In Search of Theories of Dynamic Decision Making: A Literature Review

Naiyi Hsiao
George P. Richardson

Department of Public Administration and Policy
Nelson A. Rockefeller College of Public Affairs and Policy
University at Albany, State University of New York

Center for Policy Research
Milne 300
135 Western Avenue
Albany, New York 12222
USA

+1 518 442 3852
nh7365@csc.albany.edu
http://ALPHA1.albany.edu/~nh7365/litrev1.htm

ABSTRACT

The current literature review investigates the literature of dynamic decision making. Based on the 33 empirical studies published from 1978 to 1997, the study provides five categories for grouping the dependent variables: task performance, learning, efforts for decision making, quality of decision-making process, and decision-making architecture. 24 predictors have also been conceptualized in three categories: decision makers' factors, task complexity, and decision-making interfaces and environments. Overall speaking, the research has not been able to find any single explanatory indicator of decision-makers' cognitive / learning style. Predictors related to task complexity have been mostly significant effects on task performance and verbalizable knowledge. Finally, most of the predictors related to decision-making interfaces and environments are still controversial as the decision aids for dynamic decision behavior. Theoretical foundations of expertise, task complexity, mental model, and information feedback have also been discussed to shed light on the future research directions.

1. INTRODUCTION

The present study will review these studies following the three defining characteristics (Edward, 1962) plus the real time and interaction functions expanded by the researchers. In addition, complex problem solving (CPS) and dynamic decision making (DDM) will be used interchangeably throughout the studies with notes that the European literature (particularly the German's) uses CPS, and the English literature uses DDM. The major purposes of the literature review are to provide a framework to involve the central variables, to synthesize the empirical findings extracted from the studies using various dynamic decision tasks, and to explore the theories based on which the studies hypothesize and extend their empirical examinations.

As the limit of the paper's length, the current edition is an excerpt from the full paper with the same title, which can be downloaded from the Internet at http://ALPHA1.albany.edu/~nh7365/litrev1.htm.

2. EVALUATIVE CRITERIA AND PREDICTORS

Three topics are discussed in the section. In the first place, while a thorough historical examination of research paradigm for the DDM research will not be attempted here (more details in Brehmer, 1992; Brehmer and Dorner, 1993), some methodological issues have to be briefly introduced for the background of the literature review. A summary of the dynamic decision tasks will then be provided in Table 1. Secondly, five groups for the evaluative criteria (Table 2) have been identified through examining various measures employed by the empirical work collected. Thirdly, in the same manner, three groups and 24 conceptual definitions of predictors (Table 3) can be extracted. The present study presumes that examining the measurement issues of these evaluative criteria and predictors independently would contribute to the synthesis of the empirical findings.

3. DESCRIPTIVE AND PRESCRIPTIVE FINDINGS

The foregoing discussion for the evaluative criteria and predictors for dynamic decision behavior has provided the basic construct of hypotheses – the dependent variables, independent variables, and their measurement. The major task of this section is to summarize the empirical findings, and if possible, to synthesize them.

Two types of the nature of the empirical findings can be identified, although they are in some cases intertwined in the same hypothesis. Descriptive findings are those describing dynamic decision behavior, for instance, how task performance would be affected by varying lagged effects inherent in task structure. Then based on the nature of dynamic decision behavior revealed by the descriptive findings, prescriptions to improve in terms of the evaluative criteria (Table 2) can be proposed and tested. Accordingly, most if not all of the prescriptions are those predictors related to decision-making interfaces and environments (IVC1 to IVC11 in Table 3). Some empirical findings about decision makers' factors (IVA1 to IVA4 in Table 3) may suggest prescriptions. Empirical findings involving task complexity (IVB1 to IVB9 in Table 3) are essentially descriptive. The ongoing discussion will proceed in order of the three categories of the predictors. In each category, hypotheses, as well as the empirical results, will be brought up in order of the degree of agreement among the studies based on the authors' judgment.

3.1. Decision Maker's Factors

Computing skills (IVA3 in Table 3) have been demonstrated to be irrelevant to task performance (A1 in Table 2), though only one study did this test (Trees et al., 1996). Nevertheless, the irrelevance of computing skills appears quite predictable if subjects are allowed to spend sufficient time familiarizing themselves with computerized gaming interfaces, which is exactly the case for all studies reviewed. In addition, researchers have to produce user-friendly computer interfaces so that subjects' computing skills would not interfere in their experiments. Therefore, both the direct impact of computing skills on task performance and the indirect impact through information display are usually reduced to the minimal degree.

Cognitive style (IVA1 in Table 3) has been hypothesized to be significant as certain functions of cognitive components may be necessary for performing dynamic decision tasks. Generally, the reviewed studies have revealed little effect of cognitive style / learning style on task performance (A1 in Table 2), task knowledge (B1 in Table 2), decision time (C1 in Table 2), and information use (C2 in Table 2) (Maxwell, 1995; Trees et al., 1996). The sole minor exception is that Abstract, one of the Gregorc Style Delineator scales which indicates the extent to which people prefer to learn deductively with big picture, concepts, and theory first followed by examples, has marginal explanatory power for task performance (Trees et al., 1996). The marginal effect, unfortunately, has not been replicated in other experimental settings. Compared with the English literature, the European research seems to be more intensive on the effect of test intelligence on task performance and knowledge, as detailed by Brehmer (1992), Buchner (1995), and Funke (1995). The results, in general, have been similar to those about cognitive and learning style in the English literature – the relationship between test intelligence and task performance and knowledge, if any, seems to go beyond the global intelligence score, such as IQ. A promising direction points to singling out components of intellectual ability of information processing.

Task expertise (IVA2 in Table 3) from academic background or intensive training sessions seems more relevant to dynamic decision behavior compared with the previous cognitive style and computing skills. The relevance stems from a general belief that experts usually do better than novices in dealing with the tasks on which they possess domain knowledge (Fong and Nisbett, 1991). The surveyed studies nevertheless provide contradictory evidences on task performance (A1 in Table 2). Bakken (1993), choosing student subjects with business management background, finds that they master a real estate game, which presumably requires more management expertise, better than oil tanker game. They are also found to be able to learn from the original real estate game (B5 in Table 2). Exposed to a two-day training session on simulation techniques and general knowledge of social welfare, however, Maxwell's student subjects show no performance difference from those without receiving the training (Maxwell, 1995). As the dynamic tasks used by both studies appear to be similar in terms of delays, nonlinearity, and positive feedback structure (Table 1), it is plausible that task domain knowledge obtained by enduring academic exposure, rather than pre-task training sessions, relates to task performance. Similar inconsistent findings have also been discovered in the European literature (Buchner, 1995), which has showed that experts, such as economic aid professionals with 6 to 8 years of experience, are more capable of taking into account conflicting goals and hence perform better than novices, such as postgraduates just about to start an economic aid career. However, evidences are mixed to support that experts can really develop better heuristics knowledge for specific tasks.

Note that task expertise here points to general domain knowledge rather than those strategies and decision rules tailored for specific decision tasks measured by IVC4 in Table 3. While both may serve as prescriptions for decision performance and task knowledge acquisition, few experiments have examined whether and how general knowledge (or epistemic competence) can help decision makers develop specific heuristics (or heuristics competence). Exploring the components of task domain knowledge related to heuristics-producing knowledge appears to be a research direction.

The preceding three predictors – computing skills, cognitive styles, and task expertise from academic background – stand uniquely for they have been solidly possessed by decision makers prior to tasks rather than quickly trained and infused into decision makers such as those decision heuristics (IVC4 in Table 3). In the same vein, it appears instructive to extract the enduring characteristics from decision makers' behavior. This idea has been realized by a stream of the European CPS research studying characteristics of either successful or unsuccessful decision makers in managing dynamic decision tasks. Particularly, observing the behaviors of those unsuccessful subjects leads to the pathologies of dynamic decision making, such as tendency to shift goals, sticking to one specific goal that decision makers feel doable, refusal to make decisions, blaming others for failure, and inappropriate delegation of decision-making responsibility (Dorner, 1980).

Practice and task experience (IVA4 in Table 3), appearing a straightforward predictor for decision behavior, have inspired much in-depth discussion among the literature. Almost all studies reviewed presently, with few exceptions such as the results reported by Berry and Broadbent (1987) and Sengupta and Abdel-Hamid (1993), have discovered a positive effect on task performance (A1, A2, and A4 in Table 2) both for simple tasks such as a computer person game (e.g., Berry and Broadbent, 1984) and for much more complicated tasks such as a real estate game (Bakken, 1993). Task experience through practicing in dealing with dynamic decision tasks, as has been examined for static tasks, presumably helps decision makers familiarize themselves with decision environments, explore the relationships of decisions and outcomes by trial and error, enhance their understanding of task structure, and develop reliable decision rules. All these benefits contribute to improvement for task performance. It seems fair, in the first place, to conclude that this "ultimate" purpose – improving task performance – seems to be achieved through sufficient practice based on the empirical findings reviewed. Additionally, decreasing decision time (C1 in Table 2) has also reflected decision makers' growing degree of task familiarity through practicing as reported by several studies (e.g., Brehmer, 1990; Diehl and Sterman, 1995). Brehmer and Allard (1991) also shows that task experience may affect the behavior of information use (C2 in Table 2), implying that decision makers have gradually develop their resource allocation strategy, although they may not change delegation behavior of dynamic decision making (E1 in Table 2).

More controversial yet inspiring discoveries, nevertheless, come from the experiments to examine the effect of task experience on acquisition of verbalizable knowledge (B1 in Table 2). In one of the pioneering studies previously classified as the first thread of the literature, Broadbent and Aston (1978) reveal that subjects' verbal knowledge shows no progress even though sufficient task experience has been able to upgrade task performance. This seemingly unreasonable result has been replicated in different task environments and experimental settings (Berry and Broadbent, 1984; Berry and Broadbent, 1988). Some experiments even find that task experience impairs verbal knowledge (Broadbent et al., 1986; Berry and Broadbent, 1987). Berry and Broadbent's evidences (1987) show that this surprising loss of verbal knowledge through practicing tasks only applies to the knowledge on the direct relationships of variables, rather than to that on the crossed relationships of variables. A direct relationship refers to the relationship between two semantically linked variables such as sugar output and work force in the sugar production game (Berry and Broadbent, 1984), and a crossed relationship is that between two semantically distant variables, such as sugar output and computer person behavior.

