe, explain, and predict the causal behavior of a target system. In other words, a mental model contains both knowledge of how a target system works and procedural knowledge for using this how-it-works knowledge to generate inferences (Kieras, 1988). Note that the mental model may consist of the ability to effectively use a particular type of diagram (e.g., Hegarty & Sims, 1994; Kieras, 1992). Note also that the term "user" shall refer to any person who attempts to understand or interact with any type of system. Finally, in order to explore the value of mental models for understanding kinematics, the present paper will focus on dynamic target systems (e.g., how automobile brakes work; Mayer, 1989a) rather than static target systems (e.g., the nature of density; Mayer, Dyck, & Cook, 1984).

Research on Mental Models of Dynamic Systems

Value of Mental Models

Because mental models are difficult to study directly many researchers instead present conceptual models of a system to users and then infer the existence of mental models from quantitative and qualitative improvements in problem-solving performance. Based on such inferences, mental models have been shown to improve problem solving for many different types of dynamic target systems, including pulleys (Hegarty & Just, 1993), pumps, cameras, automobile brakes, radar, the nitrogen cycle (Mayer, 1989a), calculators (Bayman & Mayer, 1984; Norman, 1983), simple control panels (Kieras & Bovair, 1984), diagram displays of engineered systems (Kieras, 1992), electricity (Gentner & Gentner, 1983), heat exchangers (Williams et al., 1983), and physics (diSessa, 1983). The conceptual model helps the user develop an appropriate mental model for understanding the system. The model helps the user think more systematically about specific causal relationships within the system and make inferences about how state changes will affect the system. For example, subjects given a conceptual model for the engineered system underlying a simple control panel device are better able to control the system (Kieras & Bovair, 1984). By forming a mental model of the system based on the conceptual model subjects can infer what actions are required given specific state changes. These inferences help subjects develop shortcut procedures and execute procedures more quickly. Similarly, an animated diagram of an engineered system can suggest an appropriate mental model to the user, which can then be used to decrease operator error (Kieras, 1992).

Appropriate mental models also facilitate problem solving with other dynamic systems such as pumps, cameras, and automobile brakes (Mayer, 1989a). Summarizing the literature, Mayer concludes that exposing subjects to annotated diagrams that depict both the components and kinematics of a system helps subjects develop better mental models of these systems. Subjects presented with such diagrams are able to generate a greater number of inferences, and more accurate inferences, regarding the causal relationships among components (e.g., why automobile brakes generate heat or what could be done to make brakes more reliable). Subjects familiar with the target system, however, may already possess a mental model of the system and therefore not benefit from mental model instruction (Mayer & Gallini, 1990).

How Conceptual Models Improve Performance

Rouse and Morris (1986) recommend distinguishing between a user's ability to abstract cues from the environment and the mental model into which those cues are integrated. Conceptual models can improve problem solving performance by helping users identify and use important cues and by suggesting a useful representation of the system upon which to base a mental model.

Cue utilization guidance. Both textual and spatial representations can guide cue utilization. Text that labels parts of a spatial diagram can improve the user's understanding of the system by directing the user to encode information that might otherwise be missed (Hegarty & Just, 1993). This difference in cue utilization based on the presence of labels explains why users develop better mental models from diagrams that integrate text than from diagrams alone (Mayer, 1989b; Mayer & Gallini, 1990). Such cue guidance is especially critical when users are trying to infer the kinematics of a system from a static diagram (Hegarty & Just, 1993). In addition, a spatial representation such as a flowchart can improve cue utilization. Subjects provided with a text and a procedural flowchart better understand whether steps are sequential or concurrent compared to those provided with text alone (Glenberg & Langston, 1992). Finally, subjects with more spatial ability may outperform other subjects by focusing on cues which allow them to encode more relevant information from the diagram (Hegarty & Just, 1993; Hegarty & Sims, 1994).

Representation guidance – mental models. Conceptual models also help the user identify an appropriate representation of the system upon which a mental model can be based. Schematics of the system assist users by representing the system's configuration, thereby freeing working memory resources that would otherwise be used to mentally represent the figure (Hegarty, 1992; Hegarty & Just, 1993; Kieras, 1992). These remaining resources can then be used for running a mental model to generate inferences, such as visualizing the kinematics of the system (Hegarty, 1992; Hegarty & Just, 1993; Hegarty & Sims, 1994). An animated topological display can relieve even more resources by directly representing not only the configuration of the components but also the kinematics of the system (Kieras, 1992). Some speculate that a mental representation of the conceptual model facilitates inferences in a similar way (Larkin & Simon, 1987). Glenberg and Langston (1992), for example, argue that mental models are a set of representational elements contained within the spatial medium of the visuospatial scratch pad. These representational elements of the mental model act as pointers to both prepositional and perceptual information in long-term memory. The mental model thus integrates both textual and spatial information into a unified image that efficiently summarizes knowledge. These mental images free cognitive resources and thereby facilitate inference generation (Glenberg & Langston, 1992).

In addition to freeing cognitive resources. mental models help users notice implicit relationships. Similar to when a user recognizes an emergent feature created by the interaction of elements in a visual display (Sanderson, Flach, Buttigieg, & Casey, 1989: Triesman & Paterson, 1984), subjects who focus attention on various elements in a model can notice how a particular component relates to other components in the visuospatial scratchpad. Such noticing enables the user to infer implicit relationships (Glenberg & Langston, 1992). For example, a user can generate inferences about the kinematics of a system by using spatial visualization to run the mental model. Subjects verifying motion using a pulley-system schematic gazed at the schematic longer, required more time overall. and made more errors if the component in question was positioned later in the causal chain (Hegarty, 1992). In addition, subjects with less spatial ability made more errors than subjects with greater spatial ability (Hegarty & Sims, 1994). These findings suggest that subjects actively used the model to generate inferences.

Interaction of cue utilization guidance and system representation guidance. A more precise understanding of mental models can be gained by distinguishing between the impact of a conceptual model on cue utilization and mental model development (Rouse & Morris, 1986). Without this distinction it is difficult to determine if an increase in performance is due to the additional information conveyed by the conceptual model or the guidance on how to best represent the target system (i.e., the mental model). Completely controlling for effect of cue guidance is not possible, however, because better mental models help users notice cues they had previously overlooked. As explained above, these higher-order cues help subjects notice implicit relationships. In the language of analogy transfer, these higher-order cues serve as higher-order predicates that increase the systematicity of the mental model and thereby sensitize users to particular cues (Gentner, 1983). In short, the bottom-up influence of cue utilization can interact with the top-down influence of mental model development.

Limitations of Mental Model Research Within Psychology

Focus on linear causality. Although a substantial amount of research has focused on the value of particular types of mental models, the research has been limited by a focus on target systems with only linear causal relationships and a focus on domain-specific mental models. Mental model research has tended to focus on target systems with only linear relationships such as pulleys (Hegarty & Just, 1993), pumps, automobile brakes (Mayer & Gallini, 1990), and simple control panels (Kieras & Bovair, 1984) rather than on target systems containing feedback. With feedback, a set of cause and effect relationships circles back on itself to form a closed loop. Feedback with an odd number of negative relationships is termed negative feedback, and reduces deviations over time (e.g., an increase in demand increases price, which decreases demand). Feedback with an even number of negative relationships is termed positive feedback, and amplifies deviations over time (e.g., Hatfield killing increases McCoy killing, which increases Hatfield killing). Mental model research may use target systems that contain feedback relationships (e.g., Mayer et al., 1984), but the dynamic pattern of deviation reduction or deviation amplification has not been explicitly addressed.

Without extensive training, subjects may have difficulty creating and using mental models of nonlinear target systems for at least two reasons. First, people do not naturally think in terms of feedback (Axelrod, 1976). When experts explain their understanding of a system they rarely identify feedback loops spontaneously, even if a set of causal relationships they identify logically form a feedback loop. People appear to conceptualize causality linearly and do not think in terms of feedback. Second, people may not have sufficient information processing capacity to handle the complexity inherent in feedback relationships. When attempting to run a mental model, the information processing load on working memory forces subjects to mentally animate models in a piecemeal fashion, thus restricting their attention at any one time to individual relationships (Hegarty, 1992). Because subjects can only focus on specific causal relationships rather than the entire model, they may have difficulty recognizing emergent, higher-level patterns such as feedback. Other findings highlight limitations in dealing with complexity. Subjects using a schematic of a simple machine have more difficulty verifying causal relationships when a component is several relationships removed from the triggering event (Hegarty & Sims, 1994) and when they must make inferences against the causal flow (Hegarty, 1992). With expertise, chunking (Chase & Simon, 1973) may allow subjects to create and utilize mental models containing feedback. However, such expertise may require extensive training. Research is needed to determine if subjects with limited training can construct and fully utilize mental models that contain feedback relationships.

Focus on domain-specific mental models. In addition to neglecting target systems with feedback, mental model research has not explored the possibility of domain-general as opposed to domain-specific mental models. As noted above, most mental model research with dynamic systems has examined domain-specific mental models (e.g., a mental model of how a particular pulley system works; Hegarty & Just, 1993). In contrast, a domain-general model could be applied to a wide range of specific systems (e.g., the basic understanding of causality as a string of causes and effects might be seen as a domain-general mental model applicable across a wide range of systems including pulleys, pumps, brakes, etc.). Wickens

(1984) argues that effective mental models tend to be domain specific, citing evidence that understanding general scientific principles of a process does not help an operator control the process (Kragt & Landeweerd, 1974; Morris & Rouse, 1985). Despite the research focus and the argument against domain-general mental models, others argue that it is difficult to account for human problem solving ability in unfamiliar situations without positing general models (Glaser, 1984). In addition, the basic concept of causality used in problem solving can be seen as a mental model (i.e., we abstract out autonomous objects, label them cause and effect, and run models to determine consequences, responsibility, and strategies). Obviously, if general models can be learned and applied across specific domains such models may have more utility than mental models that can only be used in specific domains.

One way to approach the question of domain-general mental models is to consider transfer of training. A common transfer of training research paradigm requires a subject to recognize the isomorphic deep structure that underlies two superficially distinct analogs. If the subject's training with one analog facilitates problem solving with the other analog then one can conclude that the subject has achieved a domain-general understanding of the common deep structure. A domain-general mental model is one way this understanding can be represented. Thus, if transfer of training is possible then domain-general mental models may be possible. However, at least some learning researchers are skeptical about how much transfer of training can take place across domains. The situated learning perspective argues that much of what is learned in one context cannot be applied to problem solving in another context (Lave, 1988; Greeno, Smith, & Moore, 1992). Arguments against the use of abstract rules in problem solving draw on transfer of training findings in which subjects have difficulty spontaneously abstracting a general problem solving strategy from a source analog and applying it to a target analog (Gick & Holyoak, 1980; 1983). Similarly, the situated learning perspective draws on the heuristic model of decision making, in which subjects fail to consider abstract principles such as the law of large numbers when problem solving (Nisbett & Ross, 1980; Tversky & Kahneman, 1974). In short, the situated learning perspective suggests that problem solving cannot be improved by the teaching of general, non-domain-specific mental models.

The situated learning paradigm, however, has come under attack for being too extreme (Anderson, Reder, & Simon, 1996; Nisbett, Fong, Lehman, Cheng, 1987; Smith, Langston, Nisbett, 1992). Recent reviews cite numerous cases in which transfer of training occurs (Perkins & Salomon, 1989; Singley & Anderson, 1989). For example, subjects trained in the law of large numbers were able to transfer their intuitive understanding of the principle to problems in a wide variety of situations and domains (e.g., gambling and social interactions; Fong, Krantz, & Nisbett, 1986). Transfer depends upon how the source analog is learned, whether it can be retrieved when faced with a target analog, and whether it can be mapped onto the target analog. I will briefly review a number of conditions that increase the probability of transfer.

Transfer will be more likely if the instruction emphasizes the generality of the source analog (Catrambone & Holyoak, 1989; Gick & Holyoak, 1980). For example, the description of the source analog should not be content dependent. Subjects who learned arithmetic progression as algebra (i.e., a content independent analog) could transfer their knowledge to physics (i.e., a content dependent analog) but not vice versa (Bassok & Holyoak, 1989). Transfer is also improved if subjects are provided with a specific example of the source analog (Novick & Holyoak, 1991), and even more so with the use of multiple examples (Catrambone & Holyoak. 1989; Gick & Holyoak, 1983) with diverse content (Brown, Kane, & Echols, 1986; Gick & Holyoak, 1983). Without guidance, subjects studying source analogs tend to focus on the surface structure rather than the critical features of the deep structure. Transfer is improved when subjects engage in activities that focus their attention on critical features of the source analog. For example, transfer improves when subjects compare source analogs (Cummins, 1992), explain how two analogs share an identical deep structure (Catrambone & Holyoak, 1989), or focus on problem solving with source analogs rather than memorizing (Needham & Begg, 1991).

Transfer also depends on the subject's ability to retrieve the source analogy and map onto the target problem. Transfer will be greater if the wording of the target problem stresses structural similarities with the source problem (Catrambone & Holyoak, 1989). In other words, the transparency of the similarity between target and source moderates transfer (Gentner & Toupin, 1986). Providing cues such as hints can increase transparency and thereby facilitate transfer (Catrambone & Holyoak, 1989; Gick & Holyoak, 1980). In other words, cues guide the subject in framing the domain of the problem. Knowledge can be domain specific if the subject fails to frame two problems as belonging to a common, underlying domain. Mapping is made easier if variable quantities are represented in the same way in both the source and the target. Minor semantic differences can make it difficult for a participant to map the source onto the target even when the source analogy has been retrieved (Bassok, 1990). The systematicity of analogies also facilitates mapping by providing higher order predicates that enforce structure on lower order predicates (Gentner & Toupin, 1986). For example, a jigsaw puzzle is easier to complete if the correct placement of the pieces forms a distinct visual pattern that guides the placement of individual pieces.

Although transfer of training offers guidance on the possibility of general mental models, research on general mental models per se will provide more definitive information. Researchers should attempt to teach general mental models and measure the impact of such instruction on problem solving.

The System Dynamics Approach to Mental Models

Overview

Research on mental models within the discipline of psychology can be advanced by incorporating theory and research from the field of system dynamics. Whereas psychological research has tended to examine domain-specific mental models of linear target systems, system dynamics research hsd considered domain-general mental models of complex, nonlinear systems.

Complexity of Real-World Systems

Focus on Complex Systems

The field of system dynamics examines problems that arise in complex systems that are dynamic (i.e., the values of variables change over time). This dynamic behavior is assumed to be caused by nonlinear, feedback relationships. In feedback, a sequence of cause and effect relationships circles back on itself to form a closed loop. Positive feedback amplifies the magnitude of any change to one of the variables forming the loop whereas negative feedback reduces the magnitude of any change. The complexity of such systems is often magnified by the multiple effects of single variables, interactions between feedback loops, and delays between cause and effect. Problems produced by such systems are difficult to diagnose and solve because such systems cannot be understood by simply isolating linear relationships (Richardson & Pugh, 1981). Examples of problems thought to result from the behavior of such complex systems include inner-city poverty. inadequate inventory control. over population, crime, pollution, and rising energy costs.

Difficulty of Managing Complex Systems

Unfortunately, the behavior of dynamic, complex systems is often counterintuitive (Forrester, 1971a). Users experience difficulty attempting to regulate such systems because the presence of feedback, nonlinearities, multiple loops, multiple actors, and time delays cause them to misperceive feedback cues (Diehl & Sterman, 1995; Paich & Sterman, 1993: Sterman, 1989a; 1989b). Similar to researchers in the situated learning camp (Greeno, et al., 1992; Lave, 1988), system dynamics scientists recognize the severe limitations of unaided human reasoning (Sterman, 1994). However, whereas the situated learning perspective abandons the hope of developing general expertise for coping with complexity in favor of situation specific expertise, system dynamics offers general modeling tools for coping with the complexity of many types of systems.

Modeling to Explain Complex Systems

Experts in system dynamics develop sophisticated computer-based simulations that model the behavior of complex systems and the problems they produce. Using theory from the specific domain, modelers begin by identifying critical variables and creating system flow diagrams that specify the relationships among the variables with modeling elements such as sources, stocks, flows, and sinks (Richardson & Pugh, 1981). The modelers attempt to form a closed-loop system in which all variables are nested in feedback loops. Relationships can be expressed by precise equations, often of a very high order (Forrester, 1969). Although modelers attempt to specify the exact magnitude of relationships accurately, evidence suggests that the basic structure of relationships determines the behavior of the model. Once constructed, the model is "run" using modeling software to compare the behavior of the model to the behavior of the real world system. Based on the fidelity of the simulation, the parameters are adjusted iteratively until a good fit is obtained. Given a good fit, decision makers can use the model to identify points of leverage and to simulate the impact of different actions. Sophisticated models have been constructed in a wide range of domains, as indicated by the titles of Forrester's classic works: *Industrial Dynamics* (1961), *Urban Dynamics* (1969), and *World Dynamics* (1971b).

Modeling for Learning: Developing Domain-Specific Mental Models

Learning About Specific Systems Through Modeling

System dynamics modeling can also help lay users learn about systems. Used in this manner, system dynamics modeling helps users not by providing them with a model of a system but by providing them with modeling tools so they can learn about the system for themselves. By developing a deeper understanding of the system's causal dynamics, lay modelers are better equipped to cope with the system's complexity. Although lay users may eventually create sophisticated, quantitative models, they typically begin with simpler, qualitative modeling techniques (Morecroft, 1982; 1994). Rather than directly modeling a real-world system as experts might, lay users often model the behavior of a computer simulation representing a real-world system. These virtual worlds (Schön, 1983) compress time and space so that users can more easily study the connection between actions and consequences.

Management Flight Simulators

A particular type of virtual world, the management flight simulator, has been used to help managers learn about the systems they manage (Bakken, Gould, & Kim, 1994).

Participants engage in an action research cycle of explicating, testing, and revising assumptions (Senge & Sterman, 1994). Using system dynamics modeling tools, users represent their implicit mental models so that these assumptions can be tested. Users test their models by running them over time with modeling software. The accuracy of the model is evaluated by comparing behavior predicted by the model with the actual behavior of the virtual world system. Reflecting on the outcome and their initial assumptions users refine their models. Through the modeling experience users learn about the causal dynamics of the system and develop a more accurate mental model.

Mental Models with Feedback

System dynamic modeling helps users improve their mental models by directing attention at feedback relationships. For example, managers from an insurance company discovered that their rising settlement costs were part of a feedback loop of their own creation rather than the result of exogenous forces (Senge & Sterman, 1994). Managers discovered that rising settlement costs can be caused by an underinvestment in the company's capacity for effectively adjusting claims. As the backlog of claims increases, adjusters are forced to sacrifice quality to reduce the backlog (i.e., investigate a claim less thoroughly). As quality decreases, the average cost of each settlement increases, which in turn increases pressure on management to cut costs. Unfortunately, although cost cutting may result in apparent short-term gains in profitability, this response only exacerbates the root cause of the problem by reducing adjuster capacity further. By recognizing the existence of feedback, managers can develop domain-specific mental models that are more useful.

