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Impacts of Artificial Intelligence on Organizational Decision Making*

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ABSTRACT

Of all of the new technologies emerging in the late 20th century, the production of artificial intelligence may provide the most profound impacts on organizational decision making. Because the development of artificial intelligence technologies and models has largely been based on psychological models of human cognition, the effects of their implementation in complex social settings have not been thoroughly examined. This paper is an attempt to generate research which will develop a comprehensive understanding of the impacts of artificial intelligence and its role in complex organizations. A set of 11 hypotheses has been developed which examine the relationships between artificial intelligence technologies and the dimensions of organizational decision making. It is argued here that the implementation of expert systems will lead to less complex and political decision processes, while the implementation of natural language systems will lead to more complex and political decision processes.

KEY WORDS Artificial Intelligence Organizational decision making Power and politics.

INTRODUCTION

Of all of the new technologies emerging in the late 20th century, the production of artificial intelligence (AI) may provide the most profound impacts on organizational decision making. With its ability to provide large quantities of information and expertise, AI will change the dynamics of many decision situations. This paper will discuss the dynamics of decision making in organizations and the impacts that the implementation of AI-based products might have. The naive view that AI will provide a panacea for decision makers will be rejected and in its place an analysis of the impacts of these technologies in organizations will be presented. Because the development of AI technologies and models has largely been based on psychological models of human cognition, the effects of their implementation in complex social settings have not been thoroughly examined. To date, most of the research reports in AI journals have focused on the technical elements of a single application or technology. The comparative examinations of AI in use have been largely atheoretic and non-systematic (e.g. Feigenbaum, McCorduck & Nii, 1988). This paper is an attempt to generate research

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which will develop a comprehensive understanding of the impacts of AI and its role in complex organizations. Due to the lack of systematic empirical research on the effects of AI in organizations, research and theory from AI and from organizational decision making will be integrated into a coherent model.

Exhibit 1 illustrates the framework within which this discussion will proceed. For any decision process there is associated with it a 'matter for decision' which is the problem or opportunity to be resolved. The matter for decision affects the technologies which will be brought to bear on it. In this case, it is artificial intelligence technologies which will be applied. Together, the matter for decision and the technologies utilized determine the dimensions of the decision. The decision can be characterized as having certain levels of complexity and politicality associated with it (Hickson *et al.*, 1986). And finally, the values of these dimensions determine the nature of the decision process. This paper will focus on the interaction between two AI technologies and two decision dimensions.

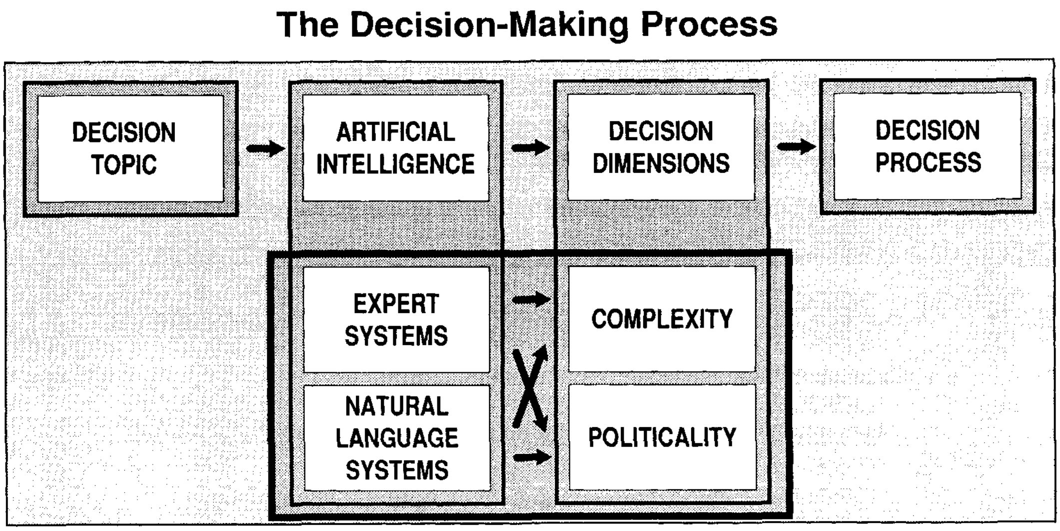

Exhibit 1

To elaborate the interaction between AI and the dimensions of decision making, this paper will proceed in three sections. The first section will develop a framework for discussion based on a review of the management decision making literature. The framework developed by Hickson and his colleagues (1986) will be the starting point to discuss the determinants of complexity and politicality. The work of earlier decision-making theorists will be drawn upon to elaborate on the determinants and introduce additional ones. The significance of the individual determinants of complexity and politicality will become more apparent in the discussion of their interaction with AI. The second section will discuss AI-based technologies which will affect the decision making process. The emphasis here will be on technologies which are either currently in, or hold great promise for, commercial use according to the most current research reports and findings. Two technologies — expert systems and natural language processing — will be discussed in detail with respect to their implementation in managerial settings. This discussion will be at a more general level in order to give the reader a richer understanding of the technologies discussed. The final section will examine how each of these technologies will alter the dynamics of organizational decision making. The main argument will generate 11 hypotheses based on the interaction of the determinants of decision making and the two AI technologies. It will be shown that the consideration of each aspect in detail was necessary for the generation of nonintuitive hypotheses.

DIMENSIONS OF DECISION MAKING

The foundation for this discussion of organizational decision making will be the framework developed by Hickson and his colleagues (Hickson *et al.*, 1986) at the University of Bradford. Although there are a large number of conceptual frameworks available for the analysis of decision making, the Bradford studies present a general set of concepts within which the work of other researchers can be utilized. Indeed, the framework provided by the Bradford studies incorporates and extends much of the previous research on decision making. Elements of cognitive (e.g. March & Simon, 1958) and political (e.g. Bacharach & Lawler, 1980) theories are integrated into a comprehensive conceptual model. Furthermore, Hickson and his colleagues provide a strong empirically-based analysis of organizational decision making. The insights provided by these researchers are based on a 10-year study of 150 strategic decisions in 30 firms, the largest and most comprehensive decision-making study to date. As others have noted, the publication of *Top Decisions* was 'a significant advance in descriptive and explanatory appreciations of strategic decision making' (Louis, 1987: 627). 'It provides systematic insights, building beyond past descriptions of strategic decision making ... It offers a typology that integrates across descriptive frameworks of the past...' (Louis, 1987: 628).

There are, of course, limits to any work and so the *Top Decisions* framework will be extended and elaborated here drawing on the work of other decision theorists and researchers. Some of the limits of the *Top Decisions* research have been noted by Dutton (1985). Dutton suggests that despite the subjective perspective claimed by the researchers, both researchers' and subjects' perceptions enter into the construction of decision types. However, this is an inextricable element of almost all field studies; the researcher invariably contributes to the development of perceptions and typologies. Dutton goes on to argue that because the *Top Decisions* researchers used a stratified sample based on decision type, the generality of their conclusions is limited. This sampling scheme was necessary, however, due to the prohibitive costs associated with obtaining a purely random sample. Finally, Dutton argues that the *Top Decisions* research ignores the context of the decisions studied. The impact of context, however, is of lesser importance when studying decision processes.

What is required for this paper is a general framework which can incorporate the insights of other decision-making scholars. The Bradford studies offer a comprehensive yet parsimonious analysis of the decision making phenomenon. For our purposes, it is the conceptual clarity and theoretical generalizability of the Bradford studies which is critical.