Sanderson (1989) suspects that the so-called dissociation between task performance and verbal knowledge may just result from insufficient task experience. He set up an experiment varying the amount of practice from 4 trial blocks to a 2-day session and found that task performance and verbal knowledge did go hand-in-hand. Note that, however, Sanderson adopts an alternative approach to assess verbalizable knowledge (B4 in Table 2) in addition to the conventional measure, the number of post-task questions correctly answered (B1 in Table 2) as described above. The confusing effect of task experience on learning seems also to interact with other predictors employed in experiments, such as lagged effects. More discussion will be brought up later.

3.2. Task Complexity

As detailed above, nine indicators reflect task complexity of dynamic decision making (IVB1 to IVB9 in Table 3). No evidence supports any differential effect of ***real time simulation tasks*** (IVB9 in Table 3) on task performance (A1 in Table 2) and on decision time (C1 in Table 2), although a real-time task appears more difficult than a decision-driven task due to the fact that clock-driven systems keep changing even without decisions entered. First of all, this finding needs to be confirmed since only a single study has done a formal test (Brehmer, 1995). Further, it is likely that other predictors of task complexity confound the effect of real-time simulation tasks. For example, the fire-fighting task used by Brehmer (1995) contains so powerful lagged decision effectiveness (IVB6 in Table 3) that it may be the major cause for degraded task performance, whether the task operates in the clock-driven or event-driven modes. Manipulating the two simulation modes in a relative simple task should be a proper research design to confirm the discovery.

With a welfare administration model, Mackinnon and Wearing (1980) examine the influence of another three predictors related to task complexity – ***total number of variables*** (IVB1 in Table 3), ***interaction between subsystems*** (IVB2 in Table 3), and ***random variation*** (IVB3 in Table 3) – on task performance (A1 in Table 2). They hypothesize that task performance would be deteriorated by the increasing number of variables, random variation built in the task, and existing interaction between task subsystems. The empirical evidences support the first two predictions at least marginally, but the effect of subsystems interaction turns out to be opposite to that expected – subjects perform better when interaction exists. Again, unfortunately, these findings have never been replicated in other studies. A note worth taking here is that it should not be totally surprising for evidences showing that subjects can perform well in a task system with the growing degree of interaction between subsystems.

Research on systems theory and system dynamics has been able to point out that negative feedback loops can stabilize systems behavior through the interaction between subsystems (for details, see Forrester, 1968; Richardson, 1991). Uncertainty and random variations would not be always detrimental in dynamic task systems as long as the error caused by decisions can be reduced through interaction of subsystems where stabilizing negative feedback loops dominate systems behaviors. The same argument applies for the impact of the increasing number of variables. Therefore, the predictors reflecting task complexity for dynamic decision making seem not exactly to be those raised in static decision environments. More precisely, crucial factors should be elicited by examining those ***task characteristics*** (IVB4 in Table 3) that have been empirically supported to have impact on task performance (A1 and A4 in Table 2). The challenge rests upon what the crucial factors of task complexity would be and how they may be operationalized.

Positive feedback and gains (IVB8 in Table 3) is one of the prominent factors discovered in this fashion. Sterman's seminal work in this respect (1989a, 1989b), the misperception of feedback hypothesis, characterizes decision makers' incapability for managing dynamic decision tasks due to their failure to identify endogenous positive feedback gains enlarging tiny decision errors and side effects. Follow-up studies along this line (e.g., Kampmann, 1992; Paich and Sterman, 1993; Diehl and Sterman, 1995) have confirmed this hypothesis by varying the strength of positive gains and measuring degraded task performance (A1 in Table 2). Diehl and Sterman (1995) also find that decision time allocated by subjects does not increase proportional to the increasing strength of positive gains. If subjects search for optimal rules, they should spend more time on decision making since the increasing dynamic complexity would require more cognitive resource and effort. Revealing the irrelevance of decision time allocation suggests that subjects either do not or fail to account for increasing task complexity anticipated by the misperception of feedback hypothesis. Young et al. (1997) report that subjects' decision scope (D1 in Table 2) has also been impaired when dynamic tasks increasingly fall into the uncontrollable positive feedback loops. The finding, beyond the previous evidence showing that subjects are insensitive for decision time required, further indicates that they basically give up developing decision rules and comply with random guess or stick to certain biased heuristics, such as anchoring and adjustment as analyzed by several studies (e.g., Sterman, 1989a; Diehl and Sterman, 1995).

Time delay / lagged effects (IVB5 in Table 3) and ***decision effectiveness / task salience built in the model*** (IVB6 in Table 3) account for another dimension of the misperception of feedback hypothesis. As explained previously, both predictors conceptualize the extent to which the delayed effect of a decision is perceived by decision makers. Analyzing decision rules employed by subjects in performing a capital investment task, Sterman (1989a) points out two facets of their failure to appreciate time delays: ignoring the time lag between the initiation of a control action and its full effect, and being overly aggressive for correcting discrepancies between desired and actual outcome. It should be logically valid to argue that the correction decision tends to be overly aggressive because subjects fail to understand that the full effect of their previous correction would not be perceived until subsequent time periods. That is, the former facet leads to the latter. Then the overly-aggressive correction results in some side effect, such as high inventory cost, and subjects need the counter-correction. The same failure to appreciate the lagged effect of decisions also applies for the counter-correction. This scenario often ends up with instability of systems behaviors and hence unsatisfactory task performance. It has been solidly supported by empirical studies adopting various tasks and experimental settings (e.g., Berry and Broadbent, 1988; Brehmer, 1990; Paich and Sterman, 1993), with a single exception reporting that task performance is not influenced by lagged effects (Broadbent and Aston, 1978). Again, the failure for ignoring lagged effects in a relatively simple task may be compensated if subjects can grasp the relationships between decisions and outcomes.

Similar to the effect of positive gains, subjects have been found to be insensitive for allocating decision time despite increasing lagged effects (Brehmer and Allard, 1991; Diehl and Sterman, 1995), although there has been a counter-evidence showing that subjects do spend more time on tasks with time delays (Brehmer, 1990). More studies are certainly needed to resolve the contradictory findings. Yet, a detailed comparison of experimental design suggests a sensible explanation for their discrepancies. In Brehmer (1990) subjects are assigned to different groups at the outset performing the same task with delay and no-delay, whereas Diehl and Sterman (1995) manipulate time delays as a continuous scale. Therefore, it is worth speculating that there might exist a delicate cut-point of time delays over which subjects would fail to manage. In addition, Brehmer and Allard (1991) report that subjects fail to adopt appropriate command delegation (E1 in Table 2) that may assist them to deal with time delays, confirming the previous misperception of feedback hypothesis. Information use (C2 in Table 2) is not either found any difference for the task conditions with time delays.

While the misperception of feedback appears satisfactory to explain why lagged decision effects degrade task performance, can it also account for the impact of time delay on verbal knowledge (B1 in Table 2)? Broadbent et al. (1986) and Berry and Broadbent (1988) have been able to conceptualize decision effectiveness as task salience built in the model. Increasing decision effectiveness, in other words reducing lagged effects and time delays, would provide a higher probability (salience) that decision makers can detect important variables and further have a better grasp of the relationships between decisions and outcomes. This better understanding of task structure should be reflected on verbal knowledge measured by the scores of post-task questions. The evidences from both studies above support this prediction. Based on the descriptive finding, one of the prescriptions to dynamic decision aids points to informing decision makers prior to lagged effects / time delays (IVC6 in Table 3), which would be brought up below. Also noteworthy is the property of tasks used by Sterman (1989a) and Berry and Broadbent (1988) to empirically confirm the hypotheses of misperception of feedback and of task salience respectively. While Sterman's capital management task involves nonlinearity and endogenous positive feedback gains, Berry and Broadbent (1988) uses a relatively simple computer person task without feedback and nonlinear relationships among variables (Table 1). Therefore, the detrimental effect of lagged effects / time delays has high degree of external validity as the confirmatory evidences come out from the diverse task properties.

Aside from the preceding positive gains and lagged effects / time delays, ***frequency of oscillations*** (IVB7 in Table 3) is another predictors characterizing dynamic decision tasks. Bakken (1993) reasons that a less frequent oscillations (low compression) resulting from a longer time-delay constant in tasks would hinder subjects from appropriate task structure (B5 in Table 2) and hence effective decisions (A1 in Table 2). Whereas his data confirm the latter prediction that subjects perform better in a highly compressed environment, the former prediction on the effect of frequency on learning only receives marginal support.

3.3. Decision-making Interfaces and Environments

As mentioned above, most hypotheses about decision aids for dynamic decision making lie in the decision-making interfaces and environments that refer to the predictors that can usually be manipulated. These DDM prescriptions generally point to the following questions: Which decision aids are helpful (in terms of those evaluative criteria in Table 2)? How are they functioning? Among the decision aids summarized, the ***decision-making architecture*** (IVC11 in Table 3) has an unique position for it reflects the communication network embedded in the organizational structure. Brehmer and Svenmark (1995) have their subjects perform a real-time fire-fighting task in either networked architecture or hierarchical architecture as defined above. Their study hypothesizes that task performance (A1 in Table 2) should be better in the hierarchical environment since the commanding subjects with complete information can respond more effectively and spend less decision time (C1 in Table 2) than the subjects in the fully-connected environment. The prediction about task performance is supported, although the difference between the two architectures is not as great as expected. The decision time allocated in the hierarchical environment, however, shows no significant difference from that in the networked environment. In other words, the subjects with a "whole picture" appears perform better, but not always spend less time.

