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Review Article

Information Technology in Support of Knowledge Management

A.R. Montazemi[1]

This article provides an overview of information technologies in support of the effective management of organizational knowledge resources. A variety of information technologies are used for knowledge management such as Enterprise Resource Planning (ERP) systems, Decision Support Systems (DSS) and Knowledge-Based Systems (KBS). Application of information technology towards managing explicit knowledge is well-known and has been implemented in many enterprises. However, the management of tacit knowledge through information technology is a challenge that has yet to be met.

INTRODUCTION

Management of intellectual capital has become a central theme in today's business literature and a commonly cited source of competitive advantage [1]. A report, released at the World Economic Forum in Davos, Switzerland, showed that 97 percent of the global CEOs surveyed stated that knowledge management is "absolutely critical to the success of their companies" [2]. For many companies - ranging from Nokia and Sprint to Prudential and Unilever - the wisdom, experience and creativity of the workforce drive a large portion of their value. For example, Chevron claims that it has saved more than $650 million since 1991 by sharing best practice among managers in charge of energy use at its oil refineries. Knowledge management programs also helped Texas Instruments save more than $1 billion by disseminating best practice throughout its thirteen semiconductor plants [1]. To this end, there is a growing interest by organizations to understand what encompasses knowledge management and to identify procedures for managing organizational knowledge effectively.

Knowledge management can be defined as a formal, directed process of figuring out what knowledge individuals within a company have that could benefit others in the company, then devising ways of making it easily available [1]. There are two types of organizational knowledge: Product-specific knowledge (explicit knowledge) and skill-specific knowledge (tacit knowledge) (see [3] for more detail). Product-specific knowledge is well known and can be documented in many forms (e.g., user manuals). However, skill-specific knowledge is acquired by the knowledge-workers through experience. There is one thing, for example, to make available the best current thinking on reorganizing a client's purchasing process and the main benefits that are likely to result. There is another thing entirely to describe clearly when and how to bring up hard issues with managers, how to price a new product and which benefits or arguments are likely to be relevant to a particular case. The former type of knowledge can be defined as explicit knowledge that can be easily communicated; the core concepts and ideas can be written down and then transmitted in discrete segments from one person to another. The latter type of knowledge, grouped under the rubric of tacit knowledge, is transmitted in a very different way - holistically, as a practice - usually through trial and error, apprenticeship and skilled coaching. Management of tacit knowledge thus requires a distinctive approach.

Present applications of information technology in support of knowledge management are mainly in support of explicit organizational knowledge. For example, integrated enterprise resource planning software such as SAP R/3, Oracle, PeopleSoft and Baan, mainly support routine transactions. However, an increasingly valuable organizational knowledge is tacit knowledge

1. *School of Business, McMaster University, Hamilton, Ontario, Canada.*

that can be supported and managed by means of Group Decision Support Systems (GDSSs) and knowledge-based systems. A GDSS is an interactive system that facilitates the solution of semi-structured and unstructured decision problems by a group of decision-makers.

This paper is constructed as follows. First, issues in need of consideration for management of organizational knowledge resources are discussed. There are many ways of categorizing organizational knowledge and the following section provides one form of categorization of organizational knowledge into explicit and tacit knowledge. This enables one to better understand the pros and cons of information technology in support of organizational knowledge management. Then, characteristics and types of information technology, used in support of explicit knowledge, are presented followed by the description of the role of knowledge-based systems in support of tacit knowledge. Finally, concluding remarks are presented.

KNOWLEDGE MANAGEMENT

Organizations support creative individuals and/or provide a context within which they may create knowledge [3]. Organizational knowledge creation, therefore, should be understood as a process that "organizationally" amplifies the knowledge created by individuals and crystallizes it as a part of the knowledge network of the organization. This process takes place within an expanding "community of interaction" which crosses intra- and inter-organizational levels and boundaries. The genesis of ideas and the authentication of knowledge are part of a continuous process that ultimately brings knowledge to bear on decisions - when the organizational environment is working ideally. In real life, the process may fail to bring knowledge to bear, even when the required knowledge is somewhere in the organization. What matters, then, is the knowledge actually used at the decision-making point, not the knowledge in the process of development or authentication, nor even the knowledge clearly apparent to particular individuals in the organization [4]. Knowledge derives from information as information derives from data. If information is to become knowledge, decision-makers must perform the following transformation [5]:

- Comparison: How does information about this situation compare to other known situations?
- Consequences: What implications does the information have for decisions and actions?
- Connections: How does this bit of knowledge relate to others?
- Conversation: What do other people think about this information?

