An Evaluation of Managerial Problem Identification Support Systems

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Contents

I. Introduction

Decision making requires at least three distinct phases: problem identification, alternative design, and solution selection (Mintzberg et al., 1976). The problem identification phase consists of problem recognition and diagnosis routines. Problem recognition is a routine to perceive the existence of problem symptoms (Pounds, 1969), whereas problem diagnosis is to discover and construct the causal structure underlying the symptoms (Smith, 1988). Problem identification is one of the most critical aspects of decision making, as it can affect the direction of all subsequent phases (Volkema, 1983; Smith, 1989). Without appropriate problem identification, decision makers are opt to solve a wrong problem (Mitroff and Featheringham, 1974).

Problem identification is a complex decision process requiring various activities, including problem detection, boundary establishment, key element identification, model formulation, and model validation (Mitroff et al., 1979; Mason and Mitroff, 1981). Problem identification is not an easy task, because most significant managerial problems are embedded in highly

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interdependent systems, and problems themselves are often too complex to be comprehended as a whole (Lyles and Mitroff, 1980; Checkland, 1981). That is, managerial problems tend to have unclear problem boundaries, multiple symptoms and multiple causes mixed with noisy data (Anderson and Janson, 1979), ambiguous and uncertain causal relationships (Einhorn and Hogarth, 1986), and no obvious technique to test the causal relationships (Lyles, 1987).

For such complex and ill-structured problems, successful problem identification is largely dependent on the decision maker's cognitive processing, knowledge, and experiences (Lyles, 1982; Volkema, 1983). Unfortunately, individuals have critical cognitive limitations in dealing with complex problems (Miller, 1956) and are subject to various cognitive biases (Sage, 1981; Hogarth and Makridakis, 1981). Furthermore, their ability to learn from experience deteriorates rapidly as the complexity of the problem increases (Argyris, 1976). Decision makers consider problem identification as the most critical, but most difficult, decision phase (Adams et al., 1990).

Given the importance of problem identification process and the difficulties that decision makers have in that process, there is a need to design support systems for problem identification. Surprisingly, decision support systems (DSS) research has paid little attention to problem identification. Most DSS assume that the decision problems have already been recognized and diagnosed (Courtney et al., 1987).

The purpose of this paper is to establish the requirements for managerial problem identification support systems (MPISS) and evaluate the capabilities of current MPISS with respect to the requirements. The second section provides a literature review on problem identification. The third section develops requirements definitions for MPISS. The fourth section evaluates current MPISS in light of the requirements. The last section provides conclusions.

II. Managerial Problem Identification Process

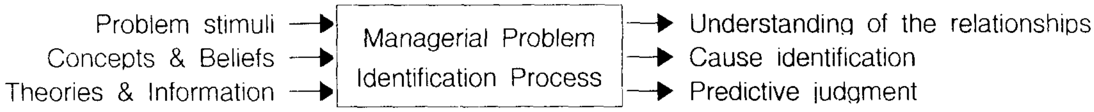
The term "problem" indicates the existence of a difference between the way things are and the way one wants them to be (Pounds, 1969; Smith, 1989). Individuals perceive a problem when the current state falls significantly below a certain aspiration level (Kiesler and Sproull, 1982). They also perceive a potential problem when the current situation is far better than expected or planned (Schoennauer, 1981). The aspiration level is not static, but shifts continuously according to the decision maker's cognitive processes (Dutton et al., 1983), workload (Volkema, 1983), and experiences (Kiesler and Sproull, 1982). Problems, thus, are conceptual entities that individuals create to cope with their environments. In dealing with a problem situation, decision makers must develop mental models of the situation (Simon, 1960). Problem identification process is concerned with recognizing a problem and developing models of the problem situation. The purpose of this section is to better understand the process of managerial problem identification.

2.1. Definition of Problem Identification

There exists a number of definitions for problem identification. Mintzberg defines it as "a process to comprehend the evoking stimuli and determine cause-effect relationships for the decision situation" (Mintzberg et al., 1976, p. 253). Bartee defines it as "a step in which representation of the problem is defined, described, and understood in terms of major problem components and boundary conditions" (Bartee, 1973, p. 442). The meaning of problem identification, however, may be better clarified by relating various definitions. Such an attempt resulted in the following description of the problem identification process.

