Foundations of Mental Model Research

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Abstract

Ongoing research at the Rockefeller College is exploring the ability of subjects in a computer-based management laboratory to manage the implementation of welfare reform. Reflections on the design of such research have pushed us to develop a firmer theoretical foundation to guide our research on mental models in dynamic decision making. We posit that mental models are multifaceted, including distinguishable submodels focused on ends (goals), means (strategies, tactics, policy levers) and connections between them (the means/ends model). These distinctions, coupled with a view of human judgment from Brunswikean psychology, lead to a rich integrated theory of perception, planning, action, and learning in complex dynamic feedback systems.

From that theory we derive classes of testable research hypotheses about decision making in dynamic environments — in particular, "design logic" and "operator logic" hypotheses — that have serious implications for system dynamics research and practice. The operator logic hypothesis suggests that systems interventions focused on understanding detailed system structure will have little impact if they are not captured in easy-to-digest chunks of strategic insight that managers can integrate into relatively simple means-ends associations. Compounding the difficulties of mental model research is the likelihood that individuals' mental models can not be directly elicited without distortion.

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The nature and importance of the problem

Decades of modeling practice aimed at improving *understandings* of policy dynamics have led the modeling community naturally to a current focus on mental models and learning (see, e.g. *Modelling for Learning,* special issue of the *European Journal of Operational Research* 59,1 (1992)). It is also natural that the approaches system dynamics practitioners have taken to research on mental models and learning have been grounded in the circular causal, feedback perspective of the field. There is a touch of hubris in such undertakings, however, as modeling practitioners invade the domain of psychologists, education researchers and learning theorists and hope to make contributions by applying their special patterns of thought to phenomena long blessed with an extensive research tradition and literature. A glance at the bibliographies of the dissertations of Bakken (1993) and Kampmann (1992) shows the large background required for well grounded scholarship here.

It was in the beginnings of such model-based research on mental models in dynamic decision making that we found we had opened questions we were not well prepared to answer. Our deliberations were facilitated by the interdisciplinary nature of the research team (two management-trained modelers, one psychologist, and one public administration-trained modeler who bridged some of the gaps among the others). The discussions were facilitated, we should say, only sometimes; many times our diverse points of view and the puzzles we encountered led to tortuously intricate discussions that frequently gave our research the feeling of two leaps forward, three steps back.

Several unfamiliar concepts and principles emerged from these deliberations, which we put forward here to test against others' perceptions, with the ultimate goal of smoothing the way for future progress in model-based research on mental models and learning in dynamic decision making. We address the following ideas:

<u>Mental models are multifaceted,</u> comprising (at least) three main components: an ends model, a means model, and a mean/ends model.

<u>The Brunswikean lens model</u> extends and improves the classic cybernetic concept of the "perceived state" of the system, moving the system dynamicist's continuous view closer to discrete human decision-making behavior.

<u>Operator logic and design logic</u> are fundamentally different means/ends models that decision-makers may employ and are grounded in very different views of the world to be managed.

<u>The mental model uncertainty principle:</u> mental models are not directly accessible or observable; efforts to elicit mental models distort what is elicited.

The ideas developed in the paper lead to a picture of decision making and learning in dynamic situations that can generate propositions and guide research. The paper concludes with the implications of these ideas for future research on mental models and learning in dynamic decision making.

Foundations for mental model research: feedback theory

At the heart of any feedback thinker's view of human decision making is the classic cybernetic loop involving the state of the system, the perceived state, goals, planned action, and, finally, action affecting the state of the system and closing the loop of perception, planning, and action. Three of the concepts in this classic loop are mental constructs: the perceived state, goals, and the planned action. A fourth mental construct is implicit: the cognitive model or "cognitive map"[2] of the ways the system is structured and functions, which gives rise to selected plans of action. We conclude that a "mental model" in a dynamic, planned action setting must be composed of (at least) these four elements: intentions, perceptions, system structures, and plans. Figure 1 shows the classic cybernetic loop overlaid on this view of mental models.