Several studies have been able to conduct Monte-Carlo simulation games to explore the effect of various decision rules on task performance (Hogarth et al., 1981; Kleinmuntz et al., 1981; Kleinmuntz, 1985). These ***heuristics built in task systems*** (IVC1), including random strategies, are programmed into task systems to implement the decision heuristics with perfect consistency. One of the significant findings is that human subjects perform (A4 in Table 2) about as well as these built-in decision rules which can not adapt to task systems and never receive information feedback (Hogarth and Makridakis, 1981; Kleinmuntz and Klienmuntz, 1981). The result implies human decision makers' incapability to interact with dynamic decision tasks. Two sources of human incapability are possible: cognitive unreliability (inconsistency) and inappropriate decision rules. Human subjects may have good decision rules but they fail only because they hardly apply the heuristics consistently. This line of argument remains nearly unexplored by the DDM research although it has attracted relatively abundant studies in static decision environments. Further, inferior task performance of human subjects may stem from the fact that they often adopt heuristics inappropriate for the dynamic tasks at hand. The following discussions will explore this possibility. The Monte-Carlo simulations provide another evidence supporting that appropriate strategies enhancing task performance (A1 in Table 2) are not always those demanding more information and computational complexity, such as the heuristics incorporating Bayesian probability (Kleinmuntz, 1985). The evidence should be interpreted as a good news for those who design decision aids since human judgment and decision making have not been good at dealing with information overload and complicated computation.

Direct Prescriptions on Decision Heuristics and Task Property

So the question remains: What would be good strategies and decision rules given certain decision tasks? Several attempts have been implemented. The first is termed ***heuristics-induced goal setting*** as defined above (IVC3 in Table 3). Yang (1996, 1997), based on goal setting theory (Locke and Latham, 1990), argues that once given a proper goal for a complex dynamic task decision makers can develop their mental models by acquiring goal-relevant knowledge, which will in turn improve task performance. The empirical studies confirm that subjects are able to achieve better control (A1, A2, and A3 in Table 2) and understanding (B3 in Table 2) of tasks by being trained with the explicit goal statements (Yang, 1996, 1997). As argued previously, the goal-setting statements, though not as detailed as decision rules, virtually lead subjects to develop relevant heuristics. Also empirically supported (Yang, 1996) is the prediction that subjects would save decision time (C1 in Table 2) and easily focus on the goal-oriented information items in task models (C2 in Table 2). Whereas the present review conceives Yang's use of the "goal" as actually heuristics-induced goal setting, a promising follow-up should be empirically exploring whether general goal statements can achieve as prominently as these heuristics-oriented goal statements.

As shown in the previous section, a rich body of the DDM literature has designed various strategies, decision rules, and explicated task property, most of which are obtained by subjects through ***verbal instructions*** (IVC4 in Table 3). Two perspectives have been provided to predict the usefulness of these various decision aids. Firstly, instructed with the relationships of relevant variables (information acquisition), dynamic decision makers can then produce decisions based on clearer task structure and more predictable outcomes and perform better. At the same time, their post-test verbal knowledge should also be more correct. Secondly, instructed with decision rules effectively, dynamic decision makers would broaden their cognitive capacity to interact with decision tasks and hence perform better by both acquiring information of relevant variables (information acquisition) and correctly combining the variables to produce decisions (information integration).

The first prediction about the decision aids on task property receives mixed support from the literature. Several experiments instructing subjects with task structure information have shown its positive effect on task performance (A1, A2, and A5 in Table 2), including Broadbent et al. (1986), Berry and Broadbent (1988), Jansson (1995), and Maxwell (1995). Note that the decision tasks of these studies range from the simple computer person task to the complex social welfare administration (Table 1), hence adding generalizability of the prescription. Some studies, however, do not find significantly better performance for the subjects receiving task information (Berry and Broadbent, 1984; Berry and Broadbent, 1987). Stanley et al. (1989) provide subjects with various experts transcripts, the verbal reports from experienced subjects, and find that only certain transcripts are proved to be helpful. To illustrate, subjects manage tasks more effectively when they are allowed to access to the verbal reports transcribed from the whole process of decision making, instead of only from a block of trials. In addition, the transcripts may be selected in different stages – first trial block, final trial block, before sudden improvement of performance, and after that sudden improvement, as defined in the previous section. Another experiment in the same study further demonstrates that the transcripts in the final block significantly assist decision-making – implying that relatively complete mental models and task knowledge have been developed.

Generally speaking, the surveyed studies reject the hypothesis that subjects receiving task information can acquire more correct verbal knowledge (B1 in Table 2) (Berry and Broadbent, 1984; Broadbent et al., 1986; Jansson, 1995). Berry and Broadbent (1987) distinguish two types of the relationships of variables, the direct relationships and crossed relationships as mentioned earlier, and presume that the crossed relationships are more difficult to be correctly developed in mental models. Provided that the two types of variables' relationships can be differentiated and measured, they find that providing subjects with task information only improve the direct relationships rather than the indirect relationships. Finally, although the effect of task information on task performance and learning is still controversial, it has been shown to increase decision time (C1 in Table 1) and information use (C2 in Table 2) (Jansson, 1995).

The second prediction about the effect of decision heuristics appears more agreed-upon – nearly all evidences support its positive effect on task performance (Stanley et al., 1989; Jansson, 1995; Maxwell, 1995), although its effect on verbal knowledge remains suspicious (Jansson, 1995). Maxwell (1995) also shows that providing subjects with decision rules is more effective for improving task performance than providing with task information.

As a summary for the direct prescriptions – providing verbal instructions on task structure information and decision heuristics – the present review has to conclude that the truth is far beyond the empirical evidences. The contribution of decision heuristics to task performance is mostly supported. The success for the provision of task complexity information is at least marginal, though not as prominent as decision heuristics. The puzzle, nevertheless, is unsettled: Why is task knowledge not going with the verbal instructions on task property and decision heuristics? One possibility is that task performance can be improved without acquiring task knowledge, which particularly explains why most studies agree upon the impact of decision heuristics on task performance rather than on verbal knowledge. Another possibility lies in the measurement issue. Decision makers may acquire task knowledge that can not be appropriately measured by written questions. It seems also plausible that providing task property and decision heuristics equips decision makers with different types of knowledge – the distinction between declarative and procedural knowledge, explicit (verbal) and implicit knowledge as described previously.

Indirect Decision Aids

Another decision aid usually accompanied with verbal instructions of heuristics or task structure is ***concurrent verbalization*** or ***thinking-aloud*** (IVC5 in Table 3), which requires subjects to explain the reasons while placing decisions and experimenters tape-record the verbal protocol or make subjects put them down in notebooks. Decision makers with concurrent verbalization may be more aware of their decision rules and in a better position to acquire task knowledge, which eventually results in better task performance. In an experiment, Berry and Broadbent (1984) find that concurrent verbalization alone can not really help task performance (A2 in Table 2) and verbalized knowledge (B1 in Table 2) unless pre-task verbal instructions are available. They also observe that subjects without pre-task verbal instructions tend to talk about their decisions at a very general level, while subjects receiving instructions are usually able to give reasons in line with specific decision rules.

Yet, McGeorge and Burton (1989) argue that providing subjects with graphical representations of systems behavior prior to task may mask the effect of concurrent verbalization. An experiment is thus set to replicate that of Berry and Broadbent (1984), except that subjects only receive numerical values of system status throughout the task. Interestingly, the results indicate that concurrent verbalization does improve task performance. To further confirm the redundancy of graphical representations and concurrent verbalization, subjects in another experiment receive graphs of systems behavior without being required to think aloud. As expected, the subjects receiving graphs outperform those who do not. Along the same line, Stanley et al. (1989) suspect that the insignificant effect of concurrent verbalization on task performance found in Berry and Broadbent (1984) could be that the limited amounts of task experience (40 trials) may not be sufficient for subjects to develop appropriate task knowledge. Accordingly they conduct an experiment where subjects extensively interact with the same task as in Berry and Broadbent (1984) (200 trials). The results support their speculation that concurrent verbalization helps subjects perform better given sufficient task experience (IVA4 in Table 3).

Providing subjects with task structure instructions and decision heuristics assists decision-making quite directly as these decision aids unveil at least a part of the "black box" of task systems. Aside from concurrent verbalization, several indirect decision aids have been attempted. Sanderson (1989) hypothesizes that task performance and learning can be enhanced simply to manipulate the ***degree of decision precision*** (IVC7 in Table 3). Requiring subjects to produce decisions more precisely, such as to the first decimal place, would force them to reason out the workings of the relationships of variables (B1 in B4 in Table 2) and hence advance task performance (A2 in Table 2). The prediction is marginally supported. Note, nevertheless, that the transportation task in Sanderson (1989) only involves four variables, and again, task complexity has to be involved in this regard. For a task with limited complexity, such as with less than seven variables, minor delays, and no nonlinear equation involved, requiring decision precision may be helpful. While task complexity increases, subjects can not handle the task any more due to their cognitive constraint. In this complex situation, perhaps short-term memory storing decision-outcome matches and simplified heuristics have more explanatory power for decision behaviors than the workings on detailed equations.

Information Feedback as a Decision Aid

Information feedback (IVC9 in Table 3) has been a unique decision aid, which firstly differs from verbal instructions on task property and decision strategies in that information feedback is available throughout decision-making process rather than just prior to tasks. Kleinmuntz and Thomas (1987) have supported that availability of Bayesian probability, though demanding more decision time (C1 in Table 2), helps decision makers with task performance (A1 in Table 2) since it makes previous decision outcomes easier to understand. As an interesting counter-argument, Sanderson (1989) argues that having previous decisions and outcomes available to subjects would prevent them from developing correct task knowledge (B1 and B4 in Table 2) and hinder task performance (A2 in Table 2) since this information may not correspond to true task structure. A mixed supporting evidence inspires the essential rationale behind the decision aid of providing information feedback: What information is really helpful? Completeness of information feedback seems not relevant provided that many studies have provided subjects with complete decisions and outcomes with no significant help being found (e.g., Sterman, 1989a).