Problem identification is a process to comprehend the evoking stimuli (Mintzberg et al., 1976). Individuals sense the stimuli by observing triggering events and scan the environment (Schwenk and Thomas, 1983). During this process, decision makers identify the problem boundaries (Bartee, 1973) and focus on important aspects of the problem (Dutton et al., 1983). To comprehend the stimuli, decision makers need to determine the causal structure of the problem (Mintzberg et al., 1976; Bouwman, 1983) by searching, hypothesizing, and testing causal relationships (Courtney et al., 1987) between the symptoms and their underlying causes (Bouwman, 1983). The problem identification process improves the certainty about a problem description (Cowan, 1986).

Another way to clarify the meaning of problem identification is to examine its inputs and outputs. As shown in <Figure 1>, the inputs to the process include problem stimuli (Mintzberg et al., 1976), concepts and beliefs held by the decision maker (Kiesler and Sproull, 1982; Dutton et al., 1983), and the assumptions, theories, and information to frame the situation (Taylor, 1975; Cowan, 1988). The most significant output of the process is an understanding of the cause-effect relationships (Dutton et al., 1983). Other outputs include identification of the specific factors responsible for the problem symptoms, determination of a category into which the problem can be classified, and development of predictive judgment (Einhorn and Hogarth, 1982; Smith, 1988). Predictive judgment means that the causal structure, identified during the problem identification process, provides a basis for designing different effects on the problem situation. Problem identification, thus, provides a critical input into the alternative generation and evaluation phases of decision making.



<Figure 1> The Inputs and Outputs of Managerial Problem Identification Process

2.2. Managerial Problem Identification Processes

Decision theorists have noted that little is known about the problem identification phase of the decision making process (Getzels, 1979). In recent years, however, a growing number of articles on this subject have appeared in managerial decision making literature, especially in the area of strategic planning (Lyles and Mitroff, 1980; Dutton et al., 1983; Volkema, 1986; Ireland et al., 1987; Lyles and Thomas, 1988; Smith, 1989). In general, problem identification requires stimuli detection, stimuli interpretation, and stimuli association activities (Kiesler and Sproull, 1982).

First, stimuli detection is a process of monitoring the environment and noting important qualities. Individuals monitor their environment through deliberate and automatic scanning (Feldman, 1981; Sage, 1981; Cowan, 1986). Decision makers have a tendency of using only easily available data and information and ignoring not easily available sources of significant information (Hogarth and Makridakis, 1981). In other words, search effort of problem identification is allocated. Accordingly, decision makers do not attend to every monitored stimulus; rather, they process the stimuli selectively by filtering out insignificant ones (Mason and Mitroff, 1981). Selective perception is a way of avoiding information overload and maintaining cognitive economies (Mischel, 1979). Individuals tend to concentrate on salient material, for example, events that are unpleasant, deviant, extreme, intense, unusual, sudden, etc. (Kiesler and Sproull, 1982). Salience of stimuli depends upon the strengths of the stimuli, one's aspiration level, and one's tolerance for discrepancy. Consequently, stimuli being attended to vary with decision task (Ireland et al., 1987), decision maker's cognitive style and experience (Feldman, 1981), and stress level (Janis and Mann, 1977).

Second, stimuli interpretation is a process to construct meaning for, or assign meaning to, the sensed stimuli. Interpretation is affected by certain assumptions that are the basic elements of individuals' frames of reference or world views (Taylor, 1975; Mitroff et al., 1979; Mason and Mitroff, 1981). To construct a meaning for the problem, decision makers often use multiple stimuli (Schwenk and Thomas, 1983; Cowan, 1988; Lyles and Thomas, 1988). Individuals show a tendency to prefer consistent information and discount conflicting evidence (Hogarth and Makridakis, 1981). Some managerial problems come with symptoms with so clear meaning that interpretation is not necessary (Smith, 1989). However, stimuli interpretation becomes an important cognitive activity when a problem needs to be discovered, constructed, created, or designed rather than being presented (Getzels, 1979; Volkema, 1986).