Two dimensions of the decision making process, developed by Hickson and his colleagues (1986), will be borrowed and expanded upon. First, a problem can be defined in terms of its complexity. Highly complex problems demand large amounts of scarce data and expertise, while simple problems do not. Second, the interested parties and their objectives determine the politicality of a situation. When the objectives of powerful parties conflict, the political activity associated with the decision process increases. 'Politicality arises in the approved influence of recognized departments or authority figures, as well as in less official or even underhand influence...' (Hickson *et al.*, 1986). These two dimensions are constituted by several factors. This paper will draw on the factors described by Hickson and his colleagues, and develop others based on previous decision making literature.

Complexity

Uniqueness and seriousness

Only recently has the organizational decision making process been examined via large-scale, rigorous empirical studies (Hickson *et al.*, 1986; Nutt, 1984; DIO International Research Team, 1983;

Mintzberg, 1976). These research programmes documented and analyzed large numbers of decisions and put forward descriptive and explanatory models of the processes involved. In the model developed by Hickson and his colleagues (1986) the decision process is characterized by two dimensions: complexity and politicality. The authors argue that the complexity of a decision topic can be measured along several dimensions: its rarity; the seriousness of its consequences; the diffusion of its consequences; its precursiveness, or the extent to which the decision sets the parameters for future decisions; and, the diversity of interests involved. For the purposes of this discussion, these measures can be grouped into two, more general, constructs: problem uniqueness and seriousness. The seriousness of consequences, diffusion of consequences, and precursiveness of a decision are all related to the importance accorded a decision outcome. Because of this interrelatedness, seriousness will be used in this discussion as a more general construct, encapsulating both diffusion of consequences and precursiveness. Because the diversity of interests impacts as much on the politicality of a situation as on its complexity, it will be considered within the discussion of politicality.

Immensity and variety

Before the comparative decision making studies were undertaken, decision theorists worked, primarily, within a psychological or social-psychological paradigm. These early models of decision making focused on the limited cognitive capacities of decision makers. Simon argues that there are insurmountable psychological barriers to rationality, where rationality is defined as 'an integrated pattern [of] ... (a) viewing the behavior alternatives prior to decision in panoramic fashion, (b) considering the whole complex of consequences that would follow on each choice and (c) with the systems of values as criterion singling out one from the whole set of alternatives' (Simon, 1976: 80). The barriers include fragmentary knowledge, the inherent difficulty in anticipation, and the broad scope of possible behaviors (Simon, 1976: 81–84). These barriers demand a more incremental, less coherent method of decision making. This is consistent with one of the first attempts to deal realistically with organizational decision making which described the process as one of 'successive limited comparisons' (Lindblom, 1959). In his seminal piece, Lindblom mapped out a comparison of the traditional view of decision making and the more realistic method of successive limited-comparisons. Similar to Simon's description of rationality, Lindblom emphasized the rational-comprehensive method's a priori clarification of objectives and comprehensive empirical means-end analysis. In contrast the method of successive limited comparisons is characterized by the close intertwining of goal selection and limited empirical analysis, and by the iterative partial achievement of goals. Lindblom argues that decision makers' limited intellectual capacities and sources of information demand the use of successive limited comparisons.

These decision making models emphasize the effects of information immensity and variety (Lenat, 1988). The human cognitive limits discussed by Simon and Lindblom can also be analyzed with respect to the decision problem. As the amount and types of information associated with a decision situation increase, the limits of rationality become sharper. If cognitive capacity is taken as a given, it is the nature of the problem which determines the limits of rationality. Increasing amounts of information and varieties of types and sources of that information demand a greater reliance on successive limited comparisons.

Nature of feedback

A more recent look at organizational decision making has emerged in the literature concerned with the escalation of commitment (Ross & Staw, 1986; Staw & Ross, 1987). This research focuses on escalation situations — 'predicaments where costs are suffered in a course of action and subsequent activities have the potential either to reverse or compound one's initial losses' (Staw & Ross, 1987: 39). Staw and Ros discuss both psychological and structural determinants of escalation. The psychological determinants which enhance commitment, and hence, escalation, occur where situational deterioration is slow or irregular, benefits are salient and immediate, and costs are distant and diffused. This combination allows for ambiguous interpretations of the situation. Hence, it is the nature of the feedback received which determines the psychological commitment and pattern of escalation. Clearly, this is an aspect of a problem's complexity. Feedback plays a critical role in all complex decision situations where there is required a series of decisions.

Politicality

Imbalance of power

According to Hickson (1986), politicality is the extent to which influence affects the outcome of a decision making process (Hickson *et al.*, 1986). The concept of influence is used broadly here and can stem from many bases (*c.f.* French & Raven, 1959). More importantly, it is the interplay of legitimate, expert, ideological, and political systems of power (Mintzberg, 1983) which constitute the overall pattern of influence. The politicality of a decision process is determined by the pattern of influence which pervades it. Determinants of this pattern include the level of external influence, the balance of power among participants, and the contentiousness of objectives. For the purposes of this discussion, we are most concerned with those variables which directly affect intra-organizational aspects of decision making. And although the implementation of AI technologies will alter many of the dynamics of decision situations, it is unlikely that any technological element will change the objectives of actors which arise out of structural and personal variables. Hence, it is the imbalance of power which will be considered here. The greater the disparity of power between the parties involved in a decision, the greater will be the level of politicality. This is a result of the potential for influence accorded powerful parties in the company of the powerless. Where there is a large power differentiation between participants, those with power are in a greater position to exert influence. In situations which are characterized by evenly distributed power structures, actors can not rely on their political influence.

Visibility

The political dimension of organizational decision making presupposes a social context wherein actors are able to observe the behavior of other actors. Visibility can affect the level of politicality associated with a decision in two ways. First, a high level of visibility will produce widespread awareness and interest in the decision process. This, in turn, will result in a large number of participants with various agendas. Thus, the level of politicality will be increased. Second, the level of commitment to an action, or decision, is often increased by public exposure. For example, face-saving behaviors often occur where a project or decision becomes publicly associated with an individual or group. This association generates demands for the success of the project or correctness of the decision to be demonstrated. Furthermore, the decision situation can take on the trappings of interpersonal conflict. For example, in the Toxicem case, recounted in *Top Decisions* (Hickson *et al.*, 1986), a firm's decision regarding self-generation of electrical power became a competition between various departments within the organization.

Coupledness of systems

A more challenging contemporary view of organizations, and hence of organizational decision making, is expressed by the action perspective (Weick, 1987; Daft & Weick, 1984). Research from within this perspective deals explicitly with both politicality and complexity. One author asserts that 'organizational settings only intermittently and locally cohere as if they were systems' (Weick, 1987: 10). Decisions made in organizational arenas are based on the 'interests of shifting sets of coalitions, presided over by one dominant coalition which spends its time maintaining dominance' (Weick, 1987: 11). Furthermore, the environment is neither objective nor unitary because it is defined in reference to various organizational interests. The implications of this for organizational decision making are profound. Because environmental stimuli are interpreted through values and interests, motivated purposeful behavior may not necessarily produce its intended results. Further, intra-organizational actions may be loosely coupled such that the behaviors of one actor or group may not be consistent with those of another. This is demonstrated in the institutional literature, where organizational departments decouple in order to preserve some artifactual structure (Meyer & Rowan, 1977).