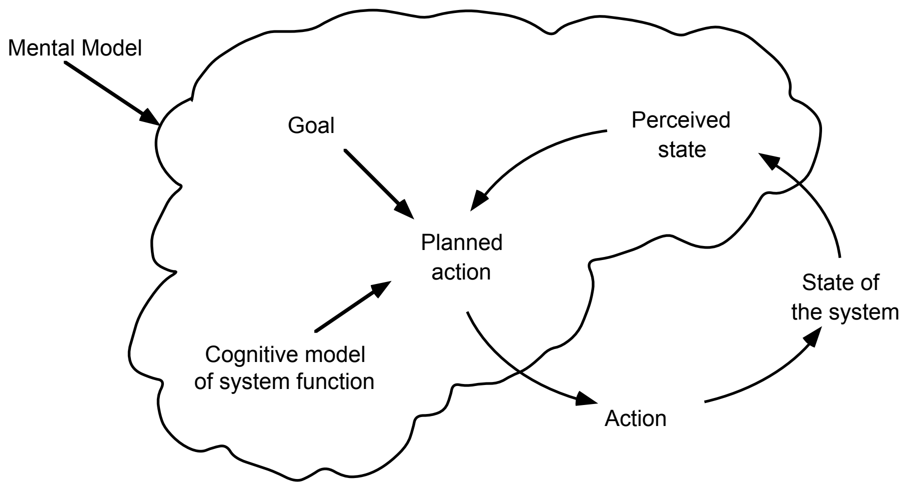

Figure 1: The components of mental models, placed in the context of the classic cybernetic process closing the loop involving the system state, the perceived state, planned action, and action altering the system state.

These considerations lead to a definition or clarification of what we mean by the term "mental model." A mental model, as the term is used in the system dynamics literature on dynamic decision making, appears to us to comprise, at a minimum, three submodels: the ends model, the means model, and the means/ends model (Andersen and Rohrbaugh 1992). These three elements of a mental model are placed in the context of (or phrased in terms of) perceived information about the state of the system, which we take to be a field of cues which make up the perceived state.

In the system dynamics literature on mental models and modeling for learning, there is a natural tendency to focus on perceptions of system structure — what we term here the means/ends model. The grounding presumption, or research hypothesis to be tested, is that "truer" perceptions of system structure lead in the direction of more effective policy decisions and system management. However, each of the other elements of a mental model shown in Figure 1 influence the results of mental model research. Ignoring their distinguishable characteristics can be misleading.

The Ends Model

[2] Strictly speaking, a cognitive map is a representation of a cognitive model of system structure and function, not the thing itself.

The Ends Model contains perceptions and information about what one is trying to accomplish in a decision or stream of decisions over time. There are local or proximal goals — goals which might be thought of as intermediary goals along the way toward more major goals. And there are global or distal goals — major or even ultimately important ends to strive toward, some perhaps unreachable. It is conceivable that there is a continuum of goals stretching between local and global ends. An individual's "ends model" in a dynamic decision-making task comprises this rich set of local-to-global goals.

There is much to know about an individual's ends model in a given task (Gardiner and Ford 1980; Andersen and Rohrbaugh 1983, 1992). Are goals perceived? Are they clear? Do they match other observers' visions of the ends or goals to strive for? Do they conflict? Do they change over time or with repeated trials? Failure to understand aspects of subjects' goals can invalidate conclusions about the role of mental models in dynamic decision making.

The Means Model

Perceptions, together with a mental model of the functioning of the system, lead to a plan of action. Or more probably, several possible plans of action are reflected upon, either intuitively or analytically. The decision maker moves back and forth between cues from the system, selection of policy intervention strategies and tactics, and the selection of appropriate policy "levers" by which plans are implemented. One of those plans is selected from this reflection process (Miller, Galanter and Pribram 1960).

The Means Model thus contains strategies, tactics, and policy levers the decision maker believes are available or usable to move toward the perceived goals. Researchers can ask What kinds of action are possible? How does the research setting limit or expand subjects' understandings of the actions available? What kinds of changes can one make to initiate actions believed to be desirable? Are the believed policy levers really connected to the things necessary to bring about the changes desired? How extensive is the decision maker's logic underlying a strategy or tactic?

The Means/Ends Model

The Means/Ends Model is most familiar to systems modelers, for in one incarnation at least it is a mental representation of the stock-and-flow/feedback structure of a complex dynamic system modelers strive to capture realistically. Alternatively, the Means/Ends Model could be a simple chain of associations linking a policy lever to an outcome. Yet even here there are crucial distinctions that can affect the design and results of mental model research. There is a continuum of means/ends models, ranging from "operator logic" to "design logic." [The distinction is related to Forrester's "operator" and "observer" (Forrester 1973), but stems from the literature on human/computer interaction (see Montmollin and De Kayser 1986).] We address design and operator logic and their implications for mental model research in the next-to-last section of this paper.