Modeling for Learning: Developing Domain-General Mental Models

In addition to developing better domain-specific mental models users also may develop a better understanding of dynamic systems in general. Proponents of system dynamic modeling argue that managers working with management flight simulators develop the capacity to see new situations systemically and dynamically (Senge & Sterman, 1994) and to recognize the similarity of feedback structures in problems with distinct surface structures (Bakken, Gould, & Kim, 1994). The models created and studied by users may function as transitional objects that help users learn about the dynamic structure of causal systems as building blocks help a child learn about the mechanical structure of physical systems (Papert, 1981). These claims suggest that users develop domain-general mental models.

The Causal Loop Diagram: Foundation for a Domain-General Mental Model

The causal loop diagram can serve as a foundation for a domain-general mental model. Users are often introduced to the general principles of system dynamics with causal loop diagrams as conceptual models (Coyle, 1977; Richardson & Pugh, 1981; Senge, 1990). These diagrams use directional arrows to indicate causal relationships between variables, pluses and minuses to indicate whether relationships are direct or inverse, and the circle formed by the arrows of feedback loop to indicate circular causality. Figure 1 shows a causal loop model for a self-fulfilling prophecy (note: when polarity is not indicated, the relationships are assumed to be direct). For some purposes, the causal loop format is inadequate (Morecroft, 1982). For example, causal loop diagrams do not allow users to distinguish between flows of energy (e.g., the rate at which water is pouring from a faucet) and flows of information (e.g., observing the level of water in the cup). Such limitations do not, however, detract from the ability of causal loop models to teach basic concepts of

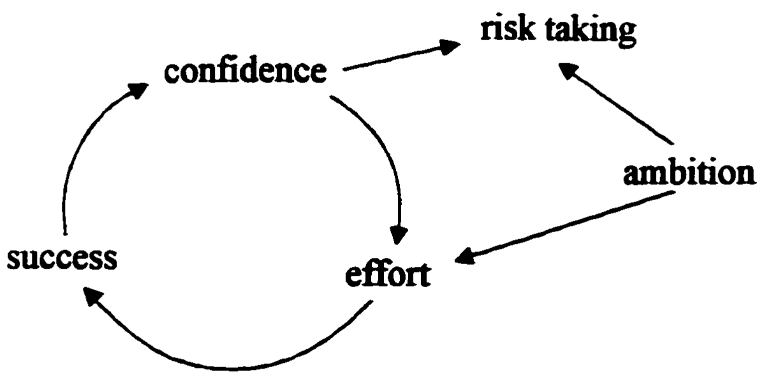

Figure 1. Causal Loop Model Depicting a Positive Feedback Loop

system dynamics. For example, causal loop models can help users learn how to incorporate feedback into their thinking about causality, something that people do not do spontaneously (Axelrod, 1976).

Comparing Conceptual Models Used in Psychology to Causal Loop Diagrams

Similarities. In several respects, the causal loop diagram is similar to conceptual models used in behavioral science research. Like representations of pulleys, pumps, and brakes (Hegarty & Just, 1993; Mayer, 1989a) the causal loop diagram presents a schematic representation of a target system. In addition, the use of a casual loop diagram as a mental model is consistent with the definition provided in this paper: a set of autonomous objects arrayed in a specific typology and runnable through qualitative inferences, that humans use to describe, explain, and predict the causal behavior of a target system. The names of variables included in the model constitute a set of autonomous objects and the arrows connecting the variables define a specific typology. A user also can make qualitative inferences to describe, explain, or predict causal behavior by imagining causality as a flow of energy within the defined paths. Furthermore, like other mental models, a causal loop model can help users notice implicit relationships. Specifically, the circle that emerges from the representation of a feedback loop suggests the notion of circular causality.

Differences. As a conceptual model, the causal loop diagram differs from conceptual models used in behavioral science research in two primary ways. First, the underlying target system represented by a causal loop model tends to be more abstract (e.g., nonspatial) than the physical systems usually used in behavioral science research (e.g., pulleys, pumps, and brakes). Second, and more importantly, the causal loop model represents nonlinear relationships.

As a domain-general mental model, the causal loop model differs from mental models studied in behavioral science research because, rather than having particular components arranged in a particular typology, a domain-general mental model must be somewhat plastic. Rather than specify such particulars, a domain-general mental model specifies broader parameters which then guide construction of situation-specific mental models. Support for this perspective can be found in the transfer of training literature concerning the last stage of transfer, adaptation (Novick & Holyoak, 1991).

Broad parameters specified by a domain-general mental model include how to represent autonomous components, how to represent the relationship among components, how components interact over time (i.e., rules for running the model), and what higher order predicates guide the interaction of components. Consider the parameters specified by a domain-general mental model based on the conceptual model of a causal loop diagram. Autonomous components are represented by variable names and relationships are represented by one-way arrows with a notation (i.e., + or -) to indicate polarity. A change in the value of one component affects the value of any component connected through a one-way arrow, in a direction indicated by the indicated polarity. The concept of feedback serves as a higher-order predicate (Gentner, 1983; Gentner & Toupin, 1986) because users attempt to construct specific models in which closed loops are formed.

Integrating the Psychological and System Dynamics Approaches to Mental Models

Although the research by psychologists on mental models is methodologically rigorous, little attention has been given to mental models of nonlinear target systems or the value of domain-general mental models. In contrast, although the system dynamics literature has addressed these two issues, rigorous methodology has not been used to evaluate the learning process or the transfer of training. Most of the research supporting the value of system dynamic modeling is anecdotal (Bergin & Prusko, 1990; Kim, 1990) and no controlled studies have demonstrated transfer of training (Bakken, Gould, & Kim, 1994). The present study will therefore integrate these two approaches to the study of mental models.

STUDY 1

Study 1 explored how best to examine the impact of a mental model on performance. Consider a case in which a partially developed mental model of positive feedback helps a person interpret a causal loop diagram and yet is not adequate for enabling the person to self-generate that diagram. Measuring the impact of a mental model in a way that requires self-generation of a diagram would be insensitive to the partial development of a mental model. Such insensitivity might be more likely when the scenario in question is complex. Findings based on similar tasks suggest that complexity hinders performance (Hegarty, 1992; Hegarty & Sims, 1994). Although a participant may not be able to generate a causal loop diagram of a complex system the participant may still be capable of interpreting a causal loop diagram of the system. The purpose of Study 1, therefore, was to determine whether participants have difficulty self-generating representations of complex causal systems.

Study 1 required participants to learn a domain-general mental model of a nonlinear system and use this mental model to generate representations of novel scenarios to understand the impact of state changes. The complexity of the novel scenarios was varied within subjects. The dependent measures included the number of errors made in representing the scenario, the accuracy of predicted state changes, and the time required to make these predictions. It was hypothesized that participants would make fewer errors in representing the scenario and predict the causal impact of state changes more quickly and accurately when the complexity of the scenario was low rather than high.

Method

Participants

The participants were 20 students at Old Dominion University in Norfolk, Virginia, who received course credit for participation. The average age was 22.5 (SD = 7.1). Thirteen women and 7 men participated.

Materials

Training

The training material explained how to identify the variables and relationships comprising a causal system and how to represent the system with a causal diagram (see Appendix A). Positive feedback was introduced as a generic phenomenon underlying common concepts like a snow-ball effect, self-fulfilling prophecy, and vicious cycle. The material addressed how to distinguish between linear and feedback relationships and how those relationships differed in their effects. Specifically, the material explained that positive feedback relationships produce continual change whereas linear relationships produce limited change.

Scenarios. The material included 16 scenarios, each providing a descriptive narrative of the variables and relationships forming a causal system. The subject matter of the scenarios was drawn from various domains including mechanics, biology, psychology, social psychology, sociology, management, and economics. The scenarios also differed in the number of variables presented and whether a positive feedback loop existed, yet each could be represented by a causal diagram with no more than one causal loop. No scenario contained negative feedback.

Instructional Method. The training material required participants to make frequent and numerous responses. For a given scenario participants did one or more of the following: selected which figure among several best represented the scenario, drew a causal diagram of the scenario, indicated whether feedback was present, predicted how a change in a specific variable would affect another variable (e.g., "If confidence increases by a limited amount, over time success will ______. : a., increase a set amount, b., increase continually, c., not change"). The training material also required participants to generate general rules for how components in similar types of configurations behave.

Testing

Scenarios. The testing material contained six novel scenarios similar in causal structure but different in specific content from those presented in training (see Appendix B). The three simple scenarios had only three variables, none of which directly affected, or was affected by, more than one other variable. In contrast, the three complex scenarios had six to seven variables, some of which were directly affected (or were directly affected by) up to three variables (e.g., A is directly affected by B, C, and D). Further, complex scenarios contained variable pairs between which there were both direct (e.g., A affects B) and indirect relationships (e.g., A affects C which affects B). The testing required participants to construct a causal diagram for each scenario.

Questions. Each scenario was accompanied by four prediction questions identical to those used in training. For each question, participants were asked to predict whether a change in one variable would lead to a limited change, continual change, or no change in another variable.

Performance Measures

Errors made in constructing a causal diagram were assessed by counting the number of errors made in identifying both variables and relationships. Variable identification errors were recorded when a variable presented in the scenario was not represented in the figure or vice versa. Relationship identification errors were recorded in the same way. For the questions, response accuracy was assessed simply by recording whether a question was answered correctly, and response time was assessed by recording the number of seconds from the presentation of the question scenario to the participant's response.

Procedure and Apparatus

Participants began by completing the training material. The training material was contained in a paper packet, except for figures which were presented on cue cards. Throughout the self-paced training, participants responded to questions by either writing or drawing their response on paper, depending on what the question required. Immediately following a response participants were provided with the correct answer and the appropriate explanation. Participants notified the experimenter when they had completed the training and were offered a five-minute rest period before beginning the testing session.

Following the break participants completed the testing portion of the experiment. A 386 IBM-compatible computer was used to present the testing scenarios and questions. A program controlled the presentation of scenarios and questions, and recorded the accuracy and latency data of the participant's responses. The order in which the scenarios were presented was partially counterbalanced. Two Latin Squares were created using the six scenarios, yielding two, 6 by 6 matrices. Participants were randomly assigned to one of the 12 resulting orders and were given instructions to work quickly and accurately. Participants first completed a practice scenario with accompanying questions before completing the six test scenarios. For each scenario participants read the text and then drew a causal diagram representing the variables and their relationships. Upon completion of the diagram, participants pressed a key on the computer's keyboard to receive the first multiple-choice question. The question appeared on the computer screen below the text of the scenario. Thus, participants were able to examine both the scenario and their causal loop diagram when answering the question. Participants responded by entering the letter of the appropriate answer, which prompted the computer to display the next question. The remaining questions were presented sequentially in the same fashion.

Results

Errors in Figures

The number of errors in the six figures produced by each participant was assessed by two raters. The ratings were compared across figures on the number of variable and relationship identification errors. Inter-rater agreement for this coding was 99%. An alpha level of .05 was used for all statistical tests performed on all dependent measures.

Participants made fewer variable identification errors across the three scenarios of low complexity ($M = 0.263$, $SD = 0.934$) relative to the three scenarios of high complexity ($M = 1.105$, $SD = 1.912$), $t(19) = 2.577$. An even larger effect for complexity was observed on relationship identification errors, with participants again making fewer errors on the three low complexity scenarios ($M = 0.737$, $SD = 2.746$) relative to three high complexity scenarios ($M = 6.684$, $SD = 5.774$), $t(19) = 5.805$.

Responses to Questions

Participants were not significantly more accurate on questions for low complexity scenarios (M = 0.700, SD = 0.332) than on questions for high complexity scenarios (M = 0.629, SD = 0.238). An examination of the data, however, raised the suspicion that the effect of complexity on accuracy was masked by participants who performed at a chance level of accuracy. A criterion was sought for selecting those participants who would have a 0.1 or lower probability of achieving their overall score by chance alone. Given 24 questions with 3 choices each, a score of 11 was determined to be the appropriate criterion (probability = $(1/3)^{11} * (2/3)^{13} *$ combinations (24, 11) = .0724). Participants meeting this criterion did perform better on the low complexity scenarios (M = 0.875, SD = 0.211) relative to high complexity scenarios (M = 0.720, SD = 0.221), t (13) = 2.879. Participants not meeting the criterion, however, did not differ statistically in their performance on scenarios of low (M = 0.292, SD = 0.126) versus high complexity (M = 0.417, SD = 0.105; t (19) = 1.464).

Finally, participants responded more quickly when answering questions about simple (M = 16.28, SD = 4.882 seconds) rather than complex scenarios (M = 21.20, SD = 6.625), t (19) = 3.251. This difference was even larger among those meeting the performance criterion described above (M = 14.42, SD = 3.530 vs. M = 21.85, SD = 7.652), t (19) = 4.681), and smaller for those not meeting the criterion (M = 20.62, SD = 5.092 vs. M = 19.67, SD = 3.258, t (19) = 0.466.

The relationship between figure accuracy and prediction accuracy was also examined. If participants applied a mental model to the figure to answer questions about the scenario, then prediction accuracy should correlate negatively with the number of errors in the figure. The results supported this reasoning. Prediction accuracy was negatively correlated with errors in variable identification (r = - 0.3701) and relationship identification (r = - 0.3657). This pattern of correlations was consistent across scenarios of both low (r = - 0.2254, r = - 0.1775) and high (r = - 0.4929, r = - 0.5441) complexity.

Discussion

It was hypothesized that participants would make fewer errors when representing low complexity scenarios than when representing high complexity scenarios. Consistent with this hypothesis, participants made fewer errors in identifying both variables and the relationships among the variables when representing low complexity scenarios. The effect of complexity on relationship identification was quite marked: on average, participants made less than 1 error across the three low complexity scenarios and more than 6 errors across the high complexity scenarios. This finding suggests that with only limited training participants have difficulty generating accurate representations of complex scenarios.

It was also hypothesized that participants would predict state changes more quickly and accurately for simple rather than complex scenarios. As predicted, participants responded more quickly to questions pertaining to simple scenarios. The effect for complexity, however, was not observed on accuracy scores for the entire sample. Instead, the effect emerged only when those participants answering at a chance level of accuracy were excluded.

In summary, the results of Study 1 suggest that with limited training participants can only be expected to generate accurate representations for the simplest of scenarios. Participants attempting to model complex scenarios failed to correctly identify all the variables and relationships presented in the scenario. These findings have implications for the design of Study 2. In the second experiment, the effects of complexity were examined in the context of other independent variables. Specifically, other types of training methods were examined. Given the results of Study 1, it is likely that a training effect could be masked on complex scenarios by a floor effect if participants were required to generate their own figures. In other words, the results of Study 1 suggest that a more sensitive measure is needed to detect differences in performance among training conditions on complex scenarios. One solution is to eliminate the requirement that participants generate their own figure to use in answering questions. Participants with an incomplete mental model of positive feedback may not be able to accurately generate their own figure, yet might be able to use a figure provided to them. Assessing performance with a provided figure may produce a more sensitive measure of mental model development. Thus, Study 2 examined the effects of complexity on the ability of participants to use a figure of a scenario rather to both generate *and* use a figure.

STUDY 2

Designs

Performance with Self-Generated Testing Aids

The primary purpose of Study 2 was to determine whether teaching participants about positive feedback with causal loop diagrams fosters the development of domain-general mental models that help users predict the behavior of nonlinear systems. Although Study 1 demonstrated that training with causal loop diagrams can produce successful performance, performance was not necessarily produced by the use of mental models *per se*. Rouse and Morris (1986) argue that training with conceptual models improves performance both through fostering the development of mental models and by simply providing guidance in how to utilize available cues. Thus, training with causal loop diagrams may affect performance simply by improving cue utilization, not because the training fosters a helpful mental model. Thus, Study 2 trained people under four different conditions. One group of participants received general training about positive feedback with specific training in how to abstract cues and represent those cues as a causal loop diagram. Another group received the same general training but with specific training only in how to abstract cues. The remaining participants received either general training alone or no training.

All participants were first tested on a set of simple scenarios for which they self-generated their own testing aids to help answer questions regarding the behavior of variables. Performance was assessed according to the accuracy and speed with which participants answered questions about scenarios. Participants trained in modeling were hypothesized to perform better than those trained in cue utilization. Modeling training should foster the development of mental models which help the user free working memory resources (Glenberg & Langston, 1992; Hegarty, 1992; Kieras, 1992) and notice implicit relationships (Glenberg & Langston, 1992). Participants trained in cue utilization were expected to perform better than those receiving general training by learning how to recognize relevant cues and ignore extraneous ones. Kessel and Wickens (1982) found that subjects trained in manual control performed better than subjects trained in automated control by learning to identify nonproprioceptive cues. In addition, the advantage of experts over novices may derive from an ability to ignore superficial cues (Chi & Glaser, 1984). Finally, participants receiving general training were predicted to perform no differently than participants receiving no training. Users typically do not think in terms of feedback relationships (Axelrod, 1976) and have difficulty understanding dynamic complexity (Sterman, 1994). Without guidance in identifying relevant cues, participants may fail to learn from their experience (Brehmer, 1980).

Performance with Provided Testing Aids

For the second set of scenarios participants were provided with testing aids. Performance was examined as a function of training (modeling, cue utilization, general, or none), testing aid (modeling aid vs. cueing aid), and complexity (low vs. high). Training was hypothesized to affect performance as described above. The type of testing aid provided was also manipulated. One reason testing aids were provided was because the design called for the presentation of complex scenarios and the results of Study 1 suggested that participants would be unable to generate their own aids for complex scenarios. In addition, the manipulation of testing aids provided an opportunity to explore the role of representational guidance versus cue guidance. Participants received either a modeling aid (i.e., a causal loop diagram of the scenario) or a cueing aid (i.e., a list of bivariate relationships in the scenario). It was expected that users trained in modeling might not be able to generate their own causal loop diagram yet be able to use one that is presented. In addition, participants not trained in modeling might spontaneously learn how to utilize the diagram. Thus, participants using modeling aids were expected to outperform those using cueing aids.

