1989

TECHNOLOGICAL SUPPORT FOR DECISION MAKING IN THE PRESENCE OF UNCERTAINTY AND EQUIVOCALITY

Ritu Agarwal
The University of Dayton

Mohan Tanniru
Syracuse University

TECHNOLOGICAL SUPPORT FOR DECISION MAKING IN THE PRESENCE OF UNCERTAINTY AND EQUIVOCALITY

Ritu Agarwal
Department of MIS and Decision Sciences
The University of Dayton

Mohan Tanniru
School of Management
Syracuse University

ABSTRACT

The informational and support requirements of ill-structured decision making activity are contingent upon the factors that have caused this lack of structure. This paper attempts to operationalize the notion of "semi-structure" by an examination of the effect of uncertainty and equivocality on the decision making process and suggests that the presence of the these dimensions creates different support requirements for the decision maker. These requirements are subsequently mapped onto the features of alternative types of technological support, with the intent of determining the efficacy of a particular technology for a particular type of decision making task. It is argued that a single technology may prove ineffective in supporting semi-structured decision making, and a rationale for technology integration is developed.

1. INTRODUCTION

An important objective in the design of any computer based information system is to match a user's needs for information and support with appropriate technical artifacts. The choice of a particular technology, e.g., Management Information Systems (MIS), Decision Support Systems (DSS), Group Decision Support Systems (GDSS) or Expert Systems (ES), to address these needs depends to a large extent on the type of system that can best provide the required support for the decision making task under consideration. MIS have been shown to be useful for routine, structured tasks, and there is little ambiguity with respect to the types of problems that can be handled effectively through this technology. GDSS, DSS and ES, on the other hand, are relatively new types of systems and the parameters within which these systems can be effectively deployed are not very well-defined.

The basic premise underlying the development of DSS is to provide support for any phase of the decision making process where successful task completion can benefit from an active two-way human/machine interaction. Thus, DSS technology has been recommended for addressing ill-structured decision making situations (Keen and Scott-Morton 1978), where these systems augment rather than replace human judgement. The lack of structure in a decision making task, however, can manifest itself in a variety of forms, and while support for semi-structured decisions is a recurrent theme in the DSS literature, we have not found an operational definition of that term. ES utilize the heuristic, judgmental, and experiential knowledge of an expert in a computer based system that exhibits expert levels of performance (Brachman et al. 1983) for both semi-structured and unstructured tasks. GDSS are systems that support activities where multiple individuals are involved in the decision making process (DeSanctis and Gallupe 1987).

Information systems exist in organizations to support the managerial activities of decision making and problem solving. The logical basis for the development of theories which suggest where different types of information systems may be useful is thus the decision making process, as the informational and support requirements of ill-structured decision making activity are contingent upon the factors that have caused this lack of structure. The process of decision making has been shown to be affected by two types of factors: equivocality and uncertainty (Daft and Lengel 1986). This paper presents a decision-theoretic perspective for analyzing the role of different technologies in the decision making process. The uncertainty/equivocality dimensions inherent in decision making are examined further. Uncertainty and equivocality are shown to manifest themselves in different ways in different phases of the decision making process. It is argued that the nature of these dimensions gives rise to different support needs for the decision maker attempting to cope with uncertainty and equivocality. These support needs immediately suggest the type of computing technology that would be most appropriate for providing the required support.

This paper presents the popular models of decision making that have formed the basis of much of the information systems research. The phases of the particular model selected in this research are elaborated upon. The manner in which uncertainty and equivocality manifest themselves in each phase of the decision making process and uses this understanding to derive the support needs of each phase are outlined. These needs are subsequently mapped onto the features of DSS, GDSS and ES technology. This mapping provides guidelines for determining the efficacy of a particular technology for a particular decision making task.

2. DECISION MAKING IN ORGANIZATIONS

Several prescriptive and descriptive models of decision making have been presented in the literature. Simon (1960) describes the decision making process as including intelligence, design, and choice phases. Mason (1981) classifies the decision making process into five steps: observation, measurement, recording of data from the source (similar to the intelligence phase), drawing inferences/predictions from this data and evaluation of these inferences with regard to the organization's value system (design phase), and choosing and implementing the chosen action (choice phase). Archer (1987) compares alternative perspectives on decision making practices and arrives at a nine step decision making process that is implicitly or explicitly used by various decision makers. Prescriptive models include statistical decision theory (Luce and Raiffa 1988).

From a support perspective, descriptive models are more useful since they attempt to describe the procedural rationality (Simon 1978) inherent in decision making and should form the logical basis for the design of decision support mechanisms. We have used the models described above to extract one unifying decision making framework. The objectives of this synthesis are two-fold: to develop a formal definition for each phase of decision making activity and to use these definitions for analyzing the precise effect of forces that impact decision making behavior. In general, a decision making activity is triggered by the existence of a problem, an opportunity, or a need for action. The first phase in the decision making process requires the decision maker to specify the precise nature of the decision making task (problem identification). The individual then generates alternate courses of action to address the situation and estimates the impact of the alternatives on organizational operations (problem analysis). Using a set of criteria that are considered appropriate in the decision making environment, the "best" course of action is selected by the individual (problem resolution).