Building on the literature of psychological decision making (Balzer et al., 1989), Sengupta and Abdel-Hamid (1993) have tested differential effects of three types of information feedback – feedforward (actually decision heuristics and strategies), outcome feedback (past decisions and outcomes), and cognitive feedback (information reflecting task structure and/or cognitive weighting scheme). The results show that subjects receiving outcome feedback alone have inferior task performance (A4 in Table 2) and tend to fluctuate their decisions (D2 in Table 2), namely low reliability. Adding cognitive feedback is demonstrated to improve task performance in the complex software project task, though meanwhile demanding more decision time (C1 in Table 2) and information inquiry (C2 in Table 2).

Another important discovery in Sengupta and Abdel-Hamid (1993) is that subjects receiving cognitive feedback outperform those receiving feedforward. This seemingly contradicts to Maxwell's finding (1995) that decision strategies (similar to feedforward) contributes more than causal-loop training (similar to cognitive feedback). Given similar complexity for the tasks used by both studies, some possibilities deserve exploration here. Firstly, note that subjects in Sengupta and Abdel-Hamid (1993) have access to more informative outcome feedback than those in Maxwell (1995). The basic outcome feedback, despite an ineffective decision aid alone, may be crucial for facilitating the use of cognitive feedback and feedforward. This point can be pursued by an experiment providing subjects with feedforward and cognitive feedback without basic outcome information feedback. Moreover, careful comparison of the design of the information feedback suggests that some parts of cognitive feedback and feedforward may be more helpful than another. For instance, the degree of detail of decision heuristics may make difference, provided that subjects in Maxwell (1995) are not only instructed with decision rules, as those in Sengupta and Abdel-Hamid (1993), but they also access to a set of decision rules linking to different scenarios and goals.

Another possible explanation for the contradictory findings about the effectiveness of information feedback involves the representation ***forms of information feedback*** (IVC10 in Table 3). As has been reported above, McGeorge and Burton (1989) find that graphical representation is helpful for task performance, which is also confirmed by Sanderson (1989). Additionally, Sanderson's series of experiments reveal that providing subjects with task structure information in abstract formula form can not guarantee better task performance (A2 in Table 2). Only does adding semantic meanings to the formula contribute to performance. Richardson and Rohrbaugh (1990) hypothesize that the subjects with gaming screens containing relevant cues and the optimal weights would outperform those with outcome feedback alone. While the prediction is not fully supported, they discover two distinct patterns of task performance for the subjects receiving the decision aid. Half of the subjects do improve their performance. Meanwhile their decision patterns can be captured by a linear regression model, which implies cognitive consistency.

The Role of Task Complexity in Prescribing Dynamic Decision Behavior

An in-depth investigation of dynamic decision making behavior, as continually argued in the present study, should take task complexity into account. Based on the reviewed studies, the results also appear to be the most intriguing compared with those reported above. Hayes and Broadbent (1988) manipulate lagged effects built in tasks (IVB6 in Table 3) to induce subjects to produce two ***learning modes*** (IVC2 in Table 3), selective and unselective modes as defined above. Evidences support their hypotheses that the subjects induced to adopt selective mode of learning perform better in both the original task (A2 in Table 2) and the transfer task with similar task structure (B5 in Table 2). Also supported is that the subjects acquire more complete declarative and procedural knowledge (B1 and B2 in Table 2) since they tend to develop explicit knowledge on task structure. One of the critical implications of the results is that solely the task complexity alone, lagged effects in this case, can affect the mode of thinking by which decision makers approach the task.

Another experiment in the same study (Hayes and Broadbent, 1988) has subjects go through three continuous phases of tasks. In the first phase two groups of subjects with the two induced learning modes experience the computer person task same as the previous experiment. They then, in addition to the original task, are introduced to a secondary task, a letter generation task. Again, for the new task, lagged effects are manipulated (with / without lagged effects) to induce the learning modes. Finally in the last phase, both groups of subjects concurrently experience both tasks as in the previous phase except that the relationships of variables in both tasks have reversed. A striking finding of the experiment is that subjects in the unselective learning outperform those in the selective mode, which is exactly a reversal of the previous experiment, and the difference of verbal knowledge for both groups is not significant. An inspiring explanation provided is that the secondary task interferes with the learning of the subjects induced to have the selective learning mode. Comparatively, the subjects with the unselective mode have “accumulated” learning experience from the first task, though not verbally explicable, and they can transfer the knowledge to another task without being interfered. In other words, the selective learning mode is not only unnecessary for learning to interact with a new task with lagged effects, but also interferes with learning.

Task complexity also plays an important role even though subjects are only instructed to focus their attention on searching for the relationships of variables. Wang (1994) adopts this pre-task ***learning inducement*** (IVC8 in Table 3) accompanied with the economic reward in hope of stimulating subjects to develop more appropriate task knowledge (B5 in Table 2) and hence improve task performance (A1 in Table 2). The effectiveness of the learning inducement receives mixed support when subjects interact with a capital investment task. Although allocated decision time (C1 in Table 2) is not found to be significantly different with the learning inducement, subjects do have more attempts on various decision rules (D1 in Table 2) in the decision-making process. Berry and Broadbent (1988) explore the pre-task learning inducement for two groups of subjects, one interacting with the computer person task with lagged effects (the non-salient task termed by the authors) and the other without lagged effects (the salient task). The subjects with the explicit search instruction are expected to outperform (A2 in Table 2) those without the instruction. The results indicate that only subjects dealing with the salient task meet the prediction. Further analyses also reveal detrimental influence of the explicit search instruction on task performance of the subjects handling the non-salient task.

Provided that task salience controlled by lagged effects is so crucial, would task performance be enhanced if the decision aid to ***increase task salience*** (IVC6 in Table 3) is available? Brehmer (1995) finds that informing subjects with lagged effects prior to tasks can not help them improve task performance (A1 in Table 2). As an alternative to increase task salience, Berry and Broadbent (1988) and Wang (1994) attempt to instruct subjects with task structure information and how lagged effects function. The decision aid has been supported to be helpful for task performance (A1 and A2 in Table 2) and verbal knowledge acquisition (B1 in B5 in Table 2)

4. DISCUSSION AND A SEARCH FOR THEORIES

The current literature review has set forth to explore the factors relevant to dynamic decision behavior and synthesize the empirical findings for the hypotheses being tested by the DDM studies. Table 1 to Table 3 as well as the foregoing discussions should succeed in the exploration of what have been regarded as important in dynamic decision making. Nevertheless, the synthesis of the empirical findings seems to be achieved in a limited success at best. An immediate difficulty comes from the following simple statistics: In the 33 empirical studies being reviewed (Table 1), 60 hypotheses involving a single predictor (24 predictors listed in Table 3) and a single evaluative criteria (five categories in Table 2) have been developed, but only 153 tests have been conducted. In other words, there are less than three tests for each hypothesis in average and many of the hypotheses have only been tested once. This suggests that knowledge of dynamic decision making and complex problem solving has not been systematically accumulated.

Subsequent discussions firstly attempt to summarize the empirical findings in the previous section. Further, the theories underlying empirical evidences reviewed will be pointed out and briefly illustrated. Explicating both the empirical evidences and theories should substantially inspires significant research questions.

4.1. Theories of Experts in Dynamic Decision Making

In summary, the empirical findings about decision makers' factors may be relatively consistent. Computing skills have been rejected to influence on task performance and argued to be irrelevant since computerized simulation environments are exactly designed for ordinary decision makers without computing skills. Few evidences have shown any single indicators of cognitive style and test intelligence to be explanatory for dynamic decision behavior. The DDM research analyzing individual differences also conclude that task expertise is less effective than providing decision strategies, although it is still unclear whether and how task expertise may help dynamic decision makers acquire verbal knowledge and develop decision strategies.

Introducing ten different aspects of expertise that have been taken in various research fields, Sternberg (1995) proposes a view regarding expertise as a prototype. That is, experts are defined depending on the problem domain and associated task characteristics. For example, competitive weather forecasters are valued by providing more accurate prediction for the weather tomorrow. Effective radiologists should be good at making correct biopsy recommendations for patients with suspicious lesions in their mammograms. Thus different task characteristics may be attached to expertise in different problem domains: Are the decisions repetitive? Is the correct answer existent and accessible? Are decision aids available? These task characteristics, as explicated in Shanteau (1992), should also be taken into account to define an expert.

In this perspective, the literature has not established the theory of experts in dynamic decision making provided the defining characteristics of dynamic decision tasks. A series of questions has to be explored: What dimensions of capability, either general (cognitive / learning style, test intelligence, and generic problem-solving ability) or specific to dynamic tasks, define an expert of dynamic decision tasks? What are the generic task characteristics attached to a dynamic decision task in addition to the specific domain knowledge, such as social welfare administration (Maxwell, 1995) or capital management (Sterman, 1989a)? How can these generic task characteristics be observed? Are effective dynamic decision makers, regardless of task domains, really outstanding in these task characteristics?

4.2. Theories of Task Complexity

Several indicators of dynamic task complexity have been examined previously, among which lagged effects and positive feedback gains account for two major sources of dynamic complexity. The foregoing empirical evidences have mostly demonstrated their detrimental influence to task performance and learning, especially positive gains. As argued, nevertheless, negative feedback loops with stabilizing functions may be another source of complexity – perhaps decreasing task difficulty. The interaction between positive and negative feedback loops may produce mysterious systems behavior that can not be easily anticipated (Forrester, 1968). Adding lagged effects just make a task system more difficult to be managed. Finally, goal structures (A1 to A5 in Table 2) based on task property (Table 1) is also an unexplored issue of task complexity. In typical complex dynamic tasks, such as social welfare system (Maxwell, 1995) and fire-fighting task (Brehmer, 1995), all these factors contributing to task complexity – positive gains, negative stabilizing force, lagged effects, goal structure, and their interactions – have been built in task equations. However, there is still no unified "complexity metric" for complex dynamic decision tasks. Based on the preceding review, the literature resolves this issue by two convenient approaches: singling out these indicators, particularly lagged effects and positive gains, and using a relatively simple task.