There are four problems associated with relying on individuals as knowledge repositories for organizations: Knowledge embedded in individuals decays [6]; individuals may not be motivated to share their knowledge [7,8]; individuals as knowledge repositories for organizations can leave and take their knowledge with them and it is hard for the knowledge workers to reach a large number of people without some degradation in communication.

The cost of coping with these problems becomes particularly significant for the organizations that produce knowledge intensive products, e.g., medical services, consulting firms, research & development units. In response to these concerns, knowledge management has become a central theme in today's business literature and a common cited source of competitive advantage. The consensus is that effective knowledge management requires a reengineering of organizational processes for an optimal flow of information and knowledge within an organization, with the support of information technology [5,9]. To this end, a variety of information technologies, such as Enterprise Resource Planning (ERP), Decision Support System (DSS) and Artificial Intelligence (AI) technologies have been adopted by organizations to better utilize organizational knowledge resources.

Enterprise resource planning systems, adopted in recent years by large and medium size firms, are defined as strategic business solutions that integrate all the business functions, including manufacturing, finance and distribution [10]. ERP systems encompass traditional transaction processing systems, as well as model-based DSS such as data warehouse, supply chain optimization, planning and scheduling systems. Such integrated systems improve management of information resources and enable decision-makers to better access required information across the organization.

Hansen et al. [11] found that the knowledge management practice at management consulting firms could be categorized in the form of "codification strategy" and "personalization strategy". They reported that large consulting companies, such as Anderson Consulting and Ernst & Young, have pursued a codification strategy. This strategy is similar to library search routines, in that knowledge is codified using a "people-to-document" approach. It is extracted from the person who has developed the original knowledge, made independent of that person and reused for various purposes. By contrast, consulting firms such as Bain, Boston Consulting Group and McKinsey emphasize a personalization strategy [11]. This strategy mainly relies on building networks of people. Knowledge is shared, not only face-to-face but also, over the telephone, by email and via video-conferencing. McKinsey fosters networks in many ways: By transferring people between offices; by supporting a culture in which consultants are expected to return phone calls from colleagues promptly; by creating directories of experts; and by using "consulting directories" within the firm to assist project teams. A similar technology has been adopted by the British Petroleum (BP) exploration division to let knowledgeable people talk to each other and share their knowledge. The hardware and software chosen for the virtual teamwork stations included desktop videoconferencing equipment, multimedia e-mail, application sharing, shared chalkboards, a document scanner, tools to record videoclips, groupware and a Web browser [5].

Successful knowledge management projects require a well-defined plan for the use of technology in support of basic knowledge management principles. For example, Table 1 presents important features of BP's program and the supporting knowledge management principles.

Information technologies in support of "personalization strategy" can be categorized as "GDSS" e.g., email and video-conferencing and those used in support of "codification strategy" are model-based DSS i.e., codification of reports and creation of directories. (See http://www.wincite.com for an example of such a system). The next two sections elaborate on the characteristics of information technology in support of explicit and tacit knowledge.

INFORMATION TECHNOLOGY IN SUPPORT OF EXPLICIT KNOWLEDGE

With the advance of enterprise-wide, client-server computing has become a new challenge: How to control all major business processes with a single software architecture in real time. The integrated solution, known as Enterprise Resource Planning (ERP), promises benefits from increased efficiency to improved quality, productivity and profitability. ERP systems are software applications that provide transaction management to enable timely execution of decision support systems to plan and manage resources across an enterprise (see Figure 1). Materials Requirements Planning (MRP) and MRPII, used in manufacturing industries, can be