Complexity was manipulated to examine theory on how mental models improve performance. If mental models add value by freeing working memory resources and highlighting implicit relationships (Glenberg & Langston, 1992) their ability to affect performance should increase as the demands on working memory increase. Research suggests increasing the complexity of the target system increases the demands on working memory. Participants using schematics for motion verification tasks have greater difficulty with complex target systems (Hegarty, 1992; Hegarty & Sims, 1994). Systems dynamics research also suggests that system complexity impairs performance (Diehl & Sterman, 1995: Paich & Sterman, 1993; Sterman, 1989a, 1989b). Thus, as in Study 1, participants were hypothesized to perform better on low rather than high complexity scenarios. More importantly, complexity was predicted to interact with both training and testing aid. Participants trained in modeling were expected to outperform those trained in cue utilization by a greater margin when complexity was high rather than low. Similarly, participants presented with modeling aids during testing were expected to outperform those using cueing aids by a greater margin when complexity was high.

Finally, spatial ability was examined as a covariate in both problem sets. Spatial ability has been shown to predict whether participants accurately use a schematic to verify the motion of a component (Hegarty & Just, 1993; Hegarty & Sims, 1994). Although causal loop diagrams usually represent a nonspatial system, the representation itself is similar in detail and complexity to the type of representation used in the motion verification methodology. Furthermore, the cognitive skill required is similar (e.g., tracking the causal "path" through various components). Spatial ability was thus predicted to correlate positively with performance.

Method

Participants

The participants were 144 students at Old Dominion University in Norfolk, Virginia, who participated in the study for course credit. The average age was 22.7 (SD = 6.0). Participants included 99 women and 43 men (2 participants failed to identify their gender).

Materials

Spatial Ability Measure

Spatial visualization ability was measured by the Paper Folding Test VZ-2 (Ekstrom, French, & Harman, 1976; see Appendix C). Each item illustrates successive folds made to a square sheet of paper. The final drawing shows a hole punched through the folded paper. Participants chose among 5 pictures depicting how the punched sheet would appear when unfolded. Participants are given two, three-minute periods to complete up to 10 items in each period. Scores are calculated by summing the number of correct responses over the two time periods and subtracting 0.2 points for each incorrect response. Interitem reliability is acceptable (.75 to .84 for males, and .77 to .84 for females; Ekstrom, et al., 1976). The test correlates highly with errors on motion-verification tasks (r = -0.70; Hegarty & Sims, 1994), a task requiring mental manipulation of a static figure similar to the mental manipulation required to infer causality from a causal loop diagram.

Training

Participants in the modeling training condition received the same training used in Study 1 (see Appendix D). By learning how to represent scenarios as causal loop diagrams participants received both cue guidance and representational guidance. Participants who received cue-utilization training were taught to list all bivariate causal relationships contained in a scenario. This instruction provided cue guidance but no representational guidance. Participants in the general training condition received the same instruction as the other two groups but without cue guidance or representational guidance. An additional group of participants was not trained (i.e., no-training condition).

Testing

There were two sets of testing scenarios. The first set consisted of six scenarios of low complexity for which no summary aid was provided. All six scenarios were low in complexity (see Study 1) and three included a feedback relationship. Each scenario was accompanied by two questions. The second set consisted of six scenarios, equally divided between high- and low-complexity scenarios, each accompanied by four questions. A summary aid was provided for each scenario, the type of which varied according to the testing-aid condition. In the modeling condition, the aid was a causal loop diagram whereas in the cueing aid condition the aid was a set of textual propositions specifying bivariate relationships. All scenarios used the same type of questions and performance measures used in Study 1.

Procedure and Apparatus

Participants began by completing the spatial ability test. Next, participants completed the training material. Unlike Study 1, the training material was presented via the computer except for the figures which were presented on cue cards. The training was self-paced with the participant advancing to the next screen by hitting the space bar or hitting the appropriate letter to answer a question. After training the participants were offered a five-minute break, after which time the testing began. During testing, subjects first completed the scenarios without aids and then those with aids. The order of scenarios was partially counterbalanced within each set. Two Latin Squares were created using the six scenarios, yielding two, 6 x 6 matrices. Ninety-six participants were assigned to the resulting 12 orders. An additional Latin Square was created with the 6 scenarios, yielding a 6 x 6 matrix, and an additional 48 participants were assigned to the resulting 6 orders. As in Study 1, accuracy and response latency for each question were measured by the computer. Participants were instructed to work quickly and accurately.

Results

Performance with Self-Generated Testing Aids

In problem set 1 participants studied a scenario, drew or wrote a description of the scenario, and then answered two questions about the scenario. ANCOVAs were conducted on both the accuracy and latency scores, using spatial ability as the covariate. The analyses used a one-way, between-subjects model with four levels of the independent variable training (modeling, cue utilization, general, no training). The Student Newman-Keuls test was used to assess differences among means. The means reported below and those used in post hoc calculations are adjusted for the covariate. Probability of a Type I error was set at .05 for all analyses.

Prediction Accuracy

Table 1 displays the source of variation table for response accuracy. Spatial ability was significant as a covariate, $F(1, 139) = 13.13$, correlating positively with accuracy. The effect of training was also significant, $F(3, 139) = 23.24$. Participants in the modeling condition ($M = .8847$) answered more questions correctly than in any other training condition. Participants receiving general training ($M = .7201$) outperformed those receiving no training ($M = .4856$), but did not differ significantly from those receiving cue-utilization training ($M = .7292$).

Table 1

Analysis of Covariance for Accuracy, No Summary Aids Provided

Source	*df*	*SS*	*MS*	*F*	ω^2
Training	3	2.92433	0.97478	23.24 *	0.333
Spatial Ability	1	0.55072	0.55072	13.13 *	0.061
Subjects (Training)	139	5.83123	0.04195		
Total	143	9.30627	0.065		

*$p \leq .05$.

Prediction Latency

Table 2 displays the results from an ANCOVA for response times measured in seconds. Unlike with accuracy, spatial ability did not covary significantly with latency. Training was significant, $F(3, 139) = 5.83$. Participants in the modeling ($M = 15.92$), cue-utilization ($M = 18.97$), and general training ($M = 17.80$) conditions took significantly less time to answer questions than participants in the no-training condition ($M = 23.28$).

Table 2

Analysis of Covariance for Latency, No Summary Aids Provided

Source	*df*	*SS*	*MS*	*F*	ω^2
Training	3	1052.432	350.811	5.83 *	0.098
Spatial Ability	1	18.357	18.357	0.31	
Subjects (Training)	139	8365.710	60.185		
Total	143	9436.499	65.990		

*$p \leq .05$.

Performance with Provided Testing Aids

In problem set 2, participants studied a scenario and then used an aid representing the scenario to answer questions. Once again, ANCOVAs were conducted on both accuracy and latency scores, with spatial ability as the covariate. The 3-way ANCOVAs reported below examined the effects of training (modeling, cue-utilization, general, or no-training), testing aid (modeling or cueing), and scenario complexity (low or high) in a mixed-model design, with training and testing-aid as between-subjects variables.

Accuracy and latency measures were calculated as they were in problem set 1 with the following exception. Approximately 25% of participants who received modeling aids during testing were exposed to two causal loop diagrams with typographical errors that could have affected responses on two questions regarding complex scenarios. These questions were thus dropped from the analyses for all participants. The measures for accuracy and latency in the complex condition are based on performance averaged across the remaining 10 questions rather than the intended 12. Dependent measures in the simple condition are based on the intended 12 questions.

Prediction Accuracy

Table 3 displays the ANCOVA for accuracy. As in the analyses for scenarios presented without summary aids, spatial ability was significant as a covariate, $F(1, 271) = 49.63$, correlating positively with accuracy. Training also had a significant effect, $F(3, 135) = 32.66$, and the same pattern of differences between levels was observed as when summary aids were not presented. Participants in the modeling condition ($M = .8295$) answered more questions correctly than any other training condition, and participants receiving general training ($M = .6769$) were more accurate than those receiving no training ($M = .4308$). Participants in the general training condition, however, did not differ from those in the cue-utilization condition ($M = .6871$). The type of summary aid provided during testing also had a significant effect, $F(1, 135) = 7.33$. Participants were more accurate with modeling aids during testing ($M = .6953$) than with cueing aids ($M = .6168$). Although the predicted effect for complexity was not observed, an interaction between training and complexity did reach significance, $F(1, 136) = 10.22$. This interaction is presented in Figure 2. Participants were significantly more accurate on low- relative to high-complexity scenarios if trained in the modeling ($M = .8792$ vs. $M = .7797$) or cue utilization conditions ($M = .7323$ vs. $M = .6420$), but significantly less accurate if they received no training ($M = .3657$ vs. $M = .4958$). The predicted interaction between testing aid and complexity did not reach significance. The difference between modeling and cueing aids at high complexity ($M = .6873$ vs. $M = .6002$) was not significantly larger than this difference at low complexity ($M = .7033$ vs. $M = .6335$), although the means were in the expected direction.

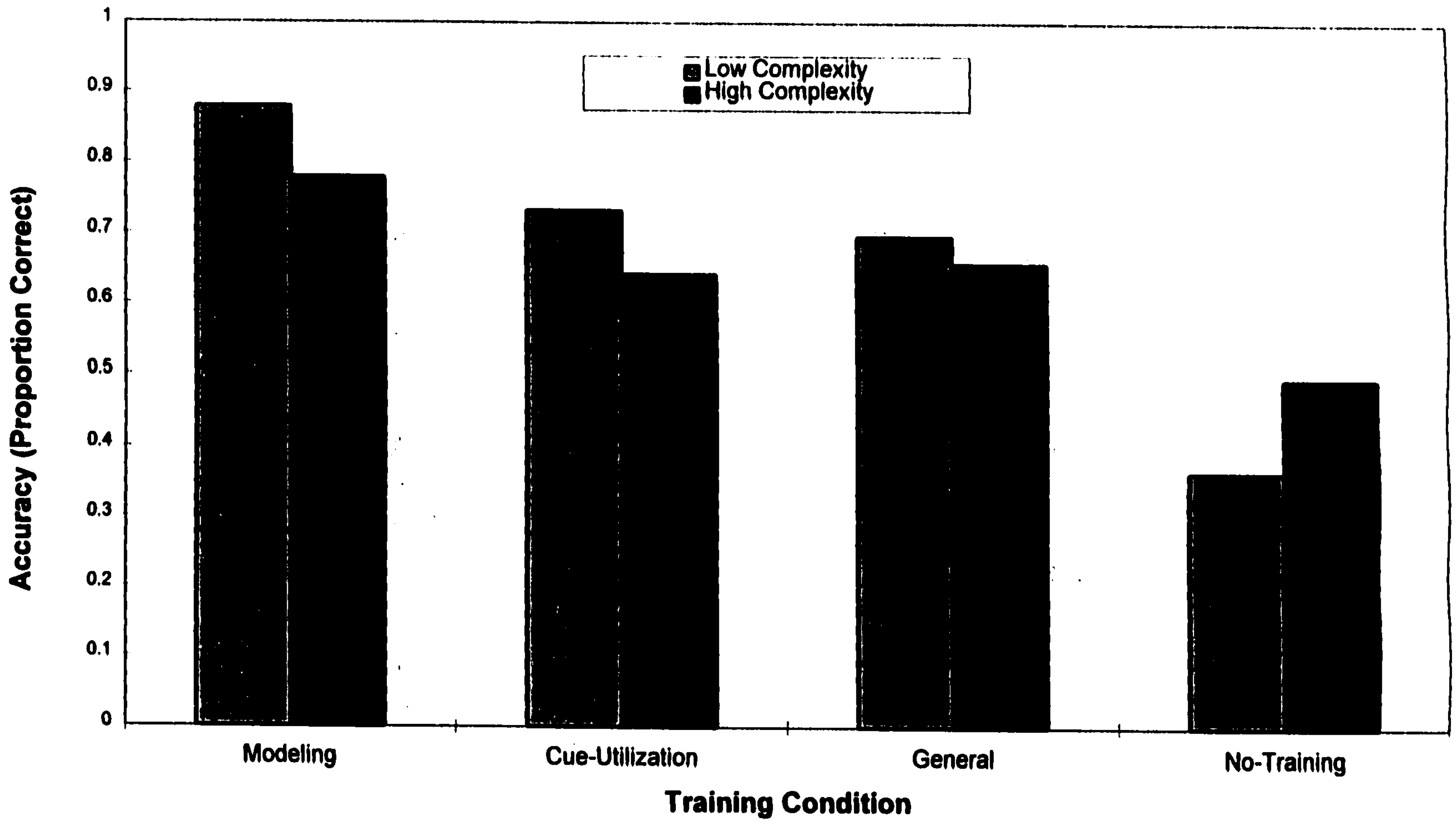

Figure 2. Effect of Training by Complexity Interaction on Accuracy

Table 3

Analysis of Covariance for Accuracy, Summary Aids Provided

Source	*df*	*SS*	*MS*	*F*		ω^2
Training	3	5.92097	1.97366	32.66	*	0.203
Test Aid	1	0.44297	0.44297	7.33	*	0.014
Training x Test Aid	3	0.12667	0.04222	0.70		
Complexity	1	0.04376	0.04376	2.19		
Training x Complexity	3	0.61314	0.20438	10.22	*	0.059
Test Aid x Complexity	1	0.00543	0.00543	0.27		
Training x Test Aid x Comp	3	0.07642	0.02547	1.27		
Spatial Ability	1	1.99234	1.99234	49.63	*	0.104
Subjects (Train x Test Aid)	135	8.15906	0.06044			
Comp x Subj (Train x Test)	136	2.72084	0.02001			
(Pooled Error	271	10.87990	0.04015)			
Total	287	20.10159	0.070			

*$p \le .05$.

A specific interaction was predicted to occur between complexity and the training levels of modeling and cue utilization. The F-test, computed using the sum of the squares for interaction term for only these levels of training (MS = .00077) and the error term from the full model (MSE = .02001) was not significant.

The overall interaction between complexity and training was explored by considering the types of questions participants answered. Nonfeedback questions addressed variables between which there was a linear relationship or no relationship whereas feedback questions addressed a feedback relationship. Participants were more accurate on nonfeedback questions (M = .7271) than on feedback questions (M = .6432), t (143) = 4.45. The proportion of question types was not constant across the two levels of complexity. The low complexity scenarios had more feedback questions (8 out of 12) than did the high complexity scenarios (3 out of 10). Thus, the simple scenarios had more of the difficult, feedback questions than did the complex scenarios.

Accuracy on Feedback Questions

To control for the effect of question type an additional ANCOVA was conducted on the accuracy scores of only the feedback questions. As can be seen in Table 4, within this subset of questions the effect for complexity is significant, $F(1, 136) = 40.29$. Although the training by complexity interaction is still significant, $F(3, 136) = 4.30$, the means are now in the expected direction for the no-training participants (see Figure 3). Participants with no training were not significantly more accurate on scenarios of low complexity (.1749) than on those of high complexity (.1517). The lack of a significant difference, however, can be explained by observing that both scores are well below a chance level of accuracy. Chance performance on these questions would produce a score of .33. Thus, the lack of understanding about feedback among the no-training participants created a floor effect that prevented complexity from reaching significance for this condition of training.

Table 4

Analysis of Covariance for Accuracy on Feedback Questions, Summary Aids Provided

Source	*df*	*SS*	*MS*	*F*		ω^2
Training	3	15.255	5.085	34.53	*	0.221
Test Aid	1	0.629	0.629	4.27	*	0.007
Training x Test Aid	3	0.040	0.013	0.09		
Complexity	1	1.82352	1.82352	40.29	*	0.086
Training x Complexity	3	0.58355	0.19452	4.30	*	0.022
Test Aid x Complexity	1	0.08111	0.08111	1.79		
Train x Test Aid x Comp	3	0.03554	0.01185	0.26		
Spatial Ability	1	1.31640	1.31640	13.70	*	0.028
Subjects (Train x Test)	135	19.88036	0.14726			
Comp x Subj (Train x Test)	136	6.15509	0.04526			
(Pooled Error	271	26.03545	0.09607)			
Total	287	45.79994	0.160			

*p ≤ .05.

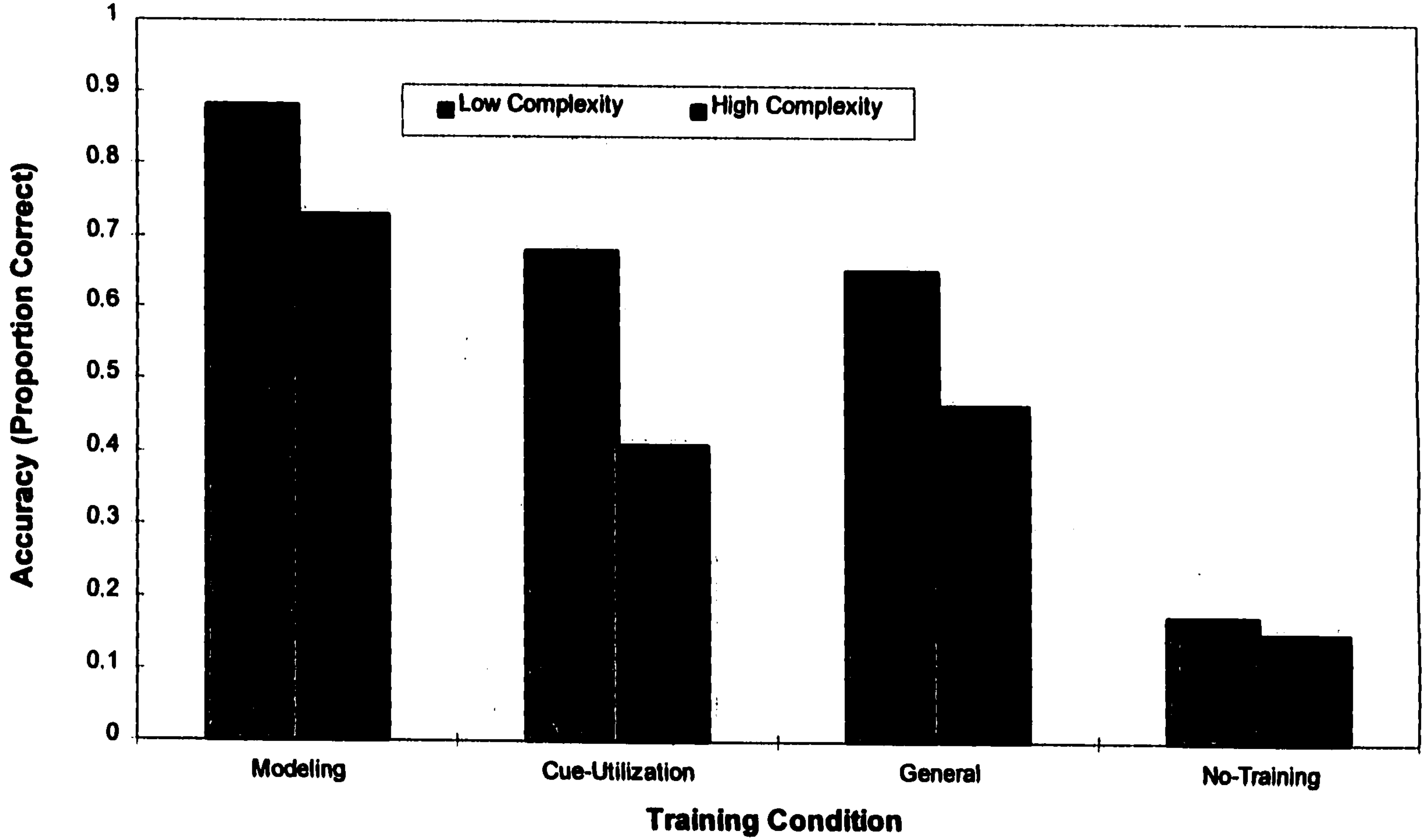

Figure 3. Effect of Training by Complexity Interaction on Accuracy, Feedback Questions

Examining only feedback questions, the predicted interaction between complexity and modeling versus cue utilization for training approached significance. The F-test, computed using the sum of the squares for only these levels of training (MS = .1329) and the error term from the full model was not significant at the .05 level, $F(1, 136) = .0386$, $p \leq .10$. However, the means were in the expected direction. The predicted interaction between complexity and testing aid also did not reach significance. The difference between modeling aids and cueing aids at high complexity ($M = .5033$ vs. $M = .3763$) was not significantly larger than this difference at low complexity ($M = .6289$ vs. $M = .5690$), although the means were in the expected direction.

