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# Information Technology and Organizational Learning: An Investigation of Exploitation and Exploration Processes

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# INFORMATION TECHNOLOGY AND ORGANIZATIONAL LEARNING: AN INVESTIGATION OF EXPLOITATION AND EXPLORATION PROCESSES

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## Abstract

*This study investigates the effects of information technology on exploration and exploitation in organizational learning. We extend an earlier computational model of organizational learning and introduce learning between individuals through three distinct mechanisms: face-to-face exchange, IT-enabled communication support, and knowledge repositories. Each of these mechanisms has a distinct effect upon the exploration and exploitation dynamics in organizational learning, and we conclude that these capabilities offer firms a more robust ability to manage the exploration and exploitation balance in organizational learning.*

**Keywords:** Computational modeling, simulation, organizational learning, exploration, exploitation

## Introduction

In this paper, we explore the impact of information technology on an organization's ability to learn. More specifically, in our study we used computer simulations, undertaken both individually and in combination, to investigate the impact of face-to-face interactions, knowledge repositories of best practices, and computer-mediated communication (e-mail) on learning processes. We consider two forms of organizational learning: exploration and exploitation. Exploration involves the development of new knowledge and/or replacement of existing content within the organization's memory (Abernathy 1978; March 1991; Pentland 1995). Exploitation refers to incremental learning focused on diffusion, refinement, and reuse of existing organizational knowledge (Lado and Wilson 1994; Larsson et al. 1998; March 1991). In studies of organizational learning, the notion of balance between exploration and exploitation has been a consistent theme (March 1991; Teece et al. 1997), and it is generally believed that the short and long-term performances of organizations (at the individual, group, and firm levels) depend on achieving an effective balance between these two processes. However, balancing the exploration and exploitation processes in organizations is not an easy task; according to March (1991), they compete for scarce resources. Various areas of the literature including innovation, creativity, organizational learning, and competitive advantage have investigated the relationships between individual attributes and contextual factors concerning exploration and exploitation processes (Benner and Tushman 2003). Missing from these investigations are studies that focus on the relationship between the IT and the explorative and exploitive learning processes.

There is a concomitant need to study these relationships considering the prevalence of IT in contemporary organizations and the potential impact of IT on the development and transfer of knowledge in organizations. IT in the form of communication support systems can greatly enhance the quality and scope of organizational knowledge development (an exploration process). On the other hand, IT applications in the form of structured databases, data warehouses, and document repositories can greatly enhance the storage, organization, search, and access to codified organizational knowledge. This in turn promotes knowledge reuse and diffusion (exploitation) in organizations.

In order to leverage the positive impacts of IT on organizational learning and to avoid the types of unintended negative consequences described in the literature (Newell et al. 2001), it is important to investigate systematically the influence of IT on

exploration and exploitation processes on organizational efficiency and adaptability. In this study, the impact of IT on exploration and exploitation is examined using a model of organizational learning in which individuals learn by sharing knowledge through social interactions (face-to-face and/or computer mediated communications) and/or by accessing codified knowledge captured in computerized best practices repositories.

## **Organizational Learning and Information Technology**

Several organizational researchers have defined learning in terms of acquiring, retaining, and transferring knowledge at the individual and group levels. For example, Huber (1991) defines learning in terms of processes of knowledge acquisition, information distribution and interpretation, and organizational memory. According to Vera and Crossan (2003), organizational learning is comprised of the continually evolving knowledge stored in individuals, groups, and nonhuman repositories. Similarly, Robey et al. (2000) define organizational learning as an intentional or unintentional process that enables the acquisition of, access to, and revision of contents of organizational memory embedded in both humans and artifacts. Given the importance of effective learning to organizational performance and survival, some organizations allocate dedicated resources to learning and knowledge acquisition (Alavi 2000). Examples include research staff positions, and research and development departments, formal training programs, and hiring employees with specialized knowledge. An emerging research area in the information systems field focuses on the application of advanced IT resources to organizational learning that support the underlying processes of knowledge sharing and organizational memory.<sup>1</sup>

