

Toward More Intelligent Organizations

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Abstract

Two beliefs motivate the authors of this paper. The first is that learning is key to the development of human intelligence. The second is that a synthesis of human expertise and information technology is key to the creation of more intelligent organizations. To explicate the first, a triarchic theory of human intelligence is presented and its implications are explored. Specifically, group knowledge-acquisition techniques for capturing and using human expertise are emphasized. To illustrate the second, a collaborative metasystem is proposed as a mechanism to help individuals and organizations manage personal and corporate knowledge systems and thereby deal intelligently with environmental uncertainty and equivocality.

Introduction

Following Sternberg (1985, 1988), intelligence is defined in this paper as purposive adaptation, shaping, and selection of environments relevant to an individual's or an organization's competencies and activities. An instrumental process that makes one experience available for use in other experiences so that they can be successfully managed, it requires use of suitable means and must result in positive outcomes. It is a concept that few people completely understand. Unaware that traditional tests measure only a small subset of the skills required for effective everyday performance, many equate human intelligence

with an IQ score. Others confuse it with academic performance. The latter typically involves tasks that: are well defined, have been formulated by other people, are almost devoid of intrinsic interest, have required information available from the beginning, are removed from an individual's normal experience, have but one correct answer, and often have only one method of correct solution (Neisser 1976). These seven characteristics rarely, if ever, apply to the situations that people must manage in everyday, as opposed to academic, settings. Similarly, the concept of intelligent organizations needs explication and clarification. A basic reason for organizing is to enable people to negotiate and communicate the relevant meanings of intelligent behavior, jointly establish appropriate goals, and share and refine their experiences so that together they can discover ways to use experience to establish more effective and profitable relations with entities in the environment. Given this, the concept of organizational intelligence, as compared with that of individual intelligence, includes the notion of interpersonal collaboration.

A general assumption of this paper is that it pays to understand intelligence and to try to improve it. To begin the attempt, it is of utmost importance to understand that intelligence is malleable and that individuals and organizations can decide to be and become more intelligent. Next, it is important to understand that knowledge is central to intelligent performance (Henmon 1921, Scribner 1986). For those whose work has a significant cognitive component, high levels of performance depend primarily upon knowledge of the problem domain as well as upon the ability to make broad searches of memory in order to re-

trieve relevant ideas and information (Frederiksen 1986). It is also helpful to know that the primary form of intellectual development in adulthood is represented by changes in declarative and procedural knowledge systems associated with education, occupational life, and other experiences of adult life (Dixon and Baltes 1986). Declarative knowledge (knowledge about "what") comprises all the facts, theories, generalizations, likes and dislikes, and personal memories that individuals store in long-term memory. It includes, for instance, information about an organization's norms for corporate performance and its marketing strategies. In contrast, procedural knowledge (knowledge about "how") is dynamic and embraces specialized rules for manipulating information. It includes procedures such as knowing how to allocate resources to goals or how to identify the most important issues in a complex situation. Declarative knowledge often facilitates creative behavior by providing insights about where known procedures might work, whereas procedural knowledge contributes to efficient performance in routine situations. Because practical knowledge of either type derives principally from experience, it can be considered fallible (e.g., Campbell 1974, Toulmin 1961).

This means that to improve their intelligence individuals and organizations need to learn and to keep on learning, constantly trying to absorb and grow from new kinds of experiences (Sternberg 1988). To do this, they need to set clear knowledge-acquisition goals, implement and monitor a learning program, and seek or create internal environments in which there is a sense of shared purpose and accomplishment so that individuals and groups are supported in these activities. In addition, organizations must develop and communicate a vision of the enterprise as a learning-centered social system in which individuals and groups are expected to challenge organizational theories and actions. Following that, they need to identify the cognitive, task, and social contributions that individuals and groups can make to corporate intelligence and to develop clear cognitive, task, and social goals for the enterprise as a whole as well as for individuals at different stages of skill acquisition. Finally, they must provide facilities and mechanisms for bringing people together so that they can share their experiences and refine their learning, task, and social behavior.

A triarchic theory of intelligence that explicates the relationship of learning to intelligent performance will be presented in the next section of this paper. Knowledge-acquisition techniques for capturing and using human expertise will subsequently be developed. Following that, a collaborative modeling system will be proposed as a mechanism for helping individuals and organizations improve their performance.

The Triarchic Theory of Intelligence

Sternberg's (1985, 1988) triarchic theory of human intelligence is composed of three subtheories that attempt to explain the context of intelligence, its relationship to the internal world of the individual, and its relationship to the experience of the individual. The first subtheory addresses the questions of what be-

haviors are intelligent and where they are intelligent. It claims that contextually intelligent behavior involves: adaptation to an existing environment; selection of a better environment; or shaping of the present environment so as to render it a better fit to the individual's skills, interests, or values. Because levels and patterns of intelligence and their manifestations are affected by socialization processes, intelligent behavior is not exactly the same thing across different cultures, but neither is it entirely different. What appears to be common to intelligent people in various contexts is the ability to adapt in order to fit their settings and, when necessary, to modify them so as to achieve a better person-environment fit. Similarly, an important characteristic of an intelligent organization is the ability to make its view of the future a reality by understanding itself and its competitive environment and then judiciously implementing and monitoring key strategies so that a better fit is realized.