Effects that were significant in the original analysis were also significant in the analysis of feedback questions: spatial ability, $F(1, 271) = 13.70$, and training, $F(3, 135) = 34.53$. Moreover, by focusing exclusively on these feedback questions, other differences emerged among the levels of training. As in the original analysis, the accuracy scores of participants in the modeling condition ($M = .8068$) were higher than those in the no-training condition ($M = .1633$). In the present analysis, however, modeling scores were higher than both cue-utilization scores ($M = .5465$) and general training ($M = .5609$), both of which now also differ significantly from the no-training scores. Testing aid also remained significant, $F(1, 135) = 4.27$, as participants presented with modeling aids ($M = .5661$) performed better than those presented with cueing aids ($M = .4726$).

Prediction Latency

Performance on problem set 2 was also assessed by measuring response latency. Table 5 displays the ANCOVA for latency. The effect of training was significant, $F(3, 135) = 3.81$. Participants trained in the modeling condition ($M = 16.38$) took significantly less time to respond to questions relative to participants trained in the cue-utilization (M = 20.61), general training (M = 21.49), or no-training (M = 21.57) conditions. The effect of testing aid was also significant, $F(1, 135) = 9.68$. Participants who received modeling aids (M = 18.05) during testing answered more quickly than those who received cueing aids (21.98). Complexity was significant as well, $F(1, 136) = 98.06$, with participants taking less time on questions pertaining to scenarios of low (M = 16.05) rather than high complexity (M = 23.98).

Table 5

Analysis of Covariance for Latency, Summary Aids Provided

Source	*df*	*SS*	*MS*	*F*		ω^2
Training	3	1308.971	436.324	3.81	*	0.021
Test Aid	1	1107.584	1107.584	9.68	*	0.021
Training x Test Aid	3	176.597	58.866	0.51		
Complexity	1	4517.909	4517.909	98.06	*	0.237
Training x Complexity	3	497.196	165.732	3.60	*	0.019
Test Aid x Complexity	1	8.965	8.965	0.19		
Training x Test Aid x Comp	3	23.483	7.828	0.17		
Spatial Ability	1	1.861	1.861	0.02		
Subjects (Train x Test Aid)	135	15444.316	114.402			
Comp x Subj (Train x Test)	136	6266.082	46.074			
(Pooled Error	271	21710.40	80.11217)			
Total	287	29352.963	102.275			

*$p \leq .05$.

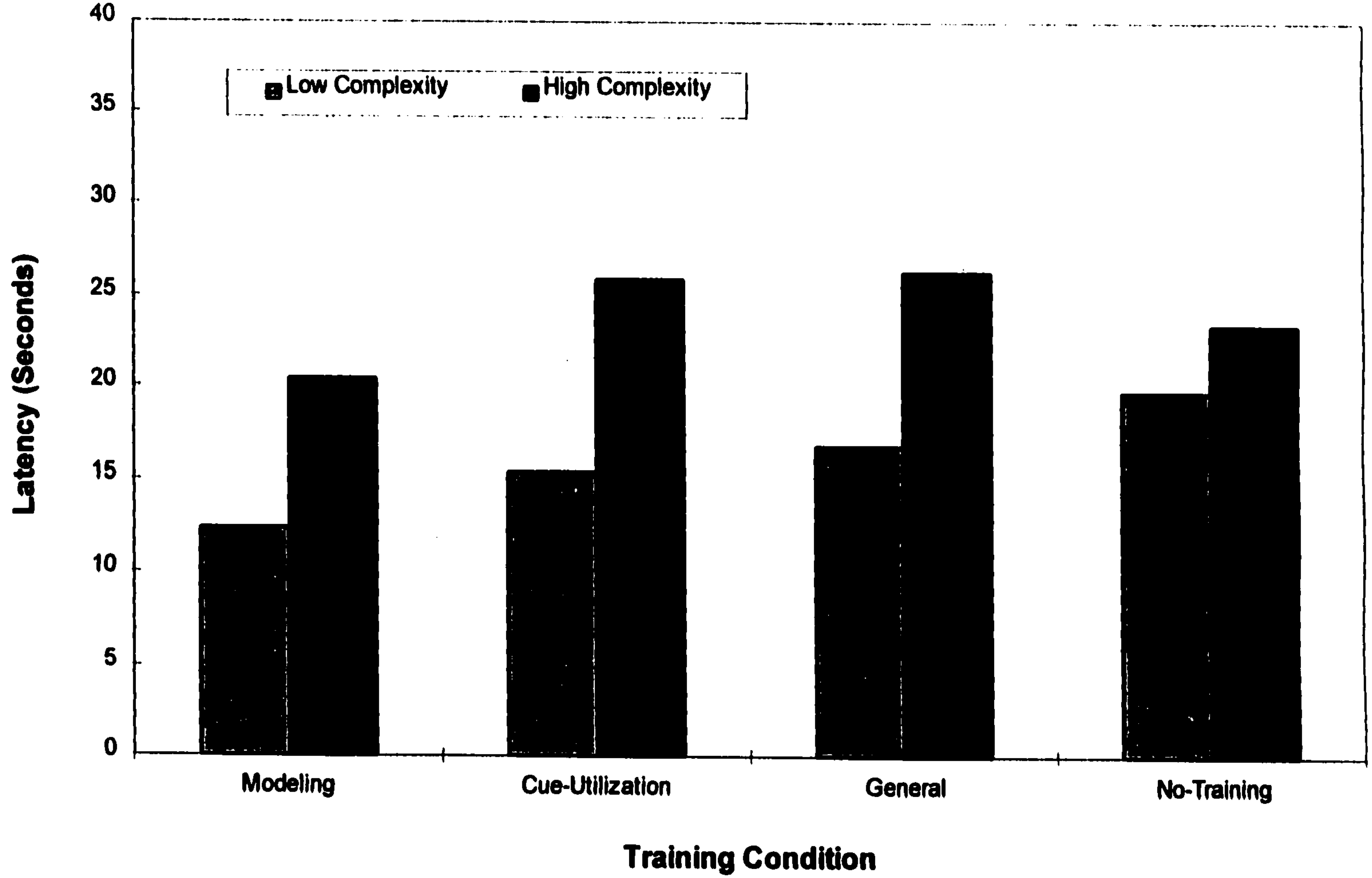

Figure 4. Effect of Training by Complexity Interaction on Latency

The predicted interaction between complexity and the modeling and cue utilization training levels did not occur. The F-test, computed using the sum of the squares for only these levels of training (MS = 35.17) and the error term from the full model was not significant, although the means were in the expected direction. The interaction predicted for complexity and testing aid also failed to reach significance. The difference between modeling aids and cueing aids at high complexity (M = 21.83 vs. M = 26.11) was not significantly larger than this difference at low complexity (M = 14.27 vs. M = 17.84), although the means were in the expected direction.

As with accuracy, however, the latencies for training and complexity did interact significantly when all levels of training were included, $F(3, 136) = 3.6$. Although the means are in the expected direction, participants who received no training did not perform significantly better on low complexity scenarios (M = 19.75) relative to high complexity scenarios (M = 23.38). This interaction is represented in Figure 4. Once again, the interaction can be better understood by considering the types of questions participants answered. Participants took longer when answering nonfeedback questions (M = 16.71 seconds) than feedback questions (M = 15.76), $t(143) = 2.32$. As stated above, high complexity scenarios had fewer questions addressing feedback relationships relative to low complexity scenarios. Thus, a second analysis was again conducted using only questions focused on feedback relationships.

Latency on Feedback Questions

Table 6 provides the ANCOVA summary for latency on feedback questions. This analysis revealed a main effect for complexity but the interaction between training and complexity fell short of significance (see Table 6). As can be seen in Figure 5, participants in the no-training condition had significantly longer latencies when responding to high complexity scenarios ($\underline{M}$ = 25.30) relative to low complexity scenarios ($\underline{M}$ = 19.36). As can be seen by comparing Figures 4 and 5, controlling for the type of question had the

Table 6

Analysis of Covariance for Latency on Feedback Questions, Summary Aids Provided

Source	*df*	*SS*	*MS*	*F*		ω^2
Training	3	1590.386	530.129	3.30	*	0.018
Test Aid	1	1526.415	1526.415	9.49	*	0.022
Training x Test Aid	3	39.600	13.200	0.08		
Complexity	1	9429.177	9429.177	84.7	*	0.214
Training x Complexity	3	740.220	246.740	2.22		
Test Aid x Complexity	1	122.667	122.667	1.10		
Training x Test Aid x Comp	3	52.015	17.338	0.16		
Spatial Ability	1	42.606	42.606	0.31		
Subjects (Train x Test Aid)	135	21710.562	160.819			
Comp x Subj (Train x Test)	136	15139.380	111.319			
(Pooled Error	271	36849.94	135.978)			
Total	287	50393.027	175.585			

*$p \leq .05$.

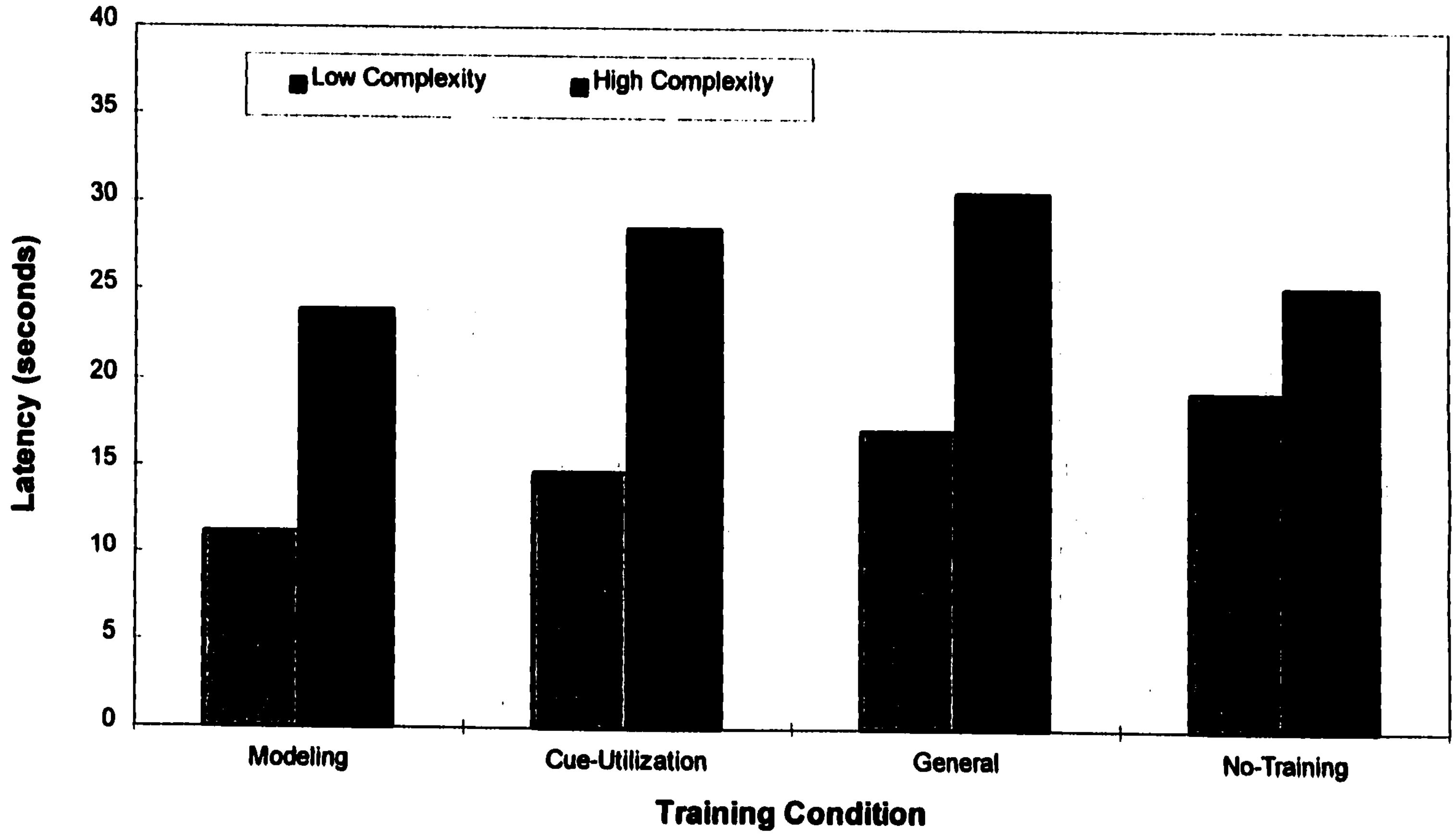

Figure 5. Effect of Training by Complexity Interaction on Latency, Feedback Questions

effect of increasing the differences between high and low complexity within each level of training. The specific interaction predicted to occur between complexity and the training levels of modeling and cue utilization was also not significant. The $\underline{F}$-test, computed using the sum of the squares for only these levels of training (MS = 11.45) and the error term from the full model was not significant, although the means were in the expected direction. The interaction between complexity and testing aid also failed to reach significance. The difference between modeling aids and cueing aids at high complexity ($\underline{M}$ = 24.11 vs. $\underline{M}$ = 30.02) was not significantly larger than this difference at low complexity ($\underline{M}$ = 13.97 vs. $\underline{M}$ = 17.27), although the means were in the expected direction.

The other effects remained largely unchanged. Training was still significant, $\underline{F}(3, 135) = 3.30$, with participants in the modeling condition ($\underline{M}$ = 17.51) responding more quickly than participants in the general training ($\underline{M}$ = 23.91) or no-training ($\underline{M}$ = 22.33) conditions. However, the difference between modeling and cue utilization ($\underline{M}$ = 21.62) obtained in the original analysis failed to reach significance. Testing aid remained significant, $\underline{F}(3, 135) = 9.49$, with participants responding more quickly when provided with modeling aids ($\underline{M}$ = 19.04) rather than cueing aids ($\underline{M}$ = 23.64). Finally, complexity remained significant, $\underline{F}(1, 136) = 84.70$, with participants answering more quickly on scenarios of low complexity ($\underline{M}$ = 152.00) rather than high complexity ($\underline{M}$ = 27.06).

FINDINGS AND INTERPRETATIONS

The present study addresses limitations in the literature for both mental models and system dynamics. Although researchers have examined the value of domain-specific mental models of linear target systems (e.g., a brake system, Mayer & Gallini, 1990), they have not examined the value of domain-general mental models applied to nonlinear target systems (e.g., a mental model of positive feedback used to understand an arms race). Although system dynamics researchers argue that people can develop domain-general knowledge about feedback structures, the research evidence is largely anecdotal (Bergin & Prusko, 1990; Kim, 1990). Therefore, Study 2 examined whether instruction in positive feedback using causal loop modeling fostered the development of domain-general mental models that could help users predict the behavior of nonlinear systems. Training with conceptual models (i.e., causal loop diagrams) was compared to training with cue-utilization instruction, general training, and no training. Measures of accuracy and latency assessed prediction performance on two sets of testing scenarios. For the first set of scenarios participants generated their own summaries whereas on the second they used testing aids provided by the experimenter. The type of testing aid provided was manipulated to compare the benefits of modeling to that of cueing aids. Complexity was also varied for the second set of scenarios to look for the possibility of interactions with training and testing-aid conditions. Finally, spatial ability was assessed as a covariate in both sets of scenarios.

The hypotheses regarding training received mixed support. As expected, participants trained in modeling generally predicted system behavior more accurately and more quickly than participants trained in cue utilization. Contrary to expectations, participants receiving cue-utilization training did not perform better than those receiving general training. Also contrary to expectations, those receiving general training generally outperformed those receiving no training. Similar to the finding for training, testing aids produced better performance when they provided modeling guidance rather than cue-utilization guidance. As predicted, participants presented with modeling aids during testing responded more accurately and quickly than those presented with cueing aids. Complexity was hypothesized to interact with training and testing aid, such that the benefits of modeling training (or modeling aids) relative to cue utilization training (or cueing aids) would be greater at high rather than low complexity. Although the means were in the expected directions on feedback questions, the specified interactions were not statistically significant. Finally, spatial ability correlated positively with accuracy scores as predicted, but not with latency scores.

Utility of Mental Models Relative to Cue Utilization

Demonstrating the value of mental models requires showing how training with conceptual models improves performance. Rouse and Morris (1986) argue, however, that training with a conceptual model both fosters mental model development and offers cue utilization guidance. To determine whether mental models improve performance, the performance of participants trained in modeling was compared to that of those trained in cue-utilization guidance. Modeling training was expected to add more value than cue-utilization training by fostering the development of mental models that help users cope with working memory limitations and notice implicit relationships (Glenberg & Langston, 1992).

Training Results

The results for the effect of training in the present study strongly suggest that mental models *per se* improve prediction accuracy. Participants trained in modeling were more accurate in predicting state changes than were participants trained in cue utilization, both when participants generated their own aids and when aids were provided during testing. The fact that modeling training offered an advantage when no aids were provided suggests that participants learned a general mental model which they could use in constructing a representation of a specific set of relationships. However, it should be acknowledged that participants constructed their own testing aids only for simple scenarios. The results of Study 1 suggested that participants had difficulty accurately representing the relationships of complex scenarios.

Modeling training also appears to produce faster response times relative to cue-utilization training. When participants testing aids were provided testing aids, participants trained in modeling responded more quickly than participants trained in cue utilization. Although the difference failed to reach significance when participants generated their own aids, the means were in the expected direction.