The elements that constitute the decision making process are formalized in Table 1. Figure 1 maps the nine steps of Archer onto the three phases: problem identification, problem analysis, and problem resolution. Problem identification includes the first four steps: the identification of variables in the decision environment, the problem environment, the decision objectives, and the diagnosis of the problem state using the functional relationship among these variables. The problem analysis phase includes the establishment of the appraisal criteria and the subsequent relating of these criteria to variables that constitute the decision objectives and the problem state in order to generate alternatives. These alternatives are evaluated in the problem resolution phase using again the functional relationship among variables in the appraisal criteria, appraisal strategies and the alternative sets, in order to determine a single alternative for implementation.

Table 1. Elements of Decision Making

problem environment	p_e
decision environment	d_e
decision objectives	d_o
problem state	P
relationships in problem identification	f_pi
appraisal criteria	a_c
alternatives	A
relationships in problem analysis	f_pa
relationships in problem resolution	f_pr

The decision making process may be described as consisting of identifying appropriate input variables (or criteria) and of relating them functionally (using criteria relationships or associations) at one phase in order to derive the output variables, which become the input criteria for the next phase as shown in Table 2.

In the problem identification phase, the decision environment is monitored and compared with the decision objectives in order to see if an unacceptable or undesirable situation has occurred. Variables in the problem environment are then analyzed to determine the underlying reason for not meeting the decision objectives and the problem state thus established. The exact meaning of the framework is illustrated through an example described below. While the example is restricted in that it describes only one type of decision related activity -- that triggered by the existence of a problem -- the extension of the framework to other types of decision making tasks is easily achieved.

In an order processing system, a decision objective (a maximum allowable error rate of one percent in invoices) is achieved by monitoring various processing characteristics