The second subtheory attempts to answer the question of when behavior is intelligent by explicating the relationship of intelligence to experience. It posits that for a given task or problem contextually appropriate behavior may not be equally intelligent when differences in individuals' experience with the task or problem are considered. In other words, the extent to which tasks or problems require intelligence depends upon an individual's experience with them. Sternberg (1988) suggests that intelligence is best demonstrated when people are confronted by relatively novel tasks or problems or when they are in the process of automatizing task or problem procedures. The better people are at one, the more cognitive resources they have available for the other. For instance, most adults' reading skills are so well practiced that they can devote most of their cognitive energies to an activity like framing an effective response to a memo rather than to the processes of translating words into meaning. Likewise, when organizational systems shoot information to those with a need to know while automatically shielding them from irrelevant or untimely reports, it becomes possible for an enterprise to exercise real-time control over strategy implementation.

The third subtheory addresses the question of how intelligent behavior is generated. In doing so, it explicates the mental processes involved in thinking. The assertion is that good problem solving always requires interactions among three sets of processes. The first includes executive activities that help people plan and assess their cognitive behavior, set performance standards, take remedial action, and determine their own rewards for effective behavior. These executive processes occur in the context of individuals' long- and short-term goals and their awareness of personal, task, and strategy variables. On the organizational level, they are reflected in activities such as discussions about the value and futurity of alternative decisions. The second includes performance processes that carry out the strategies determined by prior executive activities. For instance, it is not enough to decide to study a strategic alternative; an individual must, finally, undertake the research. Similarly, an organization must weld strategic thinking to effective strategy execution if it is to achieve its long-range objectives. Knowledge-acquisition processes complete the set of activities.

Intelligent individuals and organizations have—whether formally or informally—developed expertise in acquiring the knowledge required for effective and successful behavior in a variety of environments. For example, individuals who have explicit knowledge of the learning-to-learn strategy, elaboration, focus on related prior knowledge, experiences, and beliefs that come to mind while they are trying to learn in order to provide points of connection to ambiguous situations. In like manner, organizations can encourage individuals and groups to challenge organizational theories and actions as well as provide facilities and mechanisms for bringing people together so that they are able to share their experiences and refine their behavior. Because knowledge-acquisition processes like these are key to intelligent performance, the paper focuses on this third group of processes.

Human Performance

For more and more people, thinking (or problem solving) is becoming the essence of work (Zuboff 1988). Seldom, however, is the importance of knowledge acquisition to effective thinking made clear. Nor are people at work generally taught what learning is or how to learn. This means that the knowledge that most people have about acquiring and using information is generally incomplete and much of it is tacit. Learning is a relatively permanent change in behavior or knowledge brought about by practice or experience (e.g., Bransford 1979, Norman 1982). Information is encoded and transformed into knowledge by means of four processes. These are selection, construction, integration, and acquisition (Cook and Mayer 1983). During selection, individuals first attend to environmental stimuli and then transfer some of these stimuli from short-term memory to working memory. During construction, learners forge connections in working memory among ideas present in this new information. Building internal connections (Mayer 1982) leads to the development of a coherent schema (Bransford 1979) that holds the information together. In integrating new information, learners search for related knowledge in long-term memory. If it is found, it is transferred to working memory. Meaningful connections can then be built between new and prior information. When individuals do not have appropriate prior knowledge, integration can be difficult, if not impossible. During acquisition, learners actively transfer integrated information from working memory to long-term memory where it is held until it is required. Selection and acquisition determine how much is learned. Construction and integration, on the other hand, determine the coherence of what is learned and how it is organized. When learning is conceived of in this way, it is clear that the knowledge people acquire is, in effect, constructed by their own cognitive processing.

Cognitive psychologists have demonstrated that intelligence depends to a great degree on the use of domain-independent learning strategies as well as domain-dependent ones (e.g., Campione and Brown 1979, Weinstein 1988, Weinstein, Ridley, Dahl, and Weber 1989). Effective problem solvers use powerful, but usually informally acquired, strategies for acquiring informa-

tion, storing it in memory, retrieving it as needed, and subsequently using it to fashion and monitor their solution plans. Generally, learning strategies can be thought of as thoughts and behaviors in which learners are active in generating processes that facilitate encoding in such a way that knowledge integration and retrieval are enhanced (Mayer 1980). These are general strategies that can be learned. Moreover, they can be deliberately used to learn and thereby improve performance in any domain (Weber, Chen and Weinstein 1989a, 1989b). For instance, to function well at work, people need to select goals for which internal and external sources of support are available (Dixon and Baltes 1986). In establishing knowledge-acquisition and performance goals, managers and workers can use learning strategies that help them generate favorable internal contexts that facilitate learning. This includes contexts that help them manage the effects of anxiety on performance. Cognitive worry, a major component of anxiety, is manifested in negative self-referent statements that divert attention and energy away from learners' tasks and focus them inward on self-criticism or on irrational fears. To avoid such effects, learners need to become aware of and monitor their "self talk," replacing criticism with encouragement (Weinstein, Schulte and Palmer 1987).

People at work must also find or generate supportive external environments to support their learning and problem-solving activities. Not only do healthy individuals in supportive settings have the capacity to maintain or increase high levels of functioning in domains of interest to them, but the level and rate of their intellectual development vary as a function of cognitive complexity and demands of work environments. Practical thinking or problem solving is embedded in the larger purposive activities of daily life, and it functions to achieve the goals of those activities. These goals may involve mental and/or manual accomplishments but, whatever their nature, practical thinking is instrumental to their achievement. Because practical thinking is simultaneously adaptive to ever-changing conditions in the environment and to the purposes, values, and knowledge of the individual and the social group (Scribner 1986), it requires the acquisition and use of specific knowledge that is functionally important to the larger activities in which intelligent performance is embedded. Kusterer (1978), who studied knowledge on the job, suggested an underlying principle accounting for the remarkable selectivity of some areas of working knowledge: people at work acquire knowledge in a problem-solving mode. That is, knowledge acquisition varies greatly among individuals, but general functional principles apply. Whether an individual's fund of practical knowledge is large or small is related to the diversity of functions carried out and their degree of standardization. For example, people who must manage complex problems require more and better-organized stores of working knowledge than do those who generally deal with routine problems.