At a more micro-level, action creates commitment to a pattern of behavior (Weick, 1987). And, thinking is made less necessary because of the perceptual data generated by action. As managers go through their day-to-day work, they react to stimuli as it becomes apparent, without resorting to higher-order thought (Weick, 1987). The impact of this mindless managerial action is at least partially dependent on the nature of the environment. When the relevant environment consists primarily of symbols, beliefs, and values then managers must have the ability to focus action in order to enact or construct their reality. In contrast, when the environment is tightly coupled, such 'forcefulness is wasted and may even be detrimental because it can preclude accurate sensing' (Suedfeld *et al.*, 1977). So, the degree of coupledness within an organization, and between an organization and its environment constitutes an important political determinant in organizational decision making. The relationship between action and consequences will affect the manner in which participants approach decision making situations.

Institutionalization

Like the coupledness of systems, the phenomenon of institutionalization (*cf.* Zucker, 1977; Meyer & Rowan, 1977) is concerned with the causal link between human action and social structures. Where coupledness of systems refers to the link from action to structure, institutionalization refers to the link from structure to action. Highly institutionalized structures determine the action associated with them. For instance, the professionalization of a job function implies the establishment of a set of 'professional standards'. The purpose of these standards is to delineate the choice set available to professionals within the specified field. This institutionalization of structures reduces the politicality associated with decision situations within that domain. Because the decision maker has a legitimated set of solutions available, the political activity associated with making that choice is reduced. For instance, if a local teachers' association provides a set of acceptable books for the classroom, the selection of reading material can be dealt with in a less political manner by the individual teacher. And similarly, if some national educational body were to produce a list of approved books, the determination of local lists would be depoliticized.

Summary

As demonstrated above, management decision-making research has discovered several determinants of complexity and politicality. There are at least 5 important determinants of complexity which are discernible from the management research discussed in this paper. These are: immensity, variety of information, uniqueness, seriousness of consequences, and the nature of feedback. It is critical to remember that all of these determinants are defined in terms of the actors involved. It is the perceptions of those involved which will determine the nature of the decision making process. This is also true for a situation's political elements; what may be seen as a highly charged political battle in one setting may be routine in another. Four factors which affect a decision's politicality are: the imbalance of power, overtness or visibility, coupledness of systems, and the degree of institutionalization.

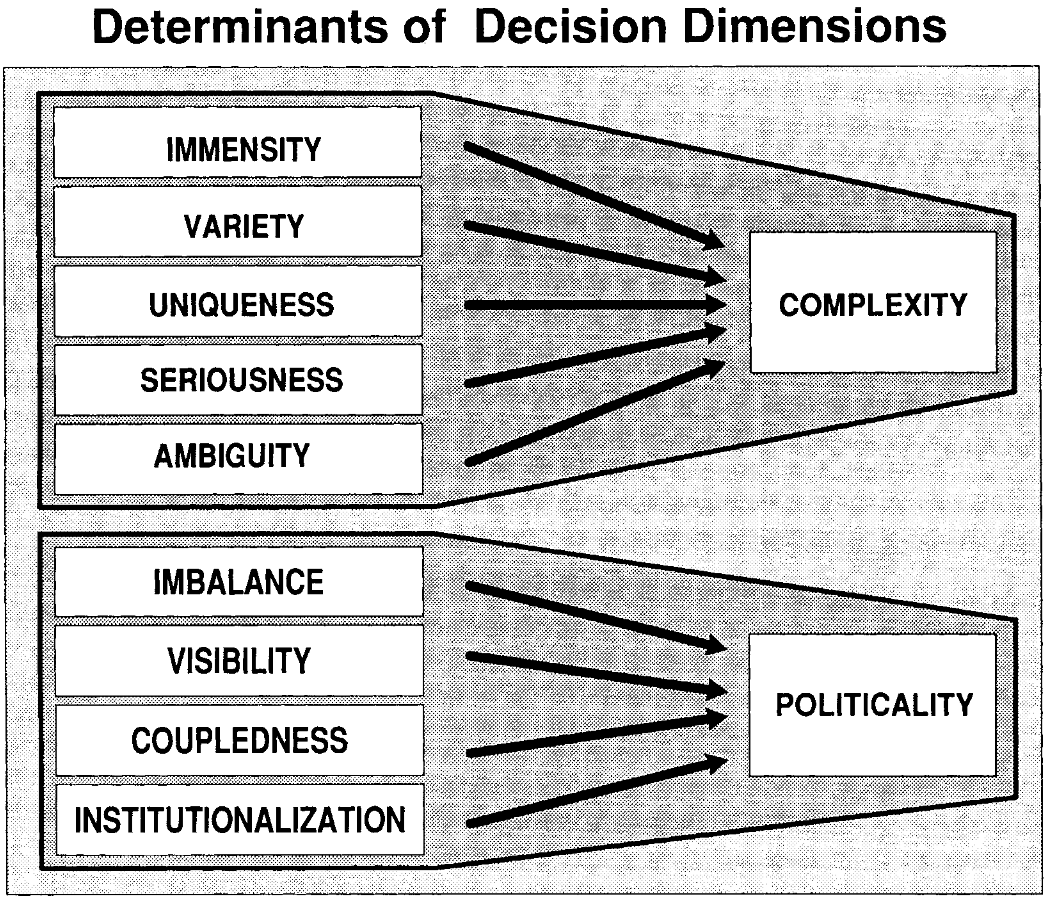

Exhibit 2

ARTIFICIAL INTELLIGENCE

Before discussing specific technologies, a definition of AI is required. AI has variously been defined as: 1) making computers smart, 2) making models of human intelligence, and 3) building machines that simulate human intelligent behavior (Trappl, 1986). For the purposes of this paper, we will adopt the latter as our definition. For we are not so much concerned with the capacity or power of the hardware, nor with the accurate modelling of our cognitive processes, as with those tools which will be able to aid, and perhaps replace, the manager in the decision making process.

As mentioned above, this section will provide a more general discussion of two AI technologies. Along with a concise definition of expert systems and natural language processing, this section will provide a discussion of the problems of implementing these technologies in managerial applications. The discussion will be based primarily on research reports and findings, so as to reflect the current state of AI research. The final section will provide a greater number of empirical examples of both expert systems and natural language processing. These examples will be drawn both from scientific research and industrial application.

Expert Systems

An expert system is a computer program in which has been captured a body of expertise and through which this expertise is made available to its user. Typically, the depth of expertise captured by the expert system is far greater than its breadth. In fact, the application of these systems has had the greatest success in areas where a tremendous amount of specialized knowledge is necessary. Such domains include diagnostic medicine, computer configuration, geology, and molecular genetics (Duda & Shortliffe, 1983). It is the nature of expertise, the possession of extensive knowledge about a narrow class of problems, which makes it possible to provide a computer program with the knowledge needed to perform those tasks effectively.

In general, the expert system is composed of two elements: a knowledge-base which is domain specific, and an 'inference engine' which houses the logic necessary to make the knowledge-base useful. The knowledge-base consists of heuristics operationalized in the form of 'if-then' rules. The inference engine directs the evaluation and chaining of these rules. Together these two components constrain the search to the most likely solution routes.

The development of expert systems has broken into two streams: those based on commercial expert system 'shells' (inference engines without any associated knowledge) and larger systems developed primarily in cooperation between University researchers and corporate or government users. Although the former constitute the majority of expert systems in use, it is more informative to examine the latter for the impact of future technologies. The history of expert system development has shown that only as technologies are developed in the research lab are they then incorporated into commercial products. An example of this phenomenon is the proliferation of rule-based shells which mimic the inference engines of 'classic' expert systems such as MYCIN and DENDRAL. The remainder of our discussion of expert systems will examine the problems facing creators and researchers of expert systems in the development of managerially oriented expert systems.