Testing Aid Results

The advantage of modeling guidance over cueing guidance was also examined by varying the type of aid presented during testing. It was expected that participants who did not receive training in modeling might still be able to utilize a causal loop diagram, and that although participants trained in modeling might be unable to generate their own diagrams, they might yet be able to use a diagram when presented. Thus, participants presented with modeling aids were expected to outperform those presented with cueing aids. The results confirm this hypothesis, as participants using modeling aids responded more accurately and more quickly. Thus, modeling guidance appears to offer additional benefits over cue-utilization guidance alone both during training and testing. Participants benefit both from the generic conceptual model learned during training and the scenario-specific model presented during testing. By controlling for cue-utilization guidance, one can infer that the conceptual model of a causal loop diagram fosters a mental model that improves performance.

A possible objection to the conclusion stated above might be the supposition that the causal loop diagrams simply provided a "key" that automatically revealed the correct answer. In other words, the diagrams may have simply shown participants a trick for answering the questions rather than a mental model for conceptualizing causal systems. At least two counter arguments can address this objection. First, not all participants provided with training in modeling or modeling aids during testing answered the questions correctly. On scenarios for which testing aids were provided, participants trained in modeling answered 81% of the feedback questions correctly, and participants presented with modeling aids answered 57% correctly. If the causal loop diagrams made the answers to questions obvious, scores in these conditions would be higher. Second, the impact of training relative to that of testing aid suggests that participants were applying mental models. When aids were provided, training accounted for 20% of the variance in response accuracy whereas testing aid accounted for only 1%. This discrepancy suggests participants can receive maximum benefit from a causal diagram only when they have developed a mental model that allows them to interpret the causal diagram. Participants must integrate information from the diagram into their mental model and "run" their mental model to generate inferences.. Given this argument, it appears unlikely that presenting a causal loop diagram simply reveals the answer.

The present study advances the mental model literature by demonstrating that conceptual models do more than improve cue utilization – conceptual models also foster the development of mental models which improve performance. The current study also demonstrates that people can learn domain-general mental models of nonlinear systems. The findings also provide rigorous, empirical support for the arguments of system dynamics researchers that training and experience with systemic principles can help people learn general skills for understanding dynamic systems (Senge & Sterman, 1994) and for seeing common feedback structures in systems with divergent surface structures (Bakken, Gould, & Kim, 1994).

Utility of Cue-Utilization Guidance

Implicit in Rouse and Morris (1986) is the argument that cue guidance in and of itself can aid performance. Therefore, participants trained in cue utilization were expected to outperform those receiving only general training. This did not occur. The are several possible explanations for this outcome. One might argue that the ability to appropriately utilize cues does not affect performance, but this explanation contradicts previous research clearly showing that sensitivity to cues affects performance (Kessel & Wickens, 1982). One might also argue that cue-utilization training did not affect performance because the presentation of the variables and relationships in the scenarios makes cue utilization straightforward. Appropriate cue utilization is more difficult to achieve when participants must infer the relationship between a cue and a criterion by observing the behavior of the system, especially when the relationship is affected by random error (Klayman, 1988). The results of Study 1, however, suggest that, at least for complex scenarios, participants do have difficulty accurately identifying the variables and relationships contained in the scenarios. This suggests that the format of the scenarios does not directly reveal the variables and relationships for the participants and that effective cue-guidance training might aid participants in identifying relevant cues.

Several methodological explanations can also be offered. It is possible that the dependent measure was not sensitive to potential differences between the cue utilization and general training conditions. When answering questions about complex scenarios during testing, participants were always provided with a testing aid. Differences in the ability of participants to utilize cues is less likely to be apparent when participants are provided with the appropriate cues. Thus, participants trained in cue utilization had no opportunity to fully demonstrate their cue-utilization ability on the types of scenarios most likely to highlight this ability. Another explanation may lie with the way participants were trained. It is possible that the cue utilization training was simply not effective. This seems unlikely given that these participants consistently outperformed participants with no training.

The most plausible explanation might be that both the cue utilization and general training conditions developed comparable cue-utilization ability. Although general training did not provide explicit instruction on cue utilization, participants in this condition may have developed the skill incidentally by reading the numerous examples, answering questions regarding variables and relationships, and receiving corrective feedback. Moreover, the additional training provided in the cue-utilization condition may have had no effect. Specifically, training in how to list bivariate relationships may not have required sufficient active elaboration relative to general training to produce any additional learning (Craik &

Tulving, 1975). Incidentally, one might surmise that training with modeling *does* lead to superior performance because causal modeling requires active elaboration. For example, by actively manipulating symbols representing variables and relationships to form a circle, participants are more likely to recognize the "circular" nature of feedback. Understanding feedback as circular gives these participants an additional cue for recognizing feedback relationships.

Regardless of which explanation is most accurate, none seriously undermine the conclusion that modeling training fosters the development of mental models which improve performance. Participants in the modeling condition answered questions about scenarios more accurately than participants in either the cue utilization or general training condition. It seems reasonable to conclude that this difference in performance was due to the use of mental models fostered by conceptual-model training.

Utility of General Training

Research suggests that people may not be able to understand the nature of feedback relationships simply through experience. Sterman (1994) found that people have difficulty understanding the behavior of complex systems containing feedback, and Axelrod (1976) found that experts in a given domain do not recognize feedback relationships as such even when they recognize the constituting elements. Thus, training may fail to foster a general understanding of feedback relationships if explicit representational or cue-utilization guidance is not provided. Therefore, participants receiving only general training were expected to perform no differently than participants receiving no training.

This hypothesis received little support. On scenarios for which no testing aids were provided, participants with general training answered questions more accurately and more quickly. When testing aids were provided, participants with general training answered questions more accurately although not more quickly. Several potential explanations can be offered for this finding. Participants receiving general training may have outperformed those receiving no training because the former simply had more experience with the testing format. It is unlikely, however, that this factor alone can explain the large differences observed. In addition, the testing session began with a practice scenario and practice questions which should have mitigated against this potential confound.

An alternative interpretation of the findings is that some of the participants with only general training could have learned to conceptualize feedback even without explicit representational or cue-utilization guidance. Participants in the general training conditions still received explicit instruction on the nature of feedback relationships. These participants were not required to spontaneously recognize feedback loops or deviation amplification. Rather, they received explicit instruction on these concepts, studied numerous examples, answered questions about relationships, and received feedback on their answers. Studies showing that participants have difficulty understanding feedback relationships did not provide explicit instruction in the nature of feedback relationships, but rather required participants to deduce the concept from a system's behavior (Axelrod, 1976; Sterman, 1994). Thus, the intensive nature of the training materials may have partially compensated for the lack of explicit instruction in representational or cue-utilization guidance. Regardless of why general training was more effective than no training, the fact that modeling training produces better performance than general training suggests that explicit training in modeling adds value.

Use of the Mental Model

How Mental Models Improve Performance

If mental models improve performance by helping users manage working memory more efficiently (Larkin & Simon, 1987; Glenberg and Langston, 1992) and notice implicit relationships (Glenberg & Langston, 1992) then users should receive more benefit from an appropriate mental model when the target system is complex. Based on this proposition, participants were expected to derive more benefit from modeling training than from cue-utilization training on high complexity scenarios. Similarly, during testing, modeling aids were expected to add more benefit than cueing aids on high complexity scenarios.

Before discussing whether the specific interactions were observed, an unpredicted overall interaction between complexity and training must be examined. This interaction can be understood by recalling that participants performed worse on feedback questions and that the low complexity scenarios actually had more feedback questions. The interaction between complexity and training probably arose because the confounding effect of question type was exaggerated for participants in the no-training condition. These participants had no training in how feedback relationships differ from nonfeedback relationships, and so question type would have an even larger impact on their accuracy scores relative to its impact on other training conditions. Thus, at the no-training level, the impact of question type appears to have overwhelmed the competing effect of complexity, thus causing the mean for low complexity to dip below the mean for high complexity. When considering only feedback questions, the means for performance on low and high complexity scenarios at this level of training *are* in the expected direction, although the difference is not significant and thus the interaction between complexity and training is still significant. The fact that the means do not differ significantly is not surprising, however, when one recognizes that both means are well below a chance level of accuracy. Thus, the lack of understanding about feedback among the no-training participants creates a floor effect that prevents complexity from reaching significance for this condition of training.

Given the confounding of complexity by question type, the significance of the predicted interactions were tested using only the feedback questions. The four interactions examined (training by complexity and testing aid by complexity, on measures of accuracy and latency) failed to reach significance. However, the interaction between training and complexity approached significance on accuracy, and the differences between means were in the expected direction. The failure to obtain significance can be interpreted in several ways. One might speculate that the expected differences did not emerge because participants who trained in modeling or used modeling aids during testing were not actually utilizing a mental model to answer the questions. One could argue that these conditions merely provided a key to the correct answers, thereby making the level of complexity irrelevant. However, as explained above, the fact that the effect of training accounts for much more variance than the effect of testing aid suggests that providing a causal loop diagram does not simply reveal the correct answer. The data therefore suggest that participants benefit from training in how to use the causal diagram as a mental model.

One might also speculate that mental models based on causal loop diagrams do not aid performance in the way theory suggests. More specifically, perhaps mental models do not help users manage working memory or notice implicit relationships. It seems unlikely, however, that a mental model based on a causal loop diagram would not serve as a memory aid. Research with schematics similar in composition to a causal loop diagram suggests that the schematics can improve performance by freeing working memory resources (Hegarty. 1992; Hegarty & Just, 1993; Kieras, 1992). It also seems unlikely that the configuration of variables in a circle would not help users notice the emergent property of feedback, given the value of emergent features in visual displays (Sanderson et al., 1989).

The lack of significant interactions might also be attributed to methodological issues. Perhaps the interactions were masked by error variance contributed by participants who never mastered the training material. To examine this possibility, ANCOVAs were computed using only those participants who scored in the upper fiftieth percentile on training performance within their training condition. The interactions were not significant among this subset of participants, however, suggesting that the effect was not being masked by poor performance. Perhaps the most plausible explanation of the findings is that there was insufficient statistical power to detect an effect. Specifically, measurement error may have masked the effect. The dependent measures for feedback questions are based on 8 questions for the simple scenarios and only 3 questions for the complex scenarios. Adding questions (and scenarios) would likely yield more reliable measurement.

Spatial Ability

The configuration and kinematics of a causal loop diagram resemble the schematics used in mental model research (Hegarty & Just, 1993; Mayer, 1989a). Because spatial ability moderates a user's ability to use these schematics in motion verification tasks (Hegarty & Just, 1993; Hegarty & Sims, 1994), spatial ability was predicted to moderate performance in the present study. The results for accuracy support this hypothesis. This finding is significant in that the target systems in the present study were not ontologically spatial (e.g., a self-fulfilling prophecy is not a spatial phenomena). Past research has shown the correlation of spatial ability with performance only for schematics of target systems that are ontologically spatial (e.g., a pulley system; Hegarty & Sims, 1994). The present research increases the generalizability of this finding by demonstrating that spatial ability correlates with performance even for target systems where only the representation of the target system is spatial.

The fact that spatial ability does not account for variation in response time is not surprising given the many factors that affect this outcome. It is surprising, however, that spatial ability accounted for less variance on feedback questions (3%) than on the full set of questions (10%). One would expect that conceptualizing a feedback loop would require more spatial ability than understanding a linear relationship or no relationship. To understand this finding, one might assume that spatial ability cannot improve performance on feedback questions if the basic concept of feedback is not understood. Answering nonfeedback questions requires no special knowledge, so performance should be fairly normally distributed. Under these conditions spatial ability would moderate performance. Answering feedback questions, however, requires special knowledge of feedback, which might produce a bimodal distribution of performance scores driven by this qualitative difference in knowledge. Participants who understood the concept of feedback would do well whereas those that did not would perform at or below chance level. Under these conditions spatial ability would be less likely to affect performance, and thus a floor effect for spatial ability arises on feedback questions. The distribution of scores supports this interpretation. The variability in scores is larger for feedback questions ($\underline{SD}$ = .40, $\underline{M}$ = .52) than for all questions ($\underline{SD}$ = .27, $\underline{M}$ = .66), and the distribution of scores is bimodal for feedback questions but not for all questions. In addition, the average accuracy score is higher on all questions than on just feedback questions, indicating that participants do have more difficulty with feedback questions.

Future Research

A limitation of the current study is that the types of tasks used in testing require only near transfer. Transfer of training research suggests that the last stage of transfer requires adaptation of the source analog to the target analog (Novick & Holyoak, 1991), which can be inhibited by even minor semantic differences (Bassok, 1990). In the current study, little adaptation of the mental model was required, as participants were only asked to determine if a given variable would change a set amount, change continually, or not change. Other tasks might require a more thoroughly developed mental model and draw on a wider range of cognitive processes. A task requiring far transfer, for example, might ask participants to suggest several ways in which they could elicit a desired state change. Alternatively, participants could be asked how the system's configuration might be modified to bring about a particular pattern of behavior. For instance, participants playing the role of a management consultant might be asked to suggest policy in -ives that would create feedback loops leading to sustained growth in worker productivity. Examining performance on such far transfer tasks would provide more information on the value of training designed to foster mental models of positive feedback.

A related limitation is that the training material covered only positive feedback. Understanding complex systems often requires understanding negative feedback and how multiple feedback loops interact. Senge (1990) has identified several common configurations of feedback loops, or archetypes. Teaching these concepts would help participants develop a wider array of mental models that can be mapped onto causal systems.

Methodologically, it would be easier to demonstrate differences between different training conditions if the training produced a richer set of mental models. For example, an interaction of training by complexity might be more robust with more extensive training and a wider range of complexity among the problem solving tasks used during testing.

Summary

The present study makes at least four significant contributions to both theory and educational practice. First, the study demonstrates that conceptual models foster mental models that aid performance over and above that provided by cue-utilization guidance. This finding further strengthens the basic validity of the mental model construct and provides empirical support for the theoretical distinction suggested by Rouse and Morris (1986). Second, the study demonstrates that people learn and apply domain-general mental models of nonlinear systems, thereby adding breadth to the mental model construct. Third, the experimental design offers a research paradigm to system dynamics researchers for rigorously studying how people develop the ability to see common feedback structures underlying various causal systems. Fourth, the study offers a brief, hands-on training program that teaches people the concept of positive feedback and how to apply the concept to simple problem solving tasks. Although previous research has shown that people do not naturally think in terms of feedback (Axelrod, 1976), little rigorous research has examined how to teach such thinking skills. One indicator of the effectiveness of the training is that even the two training conditions which did not use conceptual models produced markedly better performance than the no-training condition. Although limited in scope, this training material on positive feedback can serve as the first module for a more comprehension educational program in systemic thinking.

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APPENDIX A

TRAINING MATERIAL FOR STUDY 1

Training Material v.3 revised 7/30/97

Basic Causal Relationships

In this study you will learn about causal models. A causal model is a figure that shows the cause and effect relationships among a set of variables. For example, given the following scenario...

> Accelerator:
> As you push down more on the car's accelerator, the engine will use more gas, which increases the speed of the car.

....we can create a causal model: **SEE FIGURE 1**

Here's how you read the causal model (look at Figure 1):

- More **Accelerator** leads to more **Gas used**, which leads to more **Speed**
  .... OR ....
- Less **Accelerator** leads to less **Gas used**, which leads to less **Speed**

Here's another scenario:

> Milk:
> People that drink more milk will have more calcium in their bodies, which will help develop better bone strength.

Q1: Which of these figures correctly represents the relationships in the Milk scenario:

a) Figure 2-a
b) Figure 2-b
c) Figure 2-c
d) Figure 2-d

> Answer: xxxbxxx:

Here's how you read the figure:

- More **Milk** leads to more **Calcium in body**, which leads to more **Bone strength**
  .... OR ....
- Less **Milk** leads to less **Calcium in body**, which leads to less **Bone strength**

Let's try another one:

> ***Read very carefully!!-- every part of each sentence is important.***

> Miscommunication:
> Sometimes co-workers have difficulty working together on a project. Mis-communication about how to complete the project can cause conflict between the coworkers and miscommunication can also cause delays in completing the project. Conflict itself can also cause delays because it takes the co-workers time to resolve their conflict. Finally, as conflict increases the co-workers will tend to avoid each other more and more.

Q2: Which of these figures correctly represents the relationships in the Miscommunication scenario:
a) Figure 3-a
b) Figure 3-b
c) Figure 3-c
d) Figure 3-d

Before looking at the correct answer, double-check your choice !!! – Read each sentence one at a time and see if your choice works.

Answer: xxxcxxx: Make sure you understand that two different variables affect **Delays**.

Here's how you read the figure:

- If **Miscommunication** increases there will be more **Conflict** and more **Delays**, and more **Conflict** will cause more **Delays** and **Avoidance**

  .... OR ....

- If **Miscommunication** decreases there will be less **Conflict** and fewer **Delays**, and less **Conflict** will cause less **Delays** and **Avoidance**

Let's try another one:

Confidence #1: Steve's mom was always lecturing him about how to succeed. She would say, "You should be confident and ambitious! Confident people are more likely to take risks and are more likely to put forth effort towards accomplishing their goals. Ambition is good because it makes you put forth effort. In the end, I think that the main cause of success is plain old effort."

Double-check!!! – make sure the model shows all the necessary relationships shown but no extra relationships.

Q3: Which of these figures correctly represents the relationships in the Confidence scenario:
a) Figure 4-a
b) Figure 4-b
c) Figure 4-c
d) Figure 4-d

Answer: xxxdxxx:

Use the figure (not your opinions!!!) to answer the following questions

Q4: *True or False*: As you become more ambitious, your confidence will increase.
➔➔➔➔ HINT: Use the figure!!!. ←←←←

Answer: xxxfxxxx. Look at the figure: The model shows no connection between **Ambition** and **Confidence**

Q5: *True or False*: As someone becomes more confident, they will then become more successful.

Answer: xxxtxxxx. Look at the figure: **Confidence** affects **Success** through **Effort** and **Success**.

Q6: *True or False*: As someone becomes less ambitious, they will then become less successful.

Answer: xxxtxxxx. **Confidence** affects **Success** through **Effort** and **Risk-taking**

Q7: *True or False*: As someone becomes less successful, they will become less confident.

Answer: xxxfxxxx. **Confidence** affects **Success**, but **Success** doesn't affect **Confidence**.

Q8: *True or False*: As someone takes more risks, they will become more confident

Answer: xxxfxxxx. **Confidence** affects **Risk-taking**, but **Risk-taking** doesn't affect **Confidence**

Let's try another scenario:

Education:
Few people would argue that education isn't a valuable thing. Research shows that as people get more education they earn a higher income, have more social status, and also become more liberal. In addition, income itself tends to increase status, and it also increases the number of financial investments a person makes. Overall, it's no surprise that many people want to increase their level of education.