This may hinder the progress of the DDM research substantially. At first, the effect of any predictor can not really be confirmed since task complexity is always a potential lurking variable, particularly for those full-fledged complex dynamic tasks. For instance, providing decision makers with complete information about the relationships of variables may work well to improve their performance in a simple computer person task (e.g., Berry and Broadbent, 1988), but fail in a social welfare task (e.g., Maxwell, 1995). This is a more compelling reason why the DDM researchers should enhance and accumulate knowledge by doing experiments based on the same tasks. Several task systems have been used frequently in this fashion, such as capital management (e.g., Sterman, 1989a), sugar production (Berry and Broadbent, 1984), computer person (Berry and Broadbent, 1984), and fire fighting (Brehmer, 1990) tasks.

Another implication of the confounding effect of task complexity leads to the re-evaluation of the general conclusion that human decision makers are essentially dynamically deficient in dealing with dynamic decision tasks based on the misperception of feedback hypothesis (e.g., Sterman, 1989a, 1989b; Diehl and Sterman, 1995). Simply put, the reason why people fail in dynamic decision making is just that tasks are really difficult. More precisely, task complexity may serve as a ceiling of task performance, provided that both task complexity and task performance can be measured and their relationships can be derived. In this respect, the lens model equation appear to be a promising tool (Cooksey, 1996). Based on Brunswik's lens model framework, decision makers' judgmental accuracy can be derived based on two linear regression models composed of the relevant cues capturing human judgment and task predictability. The lens model equation then suggests that, if both linear regression models can account for most variance of human judgment and task predictability, decision makers' judgmental accuracy will always be less than task predictability. That is, provided that a task is better approximated (measured by task predictability) by a linear regression model, decision makers tend to perform better (measured by judgmental accuracy). If a task is hard to be approximated, decision makers would suffer from degraded performance, a ceiling set by the low task predictability. In this vein, human's dynamic deficiency as claimed by many DDM studies should be reconsidered on the basis of task complexity. An attempt to demonstrate this argument has been conducted by a meta-analysis of the literature of expert judgment in static tasks (Stewart and Hsiao, 1997).

4.3. Theories of Mental Models

All decision aids, prescriptions for dynamic decision behavior, would remain mysterious if no description and theories can be provided to predict and explain how these decision aids interact with human's cognitive activities. For instance, based on a series of experiments, Berry and Broadbent (1984, 1987, 1988) and the studies along the same line (e.g., Hayes and Broadbent, 1988; Stanley et al., 1989) have distinguished the mental constructs of implicit (unselective) and explicit (selective) learning modes. In addition, task knowledge can accordingly be separated into explicit (verbalizable) and implicit knowledge. A prominent factor that can affect learning modes is lagged effects (task salience), either built in task structure or induced by experimental manipulations. When the relationships of variables can be directly perceived, decision makers tend to evaluate decision rules and explicit hypotheses of decisions and outcomes based on their current state of task knowledge. In other words, the explicit learning mode dominates. As the task become less salient – because of greater lagged effects and/or other predictors, such as positive gains – the number of evaluations for the explicit hypotheses becomes unmanageable. In this situation, decision makers may adopt the implicit learning mode by which large numbers of paralleled contingencies involving decisions and resultant outcomes are stored. Decisions are generated based on a mental "look-up table" based on which a particular set of conditions (e.g., previous decisions, outcomes, and other relevant cues) give rise to a particular response (Broadbent et al., 1986). The operation is similar to a general pattern-matching process. Finally, both implicit and explicit mental models work together in the whole decision-making process and contribute to task knowledge acquisition in some form.

Mental models may also be conceived as an iterative process of information acquisition and information combination. Sterman (1989a, 1989b) and other authors (e.g., Diehl and Sterman, 1995) have been able to match empirical data with certain regression models approximating the decision rules adopted by decision makers implicitly. Yet Kleinmuntz (1993) demonstrates that two structurally distinctive linear models used to approximate decision heuristics can produce two sets of systems behaviors with only a minor difference. Provided that human decision makers can not always apply their decision rules consistently, it is quite difficult to adjust one model against the other. An explanation provided to account for dynamic decision behavior is rational allocation of limited cognitive resources. Following this line, decision aids are primarily designed to decrease decision efforts that decision makers have to expend. To illustrate, the provision of task structure information would reduce subjects' cognitive resources to build up task structure. Pre-task instructions on decision heuristics similarly equip subjects with handy information combination rules to generate decisions. Note, however, that the theoretical paths connecting task structure information, decision heuristics, task performance, and task knowledge remain unsettled based on the empirical evidences reviewed previously.

4.4. Theories of Information Feedback

Decision aids through information feedback can also be interpreted along the rationale of limited cognitive resources. Sanderson's work (1989) to visualize the variables' algebraic relationships and make them more understandable has been expanded by the research on ecological interface design in dynamic decision making (Vicente, 1996). Sengupta and Abdel-Hamid (1993), as reported previously, have been designed and tested the differential impact of outcome feedback, feedforward, and cognitive feedback. Future research may explore which components of cognitive feedback, as conceptualized by Balzer et al. (1992), really help in dynamic decision making.

Another promising research line related to information feedback points to cognitive continuum theory (Hammond et al., 1987). The theory presumes that correspondence of task continuum and cognitive continuum, both of which can be characterized as continuums from perfect analytic to perfect intuitive modes, would lead to better task performance. To illustrate, the capital management game in Richardson and Rohrbaugh (1990) requires decision makers to place weekly capital investment and hence may lean toward a analytic task environment – refer to Hammond (1987) for task continuum index to as the measurement. In this context, based on cognitive continuum theory, decision makers would receive more helpful information feedback if the information can be designed to stimulate their cognitive process to think through the task more analytically – measured by cognitive continuum index.

5. CONCLUDING REMARKS

Several limitations for the current literature review should be recognized. Firstly, the sampled English DDM research is assumed to be representative to the population literature of dynamic decision making and complex problem solving. Cross-checking the categories of the evaluative criteria (Table 2) and predictors (Table 3) with those produced by the previous literature reviews surveying the European literature is a safeguard for the assumption. Secondly, the current review depends heavily on the empirical studies conducted by laboratory experiments. There have been insightful attempts to broaden the methodological paradigm. For example, Kluwe (1995) provides two approaches to conducting single case studies for the CPS research. The first is the theory testing approach where researchers start with a theory or a model of dynamic decision behavior and single case studies can be employed to test the theory. The second is the theory construction approach where a series of single case studies may be conducted to build up assumptions and models for further investigations.

Proper application of single case studies is helpful for transforming the prevailing consulting practice that endeavors to build learning environments and microworlds as corporate training programs into an abundant source of the DDM hypotheses. On one hand, the evaluative criteria, predictors, and hypotheses of the DDM research reported above provides the theoretical foundations for designing learning environments. For example, the graphical presentation of information as a part of cognitive feedback has demonstrated to be constructive. On the other hand, establishing learning environments to facilitate decision making may be actually regarded as building hypotheses about whether and how combining a certain set of decision aids functions. This may be the most distinct aspect between the DDM research and the consulting practice on building learning environments. Whereas the DDM research manipulates and examines the descriptive and prescriptive evidences independently, the consulting practice has to design learning environments containing multiple predictors of dynamic decision behavior, for example, incorporating information feedback and verbal instructions on task property and decision heuristics in a single microworld. Provided that rigid tests for these blended hypotheses are extremely difficult if not totally impossible in practice, laboratory experiments can be conducted for this purpose. As a conclusion, the interaction between the practice of learning environments and the academic research of dynamic decision making should be further encouraged.

Another limitation for the current study concerns the research paradigm for dynamic decision-making research. Almost all experimental studies reviewed here employ a conventional research paradigm – independent variables (predictors of dynamic decision-making behavior, as those in Table 3) explain or predict dependent variables (evaluative criteria of dynamic decision-making behavior, as those in Table 2). A promising alternative is to examine the hypotheses based on a dynamic feedback perspective for dynamic decision-making behavior. Maxwell (1995: 14) provides an example in this regard. Two sectors have been identified in the diagram: the system sector in which the task model operates, and the sector of mental activity in which the mental model resides. The states of the system are perceived and assessed by the mental model, which in turn develops the means, ends, and means-ends components and determine the next action. Then these components of the mental model will also be modified according to decision maker's judged adequacy for both the outcome of the action and the interpretation of the system states. There is no study yet to examine the feedback theory of dynamic decision-making behavior as a whole set of inter-connected hypotheses.

REFERENCES

Bakken, B. E. (1993). *Learning and Transfer of Understanding in Dynamic Decision Environments*. Ph.D. Dissertation, Massachusetts Institute of Technology, Boston.

Balzer, W. K., M. E. Doherty, and J. O'Connor. (1989). Effect of Cognitive Feedback on Performance. *Psychological Bulletin*, 106(3): 410-433.

Balzer, W. K., L. B. Hammer, and K. E. Summer. (1992). Task Information, Cognitive Information, or Functional Validity Information: Which Components of Cognitive Feedback Affect Performance. *Organizational Behavior and Human Decision Processes*, 53: 35-54.

Berry, D. C. and D. E. Broadbent. (1984). On the Relationship between Task Performance and Associated Verbalized Knowledge. *The Quarterly Journal of Experimental Psychology*, 36A: 209-231.

Berry, D. C. and D. E. Broadbent. (1987). The Combination of Explicit and Implicit Learning Processes in Task Control. *Psychological Research*, 49: 7-15.