Organizational Competencies

Three primary objectives that organizations must pursue in order to improve their performance have been presented. These

include development of a learning-centered environment, identification of the contributions that individuals and groups can make to corporate intelligence, and provision of facilities and mechanisms for bringing people together so that they can share their experiences and refine their learning, task, and social behavior. In the following paragraphs, organizational competencies will be discussed. Competencies are attributes of an organization that are necessary for effective performance in a particular environment. They can be classified into two broad types: usable knowledge related to a set of functions and processes that bear on effective use of that knowledge (cf. Klemp and McClelland 1986). They include what successful managers know and ways that elicited managerial expertise can be used.

The knowledge that successful managers possess is important because it is largely on their skills that the future of the organization depends. Klemp and McClelland (1986), who looked at the qualities of successful managers, found that procedural knowledge is of utmost importance to skilled managerial performance. This involves skills like knowing how to exert power to make sure that things get done, knowing how to get cooperation from groups, and knowing how to use symbols to influence the ways that people act. Further, their research revealed that these strategies tend to be linked to levels in the organizational hierarchy. For instance, foremen need to know how to tell workers what to do. Middle managers need to know how to work with others. Top managers need to know how to use symbols to make an impact on the organization as a whole. Each of these general strategies, in turn, appears to be dependent on a level of intellectual functioning. Thus, for managers to direct people effectively, they must know how to plan and be able to see the implications of their plans. To work well with others, they need to know how to collect feedback so that they can determine where organizational changes are required and how and with whom they can work to bring about those changes. To manipulate symbols effectively, they need to know how to form the pieces of information they have collected into a coherent pattern.

It can be difficult to formalize the knowledge that helps expert managers perform in a skilled manner. A major reason for this is that after extensive experience with problematic situations, strategies for recognizing particular patterns and implementing appropriate procedures begin to be automatically applied. As automatization increases and people move from rule-guided "knowing that" to experience-based "knowing how," explicit awareness of procedural knowledge decreases. Eliciting such expertise, while difficult, is not impossible. In the research reported below, effective methods were developed for accessing and refining the knowledge of organizational experts. There are certainly many uses for it. Building expert systems comes immediately to mind. H. Dreyfus and S. Dreyfus (1986), who identified five stages of skill acquisition ranging from the rule-based behavior of novices to the nonreflective actions of experts, are convinced that because much of an expert's behavior is intuitive it is highly unlikely that expert systems will ever be able to deliver more than competent performance. Even if this is true, expert systems can be helpful to novices who typ-

ically begin by learning to identify relevant facts and features and acquiring rules for determining appropriate actions. Expert systems can also be used as decision aids in routine situations or as sources of deliberative judgments in those organizations that do not have the required human skills. Elicited expertise can be used in training programs. For instance, individuals can be taught general leadership and management skills like those identified by Klemp and McClelland (1986) as well as organizationally or functionally specific procedures and facts elicited from and verified by groups of organizational experts.

Knowledge Acquisition as a Group Process

Knowledge engineers interested in working toward improvements in organizational performance must think of knowledge acquisition as a group process. Complex problems require the talents and resources of many individuals. Organizational intelligence can be thought of as collaborative and purposive adaptation, shaping, and selection of environments relevant to an enterprise's objectives and competencies. This view of the concept implies that improvements in organizational performance are related to the ability and inclination of individuals and coalitions to jointly refine their professional knowledge as well as negotiate and communicate the relevant meanings of intelligent behavior within the organization. In other words, organizations interested in high levels of performance should concentrate their collective efforts on the goal of helping groups of individuals—as the agents of organizational intelligence—elaborate, maintain, and transform their declarative and procedural knowledge systems (Lee and Courtney 1989, Weber, Chen and Weinstein 1989a, 1989b).

Three generic knowledge-acquisition processes need to be supported. These are selective encoding, selective combination, and selective comparison. Sternberg (1988) suggests that these processes are relevant to acquisition of declarative and procedural knowledge in virtually all domains of knowledge. In selective encoding, the group must distinguish between relevant and irrelevant information (Schank 1980). When complex or ambiguous situations must be managed, this is a critical task. The group is likely to find it very difficult to identify information relevant to the organization's purposes in the masses of purpose-irrelevant information presented in the environment. Distinguishing between relevant and irrelevant information does not create new knowledge structures. The group must combine encoded information in such a way as to form it into meaningful and credible patterns (Mayer and Greeno 1972). When difficult problems are encountered, these meanings and patterns as well as their significance must be determined through consultation and negotiation. In selective comparison, the group must relate newly acquired or retrieved information to what it already knows. In the case of to-be-learned information, a relation must be noted between it and something previously encoded. In the case of newly retrieved information, an item just retrieved from memory is suddenly seen as related to something else and thereby comes to be understood in a new way. Decisions about what items of information to encode and how to

combine them are guided by what is already known. Because new information is all but useless if it is not somehow related to what someone already knows (Mayer and Greeno 1972), the composition of the group—its skills and domains of expertise—is extremely important to the overall process.