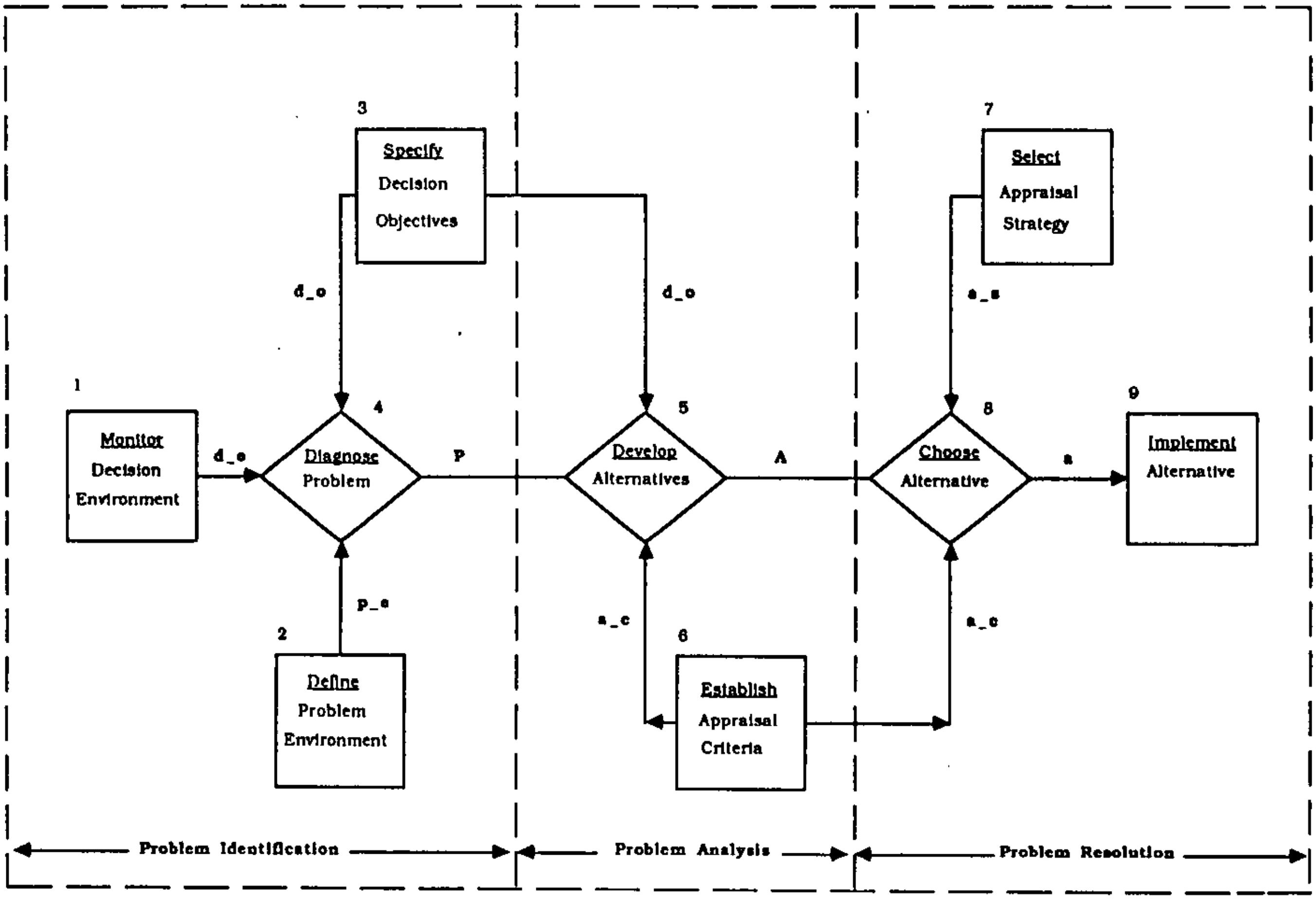

Figure 1. A Three-Phase, Nine-Step Decision Making Framework

Table 2. A Model of the Decision Making Process

	Output	Process	Input
problem identification	P	f_pi	d_o , d_e, p_e
problem analysis	A	f_pa	P, a_c, d_o
problem resolution	a	f_pr	A a_s, a_c

Notation: Output | Process | Input

(time, accuracy, volume processed, etc.) of tasks such as order validation, invoicing, shipping and payment processing. The deviation in the decision objective can be attributed to deviations in each of these processing tasks and, if so, the cause of such deviations can be attributed to variables in the problem environment (growth in orders processed, relatively less skilled new employees, frequent price changes among the products shipped, etc.). The task of problem identification or problem diagnosis is that of identifying the variables in the problem environment that have contributed to the deviation in the decision objective. If this investigation results in the recognition that frequent price changes have contributed to the observed deviation in the decision objective, then this constitutes the problem state: "invoicing errors are caused by frequent price changes."

The problem analysis phase generates a set of alternatives to correct the problem diagnosed in the problem identification step. These alternatives are generated using information on appraisal criteria, decision objectives and the problem diagnosed. The alternative generation process may use a variety of approaches such as prior experience, brain-storming among multiple individuals, creative thinking, or the use of specific tools (e.g., linear or goal programming algorithms). Thus, the problem analysis phase requires an identification of tools/procedures that are appropriate for generating a set of feasible alternatives to address the problem diagnosed.

Consider again the case of the order processing system. If the number of price changes have contributed to invoicing errors, then the objective here is to identify a set of feasible alternatives to reduce this error rate. The feasibility of an alternative may depend upon some basic appraisal criteria the organization uses in its evaluation of alternatives, such as "minimize out-of-pocket costs," or "reduce impact on user personnel," and the decision objective "reduce invoice error rate to under 1 percent," while fully cognizant of the fact that "frequent product price changes" have contributed to this problem. Multi-criteria decision making algorithms can be used to generate alternatives (tasks in the order processing system that need to change) to reduce errors in invoicing, while meeting some of the appraisal criteria. If no such algorithmic tool exists, then procedures such as brain storming, creative thinking and collective experience may be called upon to perform this task. The problem resolution phase will select an alternative from the alternative set using an appropriate appraisal strategy and the appraisal criteria. The appraisal strategy may call for a choice to be made by a single or by multiple individuals, through consensus seeking as opposed to simple majority, or by a rank ordering of alternatives on an absolute vis-a-vis a relative scale.

In the order processing system, the alternatives proposed may include the automation of certain tasks, addition of new labor, alteration of certain information flows, etc. A selection among these can be affected by estimating their impact on costs, benefits, risks, etc. The variable dependencies in the order processing system are summarized in Table 3.

Notice that the steps identified here may not all be performed in every decision situation and may, at some times, be performed repeatedly as in an iterative decision making process. For example, the problem may have been diagnosed a priori as "increase in orders processed." The decision making task is then one of generating alternatives to address this growth in orders. On the other hand, all the alternatives in the alternative set may be rejected during the choice phase, thus necessitating a regeneration of alternatives.

3. SEMI-STRUCTURED DECISION MAKING

Decisions have been categorized as structured, semi-structured or unstructured based on the extent to which procedures, types of computation and analysis, and the information requirements can be predefined (Keen and Scott-Morton 1978). Complete knowledge of the variables and their relationships is a characteristic of structured or programmable decisions, while incomplete knowledge creates a lack of structure. Structure may exist at one phase of the decision making process and not at the next, resulting in the decision being labelled "semi-structured." Semi-structure may also result within a single phase of the decision making process, such as problem analysis, where the appraisal criteria and decision objectives are well defined but the process used to generate alternatives is unclear. Again, in the order processing system, if the problem is identified as "errors caused by frequent task repetition," then the process of generating alternatives to reduce this error using appraisal criteria such as "low personnel impact and cost minimization" may not be well-defined.