This vision of mental models — expanded to identify three important submodels and illuminated at this point by reflections on feedback thinking — is still far short of an adequate foundation for mental model research on dynamic decision making and learning. Its treatment of perception is woefully weak, and it fails to incorporate structures for learning. For a richer view of perception we turn to some of the psychological literature.

Foundations: cognitive psychology - the Brunswikean lens model

With hundreds of years of thought and at least a hundred years of research on perception, it should come as no surprise that the psychological literature has much to say about the feedback thinker's "perceived state." A psychology literature quite compatible with system dynamics perspectives rests on the writings of Egon Brunswik (1956). Brunswik emphasized a study of psychological phenomena in their environments, not isolated from them in controlled experiments. His emphasis is close to the inclusiveness of the system dynamicist's system boundary and endogenous point of view. Brunswik proposed a framework for studying perception and judgment known as the "lens model."

The Brunswikean lens model

From the stream of literature originating with Brunswik (Hammond 1955; Hammond, Stewart, Brehmer & Steinman 1975; Brehmer and Joyce 1988), we learn that the "perceived state" is productively thought of as a more complex process (see Figure 2) involving *true descriptors* of the state of the system, *cues* (measurements) derived from those true descriptors, and *subjective cues* (interpretations of those measures, potentially differing among observers using different conceptual models to interpret the data).

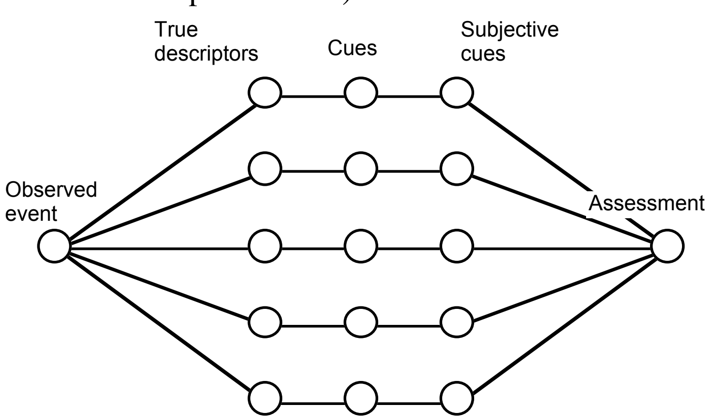

Figure 2: Brunswikean lens model (adapted from Stewart and Lusk (in press).

Subjective cues are combinations of (objective) cues, assembled in a probably nonconscious way by the individual. They result from an attention process which includes scanning the field of all possible cues, selecting combinations to attend to, and gauging or in some sense getting an estimate of the cues. The individual then subjectively interprets the assembled cues in light of experience, memory, perceptions, and the other cognitive baggage that make our perceptions subjective and unique. Assessments of the current state of the system, and predictions of future states, emerge from these subjectively interpreted cues.[3]

Judgment and decision making research in the Brunswikean tradition focuses on open-loop discrepancies between individual's assessments and predictions and the true state of the system. Considerable effort and sophistication are invested to capture accurately an individual's subjectively interpreted cues.[4] But for our purposes, the elements in Figure 2 expand richly on the "perceived state" in the classic cybernetic loop of Figure 1. They form a perceptual basis for planned action, and they contain the seeds of the mechanisms by which they change.