Contemporary organizations can draw on a wide range of IT tools to support organizational learning processes. The examples include data warehouses, expert systems, knowledge repositories of best practices, groupware, and wide-band communication networks that can either replace or complement existing interpersonal methods of knowledge sharing (Alavi and Leidner 2001; El Sawy and Bowles 1997; Stein and Zwass 1995). Contributions of these tools to organizational learning can be primarily characterized in terms of two key underlying functions: communication support and knowledge repositories (Goodman and Darr 1998; Robey et al. 2000). Communication support systems enable individuals to share and exchange knowledge more rapidly and less expensively across time and geographic distance with a relatively larger group of individuals. Communication support systems also allow individuals to control the scope and timing of their communication exchanges with relative ease (Huber 1991). For example, using e-mail distribution lists, an individual can control others' access and participation in his/her communication events. Knowledge repositories include the information processing, storage, search, and retrieval features of IT and greatly enhance organizational capacity to codify, store, process, scan, retrieve, and reuse organizational knowledge. For example, many consulting firms have developed best practices repositories to retain organizational know-how and make it readily available to their employees across various organizational units. These two primary capabilities, employed individually or in combination, can influence organizational learning processes as postulated below.

## **The Model**

Computational modeling is an established but often overlooked organizational research method in which probabilistic parameters of a theoretical model are built into a computer software program, executed, and the output of the program is analyzed (Carley 1995). These models represent theoretical abstractions of real-world organizations and focus on simulating general organizational principles and processes. They compare and contrast "ideal type" agents in which complex features are abstracted away and, thus, are somewhat limited in their realism. What is lost in the level of detail, however, is gained in the degree of control over the research environment. Researchers can model elements of the research environment that are often difficult to observe, such as longitudinal or dynamic characteristics, and can then vary the parameters of the simulation to assess the effects of these manipulations on model outcomes.

Since the researcher builds the research environment, considerable care must be taken to ensure that the computational model approximates reality closely enough to have some application to real-world environments. Several criteria have been forwarded to evaluate the validity and contribution of computational models (Taber and Timpone 1996). First, choices regarding model parameters must be grounded in existing theory and/or empirical observation, and the researcher must provide theoretical justification for choices of and modifications to these parameters. Second, parameters must be subject to sensitivity analysis in

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<sup>1</sup>This research area is developed under the banner of knowledge management systems. See Alavi and Leidner (2001) for an overview.

which they are varied within a given range to ensure that the results of the model do not stem from an arbitrary choice of parameter values. Third, computational models should be made as simple as possible to isolate the most important theoretical features being analyzed. Simulated processes should contain only the most essential characteristics of that process to minimize extraneous influence. Fourth, results of the model should have a certain degree of face validity but should also provide new and interesting insights not immediately obvious.

In order to explore the effects of IT on exploration and exploitation in organizational learning, we replicated and extended the computational model developed by March (1991). Building upon existing computational models, rather than developing new ones from scratch, is an effective method for validating existing work, developing a cumulative research tradition, and enabling deeper exploration of foundational ideas than would be possible through the continual creation of new models (Prietula and Watson 2000). A significant amount of research has extended the theoretical components of March's model of exploration and exploitation (Benner and Tushman 2003; Lee and Lee 2003), but little work has been conducted extending the original model on which the theory of exploration and exploitation was based.

In order to employ this model to address the question of the influence of IT capabilities on organizational learning, we implemented several extensions to the model. These extensions to March's original model impact it in two ways. First, we introduced the capability of individuals to learn from each other through three distinct learning mechanisms: through face-to-face interaction, IT-enabled communication support, and IT-based knowledge repositories. Second, we recognized that organizations do not use IT to support learning in the same ways, so we introduced the possibility for organizations to assemble a number of distinct configurations of these learning mechanisms.