The type of information gathered and manipulated by decision makers is dependent on which phase of the decision making process that information is intended for. While information can be gathered much more directly for structured decisions, this is not the case when a part of the decision making process exhibits a lack of structure. Further, different strategies are needed to address the lack of structure experienced in different stages of the decision making process. The lack of structure caused by uncertainty in the problem environment during the problem identification phase has to be dealt with differently from a lack of structure caused by incomplete knowledge of the appraisal criteria during the problem analysis phase. In the former, an organization has little control over the environment it is trying to monitor and gather information on, while in the latter the organization does have access to this information, if not explicitly. Keen and Scott-Morton (1978) recognize that the definition of structure is one that is difficult to grasp. In the following discussion, we attempt to define the term "structure" more precisely in light of the decision making framework developed previously.

Milliken (1987) has categorized uncertainty into three components: 1) state uncertainty, which refers to the uncertainty experienced by a decision maker when variables associated with the organizational environment are perceived as unpredictable, 2) effect uncertainty, which is present when the decision maker is unable to assess the effect of a change in environmental variables on the decision outcome, and 3) response uncertainty, where the decision maker cannot identify an appropriate strategy for action. All three uncertainties play a role in each phase of

Table 3. Variable Dependencies in the Order Processing System

Problem Identification				
(P)		(d_o)	(d_e)	(p_e)
frequent price changes	f_pi	Reduce invoice error rate	Time and accuracy of order processing tasks	Price changes, growth in sales, less skilled labor, etc.
Problem Analysis				
(A)		(P)	(a_c)	(d_o)
add labor, computerize certain tasks, restrict price change frequency	f_pa	frequent price changes	cost minimization, minimize impact on personnel, gradual shift to new technology	Reduce invoice error rate
Problem Resolution				
(a)		(A)	(a_s)	(a_c)
computerize invoice preparation	f_pr	Add labor, computerize certain tasks, restrict price change frequency	rank order based on overall risk	cost minimization, minimize impact on personnel, gradual shift to new technology

the decision making process, even though their relative impact may vary within each phase. For example, during the problem identification phase, state uncertainty may result if the decision maker is not able to identify all of the environmental variables that may have an effect on the decision objectives, effect uncertainty results if the impact of these environmental variables is difficult to predict, and response uncertainty may manifest itself as a decision maker's inability to implement the problem identification process in order to choose a "problem state" from all the likely causes. Similarly, state uncertainty during the problem resolution phase corresponds to not knowing what appraisal criteria and strategies are going to impact the selection process, effect uncertainty deals with the relationship between these criteria and the alternative set, and response uncertainty corresponds to the decision maker's choice strategy used to select a given alternative.

In terms of the framework described in Figure 1, state uncertainty deals with lack of information about the (state) variables used to define the problem state set, the alternatives set, or the chosen alternative, while effect uncertainty deals with inadequacies in defining the functional relationships. Response uncertainty is primarily concerned with the implementation procedure used by the decision maker to select a given choice at each phase. In general, state uncertainty may be dominant during the problem identification phase (due to the environmental impact), while response uncertainty may be dominant during the problem resolution phase (where a user is asked to choose a strategy).

The nature of the uncertainty inherent in any decision related task must be understood before that task can be supported in any meaningful way. For example, does "state uncertainty" imply a lack of knowledge about the environmental variables that affect a decision objective (i.e., what variables affect invoice error rate) or a lack of knowledge about their values (i.e., what is the skill level of the new employees). The former deals with the relevance of a given state variable on the problem (definitional uncertainty), while the latter deals with inadequate information about the relevant ranges of values for these variables (domain uncertainty). One can gather more information or ask specific questions if we are attempting to determine the value of a known variable. However, in the case of definitional uncertainty, information must be gathered to identify the relevant variables that affect the decision making process. Clearly there is a precedence implicit here in that definitional uncertainty must be addressed prior to addressing domain uncertainty and the informational needs to reduce each of these are different.

Organizations have been shown to process information to reduce uncertainty and to resolve equivocality (Weick 1979) in decision making. While uncertainty is defined in terms of the difference between the information that is needed to make decisions and the information an organiza-

Table 4. Framework for Uncertainty/Equivocality Discussion

Decision Making Phases	Definitional Uncertainty (Equivocality)	Domain Uncertainty (Uncertainty)
Problem Identification	**Personnel Performance Case**	**Product Quality Case**
State: d_o, p_e, d_e Effect: f_pi Response: P	How do variables affect problem? How are problems formulated? How is a problem selected?	What are their values? What is the problem set? What is the problem?
Problem Analysis	**Sales Monitoring Case**	**Cost Analysis Case**
State: d_o, a_c Effect: f_pa Response: A	How are criteria established? How are alternatives generated? How is the feasible set chosen?	What are the criteria? What are the alternatives? What is this set?
Problem Resolution	**Resource Allocation Case**	**Vendor Evaluation Case**
State: a_c, a_s Effect: f_pr Response: a	How are strategies identified? How are alternatives evaluated? How is the 'best' selected?	Which strategy is selected? What do they suggest? What is the best?