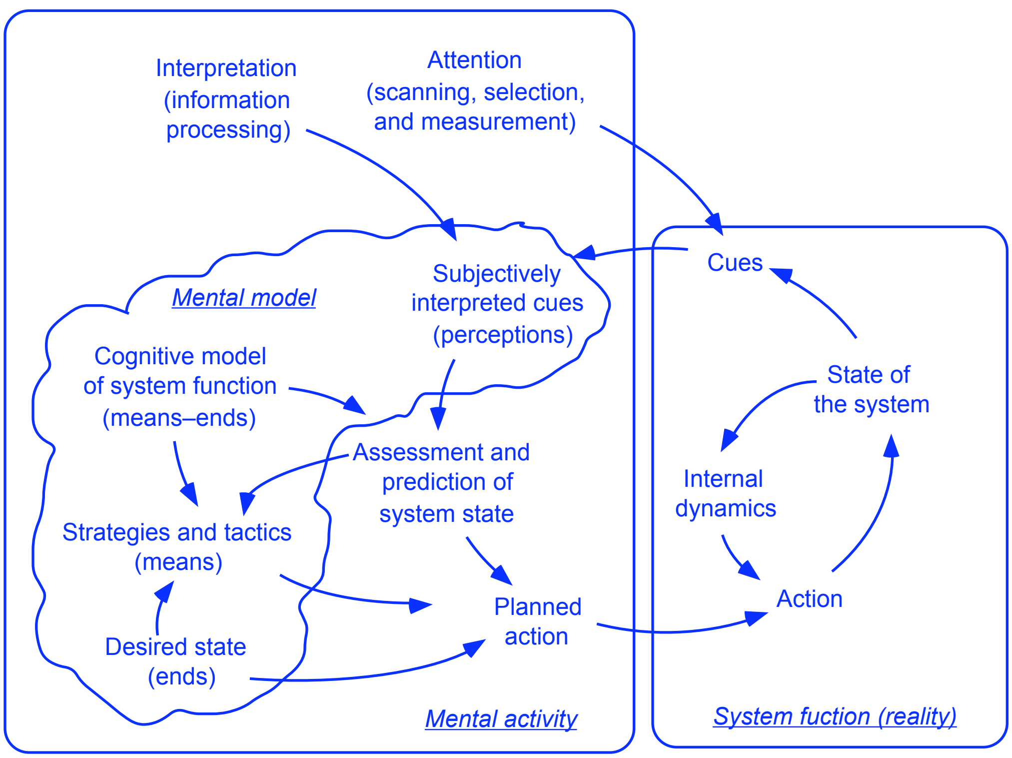

Figure 3: The cybernetic loop with a richer view of the psychology of the perceived state, showing attention and interpretation behaviors leading the selection and interpretation of cues that influence assessment, prediction and planned action.

Incorporating ideas from Figure 2 in Figure 1 yields a richer and more explicit statement of a closed-loop theory of perception, planning, and action. The individual diagramed in Figure 3 scans

3 Cues are obtained from true descriptors by a measuring or information system. For example, unemployment may be a true descriptor, but the manager only has access to an estimate of unemployment based on the survey (the cue). Temperature may be the true descriptor, but the level of mercury in a thermometer is the cue. This tranlation from true descriptors to cues is done before the manager makes an assessment, so is not part of the cognitive process.

4 Quantitatively, assessments and forecasts in the Brunswikean lens model are expressed in terms of sequences of regression equations (possibly involving nonlinear function forms) involving combinations of cues, weights on cues measuring their importance in the assessments and forecasts, and nonlinearities capturing saturation effects in cue significance. See Stewart 1988. For examples of cue detection efforts in the system dynamics literature, see Sterman (1988, 1989), Richardson and Rohrbaugh (1989), Diehl (1992), and Kampmann (1992).

the system, selects and interprets cues from it, and subjectively interprets them as a basis for assessing and predicting the state of the system. Assessments and predictions are also based on the individual's individual's cognitive model of the way the true system actually functions — the structure linking means to ends. The individual's selection of appropriate strategies, tactics, and policy levers results, as in the classic cybernetic formulation, from a comparison of the desired state and the individual's assessment of the current state of the system and predictions for the future, all considered in light of the individual's cognitive model of system function. The diagram highlights the subset of four components of mental activity that we identify as the individual's mental model.

Figure 3 is the beginnings of an adequate foundation for research on mental models in dynamic decision making. It strives to capture the elements of mental models that are necessary for taking planned action to manage a dynamic system. The changes in such a system are the result of the implemented plans and the system's own internally generated dynamic tendencies. These changes result in new cues, which the individual pays attention to and interprets, leading to new assessments and predictions and revised plans. Figure 3 sketches a theory of how planned action emerges in a dynamic setting and how implemented plans and the system's own internally generated dynamics combine to create the new conditions that individuals perceive. It emphasizes that in such settings actors may be adjusting the cues they attend to and may be changing their interpretations of them in their efforts to improve their management results.

There is a glaring omission in Figure 3, a set of elements that is involved in most management settings and most research on dynamic decision making: the mechanisms by which managers change their perceptions and behavior, that is, the mechanisms of learning.

Learning

Learning is the mix of processes by which people change their mental models. In the context of Figure 3, that definition suggests numerous feedback paths by which elements of mental models are adjusted to improve perception, planning and performance.