Berry, D. C. and D. E. Broadbent. (1988). Interactive Tasks and the Implicit-Explicit Distinction. *British Journal of Psychology*, 79: 251-272.

Brehmer, B. (1990). Strategies in Real-Time Dynamic Decision Making. In R. M. Hogarth (Ed.), *Insights in Decision Making* (pp. 262-279). Chicago: University of Chicago Press.

Brehmer, B. (1992). Dynamic Decision Making: Human Control of Complex Systems. *Acta Psychologica*, 81: 211-241.

Brehmer, B. (1995). Feedback Delays in Complex Dynamic Decision Tasks. In P. Frensch and J. Funke (Eds.), *Complex Problem Solving: The European Perspective* (pp. 103-130).

Brehmer, B. and R. Allard. (1991). Dynamic Decision Making: The Effects of Complexity and Feedback Delay. In J. Rasmussen, B. Brehmer, and J. Leplat (Eds.), *Distributed Decision Making: Cognitive Models of Cooperative Work* (pp. 319-334).

Brehmer, B. and D. Dorner. (1993). Experiments with Computer-Simulated Microworlds: Escaping Both the Narrow Straits of the Laboratory and the Deep Blue Sea of the Field Study. *Computers in Human Behavior*, 9: 171-184.

Brehmer, B. and P. Svenmarck. (1995). Distributed Decision Making in Dynamic Environments: Time Scales and Architectures in Decision Making. In J. Caverni (Ed.), *Contributions to Decision Making* (pp. 155-174). NY: Elsevier Science.

Broadbent, B. and B. Aston. (1978). Human Control of a Simulated Economic System. *Ergonomics*, 21: 1035-1043.

Broadbent, D., P. FitzGerald, and M. Broadbent. (1986). Implicit and Explicit Knowledge in the Control of Complex Systems. *British Journal of Psychology*, 77: 33-50.

Buchner, A. (1995). Basic Topics and Approaches to the Study of Complex Problem Solving. In P. Frensch and J. Funke (Eds.), *Complex Problem Solving: The European Perspective* (pp. 27-63). NJ: Lawrence Erlbaum Associates Publishers.

Cooksey, R. (1996). *Judgment Analysis: Theory, Methods, and Applications*. NY: Academic Press.

Diehl, E. and J. D. Sterman. (1995). Effects of Feedback Complexity on Dynamic Decision Making. *Organizational Behavior and Human Decision Processes*, 62(2): 198-215.

Dorner, D. (1980). On the Difficulties People Have in Dealing with Complexity. *Simulation and Games*, 11: 87-106.

Edwards, W. (1962). Dynamic Decision Theory and Probabilistic Information Processing. *Human Factors*, 4: 59-73.

Fong, G. T. and R. E. Nisbett. (1991). Immediate and Delayed Transfer of Training Effects in Statistical Reasoning. *Journal of Experimental Psychology*, 120(1): 34-45.

Forrester, J. W. (1968). *Principles of Systems*. Cambridge MA: Productivity Press.

Frensch, P. A. and J. Funke. (1995). Definitions, Traditions, and a General Framework for Understanding Complex Problem Solving. In P. Frensch and J. Funke (Eds.), *Complex Problem Solving: The European Perspective* (pp. 3-25). NJ: Lawrence Erlbaum Associates Publishers.

Funke, J. (1995). Experimental Research on Complex Problem Solving. In P. Frensch and J. Funke (Eds.), *Complex Problem Solving: The European Perspective* (pp. 243-268). NJ: Lawrence Erlbaum Associates Publishers.

Hammond, K. R., R. M. Hamm, J. Grassia, and T. Pearson. (1987). Direct Comparison of the Efficacy of Intuitive and Analytical Cognition in Expert Judgment. *IEEE Transactions on Systems, Man, and Cybernetics*, 17: 753-770.

Hayes, N. A. and D. E. Broadbent. (1988). Two Modes of Learning for Interactive Tasks. *Cognition*, 28: 249-276.

Hernandez, K. (1991). *Learning in Real Estate: The Role of the Development System in Creating Oversupply*. MS Thesis, Massachusetts Institute of Technology, Boston.

Hogarth, R. M. and S. Makridakis. (1981). The Value of Decision Making in a Complex Environment: An Experimental Approach. *Management Science*, 27: 93-107.

Jansson, A. (1995). Strategies in Dynamic Decision Making: Does Teaching Heuristic Strategies By Instructions Affect Performance. In e. a. J. P. Caverni (Ed.), *Contributions to Decision Making* (pp. 213-232). NY: Elsevier Science.

Kampmann, C. E. (1992). *Feedback Complexity and Market Adjustment: An Experimental Approach*. Ph.D. Dissertation, M. I. T.

Kleinmuntz, D. N. (1985). Cognitive Heuristics and Feedback in a Dynamic Decision Environment. *Management Science*, 31: 680-702.

Kleinmuntz, D. N. (1987). Human Decision Processes: Heuristics and Task Structure. In P. A. Hancock (Ed.), *Human Factors Psychology* (pp. 123-157).

Kleinmuntz, D. N. (1993). Information Processing and Misperception of the Implications of Feedback in Dynamic Decision Making. *System Dynamics Review*, 9(3): 223-237.

Kleinmuntz, D. N. and B. Kleinmuntz. (1981). Systems Simulation: Decision Strategies in Simulated Environments. *Behavioral Science*, 26: 294-305.

Kluwe, R. H. (1995). Single Case Studies and Models of Complex Problem Solving. In P. Frensch and J. Funke (Eds.), *Complex Problem Solving: The European Perspective* (pp. 269-291). NJ: Lawrence Erlbaum Associates Publishers.

Locke, E. A. and G. P. Latham. (1990). *A Theory of Goal Setting and Task Performance*. New York: Prentice-Hall.

Mackinnon, A. J. and A. J. Wearing. (1980). Complexity and Decision Making. *Behavioral Science*, 25(4): 285-296.
Maxwell, T. A. (1995). Decisions: *Cognitive Styles, Mental Models, and Task Performance*. Ph.D. Dissertation, State University of New York at Albany, Albany.
McGeorge, P. and A. M. Burton. (1989). The Effects of Concurrent Verbalization on Performance in a Dynamic Systems Task. *British Journal of Psychology*, 80: 455-465.
Paich, M. and J. D. Sterman. (1993). Boom, Bust, and Failures to Learn in Experimental Markets. *Management Science*, 39(12): 1439-1458.
Randers, J. (1984). *The Tanker Market*. Working Paper. Oslo: Norwegian School of Management.
Rapoport, A. (1975). Research Paradigms for the Study of Dynamic Decision Behavior. In D. Wendt and C. Vlek (Eds.), *Utility, Probability, and Human Decision Making* (pp. 349-375).
Richardson, G. P. (1991). *Feedback Thought in Social Science and Systems Theory*. Philadelphia: University of Pennsylvania Press.
Richardson, G. P. and J. Rohrbaugh. (1990). Decision Making in Dynamic Environments: Exploring Judgments in a System Dynamics Model-Based Game. In K. Borcherding, O. I. Larichev, and D. M. Messick (Eds.), *Contemporary Issues in Decision Making* (pp. 463-472). Amsterdam: North-Holland.
Sanderson, P. M. (1989). Verbalizable Knowledge and Skilled Task Performance: Association, Dissociation, and Mental Model. Journal of Experimental Psychology: *Learning Memory and Cognition*, 15: 729-747.
Sengupta, K. and Abdel-Hamid. (1993). Alternative Conceptions of Feedback in Dynamic Decision Environments: An Experimental Investigation. *Management Science*, 39(4): 411-428.
Shanteau, J. (1992). Competence in Experts: The Role of Task Characteristics. *Organizational Behavior and Human Decision Processes*, 53: 252-266.
Stanley, W. B., R. C. Mathews, R. R. Buss, and S. Kotler-Cope. (1989). Insight without Awareness: On the Interaction of Verbalization, Instruction and Practice in a Simulated Process Control Task. *The Quarterly Journal of Experimental Psychology*, 41A(3): 553-577.
Sterman, J. D. (1987). Testing Behavioral Simulation Models by Direct Experiment. *Management Science*, 33(12): 1572-1592.
Sterman, J. D. (1989a). Misperceptions of Feedback in Dynamic Decision Making. *Organizational Behavior and Human Decision Processes*, 43(3): 301-335.
Sterman, J. D. (1989b). Modeling Managerial Behavior: Misperceptions of Feedback in a Dynamic Decision Making Experiment. *Management Science*, 35(3): 321-339.
Sterman, J. D. (1994). Learning in and about Complex Systems. *System Dynamics Review*, 10(2/3): 291-330.
Sternberg, R. J. (1995). Expertise in Complex Problem Solving: A Comparison of Alternative Conceptions. In P. Frensch and J. Funke (Eds.), *Complex Problem Solving: The European Perspective* (pp. 295-321). NJ: Lawrence Erlbaum Associates Publishers.

Stewart, T. R. and N. Hsiao (1997). Judgmental Accuracy and Task Predictability. Paper presented at the *Thirteenth Annual International Invitational Meeting of the Brunswik Society*.

Trees, S., J. Doyle, and M. Radzicki. (1996). Using Cognitive Styles Typology to Explain Dynamic Decision Making in a Computer Simulation Game Environment. Paper presented at the *International System Dynamics Conference* (pp. 557-560).

Vicente, K. J. (1996). Improving Dynamic Decision Making in Complex Systems through Ecological Interface Design: A Research Overview. *System Dynamics Review*, 12(4): 251-279.

Wang, S. (1994). *Learning Laboratory Design and Learning Transfer*. Ph.D. Dissertation (in Chinese), National Sun Yat-Sen University, Kaohsiung, Taiwan.

Yang, J. (1996). Facilitating Learning through Goal Setting in A Learning Laboratory. Paper presented at the *International System Dynamics Conference* (pp. 593-596).