There are at least two major problems facing builders of expert systems with respect to managerial applications: the size and nature of the knowledge base required, and the nonmonotonic nature of managerial reasoning. The knowledge-bases needed to deal with the wide variety of problems encountered by managers would be immense; they would necessarily incorporate knowledge from the domains of finance, marketing, accounting, and organizational analysis, as well as 'commonsense' knowledge of the world. This problem is in reality composed of two sub-problems: the immense task of feeding all of the necessary information to the machine and the difficulty inherent in the representation of this knowledge including, and perhaps especially, 'commonsense'. It is generally acknowledged that the solution for the first sub-problem will be machine-learning. For if a program can not learn on its own, its knowledge base will be restricted to what the programmer can provide. For machines to be able to learn efficiently, they must not only be able to gather new data and produce new inferences, but be capable of vicarious learning as well. As with humans, the ability to share with others one's insights and information makes the species very powerful. Machine-learning will be one of the central areas of AI research in the near future.

Part of the problem in representing a manager's view, not only of the 'commonsense' world, but of the more rigorously defined arenas as well, is that conventional tools such as logic, probability theory, and set theory require information which is rigidly defined, complete, and reliable. But the nature of human intelligence allows action based on information which meets none of these criteria. One conceptual framework that holds great promise for more coherent representations is the theory of fuzzy sets (Zadeh, 1965). Within this framework, classes are not required to have sharply defined boundaries, as is the case with classical set theory. The transition between membership and non-membership is gradual rather than abrupt. For instance, membership in the set of deep-green colors has no obvious precise boundary. The same is true for the set of an organization's competitors; there are some clear competitors and there are some for whom it is not clear. This fuzzy framework, which can incorporate both logic and probability theory, allows the definition of heuristics which are lexically imprecise. One reportedly successful application of this framework to the task of management is the decision-support system STRATASSIST (Hall, 1987). This system aids the user in developing strategic plans based on Porter's (1980) prescriptive framework. STRATASSIST was tested, and shown to aid in the production of strategic plans which were judged superior to those produced by the unaided subjects (Hall, 1987).

The second major obstacle in the construction of expert systems for management is the nonmonotonic nature of managerial reasoning. It is nonmonotonic in the sense that managers often draw conclusions on the basis of partial information which they will later retract or reformulate on the basis of more complete information. The nonmonotonic nature of human reasoning and its implication for system design has been discussed in detail elsewhere (*cf.* Reiter, 1980; Moore, 1985; Krauss *et al.*, 1990; Bell, 1990). According to Krauss and his colleagues,

> 'it seems clear that we, human beings, draw sensible conclusions from what we know and that, on the face of new information, we often have to take back previous conclusions, even when the new information we gathered in no way made us want to take back our previous assumptions' (Krauss *et al.*, 1990).

For instance, if a manager is told that her company is badly in need of some scarce resource which Company X produces, then she may conclude that Company X is a viable source of that product. However, she may later find out that Company X is owned by her principal competitor, in which case it may not be a viable source of that resource. If we attempt to model this type of reasoning, we see that theorem P = {Company X can supply our needed resource} can be derived from the set of axioms A = {Company X produced the needed resource}, but not from the set of axioms A^1 = {Company X produced the needed resource; Company X is owned by the principal competitor} which is a superset of A. The set of theorems does not increase monotonically with the set of axioms, hence, this sort of reasoning is said to be nonmonotonic. Current commercial expert systems, generally, employ standard logics which model strictly monotonic reasoning. There are exceptions, however, including RAROC, a system used by Bankers Trust which establishes levels of risk for loan applications (Chorafas, 1987: 155). As well, research is being conducted (e.g. Siler *et al.*, 1987) which incorporates both nonmonotonic reasoning and fuzzy-logic theory.

It is the nonmonotonic reasoning and the immense and fuzzy knowledge sets used in management which demand sophisticated approaches to expert system development. Currently popular approaches, such as simple rule-based systems, have begun to entrench expert system technology in organizations but are fundamentally unable to deal with many aspects of managerial decision making; these systems do not incorporate the machine learning, and fuzzy and nonmonotonic logics discussed above. Without incorporating these aspects of decision making, current expert systems are limited in the range of managerial reasoning which they are able to model effectively.

This discussion has focused on the technologies which are currently in the research labs so that a consideration of the impacts of these more powerful and sophisticated systems could be developed.

However, this paper is concerned with the impacts of artificial intelligence, not the technology itself; so where there might be significant differences between the impacts of current and future systems, these differences will be noted in the final section.

Natural Language Processing Systems

One of the fundamental stumbling blocks in the development of intelligent systems is the inability of machines to understand natural human language. Natural language processing research has focused on two core areas: allowing humans to ask questions of and issue commands to machines in natural language; and developing the ability of machines to read and make sense of human-generated texts.

One of the critical factors in the success of any system is the manner in which it communicates with the user — its interface. This task can be handled via a terse command language, a simple menu scheme, or a graphical 'point and click' environment. Or, users might issue commands and queries via their own natural language. The application of natural language technology to database management interfaces has received a considerable amount of research interest. This is appropriate for a number of reasons. First, the size and complexity of available databases is growing tremendously. Users require fast and flexible access to the captured data. Second, the queries issued by users are generally simple isolated sentences or sentence fragments rooted in well-structured operational contexts. There is not the need for a large body of commonsense knowledge which confounds knowledge-based systems development.

Natural language technology is also being developed to enable machines to interpret existing human-generated texts. One of the consequences of the phenomenal increase in computing power and storage is the growth of text databases consisting not only of document surrogates such as abstracts, title headings, or key words, but entire documents including archives of memos, magazine articles, and conference proceedings. The potential inherent in these large textbases includes the development of electronic encyclopedias or encyclopedic expert systems (Weyer & Borning, 1985; Lenat, 1983), and query-answering facilities overlayed on inferential reasoning systems (Lebowitz, 1983). The practical application of any of these systems faces four major problems (Reimer & Hahn, 1988).

First, the necessary hardware must be developed. This is probably the most developed aspect of the research. Second, there must be techniques for the administration of these large textbases. This includes the construction of efficient architectures for unformatted text, and extended query languages. Third, attention must be paid to the user-level interface. Gaining access to a large and complex textbase may be confusing and intimidating. As discussed above, one possibility is the development of interfaces which accept natural language utterances. Fourth, there is the fundamental problem of content analysis. For the potential of these reserves of knowledge to be reached, there must be built into them some ability to parse and at some level understand their own contents.

This last problem is the one with the most inherent difficulty and at the same time the highest payback if it can be resolved. Approaches to content analysis include simple statistical models involving frequency of words, clustering of documents based on the frequency distributions, and probabilistic relevance measures of retrieval (Reimer & Hahn, 1988). A second approach is based on a linguistic analysis of the text. This approach has enjoyed some success when dealing with linguistically constrained texts from a limited domain (Reimer & Hahn, 1988). However, it has difficulty when it attempts to deconstruct linguistically rich texts, involving paraphrase, ambiguities, or inferential relations. A third approach to this problem feeds semantically parsed text into a frame-based (*cf.* Kahneman & Tversky, 1983) architecture (Reimer & Hahn, 1988). Reimer and Hahn's system forms a hypertext representation of the material. Hence, the user is able to access 'relevant facts, ... topical descriptions on different abstraction levels, and finally, the retrieval of significant passages of the original text' (Reimer & Hahn, 1988, p. 343). It is apparent that for any system to capture the potential inherent in these large textbases it must allow the user access to the material in a flexible, efficient manner. If this can be achieved, the users will gain an important tool for decision making.