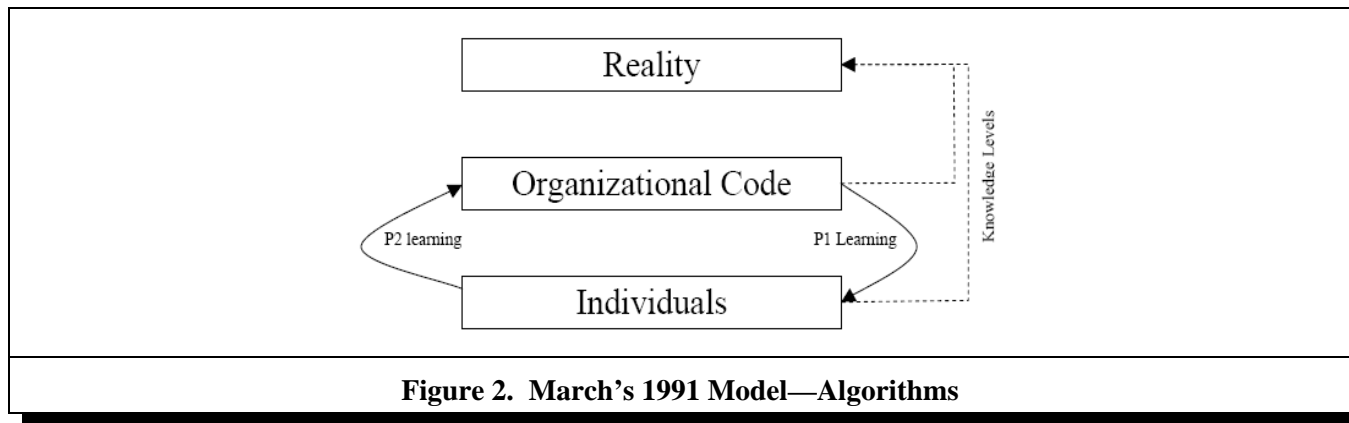
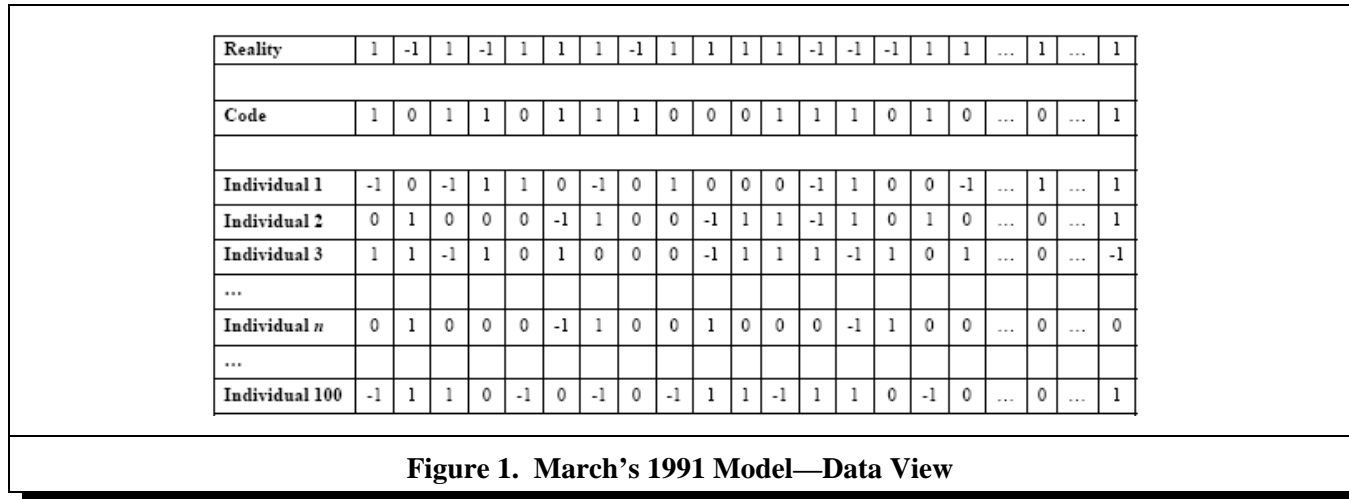
March's model of organizational learning is parsimonious, being comprised of three primary components (see Figure 1): (1) an external "reality" (reflecting what the knowledge/beliefs of the organization "should be"),<sup>2</sup> (2) an *organizational code* representing the perceived beliefs about that reality (i.e., the organization's approximation of it), and (3) *individual knowledge* representing individual beliefs about that reality (i.e., an individual's perception of it). *Reality* is modeled as a single external vector of 30 integers, where each integer  $i \in$  presents an orthogonal and independent dimension of reality. The *organizational code* is similarly modeled as a single vector of beliefs, and each belief (dimension) can additionally take on the value 0 (representing no belief). Thus  $i \in \{-1, 0, 1\}$ . *Individual knowledge* is modeled similar to the organizational code (a vector of 30 beliefs). There is a distinct vector for each agent in the simulation (100 agents).

The *knowledge level* is the proportion of reality correctly represented by either the organizational code or an individual. Both organizational and individual knowledge levels change via learning, and learning is represented in this model as specific interactions among the components occurring over 80 periods (iterations). Each period, as depicted in Figure 2, every *individual agent* will alter any given belief to conform to that of the organizational code with some probability ( $p_1$ ) reflecting the *rate of socialization* of individuals in the organization. Each period, the *organizational code* will also alter any given belief based on the dominant belief of the set of agents—the superior group,  $\Phi$ -group, defined as those agents whose individual beliefs correspond better with reality than do the beliefs of the code—and a factor  $p_2$  that reflects the *effectiveness of learning* by the code. That is, the organization will tend to adapt its code according to the set of agents ( $\Phi$ -group) that have a higher knowledge level. Neither the code nor the agents directly observe reality, but reality influences learning by defining the  $\Phi$ -group. Only through the individual knowledge level, which represents the percentage match between an individual and reality, can the code recognize which of the individuals more closely mirrors reality—but only in the aggregate across all 30 beliefs.