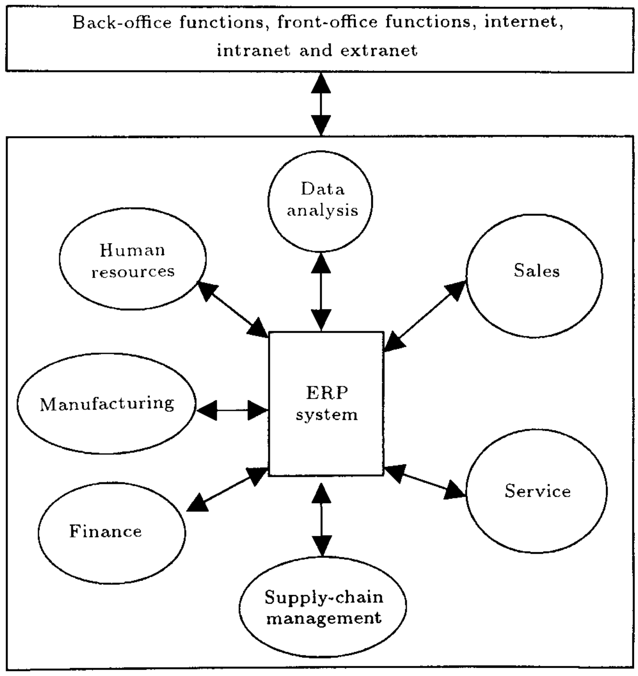

Figure 1. The basic components of an ERP system.

Table 1. British petroleum's experience with virtual teamwork project [5].

BP's Virtual Team Program	Knowledge Management Principles
Members of knowledge communities were identified, then linked by technology.	Knowledge originates and resides in people's minds
Relationships were built through actual and virtual face-to-face meetings.	Knowledge sharing requires trust.
Technology was used for communication and collaboration; training emphasized goals, not hardware and software.	Technology enables new knowledge behaviors.
Training and upper-management support emphasized the importance of new behaviors.	Knowledge sharing must be encouraged and rewarded.
Upper management initiated the project and authorized funds and the core team.	Management support and resources are essential.
Five test groups allowed for variety and clear limited goals.	Knowledge initiatives should begin with a pilot program.
Savings and productivity increases were quantified; expanding virtual teamwork use and participant enthusiasm were qualitative measures.	Quantitative and qualitative measurements are needed to evaluate the initiative.
In addition to having specific goals, the project left room for the unexpected.	Knowledge is creative and should be encouraged to develop in unexpected ways.

identified as the predecessors of ERP systems. ERP systems include applications for financial management, supply chain and distribution and requirements planning for multiple sites. It facilitates well-managed resource planning in the face of rapidly changing constraints such as materials availability, market readiness, plant capacities, personnel certification and business costs per location. Software vendors such as SAP AG, Baan, PeopleSoft and Oracle provide a host of integrated ERP products.

Successful implementation of the ERP system enables organizations to automate transaction systems and provide access to data across organizational boundaries. Although an ERP system primarily supports procedural knowledge, its implementation in an enterprise results in operational efficiency and improved productivity. Furthermore, database and procedural knowledge captured in the ERP system can be used by Decision Support Systems (DSSs).

Traditional definitions of decision support systems suggest that the purpose of a DSS is to aid decision-makers in addressing unstructured or semi-structured decisions. Figure 2 depicts a variety of possible DSS structures [12]. Nonetheless, DSSs can be grouped under three categories: model-based, knowledge-based and hybrid DSS i.e., a combination of model-based and knowledge-based techniques.

The model-based structure of DSS makes use of qualitative models i.e., Operations Research and Management Science Techniques, to assist the decision-maker in improving the effectiveness of his/her decision processes. For example, mathematical programming enables a decision maker to assess an optimal solution for his/her decision problem under a variety of assumptions and statistical techniques, such as cluster analysis, providing support for data-mining. Model-based DSS represents an explicit knowledge of the decision-maker regarding the structure of the decision problem. However, tacit knowledge is supported within the confines of knowledge-based DSS i.e., Knowledge Based System (KBS), that is explained next.

