Jour**A**nal of the **A**ssociation for **I**nformation **S**ystems

Research Article

An Evolutionary Information-Processing Theory of Knowledge Creation [1]

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Abstract

Past Information Systems (IS) research on knowledge creation has not adequately accounted for the evolutionary nature of knowledge. Research limitations also exist in depicting the roles of information in the knowledge creation process. These two problems present difficulties for practitioners when attempting to successfully implement Information Technology (IT) to facilitate knowledge creation. Based on a problem-solving paradigm, this research analyzes knowledge creation from both the evolutionary and information-processing perspectives. The resultant theory outlines a process whereby tentative knowledge is generated from varied existing knowledge and applied to a problem, producing information to test the extent to which the problem can be solved. An iterative process continues until the tentative knowledge with the highest potential to solve the problem is found, yielding the information to best meet the goal. This process is further embedded in an organization-wide problem-solving hierarchy where new knowledge is developed via the integration of knowledge elements of sub-problems. By incorporating the evolutionary nature of knowledge, this research provides a deeper understanding of the knowledge creation process and the key determinants of its success. More importantly, by clearly specifying the roles of information in the process, it offers promise in the better design of IT to improve knowledge creation performance. We develop a framework based on this Evolutionary Information-Processing Theory to aid practitioners in IS design.

Key words: knowledge creation, information processing, problem solving, evolutionary epistemology, and organizational memory

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[1] Robert Zmud was the accepting senior editor. This paper was submitted on March 5, 2004, and went through 4 revisions.

Introduction

In the knowledge-based economy, companies have invested heavily in Information Technology (IT) to facilitate knowledge creation. Unfortunately, in many cases IT fails to deliver the anticipated results (Gill, 1995; Robey et al., 2000). Given this failure it is important that we understand why and how IT influences the knowledge creation process (Alavi and Leidner, 2001). To assist in this endeavor, scholars have applied numerous theories to analyze the impact of IT on knowledge creation (e.g., Alavi and Leidner, 2001; Gray, 2001; Malhotra et al., 2005; Marakas and Elam, 1997), but few provide completely satisfying explanations. A major reason is that most of these theories are dominated by a viewpoint that does not fully consider the evolutionary nature of knowledge (see Coombs and Hull, 1998; Galende and de la Fuente, 2003; Huysman, 2000). As a result, the forces that both facilitate and inhibit knowledge creation are not properly controlled in many IT applications (Robey and Boudreau, 1999).

The role of information in the knowledge creation process is not adequately specified in most knowledge management studies. Specifically, knowledge management researchers tend to treat information as input to the process (Nonaka, 1994). This view causes difficulties in depicting the causal relationship between information and knowledge and perpetuates a situation where the terms information and knowledge are used interchangeably by many information systems practitioners. To avoid this problem and to achieve better design of IT to manage information in knowledge creation, it is necessary to correctly specify the roles of information in the knowledge creation process.

The above two problems, namely the inability to account for the evolutionary nature of knowledge and the poorly specified relationship between information and knowledge, are major obstacles to a better understanding of IT-aided knowledge creation. Based on a review of the literature, we develop a new theory to address these problems. Contrary to a deterministic view (i.e., knowledge creation as the refinement of previous experiences) and the treatment of information as input to the process, we argue that organizational knowledge creation is an evolutionary information process. In this process, tentative knowledge is generated and tested based on information produced, and the process continues until the knowledge with the highest potential to solve the problem is found. We name this theory an evolutionary information-processing theory of knowledge creation, and show how this theory provides a deeper understanding of knowledge creation.

The structure of this article is as follows. First, we summarize research from the dominant schools in knowledge creation. This analysis points to the need for a new theory incorporating components of both the information-processing and evolutionary perspectives. We further analyze these two perspectives, leading to the theoretical stance that organizational knowledge creation is an evolutionary information process. We then offer the evolutionary information-processing theory of knowledge creation, and discuss implications of the theory for IS research and practice.

Literature Review

The literature contains varying definitions of knowledge, so its meaning relative to knowledge creation needs to be clarified. Philosophers, including Plato, have defined

knowledge as "justified true belief;" while business researchers usually apply more practical definitions such as "a fluid mix of framed experiences, values, contextual information, and expert insight that provides a framework for evaluating and incorporating new experiences and information" (Davenport and Prusak, 1998, p5).

There is no doubt that knowledge is the key to business success; and knowledge creation, referring to the organizational processes that develop new knowledge or replace existing knowledge within an organization's knowledge repository (Alavi and Leidner, 2001), has become the focus of business practice. As knowledge materializes as product designs, business processes, working skills, and other capabilities, knowledge creation includes new product development, business process design, skill development, and other innovative activities.

Knowledge creation occurs at multiple levels, ranging from the individual to the organizational level; the focus of this research is on the latter. To distinguish organizational knowledge creation from individual knowledge creation, we draw upon the knowledge-based theory of the firm that depicts organizations as repositories of human knowledge (Conner and Prahalad, 1996; Nickerson and Zenger, 2004). Specifically, this perspective places organizational goals as the ultimate criteria and an important conditions of individual knowledge creation (Gallivan et al., 2003), and defines organizational knowledge creation as the collection of "organizationally managed" (Nonaka, 1994) individual activities coordinated by and conducted toward the organizational goals of knowledge enrichment. This requires that new knowledge can be transferred to other organizational members or deposited in an organizational knowledge repository (Cross and Baird, 2000). Furthermore, in order to better understand the interrelated knowledge creation activities (Amabile, 1983; Shneiderman, 2002) and the process gains or losses after IT applications (Pinsonneault et al., 1999), we take a process-based approach in this research.

Knowledge creation has been analyzed for decades in many research schools, including innovation (Rogers, 1995), organizational learning (Pentland, 1995), and problem-solving (Gray, 2001). Often scholars within these schools refer to knowledge creating processes as being subsumed in their area of inquiry (Cohen and Levinthal, 1990). In each school, a particular form of knowledge is created and becomes part of the organizational knowledge repository. Clarifying this point leads us to briefly review and compare research from these different schools to form a better understanding of knowledge creation.

Of the research schools, the innovation school has perhaps the longest history, with many theories developed (Gopalakrishnan and Damanpour, 1997). Among them, the most noteworthy is Rogers' (1995) innovation diffusion theory, depicting knowledge creation in six phases: problems and needs, research, development, commercialization, diffusion and adoption, and consequences. From a managerial perspective, this theory illustrates the management activities needed to coordinate organizational resources in knowledge creation and diffusion. Nevertheless, the theory emphasizes the diffusion of new knowledge after its creation, which limits its value in completely and accurately describing knowledge creation prior to the diffusion. The same limitation exists in other innovation theories (see Gopalakrishnan and Damanpour, 1997).
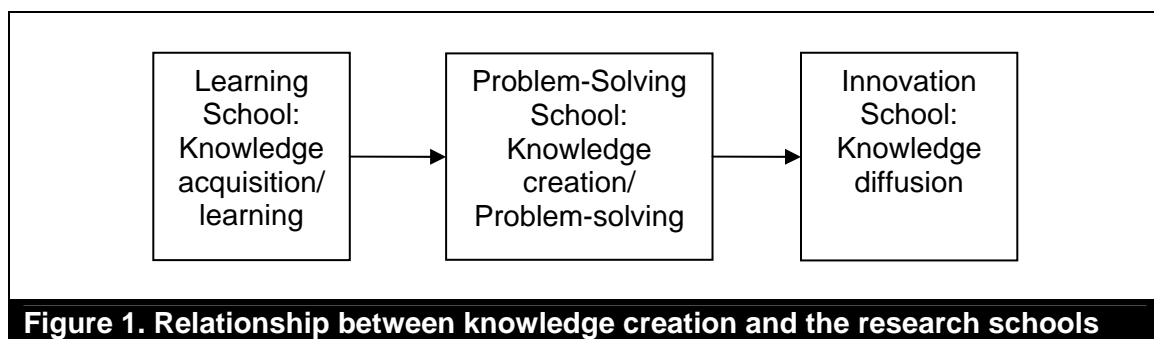
The learning school is another popular stream, as learning is a primary approach to knowledge acquisition (Crossan et al., 1999; Huber, 1991; Pentland, 1995). A milestone

in this line of research is Huber's (1991) framework of four organizational learning processes, including knowledge acquisition, information distribution, information interpretation, and organizational memory. In 1994, Nonaka introduced the very popular model of the conversion process between tacit and explicit knowledge. While there are a few exceptions, in general, this school emphasizes acquiring and converting existing knowledge from known sources rather than the process of a learner creating new knowledge.