Figure 4 extends Figure 3 to include learning loops. The figure strives to incorporate the potentials for changes in strategies and tactics, goals, the cognitive model of system function, and the perception and interpretation of cues on which these depend. The figure suggests that such changes are based on perceived needs for improvement in performance, stemming from the memory of past assessments, predictions, plans, and actions and the comparison of these memories with newly perceived information about the system. It is entirely possible that some changes result from not from systematic assessments and revisions but rather from whim or boredom or random flights of fancy, and some, of course, may result from explicit teaching. The figure, however, emphasizes the elements of learning that are endogenous, resulting from reflection, presumably on the perceived results of efforts to close the gap between goals and system performance.[5]

[5] Kim and Senge (1994) and Sterman (1994) have similar representations of learning loops and include the role of learning labs and microworlds to facilitate or enable learning about complex dynamic systems.

Researchers investigating decision making in dynamic environments are working with the structure, functioning, and change of people's mental models that are potentially at least as complex as Figure 4. Definition of the management task and the number of trials may simplify somewhat. For example, Figure 4 captures an overview of the elements that must be considered by researchers investigating dynamic decision making in situations with repeated trials, where experience and reflection may change cues and interpretations, strategies and tactics (including policy levers), the cognitive model of the structure and behavior of the system, and even one's goals. In a research setting involving just a single judgment or set of decisions that are then not altered, the simpler Figure 3 may capture the necessary elements. Learning in some form (changes in cues, interpretations, strategies and tactics, and so on) is almost certain to be present in research settings involving a single play of a game requiring a sequence of the same decisions over simulated time, as well as repeated plays of a static or dynamic game. It becomes critical to know what subjects are paying attention to, how the cues are being interpreted, what strategies and tactics are being employed, and how goals shift, as well as the nature of a subject's cognitive map or model of system structure.