Finally, stimuli association is a process to retain stimuli and relate them with other relevant concepts (Einhorn and Hogarth, 1982). Associative thinking implies that stimuli incorporation is dependent upon the knowledge and experience of individuals (Piaget, 1974) as well as the modeling constructs into which the knowledge is embedded (Lyles and Thomas, 1988). Individuals often employ causal association to structure a situation (Axelrod, 1976). Taylor (1975) notes that stimuli association is constrained by the set of schemata invoked for the problem. Yet, the use of schemata has focusing and organizing effects (Kiesler and Sproull, 1982; Ireland et al., 1987). Thus, framing a situation within one particular view may result in an incomplete understanding of the situation (Baldwin, 1989). However, when managers diagnose a problem, they tend to develop only one world view or perspective (Lyles and Mitroff, 1980).

It should be noted that the managerial problem identification process is recursive and retroductive (Dutton et al., 1983). The recursiveness of the problem identification process indicates that the mental model of the problem situation needs to be defined and redefined several times, as the decision maker discovers additional symptoms or restructures the causal relationships (Taylor, 1975; Cowan, 1986). The successive revisions of judgment imply that stimuli incorporation influences further stimuli detection, and that the sequence of detecting stimuli may change the whole problem identification process and results (Bouwman, 1983). The retroductivity of the process signifies the coexistence and interplay of both deductive and inductive modes of thinking (Einhorn and Hogarth, 1986). The mental models of the problem situation developed by individuals depend on both the cognitive maps of the individuals and the data on hand (Cowan, 1988). The deductive mode of reasoning has traditionally been highlighted, because it is the cognitive map that frames, interprets, and incorporates the data on hand. However, when the cognitive maps do not ensure a sufficient basis for deductive reasoning, decision makers need to invoke inductive modes of thinking. The inductive inferences that individuals make will influence their cognitive maps (Lyles and Thomas, 1988).

III. Requirements for Problem Identification Support Systems

The purpose of this section is to define what capabilities a computer-based system must have to support the problem identification process. In general, the most essential element of a support system is the system's knowledge about the problem situation (Sprague and

Carlson, 1982). Knowledge can be largely classified into two categories: declarative and procedural. Declarative knowledge refers to the mental models, logico-mathematical structures, cognitive schemes, or cognitive maps. Procedural knowledge refers to the basic cognitive activities, functions, or operations. A support system may need to have both declarative and procedural knowledge. In other words, a support system must have at least a knowledge base and some problem processing capabilities (Bonczek et al., 1980). In addition, the system must be able to interact with users, because the system is not likely to solve problems by itself. Thus, a support system can be examined from the following three perspectives:

	Knowledge		Problem		User-System
A Support System ->		X		X	
	Base		Processing		Interaction

Note that user-system interaction has a broader meaning than user-system interface, for example, language and presentation systems (Bonczek et al., 1980) or dialog generation and management systems (Sprague and Carlson, 1982). User-system interface design is essentially concerned with developing a user-friendly communication language (Bonczek et al., 1980). User-system interaction design (Woods, 1986), however, addresses much broader, or more fundamental, issues such as how to allocate problem solving efforts between the user and the system.

Another point is that a knowledge base consists of two elements: knowledge structure and knowledge content. Knowledge structure is a certain form used to represent the content of knowledge. The knowledge structure generally corresponds to mental constructs in psychology, representational schemes in artificial intelligence, grammar in language, modeling constructs in MS/OR, or data models and metadata in databases. The knowledge content, then, could be memory contents, facts, vocabularies, model instances, and data occurrences in respective areas. The knowledge content, however, is difficult to establish without first knowing the specific problem situations. Thus, a "generalized DSS" (Bonczek et al., 1981) can be examined from the following perspectives:

	Knowledge		Problem		User-System
A Generalized DSS ->		X		X	
	Base Structure		Processing		Interaction

This paper examines the requirements for MPISS from knowledge structure, problem processing, and user-system interaction aspects.

3.1. Knowledge Structure Requirements of MPISS

Managerial problem identification literature indicates that cognitive scheme, mental models, or logico-mathematical structures, determine how problems are identified. Thus, this paper establishes the knowledge structure requirements from the point that an MPISS should be able to help users to represent their mental models easily. A critical problem, unfortunately, is that not much is known about the complex structure of the mental models. Cognitive psychologists, however, indicate that cognitive maps are perhaps the simplest form of mental models.