The problem-solving school depicts knowledge creation as a problem-solving process where knowledge refers to the solution to a problem. For instance, Simon (1960) proposes a heuristic problem-solving theory that contains intelligence, design, and choice phases. Highsmith (1978) depicts a multi-phase design model, including problem analysis, idea generation, and solution test. Later, MacKay et al. (1992) develop a three-stage model, including problem presentation, problem representation, and problem solution. Theories from this school have been used to analyze the organizational structures and governance that facilitate knowledge creation. An example is Simon's theory, which is the basis of adaptive organization research (Anderson, 1999).

Information has long been recognized as an important factor in knowledge creation. Early on, Simon and colleagues (Simon, 1960; Newell et al., 1958) studied information in problem-solving, depicting new knowledge as the combination of multiple Elementary Information Processes (EIPs), where each EIP solves a sub-problem in a problem hierarchy. Later studies also analyzed information processing in knowledge creation (Alavi and Leidner, 2001; Huber, 1991), with most positioning information as the input or raw material of new knowledge (Nonaka, 1994) and emphasizing the antecedent roles of information sharing and exchange in knowledge creation (Malhotra et al., 2005).

Figure 1 positions the primary contribution of the schools of thought discussed above. As depicted, the learning school focuses primarily on the acquisition or conversion of existing knowledge. Although certain activities such as experimental learning (Huber, 1991) are related to knowledge creation in this school, the issue of how new knowledge is developed from the learning process is not extensively addressed. Innovation theories emphasize the diffusion of new knowledge, where the commercialization and diffusion activities (Rogers, 1995) are treated as knowledge application and transfer issues (Alavi and Leidner, 2001). As can be seen in Figure 1, of the various schools discussed, the problem-solving school is the most focused on investigating knowledge creation, and therefore, we selected it as the basis for further development.

Learning School: Knowledge acquisition/ learning	→	Problem-Solving School: Knowledge creation/ Problem-solving	→	Innovation School: Knowledge diffusion

Figure 1. Relationship between knowledge creation and the research schools

The problem-solving school offers a framework consisting of three generic phases of knowledge creation: *problem recognition*, *idea generation*, and *solution selection*

(Highsmith, 1978; MacKay et al., 1992; Simon, 1960). Knowledge creation starts from the recognition of a new or unique problem (Gray, 2001), and the complexity of the problem determines the organization and governance of activities to solve the problem (Nickerson and Zenger, 2004). Idea generation is the proposition of alternative solutions to the problem. Finally, solution selection is the judgment and selection of the alternative that best solves the problem. Each phase contains multiple activities through which new knowledge is created (MacKay et al., 1992). This activity-based goal-driven framework has been applied to various types of organizational knowledge creation, including new product development (Atuahene-Gima, 2003), process improvement (Harkness et al., 1996), and systems development (Cerveny et al., 1990). It has also been used to illustrate how companies identify problems and design governance mechanisms to organize individuals to solve organizational problems (Nickerson and Zenger, 2004).

While progress has been made toward the goal of understanding knowledge creation within the problem-solving school, limitations exist. One limitation lies in the deterministic view adopted by most studies, assuming that knowledge progresses through the accumulation of experiences and refinement of previous success. Empirical studies have found opposing results. For instance, Coombs and Hull (1998) uncover a path-dependency in innovation and illustrate the restrictions of organizational routines on the generations of alternatives. To address this limitation, Galende and de la Fuente (2003) found evolutionary theory helpful in interpreting empirical evidence of a firm's innovative behavior. Additionally, evolutionary theorists, such as Campbell (1974), question Simon's (1960) heuristic theory for local optimization, arguing that optimal solutions may be eliminated by earlier selections or heuristics.

Another limitation, often overlooked in previous research, is the misspecification of the roles of information in knowledge creation. The popular view holds that "information is a necessary medium or material for initiating and formalizing knowledge (Nonaka, 1994, p.16)." However, this view is not universally held. Drucker (1988), for instance, postulates a reversed view that knowledge is the basis of information, and converting data into information requires knowledge. Some IS scholars also share this reversed view (e.g., Langefors, 1973; van der Spek and Spijkervet, 1997; Becerra-Fernandez et al., 2004).

Thus, we are confronted with two challenges: one is to resolve the conflict between the deterministic view and the evolutionary nature of knowledge creation, the other is to specify the roles of information in the process. Some earlier efforts have been made to address the first issue, represented by the studies on exploration and exploitation in knowledge creation (March, 1991). Exploitation focuses on old certainties and includes refinement, choice, production, efficiency, and selection, while exploration focuses on new possibilities and includes search, variation, risk taking, and experimentation (March, 1991). Their relationship resembles that between the deterministic view (i.e., refinement based on previous success) and the evolutionary view (i.e., variation and risk-taking). Studies have shown that balancing exploration and exploitation is fundamental to business success (Subramani, 2004).

In an effort to achieve a balanced approach, we selected a prominent exploitative and a prominent explorative theory as theoretical starting points. As an exploitative theory, Simon's theory (1960) is particularly appealing as it has a complete depiction of the problem-solving process, it is based upon an information-processing view, and it forms the basis of other important organization theories (e.g., Anderson, 1999; Nickerson and

Zenger, 2004). For an evolutionary theory, we found Campbell's (1974) evolutionary epistemology to be the strongest source. This theory provides a scientific explanation of evolutionary knowledge creation and has been used to explain the behavior of adaptive organizations (e.g., Anderson, 1999). In the next section, we examine both theories to uncover opportunities for a better and more balanced theory of knowledge creation.

Theoretical Basis

The information-processing view of knowledge creation

The information-processing view of knowledge creation, presented in Simon and colleagues' theory of heuristic problem solving (Newell et al., 1958; Simon, 1960), suggests that human problem solving is a process conducted through a series of elementary information processes (EIPs). Each EIP is a perfectly definite operation, like a computer routine, that performs the task of converting input into useful output, and new knowledge created for a problem consists of the combination of certain EIPs. There exists an initial group of EIPs in human, computer, and organizational memory that can be used to build new knowledge. Meanwhile, the solution of a problem is put back into the memory to strengthen the initial group.

A complete knowledge creation process is as follows: When a new problem is identified, a goal is established, and the difference between the goal and the present situation is detected. To solve the problem, existing EIPs (and their combinations) are retrieved from organizational memory and applied to reduce the difference, and those with the highest potential to solve the problem are selected. Not every problem, however, can be solved directly, so a single problem is decomposed into a hierarchy of solvable sub-problems that are worked on successively until the whole problem is solved or discarded. Such a hierarchy is the typical structure of knowledge-creating companies that organize work in a pyramid of sub-tasks based on the division of cognitive labor (Marengo et al., 2000). Due to the complexity and decomposability of the problem, a company may choose either an authority-based hierarchy or a consensus-based hierarchy to manage individuals' activities (Nickerson and Zegner, 2004).

Another hallmark of Simon's theory is the dependence on heuristics in the search of solutions. According to this theory, the search for a solution is inspired by the information or heuristics derived from earlier searches, from which a simplified representation of the solution landscape is constructed (Nickerson and Zenger, 2004), and the final solution is achieved based on the refinement of earlier heuristics. Such an approach reduces the cognitive effort needed and speeds up the problem-solving process.