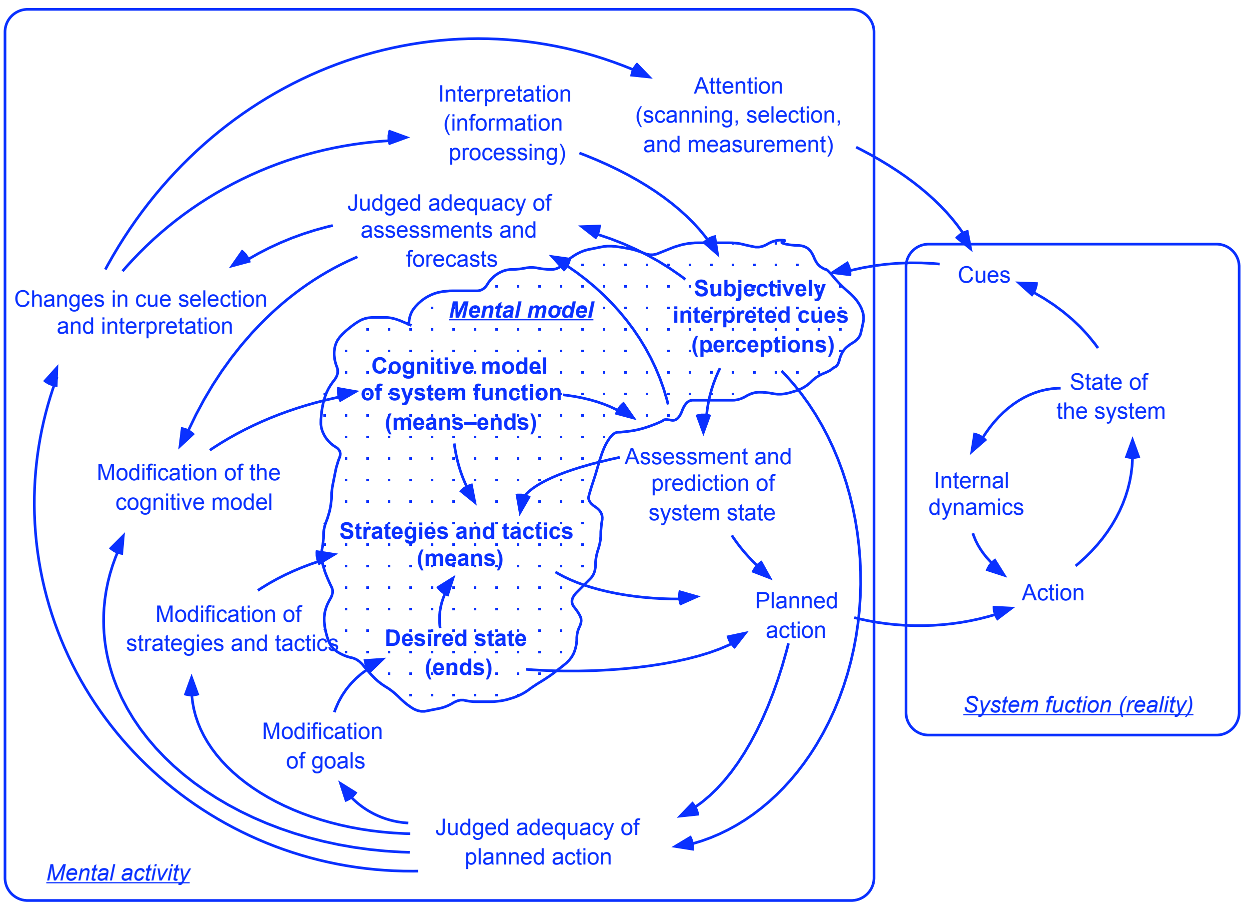

Figure 4: An integrated theory of perception, planning, action, and learning. Learning involves changes in the design of strategies and tactics (means), goals (ends), and cue selection and interpretation (perception), as well as changes in the cognitive model of system function (means-ends). Changes in any of these components of the mental model may stem from perceived

weaknesses in perceptions, beliefs, and actions, experience with simulated microworlds, teaching, or even searches for novelty, particularly in gaming situations.

Research hypotheses

The significance of Figure 4 is that it contains within it a number of potentially competing hypotheses about the operation and modification of mental models in complex, dynamic management tasks. Different parts of the figure suggest different predictions of the types of managerial interventions that will actually improve performance. The figure points toward empirically testable propositions that can help researchers to sort out the predictive power of these potentially competing hypotheses.

The left side of Figure 4 lists four ways individuals can modify their thinking to improve assessments, predictions, and/or interventions in complex dynamic systems. They can change (1) the cues they are looking at and the ways they are interpreting them, (2) the way they think the system functions, (3) the strategies and tactics (plans and policy levers) they are using, and (4) the goals they are striving toward. Furthermore, they can do these things in combination — a total of 15 (2^4 - 1) possible mixes of cognitive modifications, each one of which potentially involves many aspects of the system under consideration. These cognitive modifications can be made by actors in the system, as the figure suggests, or can be the result of interventions from the outside by consultants, systems modelers, and teachers.

To illustrate the ways Figure 4 can help to inform research, we briefly consider four hypotheses about improving performance in dynamic tasks: the Outcome Feedback Hypothesis, the Cue Selection Hypothesis, the Design Logic Hypothesis, and the Operator Logic Hypothesis.

<u>The Outcome Feedback Hypothesis.</u>

The entire structure of Figure 4 is involved in trying to learn by outcome feedback (knowledge of the results of past decisions). As depicted in the figure, people in dynamic decision making situations have four areas of their mental models they can try to improve, which they can test in controlled isolation (if they are well-disciplined scientists) or in combination (as many as 15 different mixes of areas to try to improve, each of which could involve many hypotheses). Unfortunately, as Sterman (1994) notes in his well-documented review of barriers to learning in and about complex systems, people are poor scientists. Identifying real improvements, particularly in complex or noisy decision settings, is extremely difficult and highly subject to chance. It is no wonder that the research literature on learning from outcome feedback is disturbingly negative and pessimistic (Brehmer 1988).

<u>The Cue Selection Hypothesis.</u> This hypothesis focuses on the upper half of the mental activity sector in Figure 4, the loops that contain “Judged adequacy of assessments and forecasts.” The cue selection hypothesis posits that people strive to improve their assessments by changing what

they are paying attention to and how they are interpreting the information. Research indicates that the performance of people in static and dynamic tasks can be improved solely by improving the cues to which they attend (Hammond 1971; Dawes and Corrigan 1974). For example, Richardson and Rohrbaugh (1989) demonstrated that changing the screen in the Long Wave Game (Sterman and Meadows 1985; Sterman 1987, 1989) and pointing subjects to salient cues improved their scores.

Much of the research in this area points to the importance of information processing activities associated with cue interpretation (for overviews see Baron 1988; Einhorn and Hogarth 1981; Hogarth 1987; Slovic, Fischoff & Lichtenstein 1977). For example, too many cues can overwhelm decision makers and mask truly important effects, cues that contain significant amounts of random disturbance can befuddle manager's efforts to detect the important information that is embedded in outcome feedback, and finally the presence of complexity in the actual or simulated system (such as significant delays in response to actions) can inhibit decision makers' ability to perform well the task under study.

<u>The Design Logic Hypothesis</u>. This line of research and thinking, familiar to all system dynamicists, begins with an important conclusion of years of research in the outcome feedback tradition--namely that outcome feedback by itself will rarely lead to good performance when the system being managed possesses significant random disturbances, delays, or dynamic feedback processes.