INFORMATION TECHNOLOGY IN SUPPORT OF TACIT KNOWLEDGE

Artificial Intelligence (AI) endeavors to make machines such as computers capable of displaying intelligent behavior [13]. There are a variety of AI techniques that can be employed towards the development of KBS [14]. Expert systems and case-based reasoning systems have been used increasingly to capture and manage tacit knowledge in business. In addition, application of intelligent agent technology is increasingly being applied towards improved functionality of human-computer interaction and dissemination of information throughout the organization. These three types of technique in support of knowledge management are discussed in the following sections.

Expert Systems

The area of Expert Systems (ESs) investigates methods and techniques for constructing man-machine systems with specialized problem-solving expertise [15]. Expert system methodology is based on the notion that expertise consists of knowledge about a particular domain, understanding of domain problems and skill at solving some of these problems. Expert system development methodologies assume that tacit knowledge can be elicited from experts in the form of a set of well-defined decision rules, e.g., in the form of IF, THEN rules, that can be saved in the knowledge base of the ES.

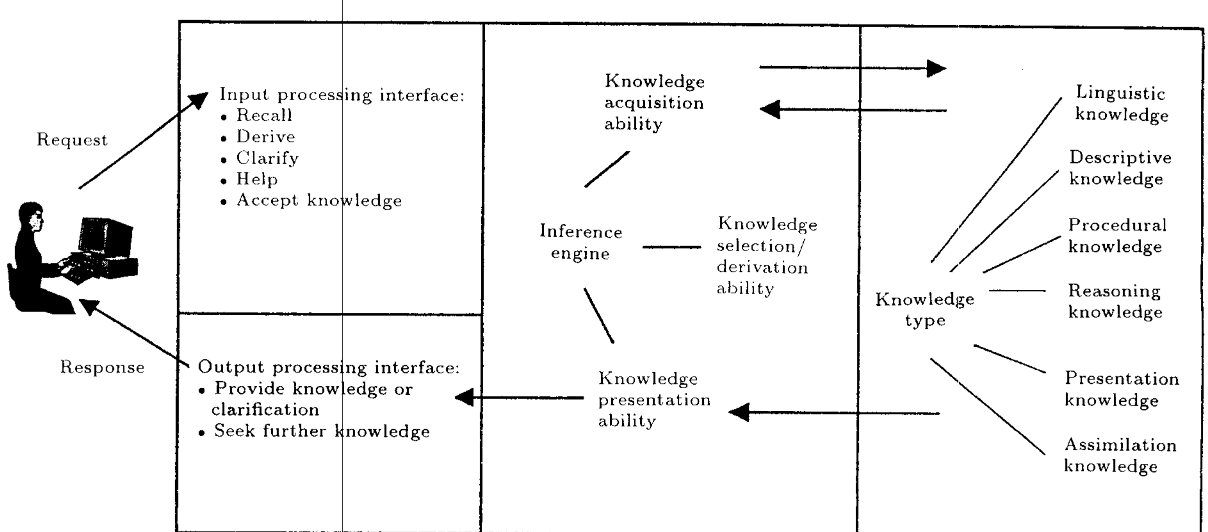

Figure 2. Generic framework of decision support systems [12].

In addition, it is assumed that these decision rules are fairly stable, i.e., they don't change significantly over time. A major challenge in the development of ES is the knowledge acquisition process i.e., figuring out the heuristics or "rules of thumb" used by the expert (see [16] for further details).

A large number of ESs have been developed to provide decision support in business. For example, American Express uses an ES called "Authorizer's Assistant" in support of credit record evaluation to protect against credit-card fraud. Westinghouse and Carnegie Mellon University have developed an ES called ISIS that schedules most-efficient use of Westinghouse's many job shops. Ford Motor Company uses an ES called "Direct Labor Management System" to improve efficiency in all phases of the production process [17].

In spite of its usefulness in support of tacit knowledge management, ESs have failed to tackle problems requiring creativity, commonsense or aesthetic judgement [18,19]. This failure can be attributed to their brittleness. The brittleness of ESs refers to their inability to provide a solution when the decision problem does not conform to the rules in their knowledge-base. This deficiency is due to the limited ability of ESs to acquire new knowledge and their inability to reason with incomplete knowledge [20]. Furthermore, the knowledge of ESs is not readily available in a usable form, therefore, it cannot provide adequate support in a dynamic decision environment. The emphasis of ES has been toward the automation of the decision making activity where a decision-maker plays a passive role. This, in turn, has led to its rejection where human judgement plays a crucial role.