Use of a GDSS Environment

The knowledge-acquisition methodology described below was designed to support groups involved in building expert systems. It was tested in the development of a help system designed for an information center in a large corporation (Liou 1989, Liou, Weber and Nunamaker in press). The Group Decision Support System (GDSS) environment was found to facilitate the group knowledge-acquisition process. A GDSS is an integrated computer-based system that is designed to help groups deal with unstructured or semi-structured tasks (DeSanctis and Gallupe 1987). Its goals are to reduce the process loss associated with disorganized activity, member dominance, social pressure, inhibition of expression, and other difficulties commonly encountered in groups and, at the same time, to increase the efficiency and quality of the end results (DeSanctis and Gallupe 1987, Huber 1984, Turoff and Hiltz 1982). As used in this paper, the term includes the notions of computer-supported collaborative work, group support systems, and group meeting systems (Dennis, George, Jessup, Nunamaker and Vogel 1988). A GDSS environment includes hardware, software, people, and facility (DeSanctis and Gallupe 1987). In addition, Dennis and his colleagues included procedures as a component of a GDSS environment. Facilitation is another important part of a GDSS environment (Vogel, Nunamaker, Applegate and Konsynski 1987). In the help-system field study, Liou found that knowledge acquisition required all six of the above.

In the field study, six advantages of using a computer-supported cooperative approach were identified. First, interaction among experts resulted in an enlarged and enriched domain of acquired expertise. Second, because knowledge extraction from individual experts was performed in parallel, time was saved. Third, conflicts were surfaced and resolved during the knowledge-extraction phase. Fourth, knowledge was documented electronically so that process loss was reduced and accuracy was increased. Fifth, the structured techniques that were used increased the efficiency and effectiveness of the knowledge-acquisition process. Sixth, because the time required to elicit information was significantly reduced, experts were not reluctant to commit themselves to the project.

The Methodology

The activities involved when knowledge engineers use a GDSS environment to elicit expertise can be decomposed into four phases: planning for knowledge acquisition, knowledge extraction, knowledge analysis, and knowledge verification. The four stages comprise fourteen steps. The steps are summarized

and mapped to the knowledge-acquisition phases in Table 1. As noted above, this methodology was designed to support groups involved in the development of expert systems. When GDSS environments are used to structure and support face-to-face meetings in other areas, for instance, planning, consensus building, and negotiation, this methodology must be modified.

Planning for Knowledge Acquisition. Like the analysis phase of the system development life cycle, planning is the most important phase of knowledge acquisition, and like analysis and design, it begins with an attempt to understand the application domain. No matter what methods or techniques a knowledge engineer uses to acquire knowledge, an understanding of the terminologies, concepts, and problem-solving strategies of the application domain is necessary. The goal is not to turn knowledge engineers into experts. Rather the goals are to increase

KA Phases	Steps
Planning for Knowledge Acquisition	Understanding the domain Defining the problem scope Identifying knowledge applications Developing the process models Identifying the participants Planning the sessions
Knowledge Extraction	Explaining the approach Discussing session objectives Conducting the sessions Debriefing the expert team
Knowledge Analysis	Analyzing session outputs Developing representations
Knowledge Verification	Developing test scenarios Verifying knowledge with team

Table 1: Knowledge-Acquisition Phases and Steps

the effectiveness with which they communicate with experts and the clarity with which they understand the domain.

The next step is to set initial boundaries on the scope of the problem. This makes it possible to identify domain experts who can then assist managers and knowledge engineers in refining and specifying the issues of interest. The degree to which types of individuals should be involved is related to the uses to which the elicited knowledge will be put. For instance, manager involvement helps ensure that an expert system will serve a meaningful purpose.

To maximize the benefits of using a GDSS environment, knowledge engineers must select tools that support the process in the most effective manner possible. To do this, they must determine the ways elicited information will be used. The sequence of user tasks must be identified and analyzed. These are then represented by one or more process models that can be implemented by computer-based tools, by group-process techniques, or by a combination of both. In a GDSS environment, it is relatively easy to provide both kinds of support.

Because participation in knowledge-acquisition sessions is usually limited to experts and facilitators, it is important that they be selected wisely. Individual attributes that should be con-

sidered include domain background, customer authorization, availability, personal characteristics, and attitudes (McGraw and Harbison-Briggs 1989). Domain background includes the experiences people have had and the ways in which they have used their expertise. Customer authorization refers to the issue of who decides whether an individual is an expert. Only those who expect to use the expert system should be able to warrant expertise. Because they may influence the transfer of information to the knowledge engineer, personal characteristics and attitudes should also be taken into consideration. These include an individual's sense of humor, ability to send as well as receive information, sense of commitment, patience, meta-knowledge, willingness to participate, honesty, and persistence (McGraw and Harbison-Briggs). Identification of the facilitator is also extremely important. Facilitation requires technical competence, communication skills, domain knowledge, and group facilitation skills. Technical competence includes understanding the group tools: how to use them, their purposes and limitations, and how they work together to support the knowledge-acquisition process. Group-facilitation skills require a sound understanding of group dynamics and the ability to work within the constraints of those dynamics to help the group achieve goals. Facilitators who are not knowledge engineers must be aware of the expectations of the knowledge engineers who plan and organize the sessions and of the experts who take part.

Planning knowledge-acquisition sessions is the final step in this first stage. Objectives of each group session must be identified. A session agenda describing objectives, participants, duration, input, processes, expected output, and the overall sequences of events must be developed. Input files such as discussion topics and background information should be prepared. Intermediate activities between sessions must be scheduled. These may include backing up and reviewing session outputs and preparing files for subsequent sessions.

Knowledge Extraction. The primary activity during this phase is to promote selective encoding, selective combination, and selective comparison. A series of sessions may be required. Each may be focused on a different objective and use different techniques and tools. The first session must begin with an discussion of knowledge acquisition, knowledge-acquisition techniques, and group-support tools. Additionally, participants must be given an overview of the objectives of the entire series of sessions in order to reduce potential misinterpretations during the process. In subsequent sessions, knowledge engineers must explain specific objectives, techniques to be used, and expected results.