The application of natural language processing tools will become especially important in situations where the acquisition of information is a source of power for decision making participants. This will occur in processes characterized by high complexity and high politicality, such as strategic decisions. Without the complexity, information would not be a strategic resource, and without the politicality participants would not be searching for sources of power.

IMPACTS OF ARTIFICIAL INTELLIGENCE ON DECISION MAKING

The manner in which decision makers operate will change in the future as a result of the technologies discussed above. With far greater access to information and problem solving expertise, the complexity and politicality of many issues will change. A simplistic view of technological 'progress' might predict a general reduction on both of these dimensions. Certainly, this view would argue, greater access to information and expertise will enable decision makers to overcome their bounded rationalities and produce rational, comprehensive solutions. And the need for political influence will be swept away by the overwhelming presence of objective, technical knowledge. However, by delineating the determinants of the situational dimensions and examining their interactions with the new technologies, it becomes clear that the effect of AI will be far more problematic. The direction and magnitude of the change will depend on the specific interactions.

This section of the paper will discuss in some detail the manner in which AI technologies might interact with the decision making process. Drawing on several empirical and hypothetical examples and the research literatures discussed previously, 9 hypotheses will be developed which explicate the relationship between the technologies discussed above and the determinants of organizational decision making. The focus in this section will be on the impacts of AI systems which will utilize the technologies now being developed in research labs. It is important for researchers and managers to consider the social and psychological effects of the technologies they are currently developing and will be employing in the near future. If the impacts of future AI systems are likely to be significantly different from those of the smaller, current systems the potential differences will also be discussed.

Complexity

Immensity

It is not surprising that AI will have a significant impact on the complexity of a situation. Indeed, this is likely the dimension of decision making to which AI researchers expect their work to be applied. As has been shown, complexity is constituted by a number of components. First, the immensity of a problem is a function of the amount and variety of pertinent information available, and the number of different potential solutions that are apparent. For immense problems, AI technologies will help to survey the problem space by searching the immense qualitative and quantitative databases and referring to contemporary expertise for interpretation. Users of these technologies will have access to the current store of applicable knowledge. However, this newfound knowledge may have unexpected effects on the decision process. As decision makers become aware of the vast stores of information available their interpretation of the situation's immensity may increase instead of decrease.

The introduction of natural language databases may result in 'paralysis by analysis'. In cognitive terms, individuals may only be able to incorporate a limited amount of information into their particular problem schemas. When more and more information is presented to them the result might only be confusion. Furthermore, as they incorporate new information they may lose their ability to reach coherent conclusions. As discussed above, the nonmonotonicity of human reasoning precludes the nonproblematic incorporation of new knowledge. New information may contradict old conclusions but not provide the basis for a new conclusion.

Expert system usage will have a distinctly different effect on immense problem domains. An expert system will reduce the immensity associated with many decisions; what was a large collection of data will be reinterpretated as a manageable set of decision rules. Even where very complex decisions require the development of several expert systems, the decision maker is still shielded from the magnitude of information input into the various systems. An expert system codifies the available information, giving the problem a highly structured appearance. The development of STRATASSIST (Hall, 1987) typifies this process. The domain of business strategy is massive and complex, and yet the STRATASSIST system appears to codify the process of strategy formation. By applying the Porter (1980) framework to the process, STRATASSIST lends to strategic decision-making the appearance of a well-defined, parsimonious activity.

Hypothesis 1: (A) The introduction of natural language technology will *increase* the perceived immensity of a decision situation.
(B) The introduction of an expert system will *decrease* the perceived immensity of a decision situation.

Variety

Related to, but distinct from, immensity is variety. Variety is encountered by decision making participants where there are either many different sources of relevant information or the relevant information is in many different forms. While variety implies immensity the converse is not true; there can be a large amount of homogeneous information available from a single source. The effect of applying AI technologies to a decision situation with high variety is similar to the effect in a high immensity situation. The various sources and forms of data will generally become more accessible and manageable through the use of natural language technology and expert systems. This will be especially true where the relevant data is in many forms; multiple expert systems will be called on to analyze different numeric and qualitative data sources. And although it might be necessary for the decision maker to access several different expert systems, each system would reduce the cognitive complexity associated with its input. So, together they would reduce the overall complexity stemming from the information variety.

Bayer, Lawrence and Keon (1988) describe a system which is 'designed to investigate the planning of consumer sales promotion campaigns' (Bayer *et al.*, 1988: 121). This system draws on multiple knowledge sources including 'survey data from 34 promotion experts, and empirical information from scanner panel data' (Bayer *et al.*, 1988: 121). This system integrates the various informational inputs and produces a promotional plan for a given product, with current performance equal to that of an MBA in marketing. Clearly, the informational variety inherent in the problem is well handled by the expert system.

As with complexity due to immensity, the application of natural language systems will increase perceived levels of informational variety. Again, due to decreasing confidence levels and nonmonotonic reasoning, decision makers will become overburdened with the newly available information. Greater awareness of the scope of available information sources and incorporation of the various data may bring participants to dizzying levels of confusion and distress. Gauch and Smith (1989) describe an expert system for searching in full-text databases. This system reformulates contextual Boolean queries to generate an appropriate number of relevant retrievals. This type of expert system reduces burden on the user with respect to their knowledge of the underlying database. Gauch and Smith's

(1989) system is an interesting example of the potential combination of expert system and natural language databases. Where these two technologies are integrated the effect on immensity and variety will be a simple combination of the two 'main effects'; the expert system will reduce the associated complexity while the natural language system will increase it. The net effect will be an idiosyncratic result of the particular implementation.

Hypothesis 2: (A) The introduction of natural language systems will have *no significant effect* on the perceived variety of a decision situation.
(B) The introduction of expert systems will *reduce* the perceived variety of a decision situation.

Uniqueness

A third component of complexity is the rarity or uniqueness of the decision issue (Hickson *et al.*, 1986). This aspect of the situation, perhaps more than any other, demonstrates the importance of defining the dimensions phenomenologically. That a situation is commonplace from a global or historical perspective does not diminish its potential uniqueness with respect to any individual actor. According to Hickson and his colleagues, rarity can play an unexpected role in decision making. If an issue has never been confronted by an organization, the organization will not have developed bureaucratic devices for dealing with it. Unlike other components of complexity, rarity may enable rapid progress to a final decision.

The effect of AI technologies on rarity will depend on the interaction with other determinants of complexity. If a unique situation is not otherwise complex, AI technologies will likely not play a significant role. The resolution of simple, but novel, problems will still proceed swiftly. However, where the situation is rare and complex in some other way AI technologies will tend to be employed. Natural language databases present a promising method of contextualizing unique situations; where there exists reports of other's experiences with similar problems, the perceived uniqueness will be diminished. The application of expert systems will depend on the availability of generic systems which address a class of problems which, while novel to an individual organization, are relatively common across organizations. Moser and Christoph (1987) describe a system designed to approximate expert reasoning in the strategic area of divestiture. Although divestment may be a rare activity on an individual firm basis, it occurs continually in the larger industrial setting. Moser and Christoph's system provides advice regarding the costs and benefits of divestment based on an economic framework. This system applies the collective knowledge base to a problem with which a firm might seldom deal. Thus, counter to traditional wisdom, it is possible to use expert systems in novel situations.