Q9: Which of these figures correctly represents the relationships in the Education scenario:
a) Figure 5-a
b) Figure 5-b
c) Figure 5-c
d) Figure 5-d

Always double-check – compare the scenario and your choice to make sure you're correct!!

Answer: xxxaxxx:

Answer the following question **USING THE FIGURE! – not your own opinions**

Q10: According to the model, you could increase the number of financial investments you make by__
a) increasing your level of education
b) earning more income
c) increasing your social status
d) a and b
e) a, b, and c

Answer: xxxdxxxx. Both **Education** and **Income** affect **Investments**, but **Status** does not.

Q11: *True or False*: As a person becomes more liberal, the person earns a higher income.

Answer: xxxfxxxx. Being politically **Liberal** does not affect a person's **Income**.

Q12: *True or False*: As a person achieves higher social status, they will eventually become more educated.

> Answer: xxxfxxxx. Although **Education** affects **Status**, **Status** does not affect **Education**.

Positive Feedback

In some situations, a variable can affect other variables that then, in turn, affect the first variable. In other words, the change in the first variable is ***fed-back*** to the first variable. In **positive feedback** relationships, any initial change (i.e., a decrease or increase in a variable's value) will be **amplified**. A **snowball effect**, a **self-fulfilling prophecy**, and a **vicious cycle** are examples of positive feedback. Think about a feud:

> Feud:
> Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge.
> - If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields.
> - If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Q13: What model is correct?
a) Figure 6-a
b) Figure 6-b
c) Figure 6-c

> Answer: xxxcxxx: Both variables affect each other, so the model must show this.

THIS IS VERY IMPORTANT:

- With non-feedback relationships, an initial increase or decrease in a variable affects other variables just a limited amount and then ***change stops***.
- With positive feedback, an initial increase or decrease in a variable leads to continual change -- the increase or decrease is ***continually amplified.***

Q14: If McCoy killing initially increases, then over time McCoy killing will ____.
a) increase a limited amount
b) increase continually
c) not change

> Answer: xxxbxxxx. **McCoy killing** and **Hatfield killing** form a positive feedback loop -- more **McCoy killing** causes more **Hatfield killing** which causes more **McCoy killing** etc. -- the change is amplified continually.

Q15: If Hatfield killing initially decreases, then over time Hatfield killing will ____.
a) increase a limited amount
b) increase continually
c) not change
d) decrease continually

> Answer: xxxdxxxx. The positive feedback will amplify the decrease. A decrease in **Hatfield killing** will lead to a decrease in **McCoy killing**, which will lead to a decrease in **Hatfield killing**, which will lead to a decrease in **McCoy killing**, etc. -- the change is continual.

Identifying Positive Feedback

Some of these scenarios will have feedback, some will not.

Q16: Create a figure for this scenario:

<u>Sales</u>: As a company makes more sales, it generates more revenue, which allows it to hire more salespeople, which leads to more sales.

- Compare your figure to **FIGURE 7** and then **make corrections to your figure**
- Is there any feedback in this scenario? yes or no?

Remember, if you can trace the effect of <u>any variable</u> back to itself then there's feedback.

Answer: xxxyxxxx: **Sales** affects itself
- <u>more</u> **Sales** will lead to even <u>more</u> **Sales**
- <u>fewer</u> **Sales** will lead to even <u>fewer</u> **Sales**

You can use abbreviations in your figures.

Q17: Create a figure for this scenario:

<u>Practice</u>: Piano players that practice longer develop more skill and therefore can play better music. The longer you practice the more fatigued you become.

- Compare your figure to **FIGURE 8** and then **make corrections to your figure** (e.g., **MAKE SURE IT HAS THE SAME BASIC SHAPE!**)
- Is there any feedback in this scenario? yes or no?

Answer: xxxnxxxx: **Practice** does not affect itself.

Unless otherwise noted, each scenario is independent of other scenarios.

Q18: Create a figure for this scenario:

<u>Satisfaction</u>: More practicing leads to greater skill and greater fatigue. Greater skill leads to better music, which leads to greater satisfaction, which leads to more practicing

- Compare your figure to **FIGURE 9** and then **make corrections to your figure**
- Is there any feedback in this scenario? yes or no?

Answer: xxxyxxxx. **Practice** affects itself.

Be sure to correct your figure so it has the same basic shape -- e.g., a circle

Q19: Create a figure for this scenario:

Jobs: As a city grows it attracts more business, which creates more jobs, which attracts more people to the city, which makes the city grow.

- Compare your figure to **FIGURE 10** and then **make corrections to your figure**
- Is there any feedback in this scenario? yes or no?

Answer: xxxyxxxx. **Growth** affects itself.

Q20: Create a figure for this scenario:

Crime: As a city grows more social problems develop which increase crime

- Compare your figure to **FIGURE 11** and then **make corrections to your figure**
- Is there any feedback in this scenario? yes or no?

Answer: xxxnxxx. **Growth** does not affect itself.

Q21: Create a figure for this scenario:

Quality: As the quality of a product improves two things happen: more products are sold and more customers are satisfied with the product

- Compare your figure to **FIGURE 12** and then **make corrections to your figure**
- Is there any feedback in this scenario? yes or no?

Answer: xxxnxxxx: **Product quality** does not affect itself.

Remember, if you can trace the effect of any variable back to itself then there's feedback.

Q22: Create a figure for this scenario:

Exposure: As the quality of a product improves more products will be sold, which means the product will get more exposure to potential customers, which means more products will be sold to these potential customers.

- Compare your figure to **FIGURE 13** and then **make corrections to your figure**
- Is there any feedback in this scenario? yes or no?

Answer: xxxyxxx. **Products sold** affects itself.

Complex Examples of Positive Feedback

Positive feedback is often mixed in with other non-feedback relationships. Before we try a scenario with words, let's try one with just letters so you can practice drawing and reading scenarios that mix feedback with non-feedback relationships.

Q23: Create a **single figure** for the following scenario:

> Generic #1:
> - **A** affects **B**, which in turn affects **C**, which in turn affects **D**, which then affects **A**.
> - **G** affects **F**, which in turn leads **F** to affect **A**.
> - **E** affects **H**; and **B** affects **E**.

When you're finished, compare your figure to **FIGURE 14**. Be sure to **correct your figure**.

Q24: If **G** increases by a limited amount, then **F** will _____
- a) increase a limited amount
- b) increase continually
- c) not change

> Answer: xxxaxxxx. **F** is not affected by positive feedback, so it will only increase a limited amount.

Q25: If **A** initially increases by a limited amount, then over time **A** will _____
- a) increase a limited amount
- b) increase continually
- c) not change

> Answer: xxxbxxxx. **A** is affect by positive feedback (**A** to **B** to **C** to **D** back to **A**), so once **A** starts increasing it will just keep on increasing.

Q265: If **F** initially decreases by a limited amount, then over time **G** will _____
- a) decrease at limited amount
- b) decrease continually
- c) not change

> Answer: xxxcxxxx. **F** doesn't affect **G**.

Q27: If **A** initially decreases by a limited amount, then over time **B** will ____
- a) decrease at limited amount
- b) decrease continually
- c) not change

> Answer: xxxbxxxx. **B** is affect by positive feedback (**B** to **C** to **D** to **A** back to **B**), so once it starts decreasing it will just keep on decreasing.

Q28: If **A** initially increases by a limited amount, then over time **E** will ____ [*be careful! -- think about what continues to happen to B over time*]

a) increase a limited amount
b) increase continually
c) not change

Answer: xxxbxxxx. **B** is affected by positive feedback, so if **B** is increasing continuously, **B** will continuously cause **E** to increase

Q29: If **A** initially decreases by a limited amount, then over time **H** will ____

a) decrease a limited amount
b) decrease continually
c) not change

Answer: xxxbxxxx. **B** is affected by positive feedback, so if **B** is decreasing continuously, **B** will continuously cause **H** to decrease.

Q30: If **E** initially increases by a limited amount, then over time **H** will ____

a) increase a limited amount
b) increase continually
c) not change

Answer: xxxaxxxx. No positive feedback has been activated, so **H** will only increase a limited amount.

Q31: If **F** initially decreases by a limited amount, then over time **D** will ____

a) decrease a limited amount
b) decrease continually
c) not change

Answer: xxxbxxxx. **F** affects **A**, which triggers positive feedback that makes **D** decrease continuously .

Q32: If **G** initially increases by a limited amount, then over time **C** will ____

a) increase a limited amount
b) increase continually
c) not change

Answer: xxxbxxxx. **G** affects **C**, which triggers positive feedback that makes **C** decrease continuously.

Review

Before we move on, let's review what you've learned.

Q33: *Write a __single__ rule that explains why the following statements are true*:

- If **G** increases by a limited amount, then **F** will increase by a limited amount (not continuously).
- If **E** increases by a limited amount, then **H** will increase by a limited amount (not continuously).

HINT!!! -- Look at the figure -- think about how the underlying relationships are similar.

Answer: If positive feedback is not activated, the variables will only change a limited amount and then stop changing. For example, increasing **G** and **E** doesn't activate the positive feedback, so the variables they affect won't change continuously.

Q34: *Write a* ***single*** *rule that explains why the following statements are true:*

- If **A** increases initially, then **B** will increase continually (not just a limited amount).
- If **B** increases initially, then **C** will increase continually (not just a limited amount).
- If **D** increases initially, then **D** will increase continually (not just a limited amount).

Answer: If you increase (or decrease) a variable in a positive feedback chain, all the other variables in that chain will also increase (or decrease) continually. For example, if you increase **A**, **B**, **C**, or **D**, all of these variables will increase continually.

Q35: *Write a* ***single*** *rule that explains why the following statements are true:*

- If **A** increases initially, then **E** and **H** will increase continually (not just a limited amount).
- If **B** increases initially, then **E** and **H** will increase continually (not just a limited amount).
- If **D** increases initially, then **E** and **H** will increase continually (not just a limited amount).

Answer: Once the positive feedback starts, variables in the positive feedback will change continuously, as will other variables affected by variables in the positive feedback. In other words, because **B** will start changing continuously, variables **E** and **H** will also change continuously as a "side-effect" of the continuous change in **B**.

Q36: *Write a* ***single*** *rule that explains why the following statements are true:*

- If **G** increases initially, then **E** and **H** will increase continually (not just a limited amount).
- If **F** increases initially, then **E** and **H** will increase continually (not just a limited amount).

Answer: Changing a variable that triggers positive feedback will lead to continuous change in any variable affected by a variable in the positive feedback. For example, an increase in **G** or **F** will trigger the positive feedback by affected **A**. Once the feedback starts, **B** will increase continuously, which will lead **E** and **H** to increase continuously.

More practice with complex examples

Now let's practice with some complex scenarios. Answer the questions based on the scenario and the figure. *Note: Except for the* ***bold*** *text, you've seen this scenario before.*

Education #2:
Few people would argue that education isn't a valuable thing. Research shows that as people get more education they earn a higher income, have more social status, and become more liberal. In addition, income itself tends to increase status, and it also increases the number of financial investments a person makes. **Finally, the more**

investments someone makes the more income they'll get from their investments. Overall, it's no surprise that many people want to increase their level of education.

STOP ➔➔➔ See FIGURE 15

Think about this -- it makes sense. The model says that the **rich get richer** -- the more they make. the more they invest, and so the more they make -- and so on.

Q37: If someone increases their income, the extent to which they are politically liberal will
a) increase a limited amount
b) increase continually
c) not change

Answer: xxxcxxxx. There is no way that a change in **Income** level can influence how **Liberal** someone is.

Q38: If someone makes more income, their level of investing will
a) increase a limited amount
b) increase continually
c) not change

Answer: xxxbxxxx. The positive feedback between **Income** and **Investments** will amplify the increase in **Income** over time, which will then increase the level of **Investments** over time.

Q39: If someone becomes more educated, their status will
a) increase a limited amount
b) increase continually
c) not change

Be careful !!! -- Look for an indirect effect.

Answer: xxxbxxx. **Education** increases **Income,** which sets off the feedback cycle so that **Income** increases continually. Once **Income** is increasing continually, then it will continually cause **Status** to increase.

Q40: If someone makes more income, their status will (*be careful!!!!*)
a) increase a limited amount
b) increase continually
c) not change

Answer: xxxbxxxx. The positive feedback between **Income** and **Investments** will amplify the initial increase in **Income.** In addition, **Income** affects **Status,** so **Status** will increase as **Income** increases. In other words, the increase in **Status** is a side-effect -- as **Income** increases, **Status** comes along for the ride.

Let's try another one. *Note: Except for the **bold** text, you've seen this scenario before.*

Confidence #2: Steve's mom was always lecturing him about how to succeed. She would say, "You should be confident and ambitious! Confident people are more likely to take risks and are more likely to put forth effort towards accomplishing their goals.

Ambition is good because it makes you put forth effort. **Ambition also makes you more willing to take risks.** In the end, I think that the main cause of success is plain old effort. **I also think that the more success you experience the more confident you become.**"

STOP →→→ See FIGURE 16

Think about this -- it's a **self-fulfilling prophecy** -- confident people (i.e., people that believe in themselves) do things that eventually make them even more confident, and people who lack confidence do things that make them less and less confident.

Q41: If someone becomes less confident initially, over time their success will
- a) decrease a limited amount
- b) decrease continually
- c) not change

Answer: xxxbxxxx. If **Confidence** decreases, the positive feedback (**Confidence** to **Effort** to **Success** back to **Confidence**) will make **Success** decrease further and further over time.

Q42: If someone becomes more confident their level of ambition will ____.
- a) increase a limited amount
- b) increase continually
- c) not change

Answer: xxxcxxxx. Nothing in the model affects **Ambition**, so it won't change.

Q43: If someone becomes more confident their level of risk-taking will
- a) increase a limited amount
- b) increase continually
- c) not change

Answer: xxxbxxxx. If **Confidence** increases, the positive feedback is triggered, so **Confidence** will increases continually, so **Confidence** will continually increase **Risk-taking**.

Q44: If someone becomes less ambitious their level of confidence will
- a) decrease a limited amount
- b) decrease continually
- c) not change

Answer: xxxbxxxx. If **Ambition** decreases, the positive feedback is triggered, so **Confidence** will decrease continually.

Q45: If risk-taking decreases by a set amount, over time success will
- a) decrease a limited amount
- b) decrease continually
- c) not change

Answer: xxxcxxxx. **Risk-taking** does not affect **Success**.

Q46: If someone becomes more ambitious, then their level of risk-taking will

a) increase a limited amount
b) increase continually
c) not change

Be careful !!! -- Look for an indirect effect!!!

Answer: xxxbxxxx. If **Ambition** increases, the positive feedback is triggered (**Ambition** affects **Effort**). Once the positive feedback gets going, **Confidence** will increase continually, and **Confidence** will increase **Risk taking** continually.

FIG. 1

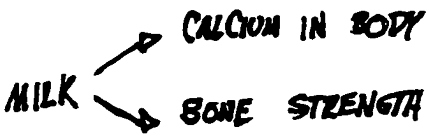


FIG. 2A

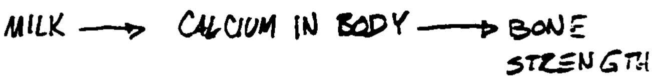


FIG. 2-B

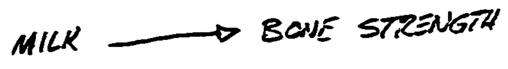


FIG. 2-C

FIG. 2-D

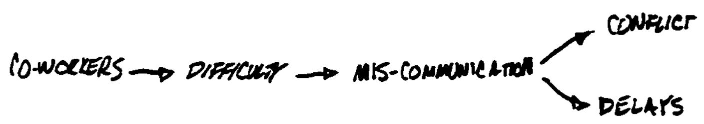


FIG. 3-A

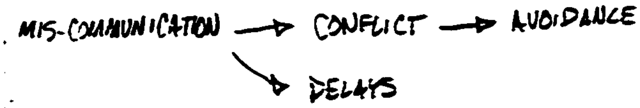


FIG. 3-B

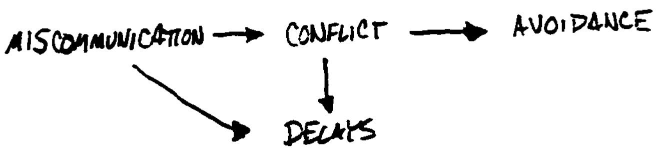


FIG 3-C

FIG. 3-D

FIG. 4-A.

FIG. 4-B

FIG. 4-C

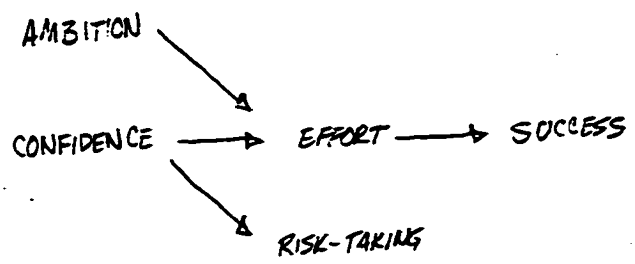


FIG. 4-D

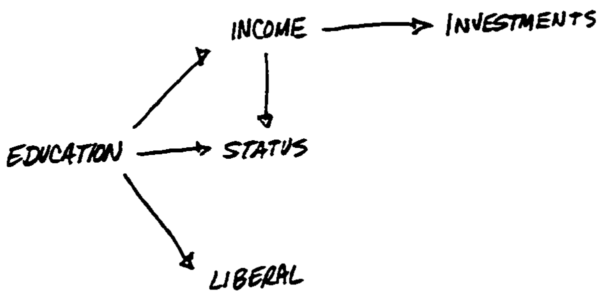


FIG. 5-A

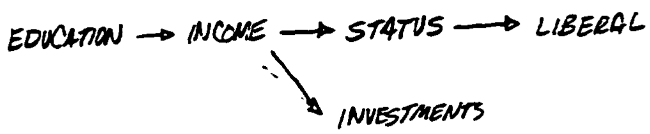


FIG. 5-B

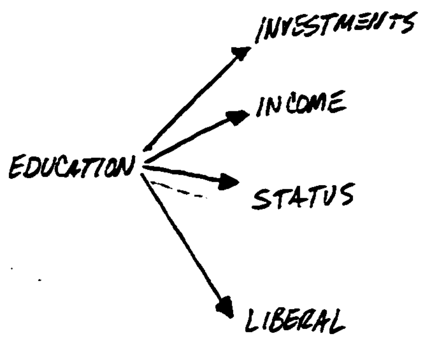


FIG. 5-C

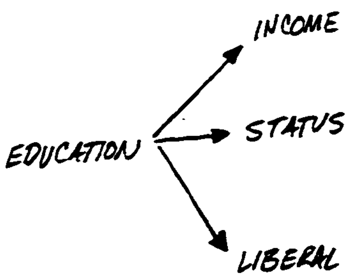


FIG. 5-D

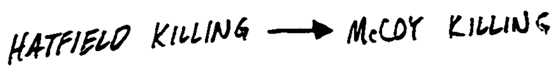


FIG. 6-A.