The deficiencies of rule-base systems have motivated the development of alternative methodologies for decision support. The result of such endeavor is the paradigm of Case-Based Reasoning [19,21,22].

Case-Based Reasoning Systems

A Case-Based Reasoning (CBR) system supports reasoning from experience to solve decision problems, critique solutions and explain anomalous situations. The CBR paradigm is based on the premise that expertise comprises experience and, in solving new decision problems, decision-makers rely on their experience gained in similar situations. For example, while designing a complex object such as an automobile or an integrated circuit, it is a common practice among designers to refer to similar previous designs. A design developed in the past for a specification is used as a base design and modified to incorporate the differences in the new and previous specifications. Changes are made to eliminate flaws in the previous design. The design thus generated is tested before it can be developed into a working prototype. Designing from the first principle poses considerable difficulty because of a large number of interrelated factors. A CBR system can be used as a DSS to access the past designs to support the current design process [23].

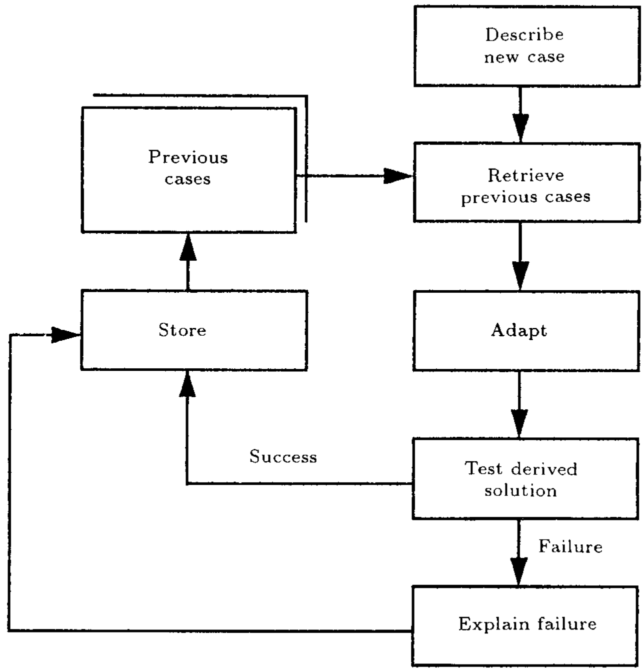

Figure 3. Processes in a CBR system.

To assist a decision-maker, the process followed by a CBR system is as follows (Figure 3): A previous case/cases similar to the new decision problem (new case) is/are retrieved. The solution of the previous case is mapped as a solution for the new case and the mapped solution is adapted to account for the differences between the new and previous cases. The adapted solution is then evaluated, for example, against hypothetical situations [22,24]. To aid in future decision making, feedback of the success or failure of the evaluated solution is obtained from the decision-maker [25]. Thus CBR makes it possible to capture and reuse tacit knowledge in the form of case management.

CBR systems have been adopted successfully in support of complex decision problems within a variety of decision environments [26]. For example, a CBR system called CASELine is used by British Airway to assist Boeing 747-400 technical support engineers with aircraft fault diagnosis and repair between aircraft arrival and departure. It advises on past defects and known successful recovery and repair procedures. Deloitte & Touche implemented a CBR system called "Top Management Fraud Diagnostic Tool" that helps auditors assess the likelihood of top management fraud occurring within a company.

Present application of CBR systems are generally in support of a specific task domain, with little ability to adjust their retrieval processes to reflect the needs of other related decision domains. For example, a diagnostic CBR system for repair of AC-Motors is unable to assist a designer with the design of a new AC-Motor [24]. Obviously, inability to share embedded knowledge among different types of knowledge workers reduces the value of such systems in the context of organizational knowledge management [27-29]. To ameliorate this problem, one can use an adaptive CBR architecture that makes use of intelligent agent information systems in support of accessing required information by different types of decision-makers.