Hypothesis 3: (A) Where the situation is *rare but not complex* on other dimensions, AI technologies have *no effect*.
(B) Where the situation is *rare and complex* on other dimensions, AI technologies will *reduce* the perceived rarity of the situation.

Seriousness

An aspect of decision making that one might expect AI to have little impact on is the seriousness and diffuseness of a decision. When these terms are defined as the perceived seriousness and diffuseness, however, AI takes on a larger role. The implementation of an expert system involves the codification of a knowledge base and automation of the decision task. The completion of this process effectively routinizes the problem domain. Thus, the perceived seriousness of the decision will be lessened due to the appearance of routine control imparted by an expert system. However, the implementation of an expert system may temporarily increase the perceived seriousness of a decision. During the development phase, the attention focused on the task domain may cause to heighten the perceived seriousness of the decision. Once the expert system is installed and used on a regular basis, the predicted decrease in seriousness will be realized. Dean (1988) reports on a system being developed to aid in decisions regarding the financing of business ventures. 'In the field of business venturing the final decisions concerning business venture evaluation, selection, and acquisition are always the responsibility of senior management at the highest level' (Dean, 1988: 192). Clearly, this is an important decision for this industry. The gravity of the situation may be undermined, however, if the implementation of the expert system is successful. If the first set of decisions based on the system is consistently correct, the wisdom of the system may come to be taken for granted. Although it was originally intended to act only as a support for decision making, the role of the expert system may develop into a more active one. If this were the case, the seriousness accorded the evaluation decisions would be lessened through their routinization.

Natural language systems will have an effect which is opposite that of expert systems. In situations where natural language databases are examined to find the consequence of a decision, there will be found a myriad of causal and semantic connections. A mass of unstructured data will serve to heighten the anxiety associated with decision making. New consequences will be 'discovered' and, hence, the seriousness of the situation will increase. The use of natural language systems may contribute to greater decision anxiety and, hence, a more sporadic decision process (Hickson *et al.*, 1986).

Hypothesis 4: (A) The introduction of natural language systems will *increase* the perceived seriousness of the decision situation.
(B) The introduction of expert systems will *decrease* the perceived seriousness of the decision situation.

Nature of feedback

AI may also play a very important role where complexity is based on the nature of feedback. As Staw and Ross (1987) demonstrate, feedback can seriously influence the outcome of decision processes. In such situations, AI systems will have three distinct roles, at least partially dependent on the politicality of the situation: provider of unambiguous feedback, interpreter of ambiguity, and provider of ambiguous feedback. In complex decision situations which are not highly political, AI products will be used to construct 'accurate' renderings of the problem and its status. This will be accomplished both through the combing of large scale natural language databases for relevant information and the interpretation of that and other relevant data by expert systems.

Where both complexity and politicality are high, AI products may be used in a very different manner. As mentioned, information might become a much sought after political weapon in these situations. In this case, participants might wish to preserve the ambiguity of the available information. Because the meaning of ambiguous information is unclear it can be manipulated to become an argument for many different opinions. Natural language systems will be an important tool in such an environment because they supply data but leave the interpretation to the user (Reimer & Hahn, 1988). In contrast, expert systems provide legitimated interpretations of data. Hence, in ambiguous decision situations, expert systems will tend to be implemented by the dominant coalition in order to codify and routinize their position. Balachandra (1988) describes an expert system which is designed to examine the decision of whether to continue or terminate an ongoing Research and Development project. These decisions are characterized by high levels of ambiguity and politicality. There are technological, market, and environmental uncertainties, along with personal egos and budgets, with which to contend. Further confounding the decision is its criticality; 'unnecessary prolonging [of] a project doomed to failure ... wastes valuable resources', while 'terminating a project which could have succeeded may result in the loss of a significant market opportunity' (Balachandra, 1988: 108). In this context, it is clear that the actual use of an expert system might not approach the objective provision of expertise envisioned by the designers.

Hypothesis 5: (A) In *low-politicality, high-ambiguity* situations, natural language systems and expert systems will *lower* the ambiguity.
(B) In *high-politicality, high ambiguity* situations, natural language systems will either *increase or not affect* the ambiguity in the decision situation.
(C) In *high-politicality, high-ambiguity* situations, expert systems will *reduce* the ambiguity associated with a decision.

This interaction between complexity and AI systems demonstrates the need to consider the political environment when discussing decision processes. The remainder of this section will explore the potential for interaction between AI technologies and the determinants of politicality in decision making.

Politicality

Imbalance

Along with altering the complexity of a situation, artificial intelligence technologies will influence the politicality associated with decision processes. The distribution of power among participants is partially determined by their access to information and expertise. To understand the effect of AI technologies on the balance of power it is necessary to explicate the role which the various technologies are likely to play. The implementation of natural language systems is motivated by the need for access to large amounts of information. In a non-mechanized environment, such access is usually the domain of some staff personnel whose expertise and power are linked to the collection and dissemination of information. If this function is automated through the use of a natural language system, the staff personnel will lose power because of the increased substitutability associated with their positions. Because these staff members are subordinate to the management which they support, a decrease in their power will increase the imbalance of power in decision making situations in which they are involved.

The implementation of expert systems may proceed through two processes which, paradoxically, will have the same effect of the balance of power. If an expert system replaces a low-power decision maker, the power imbalance will be decreased; her elimination will reduce the power variance among the interested parties. For instance, in a non-automated credit lending situation, the power difference between the primary decision maker and his or her superior makes it possible for the superior to influence the outcome for personal reasons. If the primary decision maker were replaced or supplemented with an expert system, the superior would lose some of his or her ability to influence the process; by virtue of its 'objectivity' and legitimacy, the expert system would provide a powerful counter to the influence of the superior. Where previously there was a great deal of room for discretion, the automated process constrains the effect of power and influence.

If, on the other hand, the expert system is used to supplement the skills of a low-power decision maker, her power will be increased through the increased legitimacy associated with the system and, hence, the power imbalance will decrease. In the R&D system discussed above, the decision to continue or terminate a project is marked by a high level of politicality. Often the project leader may have significantly less power than the person who makes the final decision. The introduction of the R&D expert system and its inherent legitimacy would level the playing field somewhat. So, the implementation of expert systems will decrease the imbalance of power by acting as a powerful, legitimized participant.

Hypothesis 6: (A) The introduction of natural language systems will *increase* the imbalance of power between participants.
(B) The introduction of expert systems will *decrease* the imbalance of power between participants.

Visibility

Another determinant of politicality is the visibility of the decision making process. Along with the issues discussed above, the number of decision making participants is a function of the general awareness of the decision process, and this is largely dependent on the visibility of the decision making activity. Where there is a great deal of overt action, more parties become aware of the issue and the effort being spent to resolve it. Awareness incites interest, and the number of participants increases. With the increase in the number of participants comes an increase in the number of disparate objectives and, hence, the level of political activity.