FIG. 6-B

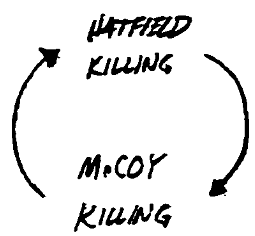


FIG 6-C

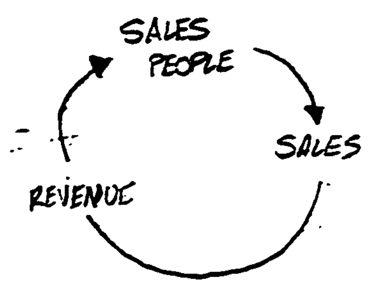


FIG. 7

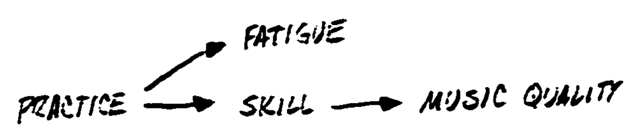


FIG. 8

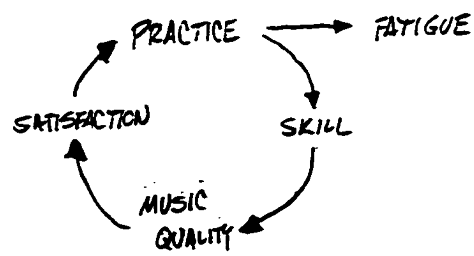


FIG. 9

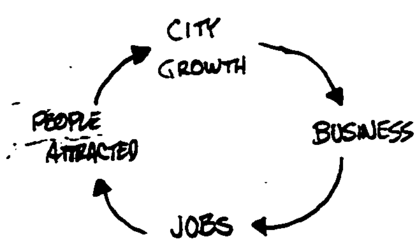


FIG. 10

FIG. 11

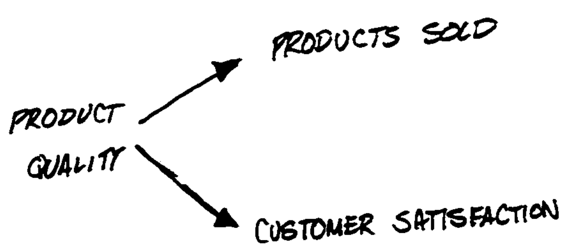


FIG. 12

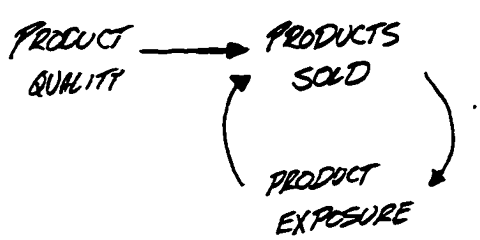


FIG. 13

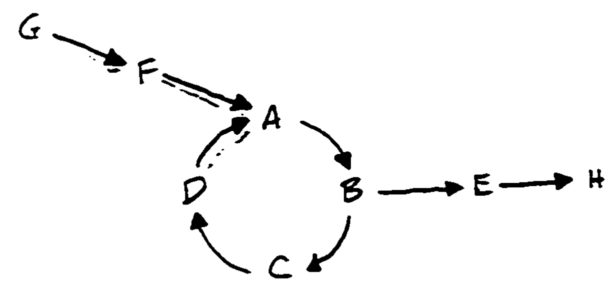


FIG. 14

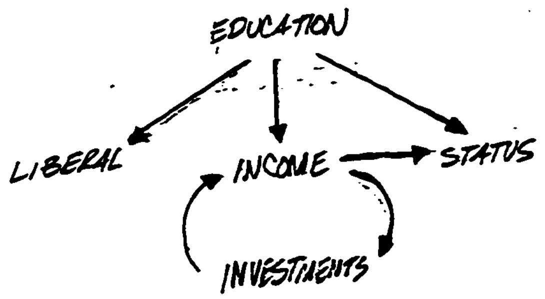


FIG. 15

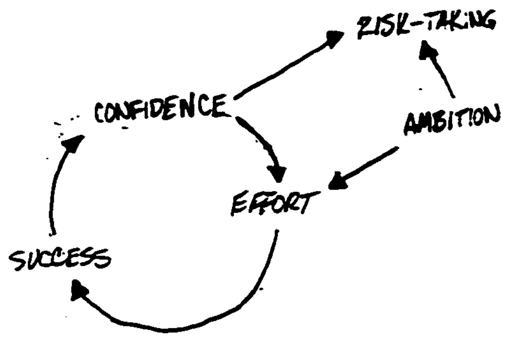


FIG. 16

APPENDIX B

TESTING MATERIAL FOR STUDY 1

You will now be presented with several scenarios. Each scenario describes a set of cause and effect relationships for several variables. For each scenario you must do the following:

1. Read the scenario on the computer screen.
2. Take notes and/or draw a picture that will help you understand the scenario.
3. Answer the questions about the scenario.

Now let's do one for practice.

Read the following scenario:

****

PRACTICE SCENARIO: FINANCIAL EXPERTISE
The more financial expertise someone has the better the quality of their investments. The better the quality of investments the wealthier a person becomes.

****

Now take notes and/or draw a picture that will help you understand the scenario. Use the pencil and sheet of paper labelled "Example."

HINT: Take your time! The better you understand the scenario, the more quickly and accurately you can answer questions about the scenaro.

Now answer questions about the scenario. You can use both your notes and the scenario itself.

NOTE: USE ONLY THE INFORMATION PRESENTED IN THE SCENARIO – DON'T JUST PICK AN ANSWER BASED ON COMMON SENSE.

P1. If a person's financial expertise increases a set amount, over time her wealth will ____
  a) increase a set amount
  b) increase continually
  c) not change

The correct answer is "a"
Financial expertise would increase investment quality, which in turn would increase wealth. The changes would then stop.

P2. If a person's wealth decreases a set amount, over time her financial expertise will ____
  a) decrease a set amount
  b) decrease continually
  c) not change

The correct answer is "c"

Wealth does not affect financial expertise.

Now let's begin the test.

Read the following scenario:

****

SCENARIO: KNOWLEDGE
As people gain more knowledge their comprehension of new material will improve. Better comprehension allows people to integrate information more effectively, which in turn helps them gain more knowledge.

****

Take notes and/or draw a picture that will help you understand the scenario.

##. As knowledge increases a set amount, over time comprehension will ____
a) increase a set amount
b) increase continually
c) not change

##. As comprehension decreases a set amount, over time knowledge will ____
a) decrease a set amount
b) decrease continually
c) not change

##. As integration decreases a set amount, over time knowledge will ____
a) decrease a set amount
b) decrease continually
c) not change

##. If knowledge decreases a set amount, then integration will ____
a) decrease a set amount
b) decrease continually
c) not change

Read the following scenario:
****
SCENARIO: SKILLED EMPLOYEES
As the number of skilled employees working at an organization increases the organization becomes more effective. As the organization becomes more effective it becomes better able to satisfy customers.
****

Take notes and/or draw a picture that will help you understand the scenario.

##. As the satisfaction of customers drops by a set amount, then over time the effectiveness of the organization will ____
a) decrease a set amount
b) decrease continually
c) not change

##. If the number of skilled employees decreases by a set amount, then over time the effectiveness of the organization will ____
a) decrease a set amount
b) decrease continually
c) not change

##. If the number of skilled employees increases a set amount, then over time the satisfaction of customers will ____
a) increase a set amount
b) increase continually
c) not change

##. If the effectiveness of the organization decreases a set amount, then over time the number of skilled employees will ____
a) decrease a set amount
b) decrease continually
c) not change

Read the following scenario:
****

SCENARIO: UNIVERSITY'S REPUTATION
As a university develops a more prestigious reputation it is better able to solicit large contributions from rich donors. As the university gets more contributions it is able to attract more prestigious faculty. By attracting more prestigious faculty the university improves its reputation.
****

Take notes and/or draw a picture that will help you understand the scenario.

##. As the number of contributions increases a set amount, over time the attraction of prestigious faculty will ____
a) increase a set amount
b) increase continually
c) not change

##. If the university's reputation increases a set amount, over time the attraction of prestigious faculty will ____
a) increase a set amount
b) increase continually
c) not change

##. As the number of contributions decreases a set amount. over time the university's reputation will ____
a) decrease a set amount
b) decrease continually
c) not change

##. As more prestigious faculty attracted decreases, over time the number of contributions will ____
a) decrease a set amount
b) decrease continually
c) not change

Read the following scenario:
****
SCENARIO: ALCOHOL CONSUMPTION
Some people have difficulty with alcohol. As they experience more problems in their life these people have more desire to avoid their problems, which leads to excessive drinking of alcohol. In addition, exposure to certain social situations can lead to more excessive drinking. More excessive drinking causes more problems. As the number of problems increases stress increases, which leads to more illness.
****

Take notes and/or draw a picture that will help you understand the scenario.

##. As stress increases by a set amount, over time illness will ____
a) increase a set amount
b) increase continually
c) not change

##. If exposure to social situations decreases by a set amount. then over time stress will ____
a) decrease a set amount
b) decrease continually
c) not change

##. As stress increases a set amount, over time excessive drinking will ______
a) increase a set amount
b) increase continually
c) not change

##. As a desire to avoid problems increases a set amount, over time exposure to social situations will ____

a) decrease a set amount
b) decrease continually
c) not change

Read the following scenario:
****

SCENARIO: TEACHING
A teacher who becomes more enthusiastic about teaching will increase the quality of the course being taught. As the quality of the course increases students will be more responsive to the teacher, which in turn will increase the teacher's self-esteem. The support of the principal is very important. If the principal becomes more supportive then the teacher will become more enthusiastic about teaching, the teacher's self-esteem will increase, and student discipline will improve. Finally, as students become more responsive to the teacher the teacher will become more enthusiastic about teaching.
****

Take notes and/or draw a picture that will help you understand the scenario.

##. If teacher enthusiasm decreases by a set amount, then over time the support of the principal will ____
a) decrease a set amount
b) decrease continually
c) not change

##. If the support of the principal increases a set amount, then over time the teacher's self-esteem will ____
a) increase a set amount
b) increase continually
c) not change

##. If the support of the principal increases a set amount, then over time student discipline will ____
a) increase a set amount
b) increase continually
c) not change

##. If teacher enthusiasm increases by a set amount, over time student responsiveness will ____
a) decrease a set amount
b) decrease continually
c) not change

Read the following scenario:
****

SCENARIO: PREJUDICE
As a society becomes more prejudice against a minority group (e.g., Hispanics) there will be more job discrimination towards that minority. This discrimination will then lead to more poverty and under-achievement for that minority. Under-achievement, in turn, leads to a greater perception of inferiority, which then leads to more prejudice. Economic problems are also important. Economic problems lead to more prejudice and to more poverty. More poverty, in turn, leads to more suffering.
****

Take notes and/or draw a picture that will help you understand the scenario.

##. If under-achievement of the minority increases a set amount, then over time poverty will ____
a) increase a set amount
b) increase continually
c) not change

##. If poverty increases by a set amount, over time suffering will ____

a) decrease a set amount
b) decrease continually
c) not change

##. If prejudice increases by a set amount, then over time economic problems will ____
a) increase a set amount
b) increase continually
c) not change

##. If economic problems increase a set amount, then over time poverty will ____
a) increase a set amount
b) increase continually
c) not change

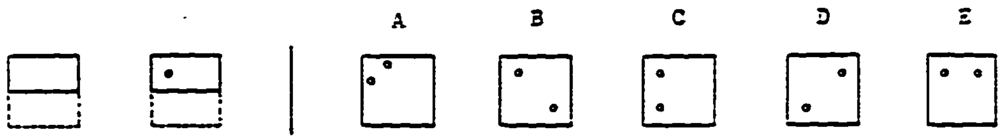
APPENDIX C

SPATIAL ABILITY MEASURE, PAPER FOLDING TEST VZ-2

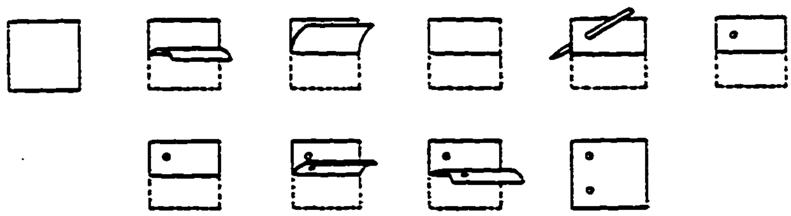
PAPER FOLDING TEST — VZ-2

In this test you are to imagine the folding and unfolding of pieces of paper. In each problem in the test there are some figures drawn at the left of a vertical line and there are others drawn at the right of the line. The figures at the left represent a square piece of paper being folded, and the last of these figures has one or two small circles drawn on it to show where the paper has been punched. Each hole is punched through all the thicknesses of paper at that point. One of the five figures at the right of the vertical line shows where the holes will be when the paper is completely unfolded. You are to decide which one of these figures is correct and draw an X through that figure.

Now try the sample problem below. (In this problem only one hole was punched in the folded paper.)



The correct answer to the sample problem above is C and so it should have been marked with an X. The figures below show how the paper was folded and why C is the correct answer.



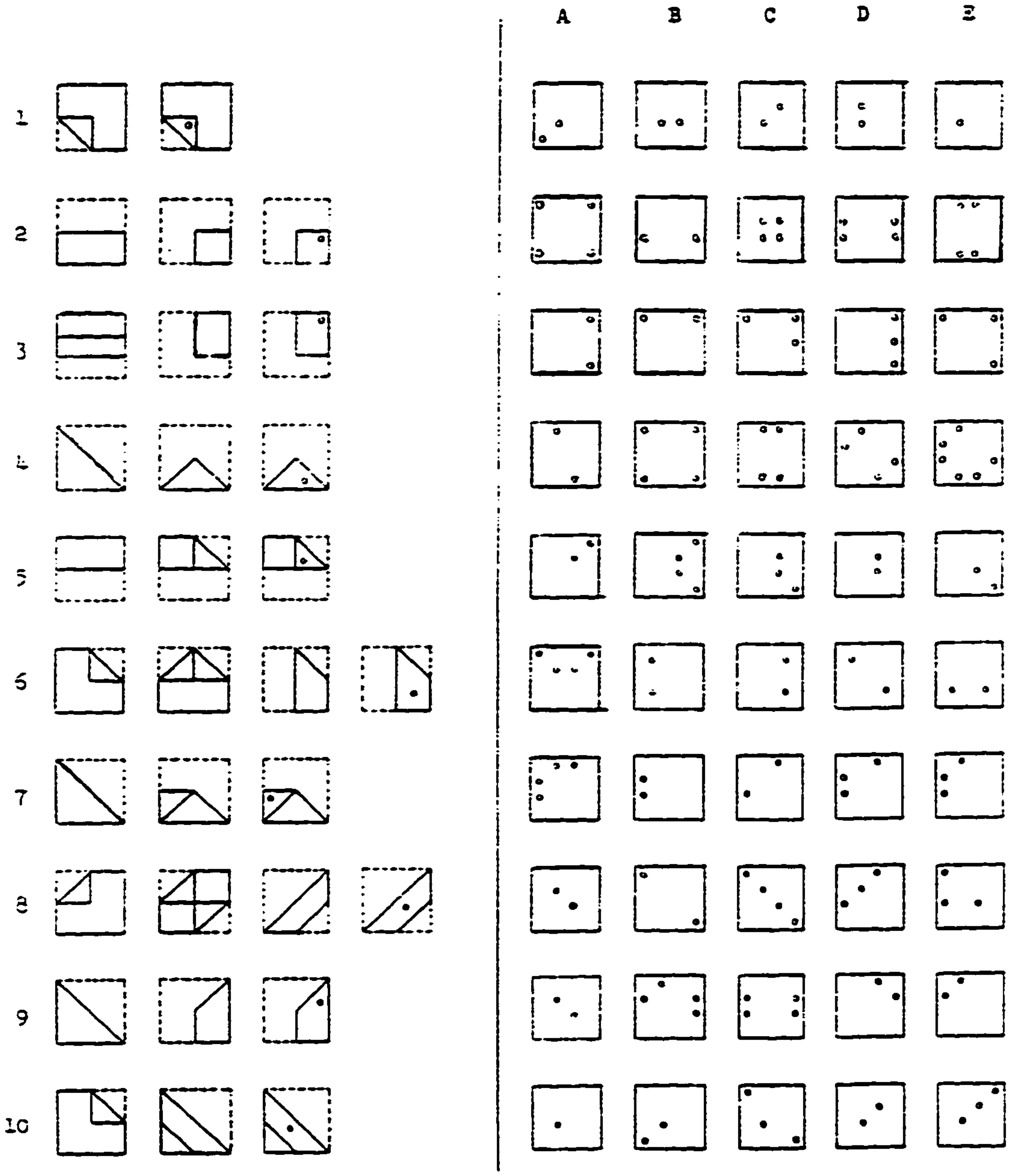
In these problems all of the folds that are made are shown in the figures at the left of the line, and the paper is not turned or moved in any way except to make the folds shown in the figures. Remember, the answer is the figure that shows the positions of the holes when the paper is completely unfolded.

Your score on this test will be the number marked correctly minus a fraction of the number marked incorrectly. Therefore, it will not be to your advantage to guess unless you are able to eliminate one or more of the answer choices as wrong.

You will have 3 minutes for each of the two parts of this test. Each part has 1 page. When you have finished Part 1, STOP. Please do not go on to Part 2 until you are asked to do so.

DO NOT TURN THIS PAGE UNTIL ASKED TO DO SO.