What is not explicitly articulated in Simon's theory is the relationship between information, EIP, and knowledge. In Simon's theory, information refers to symbols manipulated by humans or computers, and information processes are the symbol manipulating processes (Simon, 1960, p.26). We interpret this as Simon's efforts to symbolize and computerize the problem-solving process. Nevertheless, as the solution to a problem is the unique combination or synthesis of existing knowledge, we argue, without losing the faithfulness in the original theory, that the EIPs represent existing knowledge elements used for the construction of new knowledge. Furthermore, information fulfills its fundamental role of selection and decision (Langefors, 1973), as in

each sub-problem there exist several EIPs to be selected. Information is produced from the trials of EIPs and measured based on the output (such as the performance of a product design), and is then used as the basis of selection. The flow of information across the problem hierarchy therefore triggers the selection and combination of a series of existing knowledge elements that together form the new knowledge for the problem. Clarifying this point helps to further analyze the knowledge creation process.

The evolutionary view of knowledge creation

The evolutionary view of knowledge creation suggests that the creation of knowledge does not follow a linear pattern due to a chaotic external environment, and sometimes reversion happens. A representative of this view is Campbell's (1974) evolutionary epistemology. Based on research on adaptive behavior, Campbell proposes a *blind-variation-and-selective-retention* process, suggesting that knowledge is created in three major steps: (1) blind variations or mutations of behavior adaptive to environmental change, (2) selective survival of certain variations that best cope with the environmental change, and (3) the retention and duplication of surviving variations. This process resides not only at the rudimentary level but also at higher levels of knowledge creation, constituting a nested hierarchy of selective retention processes (Campbell, 1974, p.419). This process is fundamental to all types of knowledge creation, and many processes that shortcut it, such as earlier experiences, are in themselves achievements made through variation and selection.

Although mechanisms are needed to induce variation and make selection, they are by no means deterministic. Instead, uncertainty exists because: (1) variations emitted are independent of the environmental conditions of their occurrence, (2) occurrence of an individual variation is uncorrelated with the solution, and the correct variation is no more likely to occur than others at any point in a series of variations, and (3) a variance subsequent to an incorrect trial is not necessarily a correction of the previous one (Campbell, 1974, p.422). In other words, it is not guaranteed that knowledge, as the deterministic theorists assume, is refined through the accumulation of experiences; instead, new knowledge can only be postulated first and then verified/selected. Such a perspective is not nihilistic but has a strong philosophical basis, including Popper's (1992) philosophy of scientific theories. Popper (1999) argues that knowledge is not created from the accumulation of experiences but through conjectures and refutations. *A priori* knowledge always exists before any observations or experiences, even though the latter could foster the modification (*posterior* knowledge) of the former, which may not always result in an improvement.

Uncertainty exists in selection as well, as new knowledge may not be generated in a single round of variation-and-selection, but in many rounds. Since only a certain portion of early variations are selected and become the basis of further knowledge creation, the potential range of variation in successive rounds may be restricted, showing the path-dependency (Coombs and Hull, 1998). The selectivity, or heuristics, "insofar as it is appropriate, represents already achieved wisdom of a more general sort, and as such, selectivity does not in any sense explain an innovative solution (Campbell, 1974, p. 430)." Campbell's theory therefore illustrates the general rules in adaptive systems, and it has been successfully applied to interpret the behavior of adaptive organizations where vicarious selective systems are developed and experimented with (Anderson, 1999).

Toward an integration

The information-processing view and the evolutionary view depict two distinct perspectives on knowledge creation, both with strengths and limitations. Central to the information-processing view are problem decomposition and the exploitation of a myriad of pre-existing pieces of knowledge for a solution, which significantly reduces the effort and improves efficiency. However, in the long run this approach is less effective (Verspagen, 1998) and may lead to sub-optimization, as "the number of variations explored is greatly reduced by having selective criteria imposed at every step" (Campbell, 1960, p393). Feedback from successive stages may require the re-generation and re-selection of previous knowledge. On the other hand, depending on evolution or exploration alone could result in low efficiency and high cost.

It is not necessary to say which view is superior; instead, both are complementary and should be integrated to provide a better view of knowledge creation.

The Information-processing view and the evolutionary view share several things in common: 1) both treat organizational knowledge creation as the process of creating knowledge to solve organizational problems; 2) both depict the process in a hierarchical manner and suggest that new knowledge is built upon existing knowledge; and 3) both share some generic steps in knowledge creation, such as problem identification, idea generation, and solution selection.

While commonalties exist, significant differences reside in how each view treats information and experience, and the formalizations of the problem hierarchy. The information-processing view treats information as necessary building blocks of new knowledge, suggesting that new knowledge is created from the acquisition and accumulation of information (Malhotra et al., 2005; Nonaka, 1994). Information produced from earlier searches becomes the heuristic for further refinement of the solution, as shown in Figure 2. The evolutionary view, on the contrary, has no definite requirements for information and heuristics, as it suggests that they do not determine the variation and selection of new knowledge, and new knowledge is directly generated from existing knowledge (shown in Figure 2). The formalization of the problem hierarchy differs, too: the information-processing view depicts a highly structured problem hierarchy with clear boundaries between sub-problems, and the solution of a sub-problem depends on the solutions of other sub-problems; the evolutionary view, on the other hand, makes fewer efforts to formalize the problem hierarchy, as it suggests that its structure evolves over time.

Neither view alone provides a complete understanding of knowledge creation and the roles of information in the process. It would be incorrect to say, as many determinists insist, that information is the basis of knowledge, as we reject the notion that knowledge is created from information; however, we also observe that information is indispensable from knowledge creation, and this concept is ignored in the evolutionary view. This seemingly paradoxical relationship cannot be resolved in either view. Additionally, we need a more accurate account to explain the relationship between the sub-problems, the solutions of which are "combined" or "synthesized" to create the new knowledge, as well as to explain how the structure of the problem hierarchy evolves and how it influences the sub-problems.

Figure 2. Integration of the information-processing view and evolutionary view of knowledge creation
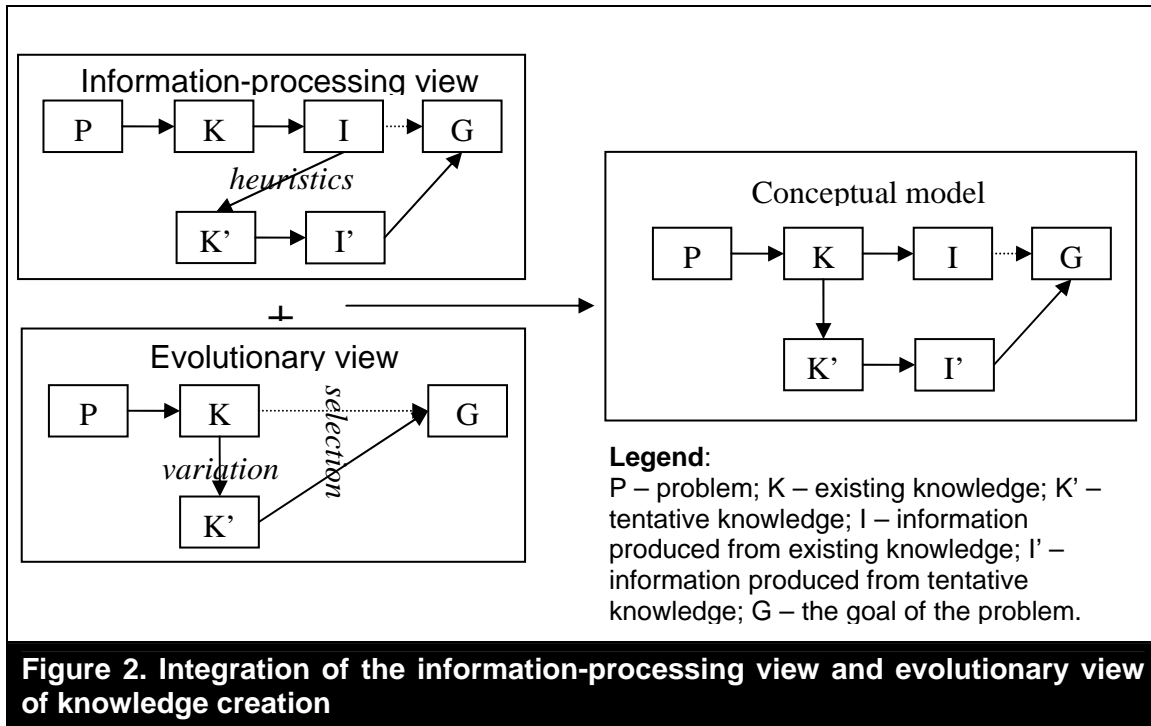
The key to resolve these conflicts is to clarify the relationship between information and new knowledge. Our solution is inspired by the evolutionary view that variance is uncertainly generated and then selected and it is the "selective function" of information that reduces uncertainty in the selection. We conceive that when existing knowledge fails to solve a problem and there is a need for new knowledge, alternative solutions (we later call them *tentative knowledge*) are generated from existing knowledge and then verified and selected based on information produced from those alternatives. Only the alternatives that pass the information-based tests become accepted new knowledge. This complies with the uncertainty in knowledge variance on one hand and the uncertainty-reduction role of information on the other. The conceptual model, built from the integration of both views, is shown in Figure 2. In the next section we develop a new theory based on this model to systematically analyze the knowledge creation issue.