March observed the tendency for the knowledge levels of the code and of individuals to converge as successive iterations are performed and a stable "knowledge equilibrium" is achieved at which knowledge levels are homogeneous across individuals (however, the equilibrium value may actually differ from reality). March found that higher individual learning ( $p_1$ ) and higher organizational learning rates ( $p_2$ ) resulted in quicker convergence of knowledge levels to equilibrium (exploitation). March also found that slower individual learning rates ( $p_1$ ) accounted for many of the higher equilibrium levels, especially when coupled with fast organizational learning ( $p_2$ ). This result occurred because slow individual learning extended heterogeneity of the individuals' knowledge, disallowing premature convergence of the organizational code to lower knowledge equilibria (exploration). Thus, the rapid diffusion and acculturation of knowledge may not necessarily be a desirable organizational characteristic if the level of knowledge matters more than quicker resolutions of agent heterogeneity.

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<sup>2</sup>The term *reality* is used in March's original paper, thus it is retained here. It is understood in our model to represent the idealized knowledge sought by the organization.



We first built this basic model in order to replicate March’s original results and to ensure that we had replicated his model correctly. Once results had been replicated, we introduced our extensions into the model.

### Extending the Model

We extended March’s original model by introducing three ways through which individuals can learn from one another: face-to-face exchange, IT-enabled communication support, and IT-based knowledge repositories. Face-to-face exchanges represent the ways in which individuals share knowledge without the use of any IT support. IT-enabled communication support (CS) facilitates interaction *between* individuals through technologies such as e-mail, on-line chat, and groupware. IT-based knowledge repositories (KR) allow individuals to access codified knowledge through best practices repositories and customer service databases without interacting with other individuals directly. Organizations may apply and employ IT in unique and organization-specific ways, but we can reduce these particularities to their most essential characteristics for simulation. In order to preserve the integrity of the original model amidst these extensions, we implemented the mechanisms and their configurations using variations on the algorithms in the original model described above.

#### Face-to-Face

A long and robust research stream examines how individuals learn directly from one another in interpersonal settings (Borgatti and Foster 2003). March (1991, p. 75) explicitly recognized the restrictions of his model that prevented learning between

individuals in the population, yet his model and the supporting theory seem amenable to such an extension. Since learning is operationalized as a function of the individual and not of the environment or of the organization (pp. 76-77), introducing learning between individuals is consistent with the theoretical basis of learning embedded within March's simulation. We labeled this direct form of learning between individuals as *face-to-face* learning (FTF).

When seeking to learn from other individuals, people tend to adopt knowledge from those they perceive as having superior knowledge (Perry-Smith and Shalley 2003). For simulation purposes, when the focal agent seeks to learn from others in the population, that agent assembles a superior group ( $\Phi$ -group) of others with a higher knowledge level than the agent. The focal agent learns from that superior group using the same algorithm as the original model, except substituting the individual learning parameter ( $p_1$ ) for the organizational learning parameter ( $p_2$ ). Learning in this model is operationalized in the same way as in the original model, except that in our extension the agents in the organization can simply learn directly from one another instead of being mediated exclusively through the official organizational code.

A theoretical limitation to FTF learning is that it is geographically dependent; individuals must be organizationally, geographically, or temporally proximate in order for them to learn from one another through face-to-face communication. Previous work on the model examined the effects of group size and composition on model outcomes (Kane and Prietula 2003), and we relied on this work to select an appropriate specification for the number of groups in our model. In terms of our simulation parameters, when agents choose to learn from one another through face-to-face exchange, they can only learn from agents with whom they are organizationally proximate. At the beginning of the simulation, the population is divided into  $n$  groups ( $n = 10$ ) and each agent is assigned to one and only one group ( $g$ ).

### **Communication Support**

One advantage of communication support capabilities is that they can overcome geographic barriers to learning (Markus 1994; Pickering and King 1995). Although individuals can theoretically use these capabilities to communicate with anyone in the organization—or, for that matter, virtually anyone in the world—empirical research has shown that the functional reach of these capabilities is not infinite. An individual's bounded rationality usually means that individuals communicate with a smaller subset of individuals who use CS (Butler et al. 2004; Van Alstyne and Brynjolfsson 2005).