Yang, J. (1997). Give Me the Right Goals, I Will Be A Good Dynamic Decision Maker. Paper presented at the *International System Dynamics Conference* (pp. 709-712).

Young, S. H., C. P. Chen, S. Wang, and C. H. Chen. (1997). An Experiment to Study the Relationship between Decision Scope and Uncontrollable Positive Feedback Loops. Paper presented at the *International System Dynamics Conference* (pp. 15-20).

TABLES AND FIGURES
(In order of appearance in the text)

Table 1: Background Information of the Reviewed Empirical Studies

Studies Reviewed	Task Descriptions (Task Domain, Task Property, and Decisions Required)
Bakken (1993)	- A stock management task in general. Real estate (Hernandez, 1991) and oil tankers (Randers, 1984) market models - Two forecasts and two decisions have to be made for both games. - Task property: delay, nonlinearity, and positive loops
Berry and Broadbent (1984)	- A sugar production game. Single decision needed. - A computer person game. Single decision needed. - Task property: delay
Berry and Broadbent (1987)	- A sugar production game (Berry et al., 1984) with a single decision - A computer person game (Berry et al., 1984) with a single decision - Task property: delay
Berry and Broadbent (1988)	- Experiment 1: A computer person game (Berry et al., 1984) with a single decision - Experiment 2: a game as in Experiment 1 plus a bus and a train task with a single decision. - Task property: delay
Brehmer (1990)	- A fire-fighting simulation game DESSY in real time mode - A single decision needed - Task property: delay, nonlinearity, and positive loops
Brehmer and Allard (1991)	- A fire-fighting simulation game DESSY in real time mode (Brehmer, 1990) requiring a single decision - Task property: delay, nonlinearity, and positive loops
Brehmer (1995)	- A fire-fighting simulation game FIRE FIGHTING in real time mode - A single decision - Task property: delay, nonlinearity, and positive loops
Brehmer and Svenmark (1995)	- A fire-fighting simulation game D^3FIRE in real time and interaction modes - A single decision - Task property: delay, nonlinearity, and positive loops
Broadbent and Aston (1978)	- ECONEX: A game simulating British economy - Multiple (three) decisions needed - Task property: delay
Broadbent, FitzGerald, and Broadbent (1986)	- A city transportation system and economy game (Broadbent et al., 1978) - Multiple (two) decisions - Task property: delay
Diehl and Sterman (1995)	- A stock management task in general (Sterman, 1989b) - Making a single decision. - Task property: delay, nonlinearity, and positive loops

Studies Reviewed	Task Descriptions (Task Domain, Task Property, and Decisions Required)
Hayes and Broadbent (1988)	- A computer person game (Berry et al., 1984) with a single decision - A game of random letter generation for the secondary task for the second and third experiments. - Task property: delay
Hogarth and Makridakis (1981)	- A marketing strategy game with multiple (more than five) decisions - Task property: delay, nonlinearity, and positive loops - An interactive game
Jansson (1995)	- Moro: Welfare development of a developing region - Multiple (25) decisions can be placed. - Task property: delay, nonlinearity, and positive loops
Kampmann (1992)	- A game of market strategy - Multiple (two) decisions - Task property: delay, nonlinearity, and positive loops
Kleinmuntz and Kleinmuntz (1981)	- A medical decision making task with a single decision - Task property: delay, nonlinearity, and positive loops - Monte-Carlo simulation
Kleinmuntz (1985)	- A medical decision making as in Kleinmuntz et al. (1981) with a single decision - Task property: delay, nonlinearity, and positive loops - Monte-Carlo simulation
Kleinmuntz and Thomas (1987)	- DOC medical decision making task built on as in Kleinmuntz et al. (1981) with a single decision - Task property: delay, nonlinearity, and positive loops
Mackinnon and Wearing (1980)	- Welfare administration simulation game - Multiple (three) decisions are required - Task property: delay, nonlinearity, and positive loops
Maxwell (1995)	- A social welfare model (JOBS) based simulation game - Make multiple (six) decisions. - Task property: delay, nonlinearity, and positive loops
McGeorge and Burton (1989)	- A sugar production game (Berry et al., 1984) - A single decision needed - Task property: delay
Paich and Sterman (1993)	- A market strategy game - Multiple (two) decisions have to be made. - Task property: delay, nonlinearity, and positive loops
Richardson and Rohrbaugh (1990)	- A capital investment simulation game STRATEGEM-2 (Sterman, 1989a) requiring a single decision - Task property: delay, nonlinearity, and positive loops
Sanderson (1989)	- A city transportation system (Broadbent et al., 1986) with a single decision - Task property: delay

Studies Reviewed	Task Descriptions (Task Domain, Task Property, and Decisions Required)
Sengupta and Abdel-Hamid (1993)	- A software project management game - A single variable decision: staffing level of a software project - Task property: delay, nonlinearity, and positive loops
Stanley, Mathews, Buss, and Kotler-Cope (1989)	- A sugar production game (Berry et al., 1984) - A computer person game (Berry et al., 1984) - Both game require a single decision - Task property: delay
Sterman (1989a)	- A capital investment simulation game STRATEGEM-2 based on Sterman (1987) - Make a single decision: capital order. - Task property: delay, nonlinearity, and positive loops
Sterman (1989b)	- A stock management game: Beer Game - Make a single decision on beer order. - Task property: delay, nonlinearity, and positive loops - An interactive game
Trees, Doyle, and Radzicki (1996)	- A capital investment game STRATEGEM-2 (Sterman, 1989a) requiring a single decision - Task property: delay, nonlinearity, and positive loops
Wang (1994)	- A capital investment simulation game STRATEGEM-2 (Sterman, 1989a) with a single decision - Task property: delay, nonlinearity, and positive loops
Yang (1996)	- Two games: 1) market growth model and 2) capital investment game STRATEGEM-2 (Sterman, 1989a) - A single decision for both games - Task property: delay, nonlinearity, and positive loops
Yang (1997)	- The prey/predator model with fixes that fail archetype. - A single decision - Task property: delay, nonlinearity, and positive loops
Young, Chen, and Chen (1997)	- A capital investment game STRATEGEM-2 (Sterman, 1989a) requiring a single decision. - Task property: delay, nonlinearity, and positive loops

Table 2: Evaluative Criteria (Dependent Variables) for Dynamic Decision Making

General Category	Conceptual and Operational Definition (Measure) and the Reviewed Studies Using this Measure[1]
(A)Task performance	(A1) Optimizing, maximizing or minimizing, specified measures or benchmarks - Cost, the higher the cost, the lower the performance (Sterman, 1989a; Sterman, 1989b; Richardson et al., 1990; Wang, 1994; Diehl et al., 1995; Maxwell, 1995; Trees et al., 1996) - Profit (Kampmann, 1992; Bakken, 1993; Paich et al., 1993; Yang, 1996; Young et al., 1997) - Patients' health conditions (Kleinmuntz et al., 1981) - Proportion of patients cured (Kleinmuntz, 1985; Kleinmuntz et al., 1987) - Number (percent) of areas lost (Brehmer, 1990; Brehmer et al., 1991; Brehmer, 1995; Brehmer et al., 1995) - Difference (percent difference) compared with a benchmark (Broadbent et al., 1978; Mackinnon et al., 1980; Bakken, 1993) - Number of decision outcomes better than a benchmark (Broadbent et al., 1986)
	(A2) Reaching specified targets - Number (percent) of attempts within a range of a specified target (Berry et al., 1984; Broadbent et al., 1986; Berry et al., 1987; Berry et al., 1988; Hayes et al., 1988; McGeorge et al., 1989; Sanderson, 1989; Stanley, et al., 1989) - Number (percent) of attempts in correct directions to reach the target (Sanderson, 1989; Yang, 1996) - Number (percent) of errors of directions to reach the target (Broadbent et al., 1986; Berry et al., 1987)
	(A3) Task systems behaviors - Number of systems destruction (Yang, 1997) - Number of appearances of an archetype "fixes that fail" (Yang, 1997)
	(A4) Goals combining two criteria - Market share and cumulative net marketing contribution (consistent goals) (Hogarth et al., 1981) - Cost and schedule (conflicting goals) (Sengupta et al., 1993)
	(A5) Goals combining multiple (greater than two) criteria - A composite index based on six indicators (Jansson, 1995)

General Category	Conceptual and Operational Definition (Measure) and the Reviewed Studies Using this Measure[1]
(B) Learning	(B1) Mean scores of pre-game and/or post-game questionnaires on the relationships of variables, including those direct and crossed relationships between variables – declarative task knowledge (Broadbent et al., 1978; Berry et al., 1984; Broadbent et al., 1986; Berry et al., 1987; Berry et al., 1988; Hayes et al., 1988; Sanderson, 1989; Bakken, 1993; Jansson, 1995; Maxwell, 1995; Trees et al., 1996)
	(B2) Mean scores of pre-game and/or post-game questionnaires same as (B1), particularly on procedural task knowledge (Hayes, et al., 1988)
	(B3) Number of correctness of mental models aligned with heuristics and goals set forth (Yang, 1996; Yang, 1997)
	(B4) Number matching certain types mental models (Sanderson, 1989)
	(B5) Performance on transferred tasks (Berry et al., 1988; Hayes et al., 1988; Bakken, 1993; Wang, 1994)
(C)Efforts for decision making	(C1) Amounts of decision time (Kleinmuntz et al., 1987; Sanderson, 1989; Brehmer, 1990; Brehmer et al., 1991; Sengupta et al., 1993; Wang, 1994; Brehmer, 1995; Brehmer et al., 1995; Diehl et al., 1995; Jansson, 1995; Maxwell, 1995; Yang, 1996)
	(C2) Amounts of information use for specific information items (Brehmer et al., 1991; Sengupta et al., 1993; Brehmer et al., 1995; Jansson, 1995; Maxwell, 1995; Yang, 1996)
	(C3) Amounts of discussion among subjects (Hogarth et al., 1981)
(D) Quality of decision-making process	(D1) Decision scope (number of different decision rules employed) (Wang, 1994; Young et al., 1997)
	(D2) Reliability (fluctuations of decisions) (Sengupta et al., 1993)
(E) Decision-making architecture	(E1) Delegation of decision making (Brehmer et al., 1991)

1: Studies cited in each definition are ordered by time of publication.