Cognitive maps (Axelrod, 1976), being consistent with a structural modeling construct, are designed to represent whether the causal relationships between pairs of variables exist. In fact, a structural model shown in <Figure 2> is perhaps the most generic way to model a problem situation. This approach of categorizing reality in terms of objects and their relationships is most natural in our minds and is widely used in almost all inquiring communities, including philosophy, metaphysics, logic, psychology, science, data base, management science, etc. (see Piaget, 1974; Axelrod, 1976). It is possible for the objects and object relationships to have values. For instance, in the standard logic, a statement about object or object relationship, i.e., a proposition, can have one of two possible values, either true or false. The type of inference that a simple structural model can produce is precisely this: whether an object exists in the model and whether an object affects the others.

<Figure 2> A Structural Model

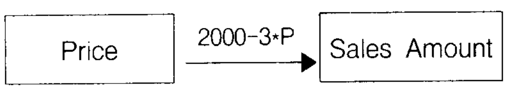
<Example>
H1: Performance(DSS group) $\neq$ Performance(Non-DSS group)

To be noted is that the objects in the structural model can represent either variables (e.g., "market growth") or events (e.g., "slowly growing market"). A variable may assume either a quantitative domain or a qualitative domain. A qualitative domain consists of a set of distinctive labels (inclusive of the truth values), while a quantitative domain consists of a set of measured numbers (often on a continuous scale). An event is a variable associated with its domain values (e.g., "market growth" > 0). When the structural model is used to represent quantitative variables and their relationships, the arcs are typically extended to denote the directions of the effects. As shown in <Figure 3>, a sign of either "+" or "-" may denote whether a variable affects the other variable positively or negatively.

<Figure 3> A Singed Structural Model

<Example>
H1: Performance(DSS group) >
Performance(Non-DSS group)

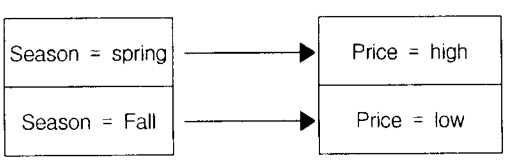
In studying the relationships, inquirers often want to know how variables are related in addition to whether they are related. That is, the inquirers are often interested in measuring the causal impacts between variables. Structural models, however, cannot provide such information. Such a relationship can be represented by using a statistical model, as shown in <Figure 4>. Statistical causal modeling provides not only a systematic way to derive the impact coefficients but also a formal way to represent the interactions among quantitative variables.



<Figure 4> A Statistical Model

<Example>
Sales-Amount = 2000 - 3 * Price

Statistical models capture the relationships among quantitative variables. Although they can handle one or two qualitative variables by using indexes, statistical models have limitations to handle the relationships among qualitative variables. That is, unless the domain of a variable is at least ordinal, it is difficult to describe the relationships in an orderly fashion with a single term, i.e., coefficient. Such relationships must be labeled instead. A modeling construct that overcomes such a difficulty is rule-based modeling. Rule-based modeling can be also used to represent the relationships among events, as shown in <Figure 5>.



<Figure 5> A Rule-based Model

<Example>

If Season = spring Then Price = high;
If Season = fall Then Price = low;

Thus, a MPISS requires, at least, the following modeling constructs to adequately represent variables, events, variable relationships, and event relationships:
(1) Structural modeling: to represent objects (events) and their relationships

(2) Statistical modeling: to describe the relationships among quantitative variables
(3) Rule-based modeling: to describe the relationships among events.

3.2. Problem Processing Requirements of MPISS

A DSS should support all phases of the decision-making process being considered (Sprague and Carlson, 1982; Adams et al., 1990). Managerial problem identification literature indicates that the problem identification process consists of at least three distinctive routines: problem detection; causal model development; and causal model application, as shown in <Figure 6> (Bouwman, 1983; Cowan, 1986). As noted by Dutton et al. (1983), these routines do not necessarily occur in a sequential manner. For example, decision makers may skip or reiterate certain routines or activities.