An Evolutionary Information-Processing Theory of Knowledge Creation

Based upon the complementation of the evolutionary view and the information-processing view, we propose an e*volutionary information-processing theory of knowledge creation*, suggesting that organizational knowledge creation is an evolutionary information process. Following the problem-solving paradigm, we propose that: *1) organizational knowledge creation is the process that improves an organization's capabilities to solve business problems and achieve business goals; 2) it is recursive and evolutionary, starting from the recognition of a new problem and ending at the discovery of new knowledge to solve the problem; and 3) within this process, knowledge is created iteratively through generation and selection, and the surviving knowledge is accumulated in the organizational knowledge repository*. We will first elaborate on this theory using an easily solvable problem and then we will extend the discussion to more complex problems.

Knowledge creation in a solvable problem

Figure 3 shows the knowledge creation process for a solvable problem. The process starts from the recognition of a new problem, and ends at the creation of new knowledge to solve the problem and fulfill the goal (Gray, 2001). During the process, tentative knowledge, referring to a temporary solution to the problem, is generated from existing knowledge and verified based on output information. If the information does not meet the selective criteria (i.e., the goal), the tentative knowledge is discarded and other tentative knowledge is generated and verified. If the information meets the criteria, the tentative knowledge is selected and becomes new knowledge, which is retained in the knowledge repository for future use. It is also worth noting that the generation and selection of tentative knowledge are subject to the organizational resources. We describe each of the six phases in the recursive knowledge creation process next.

Figure 3. The iterative process of knowledge creation
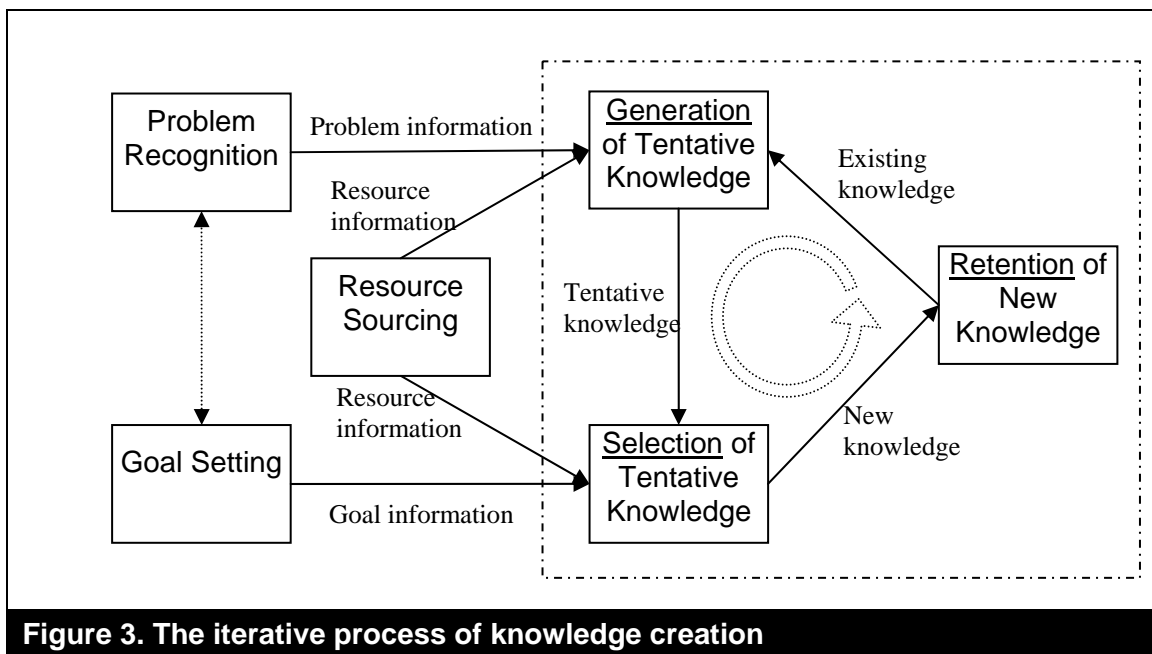
Problem recognition and goal setting

Organizational knowledge creation is triggered by the emergence of a new problem (e.g., outdated products or skills) and guided toward the goal of solving the problem (e.g., developing new products or skills). Such a problem emerges from environmental changes either internally or externally, such as adverse environmental influences, administrative fiat within and external to the organizational, and the unfolding of new cognitive strategies (Cerveny et al., 1990), and is captured and documented as problem definitions that describe its nature. As the employees who actually do the job may have different expectations and may develop their own ways of solving the problem (Nickerson and Zenger, 2004), it is important to coordinate their activities via organizational goals, usually erected by top executives and communicated to employees in the form of goal definitions. Such a goal definition specifies the purpose, scope, and time constraints of knowledge creation (Wasmund, 1993).

To recognize an important new problem is the major duty of managers and a

prerequisite to successful knowledge creation (Nickerson and Zenger, 2004). A new problem exists when there is a difference (or gap) between the organization's current state and some expected state (Cerveny et al., 1990; Mintzberg et al., 1976; Ramaprasad and Rai, 1996), and such a difference/gap cannot be reduced by existing knowledge, or existing knowledge runs into a conflict (Popper, 1999). Many techniques have been developed to help identify and manage organizational problems and goals. Goal-based management (Goldratt and Cox, 1992), for instance, is a systematic approach to tracking the status of organizations and the fulfillment of goals.

A problem and goal are not invariant, but evolve over time. Due to people's bounded rationality, the true nature of a problem is often hard to capture; as a result, the goal may not be correctly specified. A supposedly "clearly" defined problem at the early stage may prove to be an inaccurate proxy of the true problem that is uncovered during practice. Furthermore, goal setting undergoes an anchoring-and-adjustment process (Switzer and Sniezek, 1991). with changes made to the anticipated goal along the course of action. The result is that knowledge creation is quite often a recursive process with the initial problem and goal re-defined and the feasibility of earlier solutions re-investigated.

Organizational resource sourcing

An issue related to knowledge creation is organizational resource constraint, which restricts the generation and selection of possible solutions that may require certain organizational resources. To handle this, two approaches can be followed. One is a static, engineering-type approach that treats constraints as given parameters and integrates them with overall goals. For instance, the manufacturing capability of a machine is usually parameterized in the design of a new product. An alternative, more aggressive approach not only exploits available resources but also actively explores alternative resources to eliminate "bottlenecks" (Goldratt and Cox, 1992), such as the investment in new machines to elevate manufacturing capabilities. In organizational knowledge creation, a critical activity is to proactively scan the internal and external environment for complementary or alternative resources that reveal opportunities for breaking through the resource constraints. Such an activity enlarges the search space of feasible alternatives and may improve the knowledge creation performance.