Intelligent Agents

Interaction with a computerized system is a dialog between the user and the system to accomplish the user's task. The complexity of the dialog depends on the task-domain and the mode of interaction [30]. An intelligent agent can reduce the complexity of the dialog by understanding the goals of the user and assisting him/her to interact with the information system [31,32]. Intelligent agents have been used in information retrieval systems to help the users to retrieve relevant documents [31]. The need for an intelligent agent for information retrieval systems arises from the fact that the users may not know their information needs. In addition, the users are unable to use the system effectively because of unfamiliarity with the way the system and/or its content functions [33]. For example, the diversity of different processes throughout an enterprise that are supported by an integrated ERP information system, such as SAP R/3 makes it difficult for knowledge workers to access the desired information that relates to processes other than his/her own business process. Without an effective decision support, the knowledge worker has to search through very large databases that can result in information overload. Intelligent agents assist the decision-makers in their information search and retrieval. Nonetheless, most computers currently respond only to what interface designers call "direct manipulation" [34]. Nothing happens unless the end-user gives a command from a keyboard, mouse or touch screen. The computer is merely a passive entity waiting to execute specific highly detailed instructions. It provides little help for complex tasks or for carrying out information searches that may take an indefinite time. This raises the question of how computers can identify information requirements of individual decision-makers and provide assistance in support of knowledge-based tasks.

Techniques from the field of artificial intelligence, in particular so-called "intelligent agents" can be used to implement a complementary style of interaction, which has been referred to as "indirect management" [35]. Instead of user-initiated interaction via command and/or direct manipulation, the end-user is engaged in a cooperative process in which human and computer agents initiate communication, monitor events and perform tasks (Figure 4). Automation can occur either through semi-autonomous processes set in motion by the end-user or by the bypassing of stages of execution or evaluation that the end-user must otherwise perform [24,31]. An agent that searches several databases for a favorable price is an example of a semi-autonomous process. This form of closed-loop automation is found in process industries where operators establish a variety of set points for valves, breakers and proportional controllers. For automation of this sort to succeed, the user needs a relatively detailed mental model of the domain and what the automation is to do to program it (transparency) and, subsequently, the user would benefit from good display and methods for monitoring its performance (feedback) [25,31,33].

The computerized intelligent agent helps the user to define queries requiring the retrieval of relevant documents that satisfy his/her information needs [25]. The effectiveness and efficiency of dialog between the user and the system are improved, since a query can be accurately defined with fewer statements. Another advantage of the intelligent agent is the reduction in cognitive effort of the user, a result of the change in the nature of the cognitive task from recall to recognition [36]. This change can further improve the effectiveness of the information system in the form of decision support [25,33].

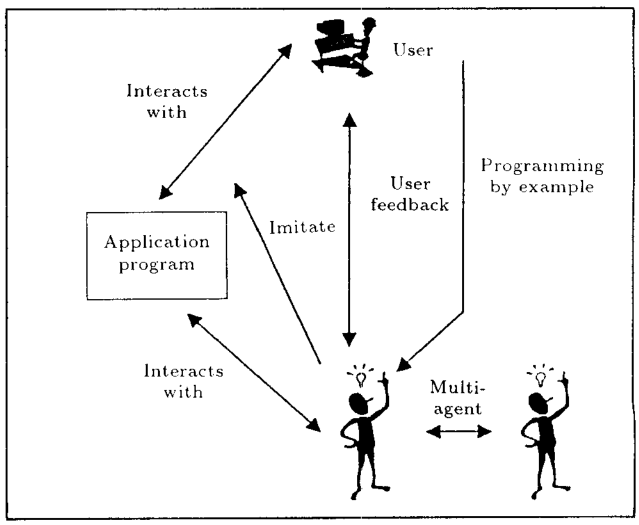

Figure 4. Basic interaction of agents with their decision environment. The interface agent learns in four different ways: (1) It observes and imitates the user's behavior, (2) It adapts based on user feedback, (3) It can be trained by the user on the basis of examples and (4) It can ask for advice from other agents assisting other users [38].