Structured procedures should be used in running sessions. A structured procedure applies such techniques as brainstorming and voting to acquire knowledge from a group of experts, organizes sessions according to particular process models, and integrates inputs and outputs from session to session. A contingency plan and frequent backup of session outputs are recommended in case of a system failure or any other unexpected problems.

Debriefing should address the tasks of summarizing and correctly recording the problems, solutions, and ideas raised by participants. Experts should be encouraged to request or suggest clarification of issues that were raised. The process offers knowledge engineers an opportunity not only to obtain consensus from experts but also to elicit data concerning an expert's degree of certainty or belief in the information obtained. While certainty or validity of rules for a knowledge base is always important, it is extremely so in situations in which more than one expert may have contributed ideas or in which ideas were consolidated based on discussion among them (McGraw and Seale 1987, 1988). As the session concludes, the knowledge engineer should identify action items, parties responsible for specific tasks, and target completion dates.

Knowledge Analysis. The primary task of this phase is to analyze outputs from knowledge-acquisition sessions. Heuristics, concepts, or classification structures are analyzed and formalized into representations that may be in the form of heuristic rules, frames, objects and relations, semantic networks, and classification schemes. These representations are then transferred into particular representation schemes that are supported by the expert system building tool. Although implementation of the expert system is not an issue in knowledge acquisition, it determines what knowledge-representation schemes can be used. Thus, knowledge engineers must decide how an expert system is to be implemented in terms of selection of expert system building tools, knowledge-representation schemes, and inference methods before the analysis phase begins.

Knowledge Verification. This phase focuses on verifying heuristics, concepts, and classification structures. Scenarios are developed to test the system's capabilities. Formalized representations are discussed with the group of experts. Demonstrations of the prototype system are also helpful. Represented knowledge can be refined by looping back to the knowledge-analysis phase, whereas reformulation of heuristics, concepts, or classification structures must be accomplished by returning to the knowledge-extraction phase. If knowledge captured in the prototype system does not provide solutions to problems, redesign of the knowledge-acquisition sessions is necessary. This requires rethinking the knowledge-acquisition approach as well as procedures to acquire knowledge.

An environment has been described that helps groups of organizational experts identify and refine the information that matters. Additionally, it has been emphasized that the performance of individuals depends primarily upon their knowledge of the problem domain and their ability to make broad searches of memory in order to retrieve relevant ideas and information (Frederiksen 1986). Consequently, it is vital that organizations interested in high levels of performance concentrate their collective efforts on the goal of helping individuals and groups of individuals—as the agents of organizational intelligence—elaborate, maintain, and transform their declarative and procedural knowledge systems. In the next section, a collaborative metasystem is proposed as a mechanism for helping individuals and organizations manage personal and corporate knowledge systems and

thereby deal intelligently with environmental uncertainty and equivocality.

Systems Support in Uncertain and Equivocal Environments

One of the greatest challenges of information professionals is to develop information-processing mechanisms that help individuals and organizations cope effectively with uncertain and ambiguous environments. Enterprises encounter uncertainty when people do not have the information they need to perform their tasks (Galbraith 1977). Consequently, managers in uncertain situations try to find decision rules, information sources, and structural designs that help them learn enough to succeed in their assigned responsibilities. Equivocality is encountered when there are multiple and conflicting interpretations of organizational reality (Weick 1979, Daft and Macintosh 1981). Managers in equivocal circumstances exchange views to clarify ambiguities, define problems, and enact a shared interpretation that directs future activities. Ambiguous situations may also require new data as well as clarification and agreement about the meaning and implications of that data (Daft and Lengel 1986).

Daft and Lengel (1986) argue that information of sufficient richness can reduce equivocality and provide enough data to reduce uncertainty. In their view, rich media are personal and involve face-to-face communication, while media of lower richness, like management information systems (MIS), are impersonal and rely on rules, forms, procedures, or data bases. They reason that MIS have a role to play in the reduction of uncertainty, but that they cannot help managers deal with equivocality. Further, they believe that to reduce ambiguity, structural mechanisms must enable debate, clarification, and enactment. Because GDSS environments support the generic knowledge-acquisition processes of selective encoding, selective combination, and selective comparison, they help managers overcome different frames of reference and process complex, subjective messages. Consequently, they can be classified as rich media. For instance, Weber, Smith and Ram (1987) and Nunamaker, Weber and Chen (1989) discussed the use of GDSS environments in crisis planning. Here the objective is to help organizational leaders enact a shared interpretation or model of the enterprise—its values, goals, strengths, and weaknesses—so that together they can intelligently meet environmental challenges and opportunities. The assumption underlying the process is that managers who have previously negotiated a model of intelligent crisis behavior have an initial frame of reference that can make concerted future action both more timely and more effective.

MetaPlex

In this section, a metasystem that nurtures managerial learning and facilitates interpersonal as well as intraorganizational interactions and communications will be discussed. MetaPlex is an object-oriented metasystem implemented in Smalltalk-80 on a PC-AT that integrates GDSS and computer-aided software en-

gineering (CASE) tools. Its interactive interface was designed to be utilized by end users. The system was developed and implemented by Chen (1988) and described in detail by Chen, Nunamaker, and Weber (1989, in press). Customized groupware captures information about the organization and its computer systems generated during crisis-planning, requirements-elicitation, and other types of meetings held in a GDSS environment. MetaPlex makes it possible for systems professionals to use this information by providing them with a metalanguage that can be utilized to create a language for describing a specific organization and its information systems. For instance, the metalanguage was used by Chen to create the critical success factor (CSF) modeling language illustrated below. The MetaPlex language itself consists of a set of object types and a set of relation types among existing object types. Attribute types can be defined to describe the characteristics of both object and relation types. Object types include organizational constructs such as organization structures and goals, business processes and strategies, strategic assumptions, tasks, CSF's, and relationships (or relation types). Information systems constructs include reports, programs, data sets, and business application systems. Because organizations can be very different, it is impossible to define a standard set of constructs that would fit every organization. This means that MetaPlex needs to allow users to debate and define unique objects, relationships, and values.