Problem recognition, goal setting, and resource sourcing are themselves problem-solving processes in which knowledge is applied to recognize the right problem, specify a proper goal, and identify the needed resources. The internal processes of these phases share the same logic as depicted in Figure 3. For simplification purposes, we assume that actions have been taken in these phases so that problem definition, goal definition, and organizational resources are all clearly specified, and they constitute the micro environment for knowledge creation, fostering the search for a "path" (i.e., new knowledge) through available resources to minimize the discrepancy between the problem and the goal. To find such a path, three recursive phases, namely generation, selection, and retention, are followed.

Generation of tentative knowledge

Generation of tentative knowledge refers to the proposition of alternatives to existing knowledge dispersed within and out of the company. This phase can also be conveniently called knowledge variation, since new knowledge is unanimously generated from the modification of existing knowledge (Campbell, 1974), this forms a

search space (Simon, 1978) or solution landscape (Nickerson and Zenger, 2004). We admit that, strictly speaking, it is individuals, not the organization, that actually generate knowledge. However, since organizations are repositories of human knowledge pulled together to solve a common problem (Conner and Prahalad, 1996), a person's private knowledge is of little value until it becomes available for the company and is used to solve the organizational problem. Therefore, we treat the generation of tentative knowledge as the aggregation of individual activities in organizations and focus on the changes in the common knowledge repository (Alavi and Leidner, 2001). Other cross-level theories (e.g., Drazin et al., 1999; Seshadri and Shapira, 2003) can be used to further investigate how individuals' knowledge becomes part of organizational knowledge.

Tentative knowledge is generated through local search (i.e., exploitation and refinement of existing solutions) and distant search (i.e., exploration and experimentation) (Fleming, 2001; March, 1991). For instance, the introduction of new knowledge elements into the problem context and the alteration of the relationship between knowledge elements in a solution (Nagasundaram and Bostrom, 1994) are both approaches to knowledge generation. Many natural science and cognitive science methods such as optimization algorithms have been developed to guide the search for tentative knowledge (Nickerson and Zenger, 2004). What a company needs to do is to develop organizational procedures and structures based on these scientific methods so that related ideas have a chance to get combined (Seshadri and Shapira, 2003).

No matter how tentative knowledge is generated, uncertainty exists, indicating that the tentative knowledge may not be a sure improvement over the existing knowledge. This is especially true when unfamiliar knowledge components and their combinations are searched (Fleming, 2001). The root reason is that we often do not know exactly what is wrong with the problem, but make a guess (Popper, 1992, p.278), which could possibly make the modified knowledge inferior to the earlier unsuccessful solutions. Even with the acquisition of information and experiences, an improvement is not guaranteed because it is the information about the existing knowledge that has been tried, not the new tentative knowledge. In other words, information functions as the indicator of whether and to what extent the existing knowledge, either from within or from outside of the company, can solve the problem, but not how that knowledge is to be improved in order to produce a better solution.

The above view does not mean that knowledge variation is totally random: it is guided by human judgment, and under certain circumstances where the search space is identifiable, a directional search becomes valid with uncertainty significantly reduced (Nickerson and Zenger, 2004). Nevertheless, such certainty, depending on the pre-selection or heuristics, may unnecessarily narrow the search space (Campbell, 1974) and result in bias or sub-optimization (Geoffrion and Van Roy, 1979; Tversky and Kahneman, 1974), which explains why some previously successful companies run into problems (Gill, 1995). In a word, the search for solutions is "necessarily uncertain" (Nickerson and Zenger, 2004, p.620), making the superiority of tentative knowledge subject to verification.

Selection of tentative knowledge

Tentative knowledge, uncertainly generated from the previous step, is verified and selected before becoming acceptable new knowledge. Practically speaking, it is tested

to determine how well the tentative knowledge solves the problem by reducing the gap between the present state and the goal (Cerveny et al., 1990). The most important issue in this step is, therefore, the establishment of the evaluation criteria and use of the criteria to select the tentative knowledge.

Although many practical approaches and analytical tools, such as AHP or decision trees, exist for the evaluation and selection of tentative knowledge, from a pure theoretical point of view, we need a common approach to describe this process and illustrate how uncertainty is reduced; information is such an approach. As we show, problem-solving aims to reduce the differences between the present status and the goal. To do so, some tentative knowledge is developed and applied, causing the status to change. Imagine that we use a lever (or a thermostat, see Ramaprasad and Rai, 1996) to indicate the changing status. If the lever shifts toward the goal after the application of the tentative knowledge, it indicates that the tentative knowledge produces a better result and is therefore selectable. If the lever shifts away from the goal or does not change, it suggests that the tentative knowledge results in an inferior solution or no solution, and is discarded. Both outcomes have an equal opportunity to occur, due to the uncertainty in the tentative knowledge, so that output information is needed to reduce the uncertainty in the selection. Such information, jointly determined by the tentative knowledge and the specific problem to be solved, symbolizes the new position or changes in the position of the lever (Ramaprasad and Rai, 1996), and it indicates whether and to what extent the problem can be solved given the tentative knowledge.

For example, Brown and Hendry (2003) describe the case of developing an exercise bicycle using 3-D software. In designing the electronic braking system of the bicycle, the requirements, such as the size of the braking system that would fit into a gearbox, were specified. The development teams working on different components of the product merge their design concepts into a single specification via a shared database, and use this specification to evaluate the impact of changes they make. The specification, shared by all the teams involved, is the information produced from the designs, and it indicates to what extent the design approaches the goal (e.g., the size of the product). This information is determined by the product design, and once it is captured, the state of the design becomes clear. Even though the output information can be further used as input to refine the previous design, it may not necessarily result in an improvement in the new design, and uncertainty still exists, as discussed in the *generation* phase. In other words, once the feedback information is dissipated in its use (Ramaprasad and Rai, 1996), new information should be collected to verify the revised knowledge.

Retention of selected new knowledge

Knowledge creation is a continuous process, sustained by unresolved problems or emergence of new problems. Hence, new knowledge created from the generation and selection phases becomes existing knowledge, which can be used in further rounds of knowledge generation and selection, or reused in other problems (Markus, 2001). Mechanisms are needed to retain new knowledge, which we call *knowledge retention*. A well-known approach to storing new knowledge is using Organizational Memory (OM) (Walsh and Ungson, 1991; Robey et al., 2000) in such forms as personal relationships, databases, work processes and support systems, and products and services (Cross and Baird, 2000). OM makes new knowledge shareable and reusable by other organizational members working on the same or similar problems. New knowledge retained in OM is not fixed, but faces competition with new alternatives. This is especially true when other

factors in the process change, such as problem re-definition, goal adjustment, or resource sourcing. When this happens, previously created new knowledge becomes the input of a new round of knowledge creation, and the evolution process starts again with newer knowledge created and retained in the OM.