Although empirical research has shown that complete strangers often share knowledge via CS (Constant et al. 1996), most often bounded rationality results in individuals using CS to learn from others who share common interests or knowledge (Pickering and King 1995; Van Alstyne and Brynjolfsson 2005). In terms of our simulation parameters, agents use CS to learn from a personal network of others who are assembled as a function of an interest parameter ( $i = 4$ ) assigned at the beginning of the simulation. Agents elect to include other agents in the CS-based network according to a probability established at the beginning of the simulation. Those who share the same interest have a higher probability of being included in the CS-network ( $p = .25$ ) than those who do not ( $p = .01$ ). Parameter specifications were chosen so that the CS network was approximately the same size as the FTF groups, and parameter values were robust with respect to these variations ( $p_i = .35, .25, .15$ ;  $p_{ni} = .01, .02, .03$ )

One characteristic of CS often noted in the literature is that it is regarded to be a relatively lean communication medium when compared to face-to-face forms of learning (Daft et al. 1987; Miranda and Saunders 2003). CS is unable to convey the contextual and non-verbal cues available through face-to-face exchange and, thus, is only capable of communicating a portion of the available knowledge. We sought to model this characteristic of CS by specifying that individuals could only learn a portion of the code from others when using this capability for learning. Although the communication medium's lack of richness resulted in an agent learning only a portion of the code using CS, the  $\Phi$ -group was still assembled using the knowledge levels of the entire code since the reputation and credentials of individuals in a network of practice are not limited by the communication medium. The agent randomly selects with equal probability a portion of the code from which to learn from the  $\Phi$ -group in a given period: the first, middle, or latter third.

Some research has suggested that CS may not be as lean a medium as early media richness theory assumed (Carlson and Zmud 1999). Sensitivity analyses were conducted for the specific percentage chosen to represent the limited richness of CS ( $r_{CS} = .20, .33, .50$ ), and they demonstrated that results were relatively robust with respect to this parameter. Thus, in terms of our simulation parameters, it matters little precisely how rich CS-based learning is in respect to FTF learning. Further, since our simulation models CS use over time, we can implicitly accommodate the findings of channel expansion theory (Carlson and Zmud 1999). As individuals share knowledge via CS, their knowledge values converge, permitting more efficient exchange of knowledge via CS over time.

**Knowledge Repositories**

Organizations use knowledge repositories in support of organizational memory to store and disseminate codified knowledge, and these KR can also organize the knowledge contained in them to facilitate this process (Krishnan et al. 2001). Organizations rarely maintain a single, monolithic knowledge source, but usually assemble a collection of knowledge repositories to support the organizational memory. These are often maintained within distinct organizational subunits (Schulz 2003; Stein and Zwass 1995). As such, in our model the organization maintains a number of knowledge repositories, each geographic group (*g*) maintaining its own repository of knowledge.

When individuals contribute knowledge via these KR, most organizations establish some process through which they can control what knowledge is codified and stored, seeking to retain only the best knowledge. Some organizations only permit particular specialists to contribute to the repository (Davenport and Glaser 2002), while others assemble a team of experts to review submissions (Massey et al. 2002). Others simply make decisions about which knowledge is included at the team level (Markus 2001). Thus, knowledge contributed through repositories is usually qualified and refined in some way. For our simulation, knowledge was compared with the majority value of the geographic group (*g*). Only those dimensions of the knowledge vector that were equal to the majority value of the group were then contributed through KR.

When accessing knowledge through KR, the agent applies algorithms similar to the other forms of learning embedded in the model. Each repository maintained by a geographic group (*g*) synthesizes the knowledge contained within it to result in a single knowledge vector by selecting the majority value for each knowledge dimension. This KR knowledge vector is compared to reality, and the knowledge level is determined in the same way as both individuals and the organizational code are determined. When agents access knowledge through KR, they assemble a  $\Phi$ -group of those repositories that have higher knowledge levels than the agent. The agent then adopts the knowledge contained within these repositories according to the same algorithm implemented for each of the other forms of learning.

A summary of how the learning mechanisms are implemented within the model can be found in Table 1.

**Organizational IT Capability for Learning**

Although organizations may have access to and employ each of these forms of organizational learning, organizations will emphasize them differently through both technological and managerial initiatives. First, organizations choose to invest in developing particular technological capabilities and may emphasize CS, KR, both, or neither as the targets of their investment dollars. Second, organizations encourage employees to use particular technologies through formal incentives, cultural norms, and training for individuals to use the IT tools effectively. Even if organizations have the same IT tools, they may choose to use them differently (Devaraj and Kohli 2003).