The visibility of a situation is heightened when the decision process requires external information and expertise. If decision-makers can gain access to the necessary knowledge without referring to outside expertise they may be able to sequester the process so that the decision appears routine. This will limit the demand for public appraisal of the solution, resulting in fewer numbers of involved parties. Direct access to expert systems and natural language systems will decrease the visibility of decisions where these systems are applicable. For example, an expert system referred to as CATS-1 was developed by General Electric in 1981 to assist its maintenance engineers in diagnosing problems in diesel-electric locomotives (Emrich, 1985). Before creating CATS-1, GE would fly a maintenance expert to the site of a malfunctioning engine to effect the repairs. Now, general maintenance staff located at the site are able to fix the engines by accessing expertise through a video-disk and computer interface. Not only does this improve the timeliness and cost of repairs, but it also serves to diminish their visibility. Staff from outside the local site are no longer needed, so other groups will be less cognizant of the breakdowns. In contrast, where external interests control the knowledge systems, decisions may become even more vulnerable to inspection. Where internal staff groups control access to the AI tools, formal requests and meetings will be required to incorporate the needed information. Similarly, if expert and natural language systems provide audit trails of their performance, visibility may be increased.

Hypothesis 7: If direct access to AI systems is available to decision-makers, then the decision process will become less visible.

Coupledness

The ability of participants to inspect and evaluate decisions also depends on the degree of coupling in the system. Where the environment or the organization is only intermittently coherent and systematic (Weick, 1987), the link between intention, action, and consequence becomes tenuous. In these situations the careful evaluation of decision alternatives is problematic. This amplifies the political dimension of decision making; political power, not rational argument is the decisive element. When systems are tightly coupled, however, the reverse is true. A solid link between intention, action, and consequence increases the technical importance of organizational decisions. Participants will be willing to spend more time evaluating and comparing decision alternatives. Correspondent with this, political influence will play a lesser role.

The effects of AI implementations on environmental coupling will depend on the specific technology introduced. As discussed above, expert systems serve to codify, routinize, and automate decision processes. Even in situations where the environment is complex and fragmented, the introduction of an expert system can produce an ordered, causally stable interpretation. The domain of industrial strategy formation includes a complex set of interrelationships and linkages (see Porter, 1980, 1985). Despite this complexity, Hall's (1987) expert system STRATASSIST implements a general approach to strategic planning, which might give the impression that the formation of business strategy is a well understood, routine activity. It is clear that the implementation of expert systems promotes the perception of tightly coupled environments, where the links between actions and consequences are explicit and understood. This perception forges a mandate for 'rational', rather than political, argument. The expansion of personal knowledge through the examination of natural language systems, however, may produce a very different effect. The numerous connections which can be traversed in a hypertext or natural language database might give the impression that 'everything is related to everything'. Such fantastic complexity precludes the employment of simple causal chains as a basis for argument. Politics again becomes the primary mode of action.

Hypothesis 8: (A) The introduction of natural language systems will *decrease* the perception of tight coupling in an environment or organization.
(B) The introduction of expert systems will *increase* the perception of tight coupling in an environment or organization.

Institutionalization

Another organizational element that can deter inspection and evaluation is the phenomenon of institutionalization. This phenomenon can occur at multiple levels. At the individual level, it is correspondent to Weick's (1987) notion of overlearned or mindless routines. These routines are so firmly entrenched in an individual's cognition, there must be a major disturbance before the individual even realizes that he or she is acting on them. A similar effect may occur at the organizational level. At this level, institutionalization is the process whereby an organizational activity or structure becomes inextricably tied to the members' concept of the organization itself. Where this occurs, the perpetuation of the activity or structure is almost never questioned. When change is considered in this type of situation, the process becomes politically charged. An attempt to deinstitutionalize a component of the organization may be viewed as direct threat to the survival of the organization.

Once again, the effects and potential uses of expert systems and natural language systems are vastly different. When an expert system is implemented within a decision situation, the preferences and power structures involved in reaching that decision become embedded in the assumptions of the system. Lee and Kang (1988) describe an 'Intelligent production planning system' which integrates quantitative considerations (e.g. labor costs, production runs) and qualitative factors (e.g. employee morale, customer goodwill). The qualitative factors are handled through a set of decision rules which constrain the results of the linear-programming based quantitative solution. One side-effect of this process is the institutionalization of assumptions regarding employee morale and customer goodwill. Although these are important elements of the production process, it is not clear that there can be unequivocal analyses of their effects. Embedded in an automated system, however, the impact of these factors may go unquestioned for long periods of time. In contrast, the use of natural language systems tends to point out the conflicts and contradictions inherent in any complex situation. This realization makes the institutionalization of any particular viewpoint problematic. Moreover, the examination of natural language databases may provoke the destabilization of previously institutionalized assumptions.

Hypothesis 9: (A) The introduction of natural language systems will *decrease* the level of institutionalization associated with a decision situation.
(B) The introduction of expert systems will *increase* the level of institutionalization associated with a decision situation.

CONCLUSION

This paper has demonstrated the complex, multifaceted nature of the relationship between AI and organizational decision making. Through the careful delineation of the two domains and their constituents, a more precise understanding of the specific interactions has been gained. Because of this detailed examination, we can also address the more general question of the overall effects of expert systems and natural language systems.

Impacts of AI on Decision Making

	COMPLEXITY	POLITICALITY
EXPERT SYSTEMS	H1: Decrease immensity. H2: Decrease variety. H4: Decrease seriousness.	H6; Decrease imbalance. H8: Increase coupling. H9: Increase institutionalization.
NATURAL LANGUAGE SYSTEMS	H1: Increase immensity. H4: Increase seriousness.	H6: Increase imbalance. H8: Decrease coupling. H9: Decrease institutionalization

Exhibit 3

In the generation of the hypotheses listed above, two patterns emerge. Exhibit 3 delineates the different effects predicted by Hypotheses 1, 2, 4, 6, 8 and 9 for the introduction of expert systems and natural language systems. It is argued here that expert systems will reduce immensity, variety, rarity, and seriousness, all contributing to a decrease in complexity. As well expert systems will lessen the imbalance between participants, increase environmental or organizational coupling, and institutionalize decision processes reducing the associated politicality. So, with a reduction in both complexity and politicality connected with the introduction of expert system technology, it is clear that these systems will change the dynamics of decision making in their subject domains. Hickson and his colleagues argue that a decrease in both complexity and politicality is associated with fluid decision making processes, which are 'steadily paced, formally channelled and speedy' (Hickson *et al.*, 1986: 120). And if the complexity associated with the decision is lowered enough, the process will become constricted, or 'narrowly channelled' (Hickson *et al.*, 1986: 122). The lower cognitive and social demands issued by the problem allow for a smoother choice process with fewer parties involved.

Hypothesis 10: The introduction of expert system technology will produce more *fluid and constricted decision processes* within the domain of the expert system.

The specific hypotheses discussed above predict a very different general effect for the implementation of natural language systems. It is hypothesized that natural language systems will increase immensity and seriousness, and possibly ambiguity. As well, these systems will increase the imbalance of power between participants, decrease environmental and organizational coupling, and serve to deinstitutionalize processes and structures. In summary, the implementation of natural language systems will increase complexity and politicality, if only slightly. According to Hickson and his colleagues such an increase would make the decision process more sporadic; it would be characterized by a greater number of interruptions and feedback loops, as well as a larger number of participants. According to Hickson and his colleagues, these processes are 'informally spasmodic and protracted' (Hickson *et al.*, 1986: 118).

Hypothesis 11: The introduction of natural language technology will produce more *sporadic decision processes* within the domain of the system.

Without the detailed discussion of the decision making determinants and the AI technologies, it would not have been possible to develop these two general hypotheses. We can now seriously question the optimistic belief that the infusion of technology will produce more 'rational' decision making.