The above analysis depicts the general procedure of knowledge creation for an easily solvable problem. Based on the condition that the problem and the goal are both defined and the organizational resources are provided, we focus on the recursive phases of knowledge generation, selection, and retention. We emphasize that during the process, tentative knowledge is first uncertainly generated and then selected based on feedback information. This sequence is a key to understanding the roles of information in knowledge creation. We illustrate in Figure 4 the proposed relationship.
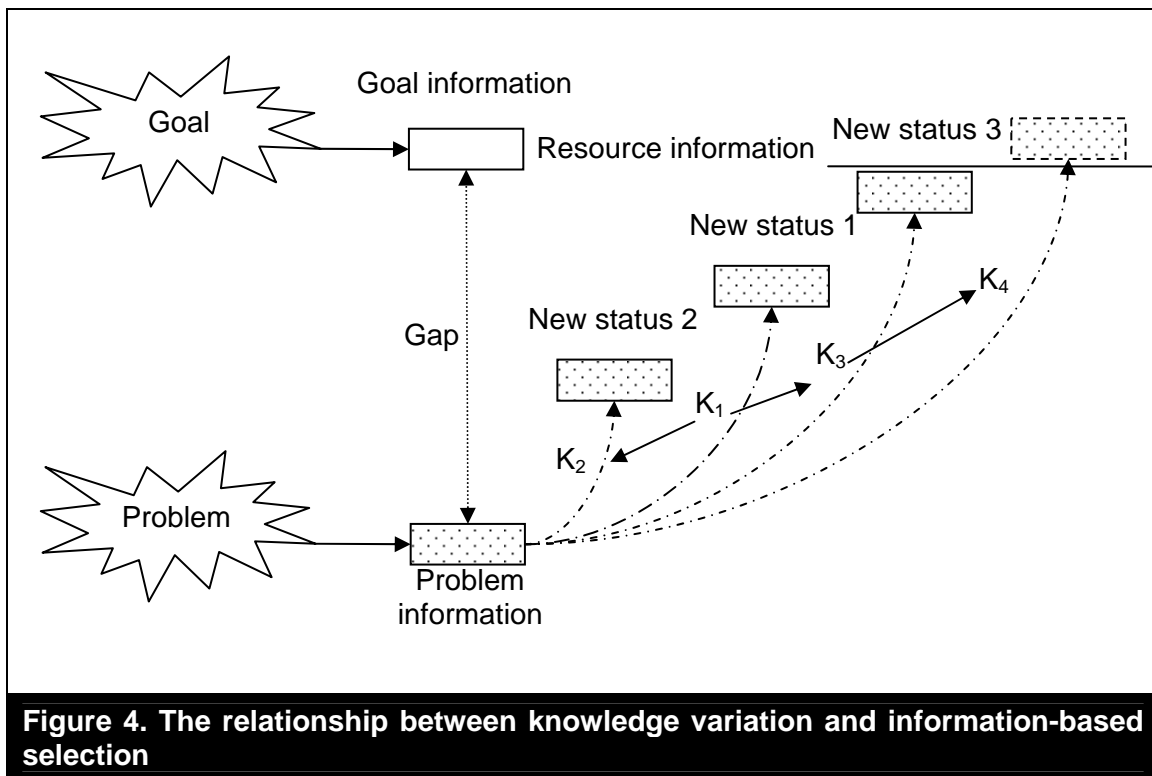
Figure 4. The relationship between knowledge variation and information-based selection

In Figure 4, a gap exists between the problem definition and goal definition, and new knowledge is to be developed to fill the gap. At the beginning, existing knowledge K1 is tried, which fails to produce a satisfying solution because the feedback information of Status 1 is below the goal; nevertheless, K1 is selected as the basis of variation since it shows some potential for success. The alternative K2 is then developed from K1, which results in an inferior result (Status 2) and is rejected. A third alternative K3 is developed from K1, which, as the feedback information of Status 3 suggests, produces an improved result; therefore K3 is selected and K1 is discarded. Variation K4 is developed from the retained knowledge K3, but is restricted by a resource constraint and is thus infeasible. After four rounds of variation and selection, K3 is finally selected as new knowledge. The whole process is an iterative generation-selection cycle, and the relationship between tentative knowledge and feedback information reflects the relationship between generation and selection. The roles of information, as shown in this model, are therefore the selection or pre-selection of tentative or existing knowledge.

It is important to reiterate that these phases are themselves problem-solving processes, where decisions are made on what problem is recognized, what goal is set, and what resources are identified. For instance, in organizations there exist many possible problems, and the problem with the highest value for the organization is to be determined by the managers (Nickerson and Zenger, 2004). The question of *how* to recognize the problems is important; but for the other phases in the process, *what* is recognized (or selected) has more direct impact, as it depicts the particular state of the organization and serves as the basis of other phases. This is the same for goal setting and resource sourcing: *what* goal and *what* resources are selected have a direct impact on other phases in the process. Based on our definition, all of the output of the three phases is information (e.g., *problem information*, *goal information*, and *resource information)*, due to their corresponding selective functions. This distinction helps to clarify the confusion of information and knowledge in contemporary research on knowledge creation by clearly distinguishing and relationally positioning each construct.

Knowledge creation in the problem hierarchy

The above analysis shows an element model of knowledge creation for a relatively easily solvable problem. In practice, most organizational problems are complex and cannot be directly solved in the manner described in the element model. A conventional approach to dealing with a complex problem is to decompose it into a hierarchy of solvable sub-problems (Simon, 2002). Both the evolutionary view and the information-processing view, for instance, support this hierarchical model. Studies also show the distinguishing advantage of hierarchy in organizational problem solving (e.g., Nickerson and Zenger, 2004). Additionally, understanding the structure of complex problem solving is the key to organizing individuals in companies and designing IT to support the process. Hence our analysis is extended to complex problems.

Compared to the previously analyzed element model, the process of complex problem-solving shows some new features. We extend our earlier discussion and propose: *1) knowledge creation for a complex problem is conducted through a hierarchy of sub-problems, 2) the search for solutions to the sub-problems is carried out interdependently via the exchange of output information between sub-problems, and 3) the decomposition of both sub-problems and their solutions is evolutionary*. We will next elaborate on the process of complex problem solving based on these propositions, and show where the element model fits.

A complex problem is solved via a hierarchy of simplified, solvable sub-problems, whether it is an authority-based hierarchy or a consensus-based hierarchy (Nickerson and Zenger, 2004). Scholars have analyzed how the overall problem can be decomposed based on the interaction among the components of the problem, such as Kauffman's (1993) NK modeling. While these studies contribute to our knowledge of problem decomposition and solution, in this research we are more interested in how the sub-problems are related to each other and to the overall problem.

As we emphasize, problem solving starts from the recognition of a problem and ends at the solution to the problem, which is the case for both the overall problem and sub-problems. Sub-problems are recognized based on the internal requirement of solving the overall problem. As the overall problem is decomposed based on the logical relationship (e.g., linear decomposability, see Simon, 2002) between its components, each

component becomes a sub-problem with its own problem definition and goal definition. These sub-problems are further decomposed into lower-level sub-problems. Since each sub-problem is associated with a certain goal, the solution to the problem hierarchy is fulfilled via the goal hierarchy, with organizational members working for sub-goals in the hierarchy. This helps explain why organizational goals are the ultimate criteria and important conditions of individuals' activities in organizational knowledge creation (Gallivan et al., 2003). Understanding this relationship is important for the design of schemes to assign tasks to individuals or groups.

With this structure identified, it is reasonable to analyze complex problem-solving in light of the element model. We use Figure 5 to support the discussion. In Figure 5, the overall problem P_0 is decomposed into sub-problem P_1 and P_2, which are further decomposed into sub-problems. For example, the development of a new product (P_0) is carried out via the design of a product that meets customer's requirements (P_1) and also the design of machines that can manufacture the product (P_2). The solution of P_0 is then based on the solutions of P_1 and P_2, which are solved via their corresponding sub-problems. For each sub-problem, the propositions of the element model apply, e.g., in Box (a) the sub-problem P_{22} is solved through the test of three alternatives, and the second solution is selected. A higher-level sub-problem, such as P_1, is solved based on the solutions of its components P_{11} and P_{12}, as shown in Box (b).
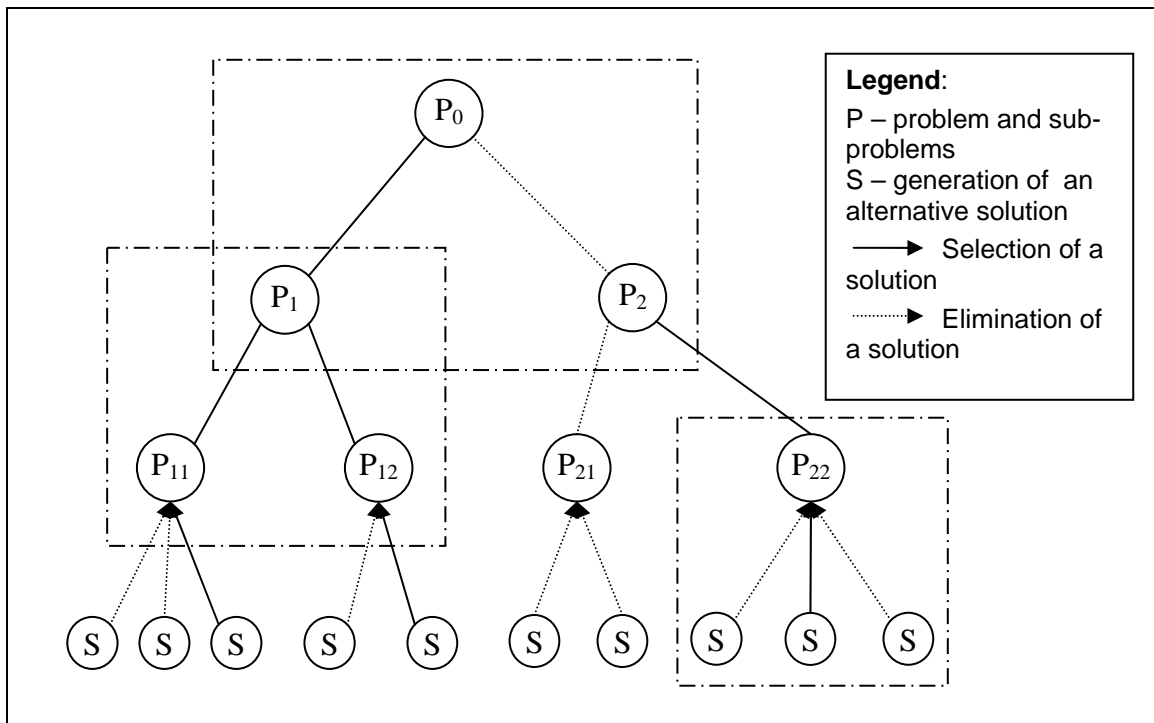
Figure 5. The hierarchical framework of knowledge creation