**Table 1. Summary of Learning Forms**

Mechanism	Characteristics	Model Specifications
Face-to-face (FTF)	Geographically dependent: Individuals learn only from those in co-located group.	Population divided into 10 geographic/organizational groups ( <i>g</i> ). $\Phi$ -group assembled only from members of <i>g</i> .
Communication Support (CS)	Bounded Rationality: Individuals assemble a network of others to learn from via CS, assembled as a function of the community of practice (COP). Lean Medium: Individuals can only communicate limited knowledge in any period through CS.	$\Phi$ -group assembled from knowledge network, established according to probability of selecting another agent as part of CS network. Exchange only limited portion (.33) of knowledge vector via CS.
Knowledge Repositories (KR)	Universal Access: All individuals can access knowledge repositories equally. Knowledge qualification: only “best practices” are stored.	Each geographic group ( <i>g</i> ) maintains knowledge repository. Knowledge contributed only includes knowledge dimensions matching the majority value of <i>g</i> . Knowledge accessed by assembling $\Phi$ -group of KR with higher knowledge level than agent.

Thus, organizations assemble these distinct capabilities into distinct portfolios of learning capabilities that are defined at the organizational level. We implemented these strategies through a series of probabilities to represent the likelihood that an individual will choose one of the three learning forms in a given period ( $p_{cap}$ ). At the beginning of the simulation, one form of learning was identified as the *dominant* mechanism and was selected by members of the population according to a particular probability ( $p_d$ ). The other forms were identified as *secondary* and were selected according to a separate probability ( $p_s$ ). Several different configurations of primary and secondary forms were modeled. In the *pure* configuration ( $p_d = 1, p_s = 0$ ), the organization relied exclusively upon one form of learning. In the *augmented* configurations ( $p_d = .8, p_s = .1; p_d = .6, p_s = .2$ ), the organization preferred a particular technology but augmented it with each of the other forms of learning. In the *blended* configuration ( $p_d = .33, p_s = .33$ ), the organization employed each of the forms equally. These configurations were modeled in order to test both the main and the interaction effects for each form of learning.

## Results

The simulation was executed 30 times for each set of parameter specifications, resulting in 933,120 total conditions executed and examined. Once sensitivity analysis parameters were analyzed and eliminated, we were left with a total sample size of 1,080 total simulations and 80 periods that focused on three primary independent variables of interest: the dominant form of learning ( $p_d = FTF, CS, KR$ ), capability configuration ( $p_{cap} = pure, augmented, blended$ ), and the individual learning rate ( $p_l = .1, .5, .9$ ). The outcome variables of interest, average population knowledge level ( $K_{lev}$ ), and population knowledge variance ( $K_{var}$ ) were examined at two different stages of the iteration: longitudinally over rounds 1 through 20 and cross-sectionally at round 80.

### IT Effects on Exploration and Exploitation

Figure 3 demonstrates the effects of the form of organizational learning on the knowledge level of the average population. Two observations are noteworthy. First, an examination of the *pure* learning configurations in which individuals use only the dominant form shows that the CS and KR have very different influences on the learning outcomes of the population. KR results in very rapid short-term performance benefits, but increases in knowledge levels tend to cease within the first few rounds of the simulation. Conversely, knowledge levels under CS tend to increase more slowly but do not plateau in the same way as the other forms of learning, surpassing the overall knowledge level of the other forms by about period 15. These distinctive learning dynamics in the model are equivalent to what March identified as exploration and exploitation in his original simulation. He labeled rapid short-term gains that resulted in a relatively early learning plateau as *exploitation*, whereas he identified slower short-term learning that resulted in higher overall gains as *exploration*. Thus, CS tends to have an *exploratory* influence on organizational learning, whereas KR have an *exploitatory* effect. Second, blending the mechanisms under different learning strategies often results in significant interaction effects. Although  $K_{val}$  is influenced in different ways as forms of learning are combined in various configurations, the most striking difference is between *pure* FTF interaction and FTF learning that is *augmented* somewhat with the other forms. In the *pure* strategy, FTF learning demonstrates the characteristic *exploitation* pattern of sharp short-term gains followed by a leveling-off of knowledge growth. In contrast, when the other forms are included even to a nominal degree, the FTF condition avoids the knowledge plateau and knowledge continues to grow through the observed period at round 20. Although there appears to be some slight reduction in short-term learning benefits, the difference is negligible when compared to the overall benefits. Thus, even nominal inclusion of additional IT-enabled capabilities can have a radical impact upon learning outcomes.