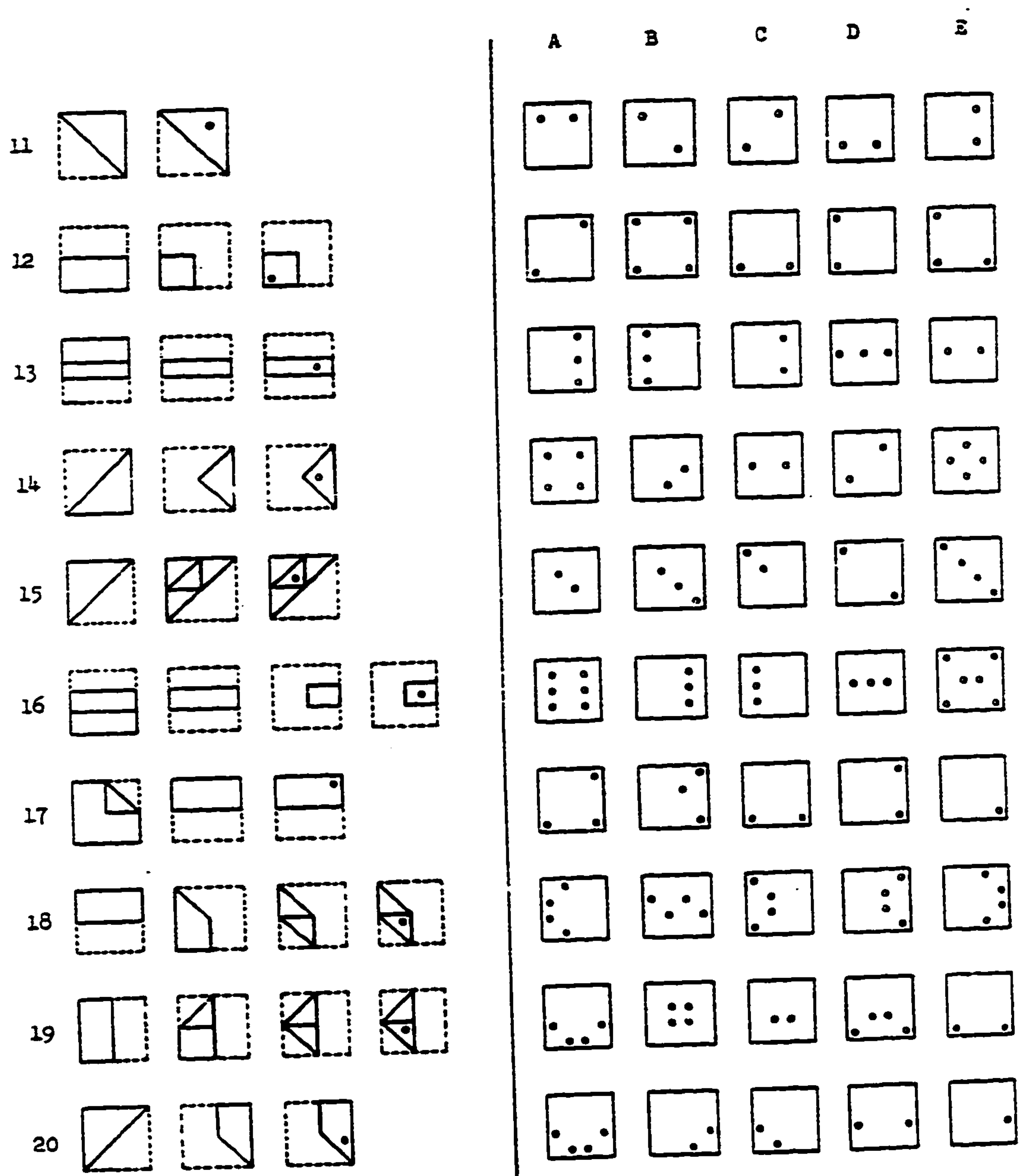
Part 1 (3 minutes)



DO NOT GO ON TO THE NEXT PAGE UNTIL ASKED TO DO SO.

STOP.

Part 2 (3 minutes)



DO NOT GO BACK TO PART 1, AND

DO NOT GO ON TO ANY OTHER TEST UNTIL ASKED TO DO SO. STOP.

APPENDIX D

SAMPLES OF TRAINING MATERIAL FOR STUDY 2

[Excerpt from materials used in modeling training condition]

*****************[New Screen]*********************
POSITIVE FEEDBACK

In some situations, a variable can affect other variables that then, in turn, affect the first variable. In other words, the change in the first variable is fed-back to the first variable.

In positive feedback relationships, any initial change (i.e., a decrease or increase in a variable's value) will be amplified.

A snowball effect, a self-fulfilling prophecy, and a vicious cycle are examples of positive feedback.

Think about a feud:

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Q13: Which model is correct?

a) Figure 6-a
b) Figure 6-b
c) Figure 6-c

*****************[New Screen]*********************
c. Both variables affect each other, so the model should look like a circle.

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Feedback affects how much change occurs.

--> With non-feedback relationships, an initial increase or decrease causes just a limited change.

--> With positive feedback, an initial increase or decrease
leads to continual change. The increase or decrease is
continually amplified.

Use this information to answer these questions:

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Q14: If McCoy killing initially increases, then over time McCoy killing will ____.
a) increase a limited amount
b) increase continually
c) not change

*****************[New Screen]*********************

b. McCoy killing and Hatfield killing form a positive feedback loop -- think of it as a circle that starts spinning and then just keeps spinning -- more McCoy killing causes more Hatfield killing which causes more McCoy killing, etc. -- the change is amplified continually.

[Excerpt from materials used in cue-utilization training condition]

*****************[New Screen]*********************
POSITIVE FEEDBACK

In some situations, a variable can affect other variables that then, in turn, affect the first variable. In other words, the change in the first variable is fed-back to the first variable.

In positive feedback relationships, any initial change (i.e., a decrease or increase in a variable's value) will be amplified.

A snowball effect, a self-fulfilling prophecy, and a vicious cycle are examples of positive feedback.

Think about a feud:

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Q13: Which model is correct?
a) Figure 6-a
b) Figure 6-b
c) Figure 6-c

*****************[New Screen]*********************
c. Both variables affect each other, so the model must show this.

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Feedback affects how much change occurs.

--> With non-feedback relationships, an initial increase or decrease causes just a limited change.

--> With positive feedback, an initial increase or decrease
leads to continual change. The increase or decrease is
continually amplified.

Use this information to answer these questions:

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Q14: If McCoy killing initially increases, then over time McCoy killing will ____.

a) increase a limited amount
b) increase continually
c) not change

*****************[New Screen]*********************

b. McCoy killing and Hatfield killing form a feedback relationship -- more McCoy killing causes more Hatfield killing which causes more McCoy killing, etc. -- the change is amplified continually.

[Excerpt from materials used in general training condition]

*****************[New Screen]*********************
POSITIVE FEEDBACK

In some situations, a variable can affect other variables that then, in turn, affect the first variable. In other words, the change in the first variable is fed-back to the first variable.

In positive feedback relationships, any initial change (i.e., a decrease or increase in a variable's value) will be amplified.

A snowball effect, a self-fulfilling prophecy, and a vicious cycle are examples of positive feedback.

Think about a feud:

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Q13: Which is correct?
a) An increase in Hatfield killing will increase McCoy killing
b) An increase in McCoy killing will increase Hatfield killing
c) a & b

*****************[New Screen]*********************
c. Both variables affect each other.

*****************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Feedback affects how much change occurs.

--> With non-feedback relationships, an initial increase or decrease causes just a limited change.

--> With positive feedback, an initial increase or decrease

leads to continual change. The increase or decrease is continually amplified.

Use this information to answer these questions:

******************[New Screen]*********************

Feud: Imagine that there is a feud between the Hatfield and the McCoy families. Whenever one family kills members of the other family, the other family seeks revenge. If the Hatfields kill more McCoys, then the McCoys will kill more Hatfields. If the McCoys kill more Hatfields, then the Hatfields will kill more McCoys.

Q14: If McCoy killing initially increases, then over time McCoy killing will ____.

a) increase a limited amount
b) increase continually
c) not change

******************[New Screen]*********************

b. McCoy killing and Hatfield killing create positive feedback -- more McCoy killing causes more Hatfield killing which causes more McCoy killing, etc. -- the change is amplified continually.

[Figures used in modeling condition of training]

HATFIELD KILLING → McCOY KILLING

FIG 6A

McCOY KILLING → HATFIELD KILLING

FIG 6-B

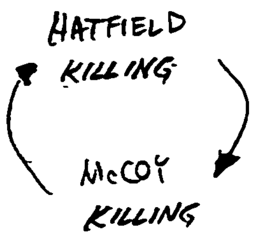


FIG 6-C

[Figures used in cue-utilization condition of training]

HATFIELD KILLING affects McCOY KILLING

FIG. 6A

McCOY KILLING affects HATFIELD KILLING

FIG. 6-B

HATFIELD KILLING affects McCOY KILLING

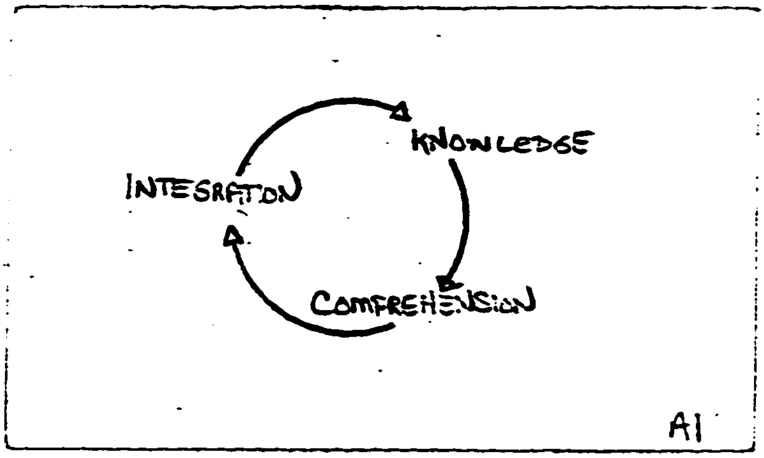
McCOY KILLING affects HATFIELD KILLING

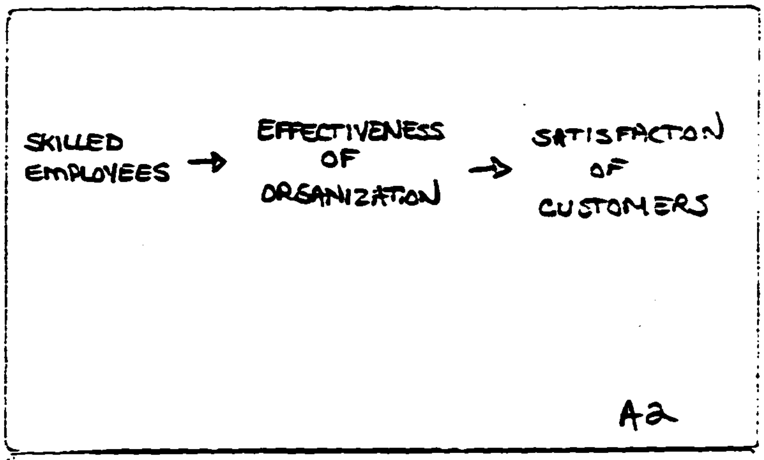
FIG. 6-C

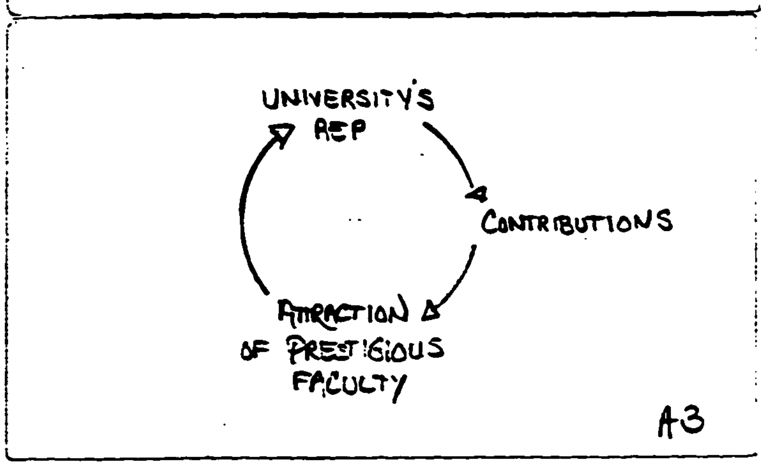
APPENDIX E

TESTING AIDS USED IN TESTING FOR STUDY 2

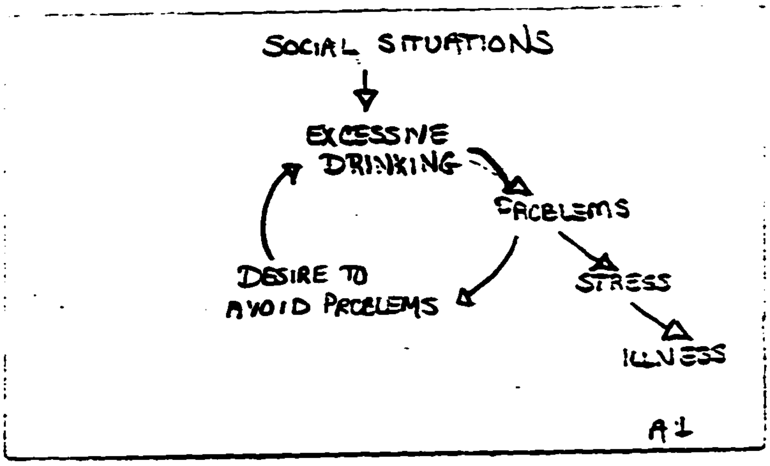
[Figures used in modeling-aid condition of testing aid]

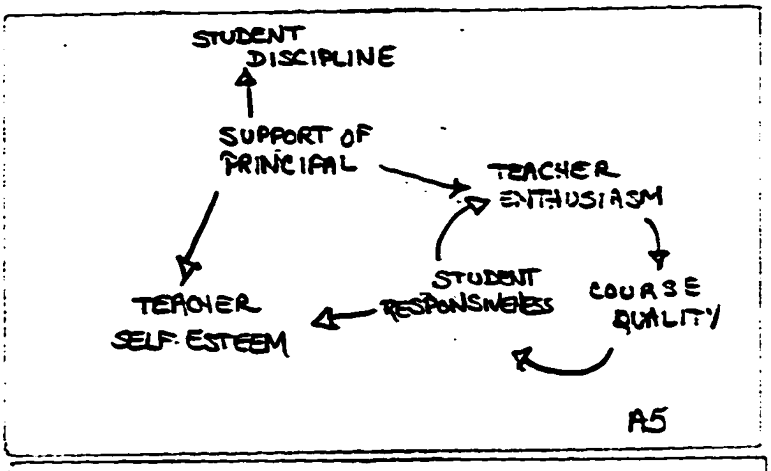


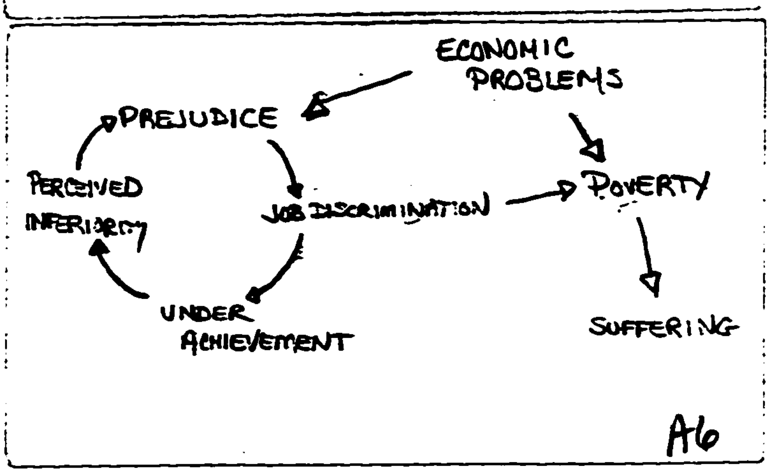




[Figures used in modeling-aid condition of testing aid (continued)]







[Figures used in cueing-aid condition of testing aid]

KNOWLEDGE affects COMPREHENSION

COMPREHENSION affects INTEGRATION

INTEGRATION affects KNOWLEDGE

A1

SKILLED EMPLOYEES affects EFFECTIVENESS OF ORGANIZATION

EFFECTIVENESS OF ORGANIZATION affects SATISFACTION OF CUSTOMER

A2

UNIVERSITY'S REPUTATION affects CONTRIBUTIONS

CONTRIBUTIONS affects ATTRACTION OF PRESTIGIOUS FACULTY

ATTRACTION OF PRESTIGIOUS FACULTY affects UNIVERSITY'S REPUTATION

A3

[Figures used in cueing-aid condition of testing aid (continued)]

PROBLEMS	affects	DESIRE TO AVOID PROB.
DESIRE TO AVOID PROB.	affects	EXCESSIVE DRINKING
EXPOSURE TO SOCIAL SITUATIONS	affects	EXCESSIVE DRINKING
EXCESSIVE DRINKING	affects	PROBLEMS
PROBLEMS	affects	STRESS
STRESS	affects	ILLNESS

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TEACHER ENTHUSIASM	affects	COURSE QUALITY
COURSE QUALITY	affects	STUDENT RESPONSIVENESS
STUDENT RESPONSIVENESS	affects	TEACHER SELF ESTEEM
SUPPORT OF PRINCIPAL	affects	TEACHER ENTHUSIASM
SUPPORT OF PRINCIPAL	affects	TEACHER SELF- ESTEEM
SUPPORT OF PRINCIPAL	affects	STUDENT DISCIPLINE
STUDENT RESPONSIVENESS	affects	TEACHER ENTHUSIASM

45

PREJUDICE	affects	JOB - DISCRIMINATION
JOB- DISCRIMINATION	affects	POVERTY
JOB- DISCRIMINATION	affects	UNDER-ACHIEVEMENT
UNDER- ACHIEVEMENT	affects	PERCEIVED INFERIORITY
PERCEIVED INFERIORITY	affects	PREJUDICE
ECONOMIC PROBLEMS	affects	PREJUDICE
ECONOMIC PROBLEMS	affects	POVERTY
POVERTY	affects	SUFFERING

46

VITA

Jeffrey S. Sinn was born May 5, 1969 in Omaha, Nebraska. He received his B.A. from Gustavus Adolphus College in Springfield, Minnesota in May 1991, graduating as valedictorian with honors in Psychology. During the course of his undergraduate studies Dr. Sinn was inducted into Phi Beta Kappa. Dr. Sinn completed his graduate work at Old Dominion University (ODU) in Norfolk, Virginia, receiving his M.S. in Psychology in December 1993 and his Ph.D. in Industrial/Organizational Psychology in August 1997. (Department address: Old Dominion University, College of Sciences, Department of Psychology, Norfolk, VA 23529-0267). While at ODU, he was inducted into Phi Kappa Phi and received the Meredith scholarship, an award given to the outstanding graduate student. During this time Dr. Sinn was employed as a teaching assistant and adjunct instructor at ODU; research associate at the Center for Pediatric Research, Children's Hospital of the Kings Daughters; and consultant for Organizational Perspectives, a human resources consulting firm based in Woodbury, New York.

Upon receiving his degree, Dr. Sinn accepted a position as assistant professor of psychology at Winthrop University in Rockhill, South Carolina.