We emphasize that, strictly speaking, the sub-problems in the problem hierarchy are not connected via the sharing of "knowledge" in the sub-problems, because for decomposable problems, knowledge sharing is largely unnecessary (Nickerson and Zenger, 2004): we do not expect that the knowledge of designing the machine should be used in the design of the product. Instead, they can only be connected via the exchange of output information from the solutions of the related sub-problems. Such information

indicates to what extent a sub-problem is solved (see the above illustration of the lever), and becomes the boundary conditions (either problem information, goal information, or resource information) of related sub-problems. For instance, the manufacturing capability of the new machine designed in P_2 becomes the resource information for new product development in P_1; meanwhile, the specification of the new product developed in P_1 is used as the target to further improve the capacity of the machine in P_2. This is the information exchange between the two sub-problems, rather than the exchange of knowledge about how each should be solved. In a word, the solution to the problem hierarchy is conducted via the search for knowledge in each sub-problem and the exchange of information between the sub-problems.

If the goal of each sub-problem can be fulfilled as expected, or the anticipated information is produced, the complex problem solving becomes straightforward. The reality is, however, that uncertainty exists in the extent to which each sub-problem can be solved, and such uncertainty is transferable to the related higher-level sub-problems and even to the overall problem. Borrowing the concepts by Cerveny et al. (1990), we categorize two patterns of uncertainty accumulation: a linear pattern and a concurrent pattern. The linear pattern refers to the transfer of uncertainty along a branch in the hierarchy, as represented by P_2-P_{21} (i.e., the design of the machine and its component). In this example we assume that a solution was not found for a key component P_{21}, therefore P_2 cannot be finished. The concurrent pattern refers to the transfer of uncertainty across branches, such as in Box (c) the overall problem P_0 (i.e., the design of the product) cannot be solved because a necessary component P_2 (i.e., design of the needed machine) cannot be finished. To reduce uncertainty in this particular case, either P_{21} should be solved or substituted by a new sub-problem (e.g., purchasing the component in market), or P_2 and its components should be altogether substituted (e.g., outsourcing manufacturing). These patterns suggest that uncertainty can be transferred vertically and horizontally in the problem hierarchy.

Strategies of knowledge sharing between individuals working on different sub-problems are not guaranteed to work. Nor are other strategies solely based on the exchange of feed-forward or pure input information, as we previously showed that such information, although important, represents the preexisting status and has no definite relationship with the success of knowledge variance. The challenge for organizations is not to control the uncertainty in each sub-problem, which should be addressed by individuals, but to control the accumulative uncertainty at the organizational level. Knowledge creation strategies will work best when executed through the exchange of output or feedback information between vertically and horizontally related sub-problems, and when indiviudals use output or feedback information as the pre-condition to trigger the knowledge variation and selection in each related sub-problem. The search for solutions to the sub-problems is then carried out interdependently via the exchange of feedback information between sub-problems (e.g. shared project progress chart).
After each round of information exchange, equilibrium is reached between the information output from the antecedent sub-problems and the information requirement (i.e., problem information, goal information, and resource information) of dependent sub-problems. This equilibrium is to be exploited via the search for the solution in each sub-problem that reduces the gap between the sub-problem and its goal. If all the sub-problem gaps are successfully resolved, the whole problem is solved; otherwise, new output information is exchanged between the sub-problems so that a new equilibrium is reached, evolving from the previous one. Following the new equilibrium, the search process starts again, until the whole problem is solved or evolves to another equilibrium.

Such a combinative evolution-exploitation, or the shift from one equilibrium to another, is the general strategy used to cope with uncertainty in the problem hierarchy. Since the search of solution is driven by the exchange of feedback information, we can say that *the tuning of the solution to a sub-problem is to modify knowledge for that sub-problem in order to produce the most suitable information contributive to the solution of the overall problem*.

The uncertainty of the problem hierarchy suggests that neither the solutions of sub-problems nor the decomposition of the problem hierarchy is static; both are evolutionary. Nevertheless, in each round of the process, certain problems are to be recognized from among a set of possible problems, certain organizational goals are to be erected from among a set of possible goals, and certain organizational resources are identified from among other potential resources. The remainder of the job is the generation and selection of alternatives that solve the problem hierarchy.

Discussions and Conclusions

In this research, we develop an evolutionary information-processing theory of knowledge creation, suggesting that a complex organizational problem is solved through the decomposition and solution of a problem hierarchy, and new knowledge created for the whole problem is the combination of knowledge elements in the sub-problems. For each sub-problem, knowledge is created iteratively via information-triggered knowledge variations and information-based selective retention.

The Evolutionary Information-Processing Theory of Knowledge Creation helps to consolidate the deterministic and evolutionary views of knowledge creation and also clarifies the roles of information in the knowledge creation process. Through the integration of the information processing and knowledge evolution schools, we show that organizational knowledge creation is an evolutionary process, driven by two competing forces, namely the exploration of new alternatives and the exploitation of old certainties, which together push the creation of new knowledge. Within the process, information plays several critical roles (see Figure 3 and Figure 4), and most importantly, it functions as the evaluation criterion rather than the raw material of new knowledge.

Such an understanding of the knowledge creation process can help companies make better decisions on IT investments designed to facilitate the knowledge creation process. As shown above, the key to the success of organizational knowledge creation is the exploration of new alternatives and exploitation of selected ones via the exchange of output information. Broadening the search space to hold previously searched solutions is therefore important to achieve knowledge creation effectiveness. However, broadening the search space requires exhaustive amounts of memory, which is typically beyond the capability of most humans. Organizational Memory Information Systems (OMIS) appear to be a suitable solution (Robey et al., 2000; Stein and Zwass, 1995). Unfortunately, previous research has given limited attention to tailoring OMIS design for knowledge creation performance.