### IT Effects on Knowledge Variance

Figure 4 demonstrates the influence of various learning mechanisms and strategies on knowledge variance. Under *pure* strategies, each of the mechanisms demonstrates distinctly different effects. KR introduce a spike in variance in the first few rounds of the simulation, followed by a steep reduction in knowledge variance to nearly zero by about round 8. CS also initially introduces an increase in knowledge variance, followed by a reduction in variance over the next rounds. The influence of CS on knowledge variance, however, appears to be much more gradual. Although the variance appears to be continually and steadily decreasing with the CS, an examination of knowledge variance at round 80 (not shown) demonstrates that CS will never entirely eliminate knowledge variance from within the population. FTF learning conditions seem to maintain a fairly consistent degree of variance within the population across all rounds.



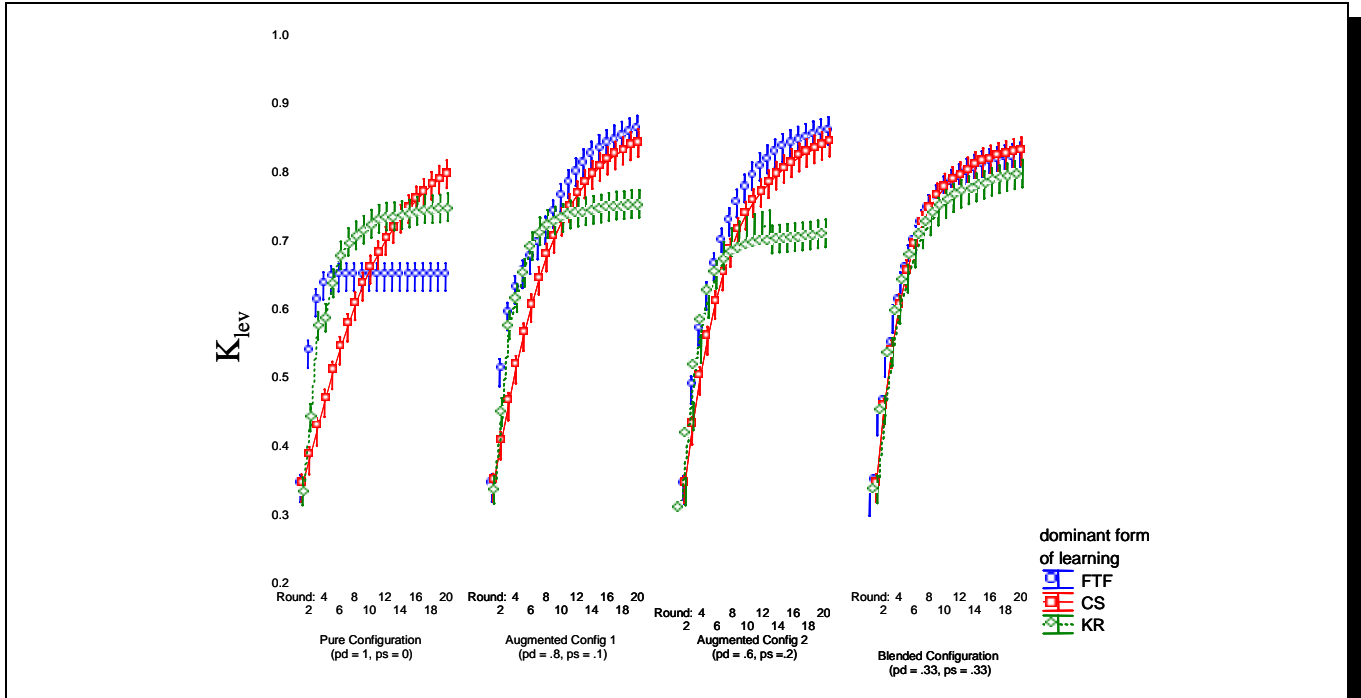


Figure 3. Effect of Learning Forms and Configurations on Round 1–20 Average Knowledge Level ( $K_{lev}$ )