The combination of AI and human decision makers adds a new category to the discussion of decision making. All but the simplest decisions made in complex organizations are aided in some manner by machines. This suggests that research in both AI and decision making should be concerned with the interaction between humans and machines in a social setting. Such research must go beyond user interfaces, cognitive models, search processes and other individualistic concerns. Effort must be made at the social and technological levels to ensure that technology is employed in a productive and beneficial manner.

REFERENCES

Bacharach, S. B. and Lawler, E. J. *Power and Politics in Organizations*, London: Jossey-Bass, 1980.

Balachandra, R. 'An expert system for R&D projects', in E. Turban and P. R. Watkins (eds.) *Applied Expert Systems*, Amsterdam: North Holland, 1988.

Bayer, J., Lawrence, S., and Keon, J. W. 'PEP: An expert system for promotion marketing,' in E. Turban and P. R. Watkins (eds.) *Applied Expert Systems*, Amsterdam: North Holland, 1988.

Bell, J. 'The logic of nonmonotonicity', *Artificial Intelligence*, 41, (1990) 365–374.

Daft, R. L. and Weick, K. E. 'Toward a model of organizations as interpretations systems', *Academy of Management Review*, 9:2 (1984), 284–295.

Dean, B. V. 'Toward an expert/decision support system in business venturing', in E. Turban and P. R. Watkins (eds.) *Applied Expert Systems*, Amsterdam: North Holland 1988.

Dutton, John M. 'Toward a broadly applicable strategic framework', in Johannes M. Pennings and Associates (eds.) *Organizational Strategy and Change*, San Francisco: Jossey-Bass, 1985.

DIO International Research Team. 'A contingency model of participative decision making: An analysis of 56 decisions in three Dutch organizations', *Journal of Occupational Psychology*, 56 (1983), 1–18.

Duda, R. O. and Shortliffe, E. H. 'Expert systems research', *Science*, 220 (1983), 261–267.

Emrich, M. 'Expert systems on the job', *Manufacturing systems*, 3–6 (1985), 26–32.

Feigenbaum, E., McCorduck, P., and Nii, H. P. *The Rise of the Expert Company*. New York: Random House, 1988.

Gauch, S. and Smith, J. B. 'An expert system for searching in full-text', *Information Processing and Management*, 25/3 (1989), 253–263.

Hall, N. G. 'A fuzzy decision support system for strategic planning', in E. Sanchez and L. A. Zadeh (eds.), *Approximate Reasoning in Intelligent Systems, Decision and Control*, Oxford: Pergamon, 1987.

Hickson, D. J., Butler, R. J., Cray, D., Mallory, G. R., and Wilson, D. C. *Top Decisions: Strategic Decision-Making in Organizations*, Oxford: Basil Blackwell, 1986.

Hinings, C. R., Hickson, D. J., Pennings, J. M., and Schneck, R. E. 'Structural conditions of intraorganizational power', *Administrative Science Quarterly*, 19 (1974), 22–24.

Kahneman, D. and Tversky, A. 'Choices, values, and frames', *American Psychologist*, 39 (1984), 341–350.

Krauss, S., Lehmann, S., and Magidor, M. 'Nonmonotonic reasoning, preferential models and cumulative logics', *Artificial Intelligence*, 44 (1990), 167–208.

Lebowitz, M. 'Intelligent information systems', *Proceedings of the 6th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, (1983) 25–30.

Lee, J. K. and Kang, B. S. 'Intelligent production planning system using the post-model analysis approach,' in E. Turban and P. R. Watkins (eds.) *Applied Expert Systems*, pp 87–106, Amsterdam: North Holland, 1988.

Lenat, D. B. 'Knoeshpere: Building expert systems with encyclopedic knowledge', *IJCAI-83: Proceedings of the 8th International Joint Conference on Artificial Intelligence*, (1983), 8–12.

Lenat, D. B. 'Computer software for intelligent systems', *Scientific American: Trends in Computing*, 1, (1988) 68–77.

Lindblom, C. E. 'The science of "Muddling Through"', *Public Administration Review*, 19 (1959) 79–88.

Louis, M. R. 'Hickson *et al.*: Top Decisions: Strategic Decision-Making in Organizations', *Administrative Science Quarterly*, 32/4 (1987), 627–629.

March, J. G. and Olsen, J. P. *Ambiguity and Choice in Organizations*, Norway: Universitetsforlaget, 1976.

March, J. G. and Simon, H. A. *Organizations*, New York: John Wiley & Sons, 1958.

Meyer, J. W. and Rowan, B. 'Institutionalized organizations: Formal structure as myth and ceremony', *American Journal of Sociology*, 83:2 (1977) 340–363.

Mintzberg, H. *Power In and Around Organizations*. Englewood Cliffs, N.J.: Prentice Hall, 1983.

Mintzberg, H., Raisinghani, D., and Theoret, A. 'The structure of "Unstructured" decision processes', *Administrative Science Quarterly*, 21 (1976), 246–275.

Moore, R. C. 'Semantical considerations on nonmonotonic logic', *Artificial Intelligence*, 25 (1985) 75–94.

Moser, J. and Christoph, R. 'Management expert systems (M.E.S.): A framework for development and implementation', *Information Processing and Management*, 23–1 (1987), 17–23.

Porter, Michael E. *Competitive Strategy*, New York: Free Press, 1980.

Reimer, U. and Hahn, U. 'Text condensation as knowledge base abstraction', *Proceedings: The IEEE Fourth Conference on Artificial Intelligence Applications*, (1988) 338–334,

Reiter, R. 'A logic for default reasoning', *Artificial Intelligence*, 13 (1980), 81–132.

Ross, J. and Staw, B. M. 'Expo '86: An escalation prototype', *Administrative Science Quarterly*, 31 (1986), 274–297.

Siler, W., Buckley, J. F. and Tucker, D. 'Functional requirements for a fuzzy expert system shell', in E. Sanchez and L. A. Zadeh (eds.), *Approximate Reasoning in Intelligent Systems, Decision and Control*, Oxford: Pergamon, 1987.

Simon, H. A. *Administrative Behavior*, New York: Free Press, 1976.

Staw, B. M. and Ross, J. 'Behavior in escalation situations: antecedents, prototypes, and solutions', in B. M. Staw and L. L. Cummings (eds.), *Research in Organizational Behavior*, 9 (1987), 39–78. Greenwich, Conn.: JAI Press.

Suedfeld, P., Tetlock, P. E., and Ramirez, C. 'War, peace, and integrative complexity'. *Journal of Conflict Resolution*, 21 (1977), 427–442.

Tolbert, P. S. and Zucker, L. G. 'Institutional Sources of change in the formal structure of organizations: The diffusion of civil service reform', 1880–1935, *Administrative Science Quarterly*, 28 (1983), 22–39.

Trappl, R. 'Impacts of artificial intelligence: An overview', in R. Trappl (ed.), *Impacts of Artificial Intelligence*, Amsterdam: North-Holland, 1986.

Weick, K. E. 'Perspectives on action in organizations', in J. W. Lorsch, (ed.), *Handbook of Organizational Behavior*, Englewood-Cliffs, NJ.: Prentice-Hall, 1987.

Weyer, S. A. and Borning, A. H. 'A prototype electronic encyclopedia', *ACM Transactions on Office Information Systems*, 1 (1985), 63–88.

Zadeh, L. A. 'Fuzzy sets', *Information Control*, 8 (1965), 338–358.

Zucker, L. G. 'The role of institutionalization in cultural persistence', *American Sociological Review*, 42 (1977), 726–743.

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