Once the organization and its systems are described by systems personnel using a language like the CSF modeling language, a GDSS environment is again used to present the maps or models to managers so that they can be verified and the complicated linkages between them can be specified. When organization models are integrated with information systems models, the enterprise's goals, norms, assumptions, and strategies are aligned with its information technologies. Thereafter, any changes in the enterprise's information systems can immediately be propagated to corresponding business counterparts, and the dynamics of the business environment can be extended to the supporting information systems so that the alignment remains functional and clear. Additionally, the information flows among organizational units depicted in an integrated model and associated data about the units' information-handling capabilities can be used in creating new, more realistic organizational designs. The integrated models make it easier to evaluate the impacts of new information systems on an enterprise, and they also help managers make certain that systems serve important organizational goals.

Modeling also benefits the individuals involved. Systems developers no longer need to begin each development project wishing they had information generated in previous projects that was subsequently lost. Formally documented and integrated models are also a boon to managers. Here, they have a dual function. They describe actual patterns of activity, and they are guides to future action. In this respect, they can be thought of as the media of organizational learning (Argyris 1980, Argyris and Schon 1978). People learn as they create them, and they learn by studying them. For example, reports

all too frequently deliver information that is either no longer required or, even worse, meaningless. The relationships among tasks, goals, and the information delivered by the enterprise's systems are often ambiguous or confusing. Group analysis of the models clarifies these relationships. As a result, managers are able to approach their information requirements from a managerial rather than an information-systems perspective. The ability to move among managerial responsibilities, organizational goals, and relevant information can do a great deal to infuse meaning into system outputs. An integrated model can also be an important resource to new managers who need to understand the organization and its technology as quickly as they can.

CSF Modeling

The CSF systems-planning methodology designed by Rockart (1979) asks individual executives to think about areas of their work where things must go right in order for the organization itself to flourish. These critical domains are identified so that current information needs can be made explicit. After requirements are elicited, managers are asked to establish measures

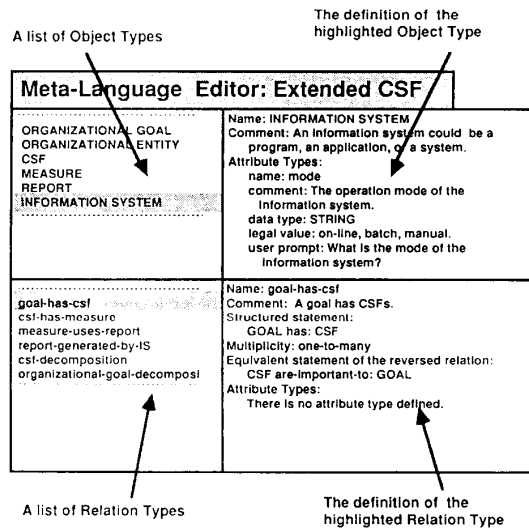


Figure 2: An Abstract CSF Model

Originally utilized to determine the current information requirements of individual managers, the CSF methodology was extended by Chen and Nunamaker (1989) to help systems personnel establish the requirements of an entire enterprise. Chen (1988) also used MetaPlex to create a CSF language. Use of the metalanguage editor is illustrated in Figure 1. Some of the object and relation types in the language are shown in Figure 2. Object types are enclosed in rectangles, and relation types are represented as labeled arrows (only one direction is shown). As illustrated in the figure, the CSF language contains object and relation types in both information systems and organization systems domains and thereby provides linkages to bridge the gap between the two. Each object type can have a set of attribute types. For example, information system can have the attribute types: mode (i.e., on-line or batch) and system-type (i.e., system, program, or module). Attribute types, however, are not illustrated in the figure.

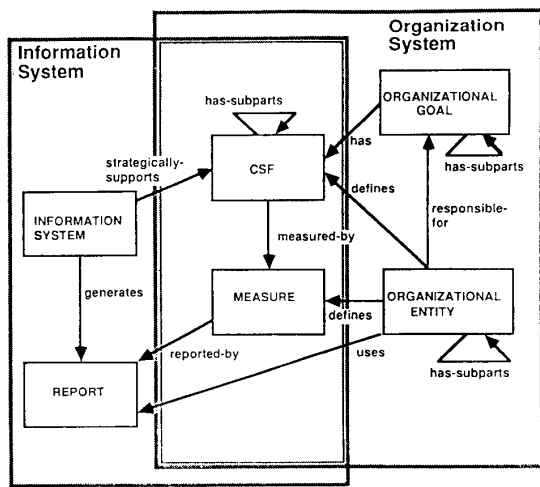


Figure 1: Using the Metalanguage Editor to Create the CSF Language

for evaluating their success in these areas. When it is difficult to quantify a particular CSF, qualitative measures are often used. Next, executives or their representatives work with systems builders to define information products, typically printed reports and online displays, that report on the measures linked to these key areas. Last, systems professionals design and implement the systems that generate these communications.