Agents perform tasks on behalf of the user to enhance the human computer dialog. An agent is considered adaptive when it uses knowledge and conditions in the environment to determine its actions. Two types of knowledge are needed to determine the actions: Domain knowledge and user knowledge. Domain knowledge is needed to perform actions in a particular domain and user knowledge is needed to adapt the actions to differences among individual users. For example, in the context of CBR in support of ERP, the task of an adaptive agent to retrieve applicable cases would be to assist decision makers describe new cases by recommending relevant descriptors. The task of an adaptive agent, to present the retrieved cases to the decision-maker, would be to select the pertinent part of the previous cases and use that as a base for recommending a solution in support of solving the new problem/case. Application of the adaptive interface agents to define a decision problem and recommend solutions has been proven to be useful for a single-type of decision-maker e.g., decision-makers required to diagnose and repair AC Motors (see [24]). The challenge is to extend access and use of CBR systems by decision-makers with diverse needs and backgrounds. This challenge can be handled by means of multiagent systems (MASs).

Research in MASs is concerned with the study, behavior and construction of a collection of autonomous agents that interact with each other and their environments. MAS can be defined as a loosely coupled network of problem solvers that interact to solve problems that are beyond the individual capabilities or knowledge of each problem solver. These problem solvers, often called agents, are autonomous and can be heterogeneous in nature [37]. The characteristics of MASs are: Each agent has incomplete information or capabilities for solving the problem and, thus, has a limited viewpoint; data are decentralized, and computation is asynchronous. Multiagent systems offer modularity. If a problem domain is particularly complex, large, or unpredictable, then the only way it can reasonably be addressed is to develop a number of functionally specific and nearly modular components (agents) that are specialized at solving a particular problem aspect [37]. This decomposition allows each agent to use the most appropriate paradigm for solving its particular problem. When interdependent problems arise, the agents in the system must coordinate with one another to ensure that interdependencies are properly managed. This methodology can be adopted in accessing embedded knowledge from different domain-specific case-bases.

Now, the above concepts are briefly applied to a business process, such as a market driven target costing system for a manufacturer of computers contemplating the introduction of a new computer system. Market requirements for the project are first identified via market research, the conduct of which the marketing executive directs using his/her past experience/knowledge. This allows the manufacturer to establish a target price for the product. Product target cost is then determined by subtracting target profit from the target price. The calculation of target profit is a function of cost of capital, which, although can be computed based on concepts in the field of finance, is, normally, determined using the past experience and judgment of the chief financial officer. At this time, the manufacturer embarks on determining target costs and cost drivers for various parts/activities. Alternative designs/processes are investigated to minimize costs while preserving quality. If the project is found to be feasible upon the management's review, the manufacturer proceeds with detailed design and production plans and sets a final price for the product. The project is tracked to continually improve the product quality and reduce costs. This process is depicted in Figure 5.

The above process requires sharing knowledge about customer requirement, profit requirement for the risk involved and the feasibility of the project as to cost. Such knowledge is mostly skill specific. For example, the chief financial officer uses his/her knowledge to establish a target profit that generates adequate return for the risk the company faces by embarking on the project. The design and production engineers use their knowledge and

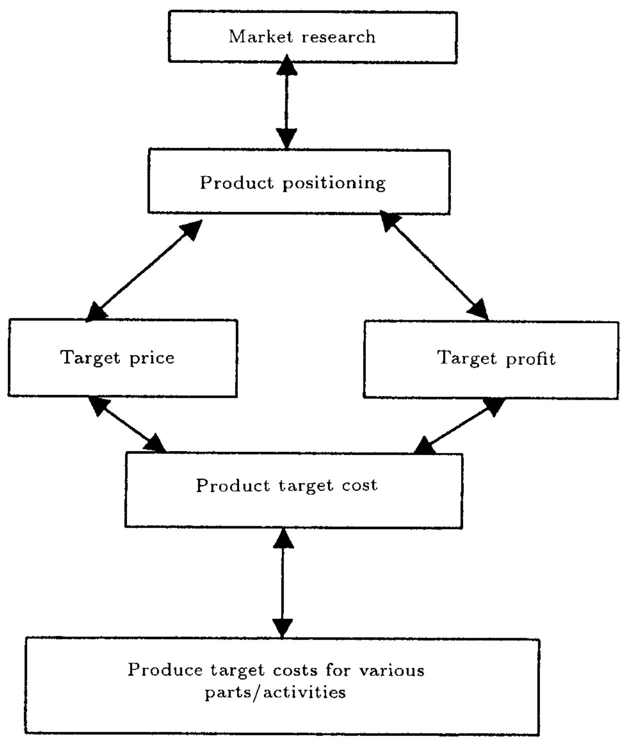

Figure 5. Market driven target costing.