<Figure 6> Problem Diagnosis Routines

Problem Detection	Perceive stimuli from a problem situation and identify the parts of situation that require cognitive processing
Model Development	Develop and refine an understanding of the causal structure of a problem situation
Model Application	Produce a diagnosis and explain the causal structure of the problem situation

Problem detection is a routine that identifies symptoms indicative for the current state of the problem situation. Detected symptoms are interpreted according to the mental models. If the mental model does not satisfactorily explain the symptoms, the decision maker will either develop a new model or refine the existing model. Causal model development is a routine that identifies key variables (events) and hypothesizes/tests cause-effect relationships among them. Causal model development becomes a critical routine especially for semi-structured or unstructured problems. Causal model application is a routine that formulates alternative diagnoses based on the detected symptoms and causal models, evaluates the alternatives, and produces diagnostic conclusions and justifications.

To be noted is that the model development routine and the model application routine both require hypotheses formulation and testing activities. In fact, alternative diagnoses generation is called "problem-hypotheses" formulation (Bouwman, 1983, p. 664). The difference is that the model development is concerned with finding the cause-effect relationships in general, while model application is concerned with finding the cause-effect relationships for the given problem instance. That is, model development requires inductive and deductive thinking, while model application requires deductive and abductive thinking.

Therefore, a MPISS must have problem processing functions that help:

(1) Problem detection: to identify symptoms
(2) Model development: to establish or refine cause-effect models
(3) Model application: to identify causes from the identified symptoms and models.

3.3. Interaction Requirements of MPISS

A DSS can be viewed as a system embedded in a human decision making system. A synergistic problem solving requires interactions between these two systems (Woods, 1986). From the user's viewpoint, an interface of the DSS that defines the interactions "is the system" (Dos Santos and Holsapple, 1989, p. 1). That is, the cooperation between the users and system can be discussed in terms of the knowledge exchanged between the systems.

A MPISS requires at least two generic interaction functions for knowledge exchange: TELL and ASK. Originally defined by Levesque (1984), TELL allows a user to provide knowledge to the system; and ASK allows the user to seek knowledge from the system.

TELL: system knowledge <-- system knowledge x user assertion.
ASK: system answer <-- system knowledge x user query.

the symbol "<--" means that the elements on the right-hand-side are combined to produce the element on the left-hand-side. Thus, TELL states that the system updates system knowledge based on user assertion. System knowledge on the right-hand-side is the system's a priori knowledge; the one on the left-hand-side is the system's a posteriori knowledge (which becomes a priori knowledge on the next call).

The utility of TELL and ASK depends much on the knowledge held by the problem solving agents. For instance, ASK is of no practical use, when knowledge base is empty. On the other hand, TELL has no value, if knowledge base is complete and truthful. In general, system knowledge is neither empty nor perfect. It is also safe to assume that the same is true for the user's knowledge about the problem situation. Thus, a cooperative MPISS must support both TELL and ASK operations. TELL supports a user-drive problem identification, while ASK supports a system-driven problem identification. It should be noted that the redundant design concept by Woods (1986) suggests that a better view may be derived by overlapping user assertions and system answers.

A PDSS may need to interact with users to develop the following views (in addition to the structural model views, statistical model views, and rule-based model views discussed in Section 3.1): problem state views, goal state views, performance discrepancy views, alternative diagnosis views, and final diagnosis views. The first three view types are necessary for problem detection; the remaining two are for model application or diagnosis generation.

In summary, a MPISS must interact with users to develop:

(1) Problem state views: to represent the information about the problem being evaluated
(2) Goal state views: to represent the desired state of the problem
(3) Discrepancy views: to represent the gaps between a problem state and a goal state
(4) Structural model views: to represent the causal connections between variables
(5) Statistical model views: to describe the relationships among the quantitative variables
(6) Rule model views: to describe the relationships among the events of the variables
(7) Alternative diagnosis views: to represent the causes for the discrepancies
(8) A final diagnosis view: to summarize the alternative diagnoses

IV. Evaluation of Managerial Problem Identification Support Systems

In recent years, a line of research has emerged with a special emphasis on computer-based support for managerial problem identification. These systems have a variety of capabilities: discovering causal relationships from empirical data (Billman, 1989), providing a tool to represent and examine causal relationships (Ramaprasad and Poon, 1985; Yadav and Khazanchi, 1992), evaluating user-asserted causal relationships with empirical data (Paradice and Courtney, 1986), and searching for most probable causes for a given set of observed symptoms based on predetermined causal models (Ata et al., 1988; Jung and Burns, 1993). The purpose of this section is to evaluate the capabilities of such extant MPISS with respect to the requirements established in the previous section.