Based on the generic, four-subsystem OMIS architecture developed by Stein and Zwass (1995), we propose a *knowledge creation oriented OMIS*, as shown in Figure 6. The four OMIS subsystems directly correspond to the knowledge creation activities we described in Figure 3.
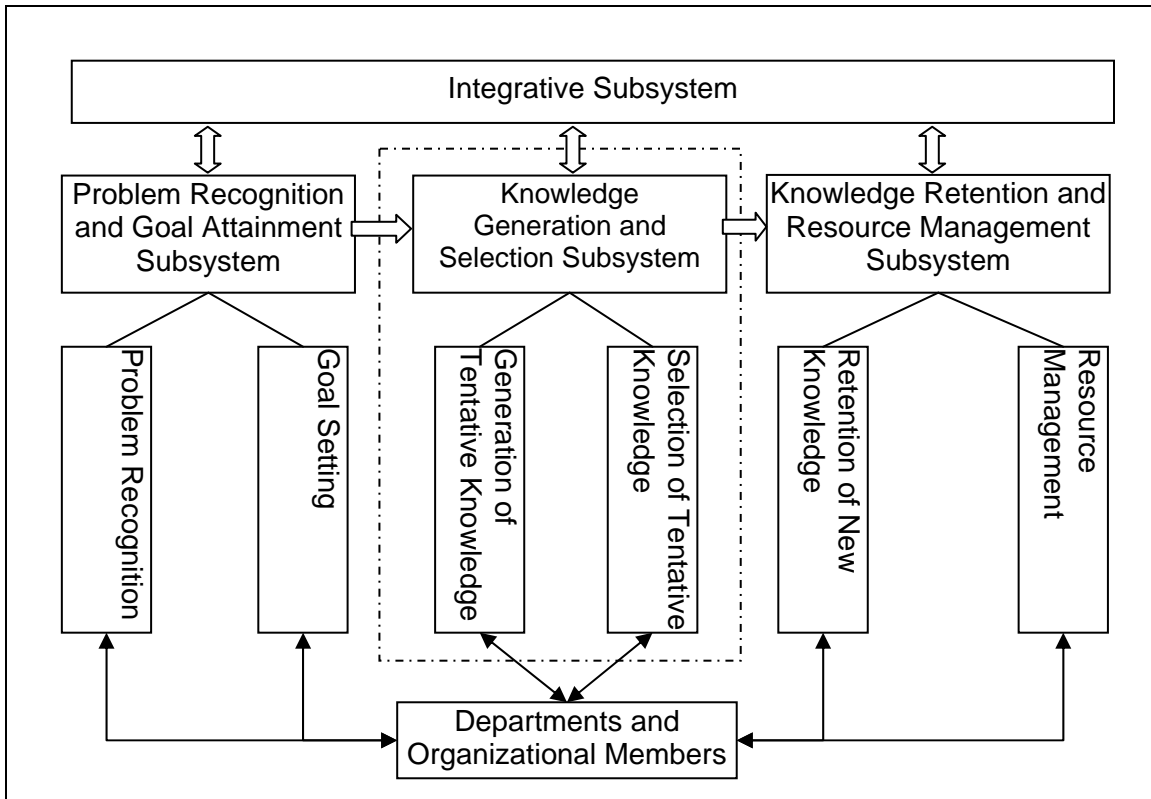
Figure 6. Knowledge creation effectiveness oriented Organizational Memory Information Systems and the member functions

Problem Recognition and Goal Attainment Subsystem.

The Problem Recognition and Goal Attainment Subsystem performs two related functions: problem recognition and goal setting. It is the starting point of each round of knowledge creation activities. The meta-requirements of this subsystem are to enable the companies to timely and accurately recognize organizational problems and to specify and manage the goals of the problems. As the whole knowledge creation process is hierarchical and evolutionary, the meta-design of this subsystem should include two capabilities: one is to decompose the problem into a manageable hierarchy of tasks and assign the tasks to organizational members; the other is to timely and accurately measure progress in knowledge creation and update the problem status. A typical example is the application of 3-D CAD systems in concurrent product design (Baba and Nobeoka, 1998), which supports the decomposition of a product definition into multiple concurrent components, determines the key design features of each component digitally, and assigns the tasks to concurrent design teams. Meanwhile, the design teams can watch the progress of the whole problems or certain components via a shared database in order to balance their progress.

Knowledge Generation and Selection Subsystem.

The Knowledge Generation and Selection Subsystem, similar to Stein and Zwass' (1995) adaptive subsystem, is where new knowledge is created to adapt to the environmental change, and it performs the functions of tentative knowledge generation

and selection illustrated in Figure 3. The successful design of this subsystem is the key to the success of the whole system. Meta-requirements include the support of boundary-spanning activities to recognize, capture, organize, distribute (Stein and Zwass, 1995), and combine existing knowledge both within and outside the company to generate new knowledge. It should also support the specification of selection criteria and the utilization of the criteria to measure and select tentative knowledge along the process. Advanced IT can improve adaptability by facilitating both the generation and selection of design ideas. For instance, the full-visualization of products in 3-D CAD systems enables designers to engage in more advanced hypothesis formation than was possible in the non-IT environment of pen-and-pencil; it also helps to quickly carry out a number of iterations in the formation and verification of competing hypotheses in order to select the best one (Baba and Nobeoka, 1998). Another example is to provide individuals with easy access to organizational knowledge repositories.

Knowledge Retention and Resource Management Subsystem.

Similar to Stein and Zwass' (1995) pattern maintenance subsystem, the Knowledge Retention and Resource Management Subsystem performs the functions of new knowledge retention and resource management. The concept of knowledge retention has been discussed above; what needs to be emphasized is that new knowledge retained in the OMIS is to be used in new rounds of knowledge creation and also reused in similar problems in the future. The resource management function is an extension of the resource sourcing activity in Figure 3, as knowledge creation involves not only the identification of needed resources, but also the actual use of the resource. The requirements of the resource management function, therefore, include the flexible allocation of needed resources (such as human resource, materials, machines, etc.) during the knowledge creation process, and also the reconfiguration of organizational resources based on the new knowledge created.

Integrative Subsystem.

The above three subsystems and their member functions do not work independently, rather they are coordinated by the integrative subsystem. This coordination is especially important when the six element activities in the knowledge creation process are performed by different departments, teams, or individuals. For instance, the marketing department recognizes new customer needs and initiates a request for new products; the R&D department then develops the new products based on the request; and then the manufacturing department adjusts the production line in order to manufacture the products. Uncertainty exits during the process, as the marketing department may not clearly specify the problem definition or goal definition, or the R&D department proposes a design that cannot be manufactured. To reduce uncertainty, a high level of cooperation between the subsystems and their functions should be achieved via the information exchange over the integrative subsystem. The requirement of this subsystem is therefore to facilitate communication and information exchange among other subsystems over time (i.e., succession in process) and space (i.e., departments or individuals fulfilling different tasks). A common approach is to use a shared database where information is integrated and accessible by users; another approach is to use communication technology to build direct link between problem solvers.

Successful knowledge creation depends on a seamless integration of each of the

subsystems. In the future, integration should follow the instructions of the meta-requirements and meta-design discussed above. Of course, an OMIS will not work without other supportive IT, such as the creativity-enhancing software (Shneiderman, 2002) and organizational decision support system for R&D project selection (Tian et al., 2005). These technologies will have a stronger impact on organizational knowledge creation when integrated with the knowledge creation oriented OMIS.

Limitations and research opportunities

While the Evolutionary Information-Processing Theory of Knowledge Creation offers considerable promise, it does have several limitations that must be addressed. First, our discussion of organizational knowledge creation is carried out from a purely theoretical perspective that focuses on how an organizational problem is decomposed and solved via its components. We did not have a detailed discussion of how those activities are performed by individuals and what impact different people have on completing tasks. Further research could be done to integrate our problem-based knowledge creation theory with other human-based theories (e.g., Woodman et al., 1993).

Second, knowledge generation is described as an uncertain variation process, which has theoretical rigor but has limited immediate practical relevance. Future research must extend the theory to uncover practical patterns of knowledge creation.

Third, we treat our model as a *meta-theory* with many details left to explore. For instance, we assume that problem recognition, goal setting, and resource sourcing are all problem-solving activities sharing the same logic as the element model. Of course, factors that have direct impact on these activities may differ. These issues need to be further analyzed.

Despite these limitations, we suggest that our theory is a cornerstone in providing a much clearer view of knowledge creation by establishing a logical link between knowledge creation and information processing and between evolution and heuristics.

Acknowledgement

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