tion already has (Galbraith 1977), equivocality implies the existence of multiple and conflicting interpretations about an organizational situation (Daft and Macintosh 1981). Uncertainty is reduced by gathering more information, while equivocality is resolved by collecting richer information (Daft and Lengl 1986). In our framework, definitional uncertainty corresponds to the concept of "equivocality," while domain uncertainty is equivalent to simply "uncertainty." Daft and Lengel (1986) discuss the role of uncertainty and equivocality on informational needs associated with the decision making process and suggest various information acquisition strategies to reduce uncertainty and resolve equivocality. An understanding of the extent to which each of these dimensions affects a particular phase of the decision making process can help us identify the appropriate technique to acquire knowledge and the right technology to store and manipulate this knowledge. The next section examines how the equivocality and uncertainty dimensions in each phase of the decision making process can be used to identify the support requirements of that phase.

4. SUPPORT MECHANISMS TO RESOLVE DOMAIN AND DEFINITIONAL UNCERTAINTY

In this section, state, effect, and response uncertainty in each phase of the decision making process are studied under both the uncertainty and equivocality dimensions and appropriate support mechanisms to reduce uncertainty and resolve equivocality are proposed. Six different example cases are used to highlight these differences. Table 4 describes the framework that will be used for discussion.

Phase I: Problem Identification

In a personnel performance evaluation system, personnel productivity is measured in terms of the number of items produced in a week. However, an employee's performance may be affected by numerous factors such as task characteristics, operating policies, performance evaluation procedures, etc. (variables in the problem environment). The exact nature of this relationship may be ill-defined, thus making it difficult to diagnose the problem state. Since there are multiple variables that affect labor productivity and their impact is not always known a priori, this results in state equivocality. A synthesis of multiple perspectives in a group setting or access to expert opinion on such issues can help reduce this equivocality. If the relevant variables have been identified, the decision maker needs to construct hypotheses about what variables have contributed to the decline in productivity, necessitating an understanding of the effect of these variables on productivity. Again, expert opinion or prior experience may provide the information to resolve this type of equivocality. Responding to this situation by selecting a single hypothesis from the set generated can also be equivocal, and this can be resolved only by defining, a priori, a reasoning strategy in the form of a hypothesis evaluation procedure. Thus, the support mechanisms to address equivocality in problem identification include:

state equivocality:	group meetings, expert opinion
effect equivocality:	a knowledge base of hypotheses derived from experts, or prior experience
response equivocality:	reasoning strategies for rank ordering plausible hypotheses

In a product quality control system, the reduction in the quality level of a product can be attributed to either changes in various machine settings used in the production process or to the quality levels of the incoming raw materials. These variables and their design relationships are well defined. A product may go through multiple stages and several machine settings, with each stage affecting the ultimate quality of the product. To assess the cause of poor quality, information on each setting for each part is required. If this information is not available, state uncertainty is experienced in the form of lack of information on possible problem states. A random sampling of the operating data can be used to match output quality to selected machine settings. If the design relationships are simple, a model can be constructed and the possible culprit identified using sensitivity analysis. However, if the problem is complex in that design relationships are difficult to express in mathematical terms, the "effect" uncertainty can be reduced by either using a simplified version of the model or by formulating plausible hypotheses to diagnose the problem. The selection of the most likely cause is less uncertain if the model is simple and its performance can be simulated. However, if the model is complex, the decision maker has to either simulate a simpler version of the system or examine the system response to various hypotheses and select the most plausible one. The support mechanisms in such an uncertain environment include:

state uncertainty:	selective sampling or frequent data gathering
effect uncertainty:	modeling, simulation, knowledge base of heuristics
response uncertainty:	sensitivity analysis

Phase II: Problem Analysis

Consider the case of a sales monitoring system in a manufacturing company. Any decline in sales may be attributed to several factors such as a loss of brand loyalty, population shifts, etc. State equivocality here results if there is no clear, well-defined goal or consensus on the appraisal criteria to be used to generate alternatives that address an established problem state: "sales are declining due to new competition." To rectify this problem, several appraisal criteria such as increase brand loyalty, penetrate into new markets, or reduce the markup may be used. State equivocality is caused due to a lack of agreement on a given appraisal criterion and this can be resolved using group consensus seeking procedures or corporate policies, if any. If an appraisal criterion is selected, then the relationships between appraisal criteria, objectives and the problem state have to be modeled in order to generate a set of alternatives. The non-deterministic nature of these relationships may render this type of modeling infeasible, thereby causing effect equivocality. This can be resolved using various stochastic models, past experiences on what has been effective in prior situations, expert opinion, or normative marketing theory, among others. Once an approach is chosen, the selection of a set of alternatives that are acceptable requires sensitivity analysis and an evaluation of the alternatives in the context of the organizational environment that could not be explicitly modeled. The support features here include:

state equivocality:	group consensus seeking procedures, policy directives
effect equivocality:	stochastic modeling, prior experience, expertise
response equivocality:	sensitivity analysis