The language can be used to develop an enhanced managerial interface. As was mentioned above, the delivery mechanisms of many information systems are poorly planned. Consequently, managers are all too frequently flooded with meaningless reports. Likewise, in their search for on-line information, executives must often work their way through a series of incomprehensible screens, each of which appears to be randomly generated rather than organized around an organizationally meaningful multi-dimensional model. When a CSF model is embedded in an interface, managers using the system are able to move back and forth between a managerial and a systems' view of the enterprise before eventually executing a program to generate required information. The integrated model guides their search activities, the context of each search path helping them better understand the organization and its goals and norms as

well as its information systems.

Conclusion

Individuals and organizations can decide to be and become more intelligent. Individuals can do so by learning how to learn and by continually adding to and refining their declarative and procedural knowledge systems. A synthesis of human expertise and information technology is key to the creation of more intelligent organizations. For instance, organizations can improve their performance by encouraging individuals and groups to challenge organizational theories and actions and by providing facilities and mechanisms for bringing people together so that they can share their experiences and refine their learning, task, and social behavior. This paper has identified ways that groups of individuals can jointly refine their professional knowledge as well as debate and communicate the relevant meanings of intelligent behavior within an enterprise. GDSS environments were described as facilities that provide considerable support to these activities. MetaPlex was presented as a mechanism that helps managers learn about the enterprise and its technologies so that they can cope intelligently with uncertain and ambiguous environments. In the end, the best way to improve performance is to thoroughly understand the concept of intelligence so that effective techniques for supporting individual and group learning can be devised and explored.

References

- [1] Argyris, C., *Inner Contradictions of Rigorous Research*, Academic Press, New York, NY, 1980.
- [2] Argyris, C. and D.A. Schon, *Organizational Learning: A Theory of Action Perspective*, Addison-Wesley, Reading, MA, 1978.
- [3] Bransford, J.D., *Human Cognition: Learning, Understanding and Remembering*, Wadsworth, Belmont, CA, 1979.
- [4] Campbell, D.T., "Evolutionary Epistemology," in P.A. Schilpp (Ed.), *The Philosophy of Karl Popper*, Open Court, La Salle, IL, 1974.
- [5] Campione, J.C. and A.L. Brown, *Toward a Theory of Intelligence: Contributions from Research with Retarded Children*, Ablex, Norwood, NJ, 1979.
- [6] Chen, M., *The Integration of Organization and Information System Modeling: A Metasystem Approach to the Generation of Group Decision Support Systems and Computer-Aided Software Engineering*, unpublished doctoral dissertation, The University of Arizona, Tucson, 1988.
- [7] Chen, M. and J.F. Nunamaker, Jr., "Integration of Organization and Information Systems Modeling: An Object-Oriented Approach," *Proceedings, The 22nd Hawaii International Conference on System Sciences*, 3 (1989), 70-79.
- [8] Chen, M., J.F. Nunamaker, Jr. and E.S. Weber, "Computer-Aided Software Engineering: Present Status and Future Directions," *Data Base*, 20 (1989), 7-12.
- [9] Chen, M., J.F. Nunamaker, Jr. and E.S. Weber, "The Use of Integrated Organization and Information Systems Models in Building and Delivering Business Application Systems," *IEEE Transactions on Knowledge and Data Engineering*, in press.
- [10] Cook, L.K. and R.E. Mayer, "Reading Strategy Training for Meaningful Learning from Prose," in M. Pressley and J.R. Levin (Eds.), *Cognitive Strategy Training*, Springer-Verlag, New York, NY, 1983.
- [11] Daft, R.L. and R.H. Lengel, "Organizational Information Requirements, Media Richness and Structural Design," *Management Science*, 32 (1986), 554-571.
- [12] Daft, R.L. and N.B. Macintosh, "A Tentative Exploration into the Amount and Equivocality of Information Processing in Organizational Work Units," *Administrative Science Quarterly*, 26 (1981), 207-224.
- [13] Dennis, A.R., J.F. George, L.M. Jessup, J.F. Nunamaker and D.R. Vogel, "Information Technology to Support Electronic Meetings," *MIS Quarterly*, 12 (1988), 591-624.
- [14] DeSanctis, G. and R.B. Gallupe, "A Foundation for the Study of Group Decision Support Systems," *Management Science*, 33 (1987), 586-609.
- [15] Dixon, R.A. and P.B. Baltes, "Toward Life-Span Research on the Functions and Pragmatics of Intelligence," in R.J. Sternberg and R.K. Wagner (Eds.), *Practical Intelligence: Nature and Origins of Competence in the Everyday World*, Cambridge University Press, Cambridge, UK, 1986.
- [16] Dreyfus, H. and S. Dreyfus, *Mind Over Machine: The Power of Human Intuition and Expertise in the Era of the Computer*, Free Press, New York, NY, 1986.
- [17] Frederiksen, N., "Toward a Broader Conception of Human Intelligence," in R.J. Sternberg and R.K. Wagner (Eds.), *Practical Intelligence: Nature and Origins of Competence in the Everyday World*, Cambridge University Press, Cambridge, UK, 1986.
- [18] Galbraith, J. *Organizational Design*, Addison-Wesley, Reading, MA, 1977.
- [19] Henmon, V.A.C., "Intelligence and its Measurement: A Symposium," *The Journal of Educational Psychology*, 12 (1921), 195-198.
- [20] Huber, G.P., "Issues in the Design of Group Decision Support Systems," *MIS Quarterly*, 8 (1984), 195-204.
- [21] Klemp, G.O., Jr. and D.C. McClelland, "What Characterizes Intelligent Functioning Among Senior Managers?" in R.J. Sternberg