The design logic hypothesis focuses on decision makers' mental models of system structure and function. Such cognitive models of structure and function are seen as intervening constructs decision makers use to select management strategies to meet their goals. In fact, to a large degree the point of most system dynamics interventions is to create more sophisticated mental models in key decision makers — to capture in managers' minds a structure that is close in essential details to the way the system is designed. When real systems are characterized by delays, feedback, and nonlinear interacting processes, it is critical that managers understand these complexities and somehow integrate them into their thinking processes. The design logic hypothesis predicts that when managers are exposed to the structural cause-effect/feedback/delay complexity that truly exists in the real system, their thinking patterns become correspondingly sophisticated and hence their abilities to predict system responses and manage effectively are increased. As shown in Figure 4, this hypothesis posits that interventions altering managers' cognitive models of system function can impact planned action by affecting assessments and predictions and the strategies and tactics selected to meet managerial goals.

Presumably, the design logic hypothesis about mental models can yield a number of smaller and testable hypotheses concerning what is important about cognitive models of system function and how they can be improved to enhance decision making. Activities that should increase the quality of cognitive models of system function would include more detailed understandings of causal feedback loops acting within a system, richer understandings of feedback loops and their dynamic effects, and more sophisticated understanding of concepts such as generic structures and their applicability to the task at hand. The list of such potentially testable hypotheses is probably quite large and laid out with various degrees of explicitness in the system dynamics and systems thinking literature.

The notion of generic structures leads to an interesting extension of the design logic hypothesis, which might be called the *systems archetype hypothesis*. The effort to codify and teach dynamic feedback system archetypes (Senge 1990; see also Forrester 1969 and Meadows 1982) is aimed at providing decision makers with a rich inventory of generic elements of system design. Systems archetypes, as thought of in the system dynamics literature, are insightful feedback structures capturing dynamic complexity rather than detail complexity, and as such they are concise elements of the feedback design of complex systems. The systems thinking hypothesis postulates that having a rich inventory of insightful generic structures increases the likelihood that decision makers will incorporate feedback design elements in their mental models of particular system structure and thereby improve managerial performance in that particular setting.

The Operator Logic Hypothesis. In contrast to the design logic hypothesis, the operator logic hypothesis proposes that managers and decision makers do not, in fact can not, create highly sophisticated cause and effect, feedback-oriented cognitive models of system structure and function. The operator logic hypothesis suggests that a more direct route to improving managerial decision making lies in providing managers not with design logic but with improved strategies and tactics for accomplishing their aims (see Figure 4) . We term the strategies and tactics managers employ operator logic.[6]

By definition, all operators (managers, decision makers, senators, truck drivers) have operator logic; those who also possess detailed, complex structural understandings have design logic. Operator logic may be informed by design logic (see Figure 4, the link from the cognitive model to strategies and tactics) — one may be able, on reflection, to produce a detailed design-level explanation of an operating heuristic which can be represented in a rich cognitive map — but such a detailed picture of system structure is not necessary for operator logic. We note that a grounding premise in much system dynamics consulting work and research in dynamic decision making holds that *operator logic can be improved and performance enhanced by improving the design logic of clients,* usually through model-based experiences and reflection.

The operator logic hypothesis predicts that humans always use simple associative networks to manage complex systems. Enriching managers' mental models actually reduces to merely adding a

6 There are subtleties in the distinctions between design and operator logic. The two may be thought of as polar extremes on a continuum, with some fuzzy boundary somewhere along the continuum dividing the two. Design logic may be thought of as whatever justification people have for the operator logic they exhibit. We prefer to limit the idea of design logic to "rich" or "complex" cognitive maps of causal structure underlying the dynamics of a system to be managed or influenced. We acknowledge at this point an inability to pin down "rich" or "complex" here.

few cleverly designed new associations to manager's limited repertoire of means-ends response reactions. This prediction has important, if somewhat disheartening, implications for what a good system dynamics or systems thinking intervention must be: all insights must be reduced to strategic "chunks" that must then be integrated into managerial thinking.[7] If the insights are unchunked then they are useless and unused. Sophisticated insights matter for naught.