MPISS examined in this paper include some of the systems reviewed by Courtney and Paradice (1993) and two additional systems (Yadav and Khazanchi, 1992; Jung and Burns, 1993). These systems satisfy the following conditions: (1) they are specifically developed for supporting managerial problem identification; (2) their capabilities are demonstrated by actual systems or, at least, by prototype systems. The major features of these systems are presented in <Figure 7>.

4.1. Knowledge Base Structure

<Figure 8> shows the modeling constructs adopted by the MPISS. A majority of the systems utilize the structural modeling construct only. The systems by Pracht (1986) and Yadav and Khazanchi (1992), for example, manage simple structural models denoting the arcs with the values of −1, 0, and +1. Ramaprasad and Poon (1985) used a slightly extended scale of {-3, -2, −1, 0, +1, +2, +3}. Jung and Burns (1993) extends the structural

<Figure 7> Managerial Problem Identification Support Systems

Developers	System's Major Features
Ramaprasad and Poon (1985)	A structural modeling system. The user categorizes the variables into decision, environmental, and goal elements. The system can analyze, compare, and integrate structural models.
Paradice and Courtney (1986)	An interactive statistical modeling support system. The user enters a model statement, and the system fits the statistical model. The system can analyze the statistical model.
Pracht (1986)	A structural modeling support system. It allows the users to save, retrieve, and modify the structural models. The system can analyze a structural model.
Ata et al. (1988)	An automatic cause-finding system. The system stores an extended structural model. The user specifies the current state. The system identifies "symptoms" and the "causes."
Billman (1989)	An automatic pattern discovery system. The system analyzes how the changes in variables are related. If the changes meet certain patterns, the system reports it as a causal relationship.
Yadav and Khazanchi (1992)	An interactive structural modeling system. The user edits a structural model. The system analyzes the structural model. The system can compare and integrate structural models.
Jung and Burns (1993)	An extended structural modeling system. The system refines an extended structural model by adjusting coefficients. The system can explain how strongly variables are related.

<Figure 8> Modeling Constructs Adopted

Developer	Structural model	Statistical model	Rule-based model
Ramaprasad & Poon (1985)	Extended		
Paradice & Courtney (1986)	Extended	Yes	
Pracht (1986)	Simple		
Ata et al. (1988)	Extended		
Billman (1989)	Implicit		
Yadav & Khazanchi (1992)	Simple		
Jung & Burns (1993)	Extended		

model by denoting the arcs with weights ranging from -1 to 1. Ata et al. (1988) assigns causal impact coefficients to the arcs. Paradice (1986) overcomes the limitations of the structural models by allowing the users to develop statistical models. None of the systems, however, support all three modeling constructs.

4.2. Problem Processing Capabilities

<Figure 9> evaluates the systems with regard to the problem identification routines they support. With an exception of Ata et al. (1988), all the previous MPISS focus only on structural model development. They are not particularly concerned with how the developed models can be applied. This, however, is not surprising for the systems developed by Ramaprasad and Poon (1985), Pracht (1986), Billman (1989), and Yadav and Khazanchi (1992), because a simple structural model does not have a mechanism to interpret individual cases. From the point that models are built to interpret, explain, and predict events, a system that also handles the specific problem instances should be considered better. As the figure shows, none of the systems support all three major problem identification routines.

<Figure 9> Problem Identification Routines Supported

Developer	Problem Sensing	Model Development	Cause Finding
Ramaprasad & Poon (1985)		Yes	
Paradice & Courtney (1986)		Yes	
Pracht (1986)		Yes	
Ata et al. (1988)	Yes		Yes
Billman (1989)		Yes	
Yadav & Khazanchi (1992)		Yes	
Jung & Burns (1993)		Yes	Yes

4.3. Interaction Requirements of MPISS

<Figure 10> shows major inputs and outputs of the systems. Together with <Figure 7>, it shows the systems' overall functionalities. It also shows the interactions between users and the system. Those systems developed by Ramaprasad and Poon (1985), Pracht (1986), and Yadav and Khazanchi (1992) accept structural models from a user and provide to the user a simple analysis of how variables are related. Therefore, they are essentially memory-aid systems with minimum inferencing capabilities. On the other hand, the systems developed by Ata et al. (1988), Paradice and Courtney (1986), Billman (1989), and Jung and Burns (1993) employ system-driven problem identification, because their main functionality is to provide system answers to querying users.