Consider the case of a cost analysis system in a retail organization. The objective is to reduce shipping costs and several strategies can be used to accomplish this objective, including reducing purchasing costs, reducing distribution costs, altering stocking policies, etc. State uncertainty results when there is no effective way of selecting one of these strategies. This can be reduced by gathering more information on their features and appropriateness under different operating scenarios. Once an application criterion is chosen (for example, alter stocking policies), modeling the system to achieve the objective requires relating inventory, stock-out, purchasing, and receiving variables. A lack of information about the values that these variables can assume may create effect uncertainty and this can be reduced by information gathering and modeling of important relationships. Response uncertainty occurs if the set of feasible alternatives has to be somewhat subjectively evaluated, since not all the relevant information may be modeled explicitly. This can be reduced by having these alternatives evaluated by experts on various qualitative dimensions and by allowing the decision maker to perform sensitivity analysis. The support features for a reduction of uncertainty here include:

state uncertainty:	appraisal criteria, assumptions, appropriate tools to support these criteria
effect uncertainty:	modeling facility and availability of algorithmic tools
response uncertainty:	output interpretation, sensitivity analysis, access to expert opinion when qualitative factors are taken into account

Phase III: Problem Resolution

Consider a resource allocation decision in a corporate setting. In this case, a set of projects have to be evaluated based on corporate risk, cost, and goal congruence considerations. State equivocality is manifest when the strategy the corporation may choose to combine corporate risk, cost/benefit analysis, and other strategic considerations is ambiguous. The appraisal strategies may include rank ordering of projects on multiple dimensions and a subsequent synthesis of the rankings, rank ordering within groups (first on criticality, then within criticality, on internal rate of return), etc. This type of equivocality can be resolved by talking to the group of individuals involved in the resource allocation process or by using past experiences relating to the effectiveness of appraisal strategies. Effect equivocality arises when it is difficult to rank order the candidate projects on the chosen appraisal criteria since the extent to which a project contributes to, say, a reduction in corporate risk is unclear. Again, this can be resolved by using group consensus seeking procedures or by consulting a knowledge base of expert opinion on such matters. Response equivocality results if the group that allocates resources is ambiguous as to how to use this information in making a final choice. A resolution of response equivocality requires the provision of a multi-dimensional perspective of the alternatives, user-friendly explanations where appropriate, and the use of graphics.

state equivocality:	group discussion, prior experience
effect equivocality:	group consensus seeking procedures or models, expert opinion
response equivocality:	multi-dimensional perspectives, user-friendly interpretations, graphics

Consider a vendor evaluation system used to purchase a product or equipment. There are a number of candidate criteria that can be used to evaluate vendors and information can be collected on each one of these (price/performance ratio, delivery dates, reliability), along with information on when each criterion is appropriate, to reduce state uncertainty. Modeling the relationship between appraisal criteria and strategies is feasible except when all the vendor's proposals do not provide sufficient information for an effective evaluation of each. Response uncertainty is caused by a lack of information on how the decision maker may rank order these (i.e., objectively or subjectively) and what information is needed to assist in this comparison. The support features here include:

state uncertainty:	classification on multiple criteria, clustering similar entities
effect uncertainty:	modeling with incomplete information
response uncertainty:	multi-dimensional presentations, sensitivity analysis

The support mechanisms identified above can be instrumental in reducing uncertainty and resolving equivocality in different phases of the decision making process. These are summarized in Figure 2. The next section demonstrates how different technologies can be utilized to effectively provide these support features, depending on the nature of the decision making task.

5. TECHNOLOGICAL SUPPORT FOR SEMI-STRUCTURED DECISIONS

Decision making processes that do not experience any domain or definitional uncertainty in all phases (the so-called structured decisions) can be supported quite effectively by traditional MIS technology. More interesting from a technological support perspective are decisions that exhibit "semi-structure" in any of the forms described above. In this section we map the different types of semi-structure to the technology that best provides the needed support. The candidate technologies are Decision Support Systems, Group Decision Support Systems (GDSS) and Expert Systems.

Figure 2 summarizes the atomic support characteristics for each phase of decision making activity identified in the previous section. Note that the partitioning of the support features along the lines of state, effect, and response provides a contrast to the data, model, and dialog support categorization that is prevalent in the DSS literature. The division of this support under the equivocality and uncertainty dimensions allows for an examination of data, model, and dialog support separately under each dimension. Several observations are in order.