experience to design and manufacture the product in a manner consistent with the mission and objectives of the company. This process becomes efficient when the knowledge workers involved can benefit from each other's knowledge in regard to different parts of the puzzle i.e., market driven target costing. A research challenge is to develop knowledge-based systems to store knowledge and to enable the knowledge workers to receive the knowledge pertinent to their decision problem through intelligent agents.

CONCLUDING REMARKS

A major reason for the recent surge to better manage organizational knowledge is the fact that the foundation of industrialized economies has shifted from natural resources to intellectual assets [39]. Therefore, executives have been compelled to examine the knowledge underlying their business and how that knowledge is used. In addition, improved cost and performance of hardware and software technologies make it increasingly feasible to capture and share organizational knowledge. Procedural knowledge can be captured and shared throughout the organization by means of ERP systems. However, the challenge faced is to identify procedures for codifying and sharing the tacit knowledge by means of model-based DSSs and KBSs. A major problem in the use of model-based DSS is the lack of compatibility among different types of DSS in support of different phases of decision-making processes. As a result, a new non-profit organization called Analytical Solution Forum (ASF), based in Cambridge, Massachusetts, has recently been formed to bring together technology business leaders for educating end-users about decision support technology. In addition, ASF intends to standardize performance criteria and interoperability requirements among analytical software applications in a way that benefits the end-user.

Although model-based i.e., analytical, DSSs are in support of ill-structured decision problems, their embedded model-base can be categorized as procedural knowledge. The objective of KBS is to codify and enable sharing of tacit knowledge. To this end, artificial intelligence technology has been applied in the design and development of KBS in a variety of domains. Nonetheless, application of AI in support of tacit knowledge is at an early stage of its life cycle. The present limitations of machine intelligence stem largely from seeking unified theories incapable of reasoning well, while the purely symbolic logical systems lack the uncertain, approximate linkages that can help one make new hypotheses [14]. Some of the challenges faced by the organizations to use KBS in support of organizational knowledge management are as follows.

- There is no universal model for knowledge creation and dissemination within the enterprise. Therefore, identification of the organizational knowledge for reuse among the knowledge workers is best achieved through business process reengineering activity, supported by the senior management;
- Knowledge management is based on the assumption that organizational members share expertise to improve their decisional effectiveness collectively. Reuse and dissemination of knowledge requires creation of an organizational environment that is conducive to knowledge sharing among knowledge workers. However, knowledge management as a conscious practice is so young that executives lack successful models to guide them. Thus, each organization has to develop a unique strategy of its own to share and reuse organizational knowledge;
- KBSs make use of advanced and complex AI technology to capture and disseminate tacit knowledge. Therefore, those organizations that have reached the mature stage of the information system life cycle are best positioned to implement complex systems such as KBS [33];
- Design and development of KBSs is complex and requires expertise in knowledge engineering to acquire pertinent knowledge from knowledge workers. It also requires knowledgeable experts in the use of AI technology to code the acquired knowledge into the knowledge-base. In addition, development of an intelligent interface requires significant insight into the area of human-computer dialog to satisfy the users' needs for the most relevant information from the knowledge-base [14]. Market availability of specialists in human-computer interaction methodology and design, as well as knowledge engineers and AI experts, is a limiting factor for implementation of KBS;
- Finally, state of the art on management of tacit knowledge is at early stages in its life cycle. Thus, significantly more research is needed in all aspects of knowledge management such as: Procedures for identification of required knowledge within the organization, development of more robust knowledge acquisition tools and techniques and powerful methodologies for coding tacit knowledge and disseminating it on demand.

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