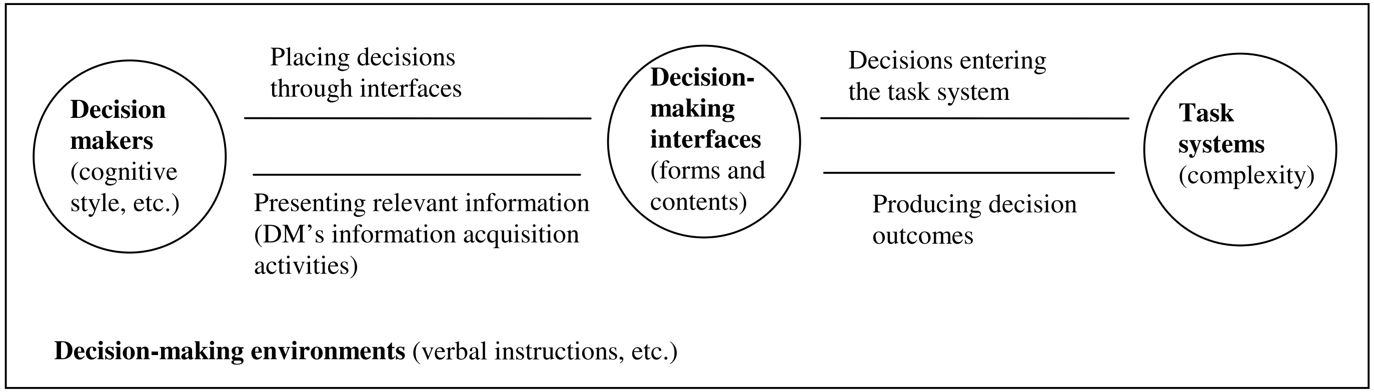

Figure 1: A Tentative Research Framework of Dynamic Decision Making

Table 3: Predictors (Independent Variables) for Dynamic Decision Making

Category	Conceptual Definition	Operational Definition (Measure) and Reviewed Studies Using the Measure[1]
(IVA) Decision makers' factors	(IVA1) Cognitive style (ability)	- MBTI (Myers-Briggs Type Indicator) (Maxwell, 1995; Trees et al., 1996) - Gregorc Style Delineator (four mediation channels) (Trees et al., 1996) - Gordon's Cognitive Style Indicator (four types) (Trees et al., 1996)
	(IVA2) Task expertise / academic training on general task knowledge	- Whether subjects have task domain expertise in terms of their academic background (Bakken, 1993) - Whether subjects receive a 2-day session involving simulation of the JOBS program (Maxwell, 1995)
	(IVA3) Computing skills	- Subjects' self-rating evaluation about their computer use skills (Trees et al., 1996)
	(IVA4) Practice / task experience	- Whether subjects experience repeated trials (not explicitly manipulated) (Broadbent et al., 1978; Kleinmuntz et al., 1987; Berry et al., 1987; Berry et al., 1988; Stanley et al., 1989; Brehmer, 1990; Brehmer et al., 1991; Bakken, 1993; Sengupta et al., 1993; Paich et al., 1993; Wang, 1994; Diehl et al., 1995) - Amounts of practice from repeated trials (Berry et al., 1984; Broadbent et al., 1986; Sanderson, 1989) - Whether subjects experience a conceptually similar task for the next trial block (Berry et al., 1988)
(IVB) Task complexity	(IVB1) Total number of variables	- Total number of variables in task systems (Mackinnon et al., 1980)
	(IVB2) Interaction between subsystems	- Whether interaction exists between variables or subsystems (Mackinnon et al., 1980)
	(IVB3) Random variation	- Whether random variation exists at strategic points in tasks (Mackinnon et al., 1980)
	(IVB4) Miscellaneous task characteristics	- Initial health, treatment risk, and symptom diagnosticity (Kleinmuntz, 1985) - Treatment risk (Appearance or strength) (Kleinmuntz et al., 1987)

Category	Conceptual Definition	Operational Definition (Measure) and Reviewed Studies Using the Measure[1]
		- Levels of price regime (Kampmann, 1992) - Types of software project (Sengupta et al., 1993)
	(IVB5) Time delay / lagged effects (appearance or strength)	- Lagged effects (Broadbent et al., 1978; Broadbent et al., 1986; Berry et al., 1988; Paich et al., 1993) - Time constants (Sterman, 1989a; Sterman, 1989b; Brehmer, 1990; Brehmer et al., 1991; Kampmann, 1992; Brehmer, 1995; Diehl et al., 1995)
	(IVB6) Effectiveness of decisions on outcomes / task salience built in models	- Treatment effectiveness (Kleinmuntz, 1985) - Reducing stability by enlarging effects of a decision on outcomes (Broadbent et al., 1986) - Effectiveness of fire-fighting units (Brehmer et al., 1991)
	(IVB7) Frequency of oscillation	- Number of peaks of prices (Bakken, 1993)
	(IVB8) Positive feedback and gains (appearance or strength)	- Positive gains built in the task model (Sterman, 1989a; Sterman, 1989b; Kampmann, 1992; Diehl et al., 1995) - Strength of "word of mouth" (Paich et al., 1993) - Number of intervals a system falls in the uncontrollable positive loops (Young et al., 1997)
	(IVB9) Real-time simulation tasks	- Whether a task system is clock-driven or event-driven (Brehmer, 1995)
(IVC) Decision-making interfaces and environments	(IVC1) Heuristics (decision rules) built in task systems	- 3 levels: 1) arbitrary consistent, 2) arbitrary-random, and 3) none (left for human judgment) (Hogarth et al., 1981) - 3 levels of strategies with increasing computational complexity: 1) generate-and-test, 2) heuristic, and 3) EU-bayesian (Kleinmuntz et al., 1981) - Random vs. schema-driven strategies, 2 levels of information acquisition, 2 levels of base-rate utilization, 3 levels of computational complexity (Kleinmuntz, 1985)
	(IVC2) Modes of learning induced by lagged effects	- Selective-mode or unselective mode by varying lagged effects of decisions (Hayes, et al., 1988)
	(IVC3) Heuristics-induced goal	- 2 types: 1) total assets goal (long-term wholesystem goal) and 2) total assets and order growth goal

Category	Conceptual Definition	Operational Definition (Measure) and Reviewed Studies Using the Measure[1]
	setting that subjects receive through verbal instructions	(short-term subsystem goal) (Yang, 1996) - 3 types: prey/predator (whole-system) ratio, prey/predator (whole-system) number, and prey (sub-system) number (Yang, 1997)
	(IVC4) Task property, strategies, and heuristics (decision rules) that subjects receive through verbal instructions	- Training / no training concerning task property (Berry et al., 1984; Berry et al., 1987; Berry et al., 1988) - 3 levels of task property: 1) no preliminary training, 2) trained with relationships of variables, and 3) practicing each pair of relationships separately (Broadbent et al., 1986) - 3 levels of expert transcripts: 1) no transcript, 2) block-by-block transcript, and 3) whole transcript (Stanley et al., 1989) - 5 levels of instructions: 1) no training, 2) expert transcript, 3) memory training, 4) rule construction, 5) simple rule (Stanley et al., 1989) - 5 types of expert transcripts: 1) no training, 2) initial blocks, 3) final blocks, 4) pre-cutpoint of performance, 5) post-cutpoint of performance (Stanley et al., 1989) - 2 levels of instructions: 1) systematic-elaborate: variables' relationship, 2) goal-planning: detailed measures of decisions and outcomes (Jansson, 1995) - 3 levels of training: 1) causal loop, 2) strategic time plots, and 3) strategic heuristics) (Maxwell, 1995)
	(IVC5) Concurrent verbalization / thinking-aloud	- Whether, while playing the game, subjects are required to verbally describe tasks and heuristics employed (Berry et al., 1984; McGeorge et al., 1989; Stanley et al., 1989)
	(IVC6) Increasing task salience	- Between trial blocks, instruct subjects with task structures and effects of decisions and time delay (Berry et al., 1988; Wang, 1994) - Whether subjects are informed with appearance of delay (Brehmer, 1995)
	(IVC7) Degree of decision precision required	- Whether subjects are required to place decisions to the first decimal place (Sanderson, 1989)
	(IVC8) Learning inducement	- Prior to tasks, instruct subjects to focus on searching for task pattern and structure (Berry et al., 1988) - Prior to tasks, induce learning by instructing subjects that learning is crucial and task performance does not affect economic reward (Wang, 1994)
	(IVC9) Contents of information	- Whether Bayesian strategy is available (Kleinmuntz et al., 1987)

Category	Conceptual Definition	Operational Definition (Measure) and Reviewed Studies Using the Measure[1]
	display	- Whether subjects' previous decisions and outcomes are available (Sanderson, 1989) - 3 levels: 1) Feedforward: whether the subjects learned the three formula; 2) cognitive feedback: whether the subjects received task information; 3) outcome feedback: project status reports in numerical forms (Sengupta et al., 1993)
	(IVC10) Forms of information display	- Whether subjects receive graphical representations of system status (McGeorge et al., 1989; Sanderson, 1989) - Whether subjects receive formula for decisions (Sanderson, 1989) - Whether subjects only receive variables' names without semantic meanings (Sanderson, 1989) - 3 levels: 1) no cue highlighted, 2) all cues highlighted (cue discovery), and 3) all cues highlighted plus heuristics (feedforward) (Richardson et al., 1990)
	(IVC11) Decision-making architectures	- Whether subjects use hierarchical or networked decision-making (Brehmer, et al., 1995)

1: Studies cited in each definition are ordered by time of publication.