	Equivocality	Uncertainty
	STATE	
PI	group meetings, expert opinion	selective sampling of data
PA	group consensus seeking procedures, policy directives	appraisal criteria, assumptions, information on tools & criteria
PR	group discussion, prior experience	classification on multiple criteria, entity clustering
	EFFECT	
PI	hypotheses derived from experts or prior experience	modeling, simulation, knowledge base of heuristics
PA	stochastic modeling, prior experience and expertise	model management facility and access to tools
PR	group consensus seeking procedures or models, expert opinion	modeling with incomplete information
	RESPONSE	
PI	rank ordering plausible hypotheses	sensitivity analysis
PA	sensitivity analysis	output interpretation, sensitivity analysis, access to expert opinions and views
PR	multi-dimensional views, user-friendly interpretations, graphics, etc.	multi-dimensional presentations, sensitivity analysis

Figure 2. Support Features for Uncertainty and Equivocality

In general, the presence of the equivocality dimension requires "rich" information that must be gathered and synthesized in order to arrive at a consensus when a group is involved in the decision making process, or to increase the confidence if a single individual is involved. Many GDSS tools discussed in the literature that support communication (DeSanctis and Gallupe 1987), allow for the utilization of multi-criteria decision making models, and provide mechanisms for seeking group consensus (Hwang and Lin 1987) are appropriate when equivocality is high. In the case of a single individual making a decision, access to multiple views, expert opinions, and prior scenarios can all prove useful in reducing the equivocality experienced in reaching a decision.

The ability of expert systems to store symbolic knowledge and manipulate it using heuristics renders them appropriate for managing qualitative data in the form of heuristics and hypotheses. Most of the formalisms used in expert systems allow a user to formulate a hypothesis (specify a goal) and search the knowledge base to confirm or disconfirm the hypothesis. ES technology, through its ability to manipulate knowledge that is incomplete or uncertain, is best suited for any task that needs to utilize this type of information. Most of the basic algorithmic tools such as simulation and optimization, however, are more effectively employed in traditional DSS mode. Both DSS and ES technologies have the ability to store and provide access to numeric and symbolic data. Traditionally, numeric and performance related data have been stored in databases that can be interfaced with algorithmic models, while knowledge representing hypotheses, experts' opinions, and decisions have been stored in knowledge bases to accommodate uncertainty in this knowledge. This distinction is becoming blurred since many expert systems allow access to databases, while DSS are able to access knowledge stored using ES technology.

The presence of uncertainty can be addressed by much of the DSS technology discussed in the literature. This includes model management for selecting, building and formulating models (Dolk and Konsynski 1984), algorithmic tool management, database management for allowing access to a wide variety of data, and dialog management to provide user-friendly interfaces (Sprague 1980). ES technology is useful for facilitating the selection of models and tools (Binbasioglu and Jarke 1986), reducing the problem search space using heuristics, and providing natural language interfaces in problem formulation and resolution. These general observations suggest the following classification of support:

	Equivocality	Uncertainty
STATE	access to corporate policies, prior experience on such situations, expert opinion	access to operating data, assumptions, criteria, information on tools
	facility for the group to communicate and discuss	facility to classify data on several dimensions
EFFECT	facility to access and evaluate various hypotheses, to manage multi-criteria decision making models, access to expert opinion	facility to access, build, and select models, to access various tools, to handle incomplete information
RESPONSE	facility to allow a group to reach a consensus, to perform sensitivity analysis and obtain user-friendly presentations	facility to perform sensitivity analysis, interpret output, access expert decisions, obtain user-friendly presentations

Figure 3. A Recategorization of Support Features

	Equivocality	Uncertainty
State	Level 1 GDSS/ ES	Data Base Mgmt./ES
Effect	Level 2 GDSS/ES	Model Base Mgmt./ES
Response	Level 3 GDSS/ES	Dialog Mgmt./ES

Figure 4. Categorization of Technological Support

	Equivocality	Uncertainty
Technology Support	GDSS/ES	DSS/ES

Figure 3 resummarizes the information in Figure 2 so as to allow an examination of the technical support details. This resummarization exhibits clearly how the state, effect, and response equivocality dimensions are best supported by Level 1, Level 2, and Level 3 GDSS (DeSanctis and Gallupe 1987), with knowledge base/expert system access when appropriate. State, effect, and response uncertainty dimensions are most effectively supported with traditional data, model, and dialog management capabilities, again with appropriate knowledge base/expert system access.

A single technology cannot be effective in supporting all phases of the decision making process. Our intent in using the uncertainty/equivocality dimensions to analyze decision making was to tentatively suggest that the boundaries between different types of technological support may be artificial. These technologies must be integrated, as demanded by the type of "lack of structure" present in the decision making task. This integration is already taking place in the form of new programming paradigms such as constraint logic programming (Lassez, McAloon and Yap 1987) which combines expertise with algorithmic models like linear programs, the incorporation of expertise in DSS to assist in model/tool selection (Turban and Watkins 1986), and in the design of intelligent GDSS (Agarwal and Prasad 1989). The need for this integration is evident and the lines along which this integration must proceed to provide the maximum benefit for decision support is presented in Figure 4.