<Figure 10> Major Views Exchanged

Developer	User Inputs	System Outputs
Ramaprasad & Poon (1985)	Structural models	Structural model analysis
Paradice & Courtney (1986)	Model specifications	Statistical models & analysis
Pracht (1986)	A structural model	Structural model analysis
Ata et al. (1988)	A problem state	Identified causes
Billman (1989)	Training data	Structural models
Yadav & Khazanchi (1992)	Structural models	Structural model analysis
Jung & Burns (1993)	A structural model	Analysis & cause identification

V. Summary and Conclusions

The analysis shows that the previous managerial problem identification support systems exhibit a number of limitations. First, the majority of these systems (e.g., Ramaprasad and Poon, 1985; Pracht, 1986; Yadav and Khazanchi, 1992) employ a simple modeling construct as the sole basis of approaching problem identification. Structural models, however, are designed only to represent whether the causal relationships between pairs of variables exist. Because of its simplicity, the structural modeling construct has critical limitations in representing the complex relationships observed in the management domain (Paradice and Courtney, 1986). It is unlikely that managerial problem identification can be successfully carried out based on this simple modeling construct.

Therefore, future MPISS research should attempt to combine different modeling techniques for the purpose of problem identification support. DSS research has long proposed the integration of rule-based modeling with the traditional quantitative modeling (Turban and Watkins, 1986; White, 1990). By integrating structural, statistical, and rule-based modeling approaches, MPISS may provide ways to: handle both numeric and categorical data; represent event relationships as well as variable relationships; deal with complex, non-linear relationships; and systematically develop more intricate causal models by building rule-based models upon statistical and structural models.

Second, previous MPISS have focused on different phases of the problem identification process. Billman (1989) and Paradice and Courtney (1986) emphasize causal model formulation; Pracht (1986) concentrates on causal model representation; Ramaprasad and Poon (1985) and Yadav and Khazanchi (1992) focus on causal model comparison and integration; Jung and Burns (1993) underscores the importance of causal model refinement; and Ata et al. (1988) highlights the importance of causal model applications. They devoted little effort to studying the overall problem identification process and designing a system to support the entire range of problem identification activities. In other words, previous MIPSS have been developed in a fragmented fashion. An argument can be made that the fragmented systems, as a group, can support the overall problem identification process. However, the matter is not that simple. First of all, interconnecting independent systems is not an easy task. More importantly, a system is a set of elements that work together; i.e., the whole is greater than the sum of its parts (Checkland, 1981). A simple collection of the systems may not support the interactive, retroductive problem identification process.

Therefore, future research should focus on providing a process-oriented problem identification support as suggested by theoretical DSS researchers (Keen and Scott Morton, 1978; Sprague and Carlson, 1982; Adams et al., 1990). Process-oriented DSS have been seldom designed and developed, because they require extensive research efforts (because of the wide spectrum of activities to be supported).

Third, the systems tend to emphasize either a user-driven approach or a system-driven approach to problem identification. For example, the systems developed by Ramaprasad and Poon (1985), Pracht (1986), and Yadav and Khazanchi (1992) are essentially user-driven. On the other hand, those systems developed by Ata et al. (1988), Billman (1989), and Jung and Burns (1993) are mainly system-driven, requiring almost no interaction with users. An effective support system, however, must combine both user-driven and system-driven approaches (Keen and Scott Morton, 1978).

In summary, the computer-based managerial identification support research, to date, exhibits at least three major limitations. First, it relies on a very simple modeling construct. Second, it focuses on different phases of the problem identification process. Third, it emphasizes either a user-driven approach or a system-driven approach.

Problem identification is essentially an inquiry process; or, the process of creating knowledge about problem situations. A fundamental premise of DSS research is that decision making can be enhanced by forming a cooperative inquiry community between a decision maker and a computer-based support system (Licklider, 1960). To form a cooperative inquiring community, the systems must structure complex causal relationships, support the entire problem identification process, and maintain extensive interactions with users.

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