At a rather cynical level, the operator logic hypothesis suggests that successful systems intervention reduces to spoon feeding strategic chunks to managers. More elaborate systems thinking exercises such as discussing feedback effects, eliciting system structure from a group, or showing and discussing simulation runs are all complicated forms of superstitious behavior designed to enhance managers' confidence in the consultants with whom they are working. But these elaborate and complicated exercises do not have any effect unless they result in easy-to-digest chunks of strategic insight that managers can integrate easily into relatively simple means-ends associations. Of course, there is still a crucial role for systems modelers to uncover the helpful strategies and tactics, but the operator logic hypothesis suggests that otherwise excellent interventions that do not come to fully chunked conclusions will fail to have any impact on managerial thinking and performance. Fortunately, these predictions from the operator logic hypothesis are testable. Preliminary results from one such empirical test are contained in Andersen, Maxwell, Richardson and Stewart (1994).

Implications for Experimental Design

The distinctions between design logic and operator logic have serious implications for research on mental models and dynamic decision making. Operator logic captures ends (goal statements), means (policy levers and tactics), and heuristic statements linking means and ends (strategies, policy guidelines, rules of thumb). Design logic captures upstream influences (antecedents, causal influences), downstream effects (consequents, effects), delays, and circular causal processes (feedback loops). In any given research context, details of design and operator logic can be specified. Researchers studying mental models in dynamic decision making using simulated microworld environments can specify the “true” state of perfect design logic and can identify (through simulation analyses) the elements of operator logic that produce optimum performance. The research task is then to assess subjects’ operator and design logic structures and compare to the optimal, with appropriate reference to treatments, cognitive characteristics of subjects, and other experimental frameworks.

7 Simon (1969, 1981) measures the capacity of short-term memory in “chunks,” which he defines as a “maximal familiar substructure.” We intend the same sense of conceptual units that can be represented by a phrase or icon and mentally manipulated (thought about and with) as a whole.

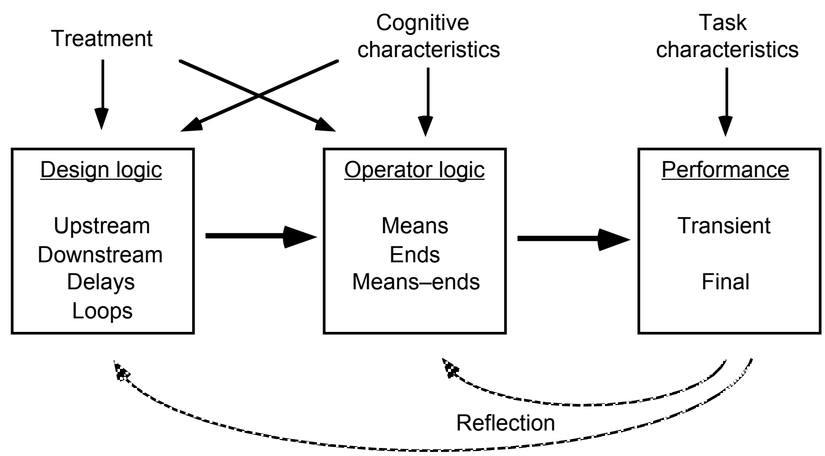

Figure 5: Overview of experimental design for mental model research. Treatments may influence design logic or operator logic or both. Cognitive characteristics of the subjects influence design and operator logic, and the effects of the treatments. Performance has at least two components, transient behavior and final results, both of which may be assessed. The potential for learning is represented in the shaded arrows: with reflection, transient performance can alter both operator and design logic, as can final performances in repeated trials.

Figure 5 sketches an overview of the research design framework that emerges from these considerations. The framework suggests that performance on a dynamic decision-making task is influenced by subjects' mental models in a particular way. Operator logic — system specific heuristics identifying means to desired ends — can influence performance; design logic, to the extent it is influential, acts through operator logic. Learning can take place through reflection on transient performance during a task, or through reflection on final performances in repeated tries. Experimental treatments can thus influence subjects' mental models in two ways: in developing or influencing design logic structures and in affecting operator logic.

A principle concern in such research is how to elicit or uncover elements of a subject's mental model in a dynamic task environment. Our efforts and reflections have convinced us of a *mental model uncertainty principle:* subjects' mental models — the cues they are using and their interpretations of them, their cognitive models of system function, their strategies and tactics, and their goals — can not be directly elicited without distortion. Any process of direct, guided elicitation tells subjects something about what the researchers are looking for and subjects respond accordingly. We note this crucial issue here but explore it in more detail and offer our research design work-around in Andersen, Maxwell, Richardson and Stewart (1994). Our preliminary research results reported there tend to support the operator logic hypothesis, suggesting that treatments that influence the design logic level but that fail to be chunked at the level of operator logic will not significantly affect performance.

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