- and R.K. Wagner (Eds.), *Practical Intelligence: Nature and Origins of Competence in the Everyday World*, Cambridge University Press, Cambridge, UK, 1986.
- [22] Kusterer, K.C., *Know-How on the Job: The Important Working Knowledge of "Unskilled" Workers*, Westview, Boulder, CO, 1978.
- [23] Lee, S. and J.F. Courtney, Jr., "Organizational Learning Systems," *Proceedings, The 22nd Hawaii International Conference on System Sciences*, 3 (1989), 492-503.
- [24] Liou, Y.I., *The Use of a Group Decision Support System Environment for Knowledge Acquisition*, unpublished doctoral dissertation, The University of Arizona, Tucson, 1989.
- [25] Liou, Y.I., E.S. Weber, and J.F. Nunamaker, Jr., "A Methodology for Knowledge Acquisition in a Group Decision Support System Environment," *Proceedings, Fourth Knowledge Acquisition for Knowledge-Based Systems Workshop of the American Association for Artificial Intelligence*, (in press).
- [26] Mayer, R.E., "Elaboration Techniques That Increase the Meaningfulness of Technical Tests: An Experiential Test of the Learning Strategy Hypotheses," *Journal of Educational Psychology*, 72 (1980), 777-784.
- [27] Mayer, R.E., "Instructional Variables in Text Processing," in A. Flammer and W. Kintsch (Eds.), *Discourse Processing*, North-Holland, Amsterdam, NE, 1982.
- [28] Mayer, R.E. and J.G. Greeno, "Structural Differences Between Learning Outcomes Produced by Different Instructional Methods," *Journal of Educational Psychology*, 63 (1972), 165-173.
- [29] McGraw, K.L. and K. Harbison-Briggs, *Knowledge Acquisition: Principles and Guidelines*, Prentice Hall, Englewood Cliffs, NJ, 1989.
- [30] McGraw, K.L. and M. Seale, "Knowledge Elicitation with Multiple Experts: Considerations and Techniques," *Artificial Intelligence Review*, 2 (1988), .
- [31] McGraw, K.L. and M. Seale, "Multiple Expert Knowledge Acquisition Methodology: MEKAM," *Proceedings of the Third Australian Conference on Applications of Expert Systems*, The New South Wales Institute of Technology, Sydney, 1987, 165-197.
- [32] Neisser, U., "General Academic and Artificial Intelligence," in L. Resnick (Ed.), *The Nature of Intelligence*, Erlbaum, Hillsdale, NJ, 1976.
- [33] Norman, D.A., *Learning and Memory*, W.H. Freeman, San Francisco, CA, 1982.
- [34] Nunamaker, J.F., Jr., E.S. Weber and M. Chen, "Organizational Crisis Management Systems," *Journal of Management Information Systems*, 5 (1989), 7-32.
- [35] Rockart, J. F., "Chief Executives Define Their Own Data Needs," *Harvard Business Review*, 57 (1979), 81-93.
- [36] Schank, R., "How Much Intelligence is There in Artificial Intelligence?" *Intelligence*, 4 (1980), 1-14.
- [37] Scribner, S., "Thinking in Action: Some Characteristics of Practical Thought," in R.J. Sternberg and R.K. Wagner (Eds.), *Practical Intelligence: Nature and Origins of Competence in the Everyday World*, Cambridge University Press, Cambridge, UK, 1986.
- [38] Sternberg, R.J., *Beyond IQ: A Triarchic Theory of Human Intelligence*, Cambridge University Press, Cambridge, UK, 1985.
- [39] Sternberg, R.J., *The Triarchic Mind: A New Theory of Human Intelligence*, Viking, New York, NY, 1988.
- [40] Toulmin, S., *Foresight and Understanding: An Inquiry Into the Aims of Science*, Harper, New York, NY, 1961.
- [41] Turoff, M. and S.R. Hiltz, "Computer Support for Group Versus Individual Decisions," *IEEE Transactions on Communications*, 30 (1982), 82-91.
- [42] Vogel, D.R., J.F. Nunamaker, Jr., L.M. Applegate and B.R. Konsynski, "Group Decision Support Systems: Determinants of Success," *DSS-87 Transactions*, 1987, 118-128.
- [43] Weber, E.S., M. Chen and C.E. Weinstein, "Developing Experts: Designers Who Stimulate Human Learning," *DSS-89 Transactions*, 1989a, 184-206.
- [44] Weber, E.S., M. Chen and C.E. Weinstein, "Developing Human and Organizational Intelligence," *Working Paper WPS-88-33*, University of Arizona, Department of Management Information Systems, Tucson, AZ, 1989b.
- [45] Weber, E.S., C.A.P. Smith, and S. Ram, "Crisis Support Systems: Recognizing and Managing Crises," *DSS-87 Transactions*, 1987 43-53.
- [46] Weick, K.E., *The Social Psychology of Organizing* (2d ed.), Addison-Wesley, Reading, MA, 1979.
- [47] Weinstein, C.E., "Assessment and Training of Student Learning Strategies," in R.R. Schmeck (Ed.), *Learning Styles and Learning Strategies*, Plenum, New York, NY, 1988.
- [48] Weinstein, C.E., D.S. Ridley, T. Dahl and E.S. Weber, "Helping Students Develop Strategies for Effective Learning," *Educational Leadership*, 46 (1989), 17-19.
- [49] Weinstein, C.E., A.C. Schulte and D.R. Palmer, *LASSI: Learning and Study Strategies Inventory*, H & H Pub. Co., Clearwater, FL, 1987.
- [50] Zuboff, S., *In the Age of the Smart Machine: The Future of Work and Power*, Basic Books, New York, NY, 1988.