6. CONCLUSION

A phase in the decision making process or multiple phases may be repeated if the decision maker is not certain of the decision outcome of that particular phase. Thus, uncertainty or equivocality at any phase may result in an iterative decision making process and any reduction in uncertainty or the resolution of equivocality through the use of computing technology can only reduce the number of iterations needed.

Given that equivocality may be high at one phase and uncertainty high at another, a decision maker may need to access various technologies to support his/her decision. In addition, a decision maker may use office automation and communication technologies to communicate the decision to others. Thus, the support that is provided to a manager should consider the problem that needs to be solved first and tailor the technological support accordingly by exploiting the synergism of technologies. We have argued in this paper that the presence of uncertainty and equivocality in decision making environments warrants different modes of computing support.

The ultimate problem in providing decision support to an individual is in determining what technology is appropriate to solve a problem and when. If the interplay of these technologies is to remain relatively transparent to the user, then it is critical that a meta-level support interface be provided. This interface would examine the task and select the technology based on the degree of uncertainty and equivocality present in the decision situation and choose the right tool within that technology to support the state, effect and response needs.

7. REFERENCES

Agarwal, R., and Prasad, K. "Enhancing the Group Decision Making Process: An Intelligent Systems Architecture." *Proceedings of the Twenty-Second Hawaii International Conference on System Sciences*, Volume 3, 1989, pp. 273-279.

Archer, E. R. "How to Make a Business Decision: An Analysis of Theory and Practice." In S. Withane, *Organization Design: Theory and Applications*, Littleton, Massachusetts: Copling, 1987.

Binbasioglu, M., and Jarke, M. "Domain-Specific DSS Tools for Knowledge-Based Model Building." *Decision Support Systems*, Volume 2, 1986, pp. 213-223.

Brachman, R. J.; Amaral, S.; Engelman, C.; Engelmore, R. S.; Feigenbaum, E. A.; and Wilkins, D. E. "What are Expert Systems?" In F. Hayes-Roth, D. A. Waterman, and D. B. Lenat, Editors, *Building Expert Systems*, Reading, Massachusetts: Addison-Wesley, 1983.

Daft, R. L., and Lengel, R. H. "Organizational Information Requirements, Media Richness, and Structural Design." *Management Science*, Volume 32, Number 5, 1986, pp. 554-571.

Daft, R. L., and Macintosh, N. B. "A Tentative Exploration into the Amount and Equivocality of Information Processing in Organizational Work Units." *Administrative Science Quarterly*, Volume 26, 1981, pp. 207-224.

DeSanctis, G., and Gallupe, B. R. "A Foundation for the Study of Group Decision Support Systems." *Management Science*, Volume 33, Number 5, 1987, pp. 589-609.

Dolk, D. R., and Konsynski, B. R. "Knowledge Representation for Model Management Systems." *IEEE Transactions on Software Engineering*, Volume SE-10, Number 6, 1984, pp. 619-628.

Galbraith, J. *Organizational Design*, Reading, Massachusetts: Addison-Wesley, 1977.

Hwang, C. C., and Lin, M. J. *Group Decision Making Under Multiple Criteria*, New York: Springer-Verlag, 1987.

Keen, P. G., and Scott-Morton, M. S. *Decision Support Systems: An Organizational Perspective*, Reading, Massachusetts: Addison-Wesley, 1978.

Lassez, C.; McAloon, K.; and Yap, R. "Constraint Logic Programming and Option Trading." *IEEE Expert*, Fall 1987, pp. 42-50.

Luce, R. D., and Raiffa, H. "Individual Decision Making under Uncertainty." In P. Gardenfors and N. Sahlin, Editors, *Decision, Probability, and Utility*, Cambridge University Press, 1988, pp. 48-79.

Mason, R. O. "Basic Concepts for Designing Management Information Systems." In R. Mason and E. B. Swanson, Editors, *Measurement for Management Decision*, Reading, Massachusetts: Addison-Wesley, 1981, pp. 81-95.

Milliken, F. J. "Three Types of Perceived Uncertainty about the Environment: State, Effect, and Response Uncertainty." *Academy of Management Review*, Volume 12, Number 1, 1987, pp. 133-143.

Simon, H. A. "On How to Decide What to Do." *Bell Journal of Economics*, Volume 9, 1978, pp. 494-507.

Simon, H. A. *The New Science of Management Decision*, New York: Harper and Row, 1960.

Sprague, R. H., Jr. "A Framework for the Development of Decision Support Systems." *MIS Quarterly*, Volume 4, Number 4, 1980.

Turban E., and Watkins, P. R. "Integrating Expert Systems and Decision Support Systems." In R. H. Sprague, Jr. and H. J. Watson, Editors, *Decision Support Systems: Putting Theory into Practice*, New Jersey: Prentice-Hall, 1986, pp. 138152.

Weick, K. E. *The Social Psychology of Organization*, Reading, Massachusetts: Addison-Wesley, 1979.