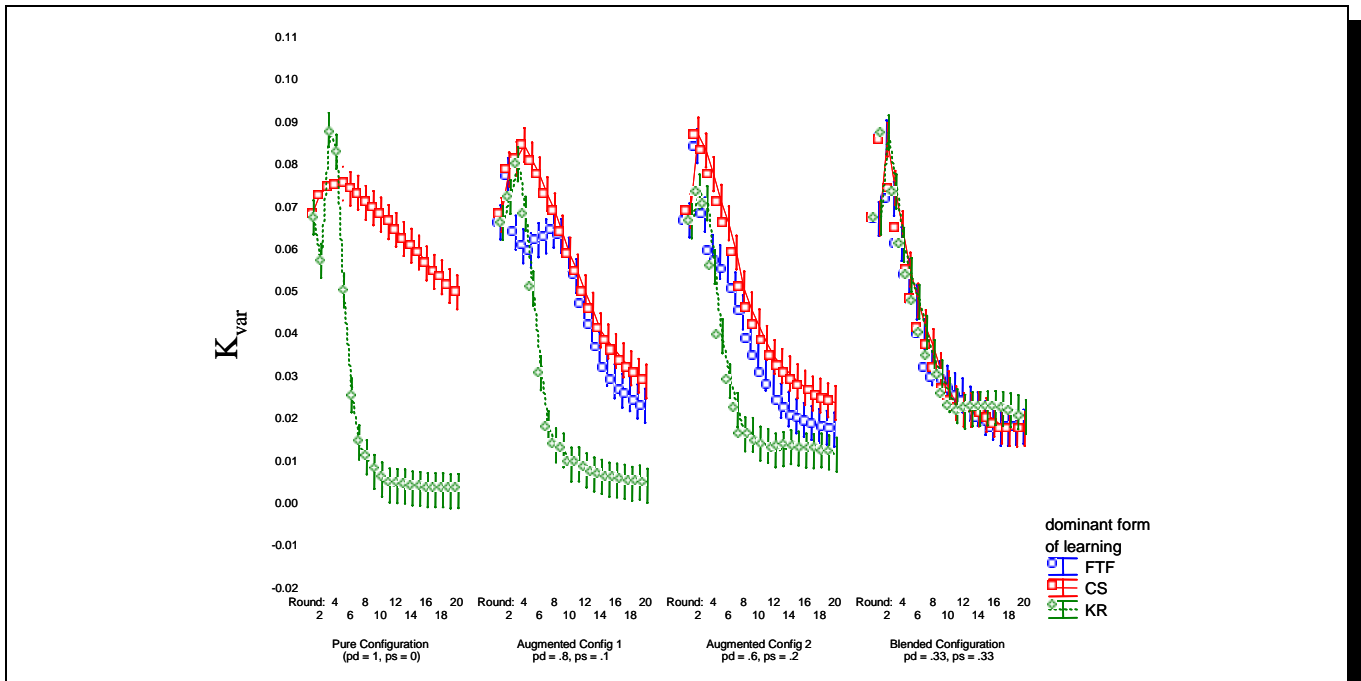


Figure 4. Effect of Learning Forms and Configurations on Round 1–20 Average Knowledge Variance ( $K_{var}$ )

Another observation regarding KR influence on knowledge variance is possible when one compares the influence of various strategies on  $K_{var}$  in rounds 1 through 20, which demonstrates that KR seem to have the dominant influence when it comes to reducing knowledge variance within the population. First, comparing the *augmented* (i.e., the provision of secondary learning forms to supplement the dominant form) and *blended* (i.e., the equal balance of all three learning forms) configurations, both the CS and FTF dominant conditions seem to be significantly affected by the influence of other forms. However, the configurations in which KR represent the dominant learning form appear largely unaffected by the introduction of other mechanisms. Second, an examination of the *blended* configuration demonstrates striking similarities to the curve of the pure KR conditions: the variance reduction pattern of a sharp spike in variance followed by rapid reduction. Each of these observations seems to suggest that KR have a significant and dominant effect upon knowledge variance in the population when compared to CS and FTF.

### IT Effects on Overall Knowledge Levels

Two observations are noteworthy when one examines the results of the learning forms and configurations of knowledge levels at the final round 80, shown in Figure 5. First, regardless of which form of learning is dominant, *augmented* and *blended* strategies tend either to match or outperform *pure* strategies. These results suggest that the forms of learning used together in some fashion tend to perform better than any single one alone. Second, the performance differences are influenced by organizational conditions, as represented by organizational learning rates. For instance, under slow learning rates ( $p_l = .1$ ), all of the configurations in which CS is dominant are relatively consistent in terms of performance outcomes, whereas under fast learning conditions ( $p_l = .9$ ), the difference between the pure and augmented configurations are relatively significant. Furthermore, under slow learning conditions, the augmented FTF configurations perform the highest, whereas this performance advantage disappears in medium ( $p_l = .5$ ) to fast ( $p_l = .9$ ) learning conditions.

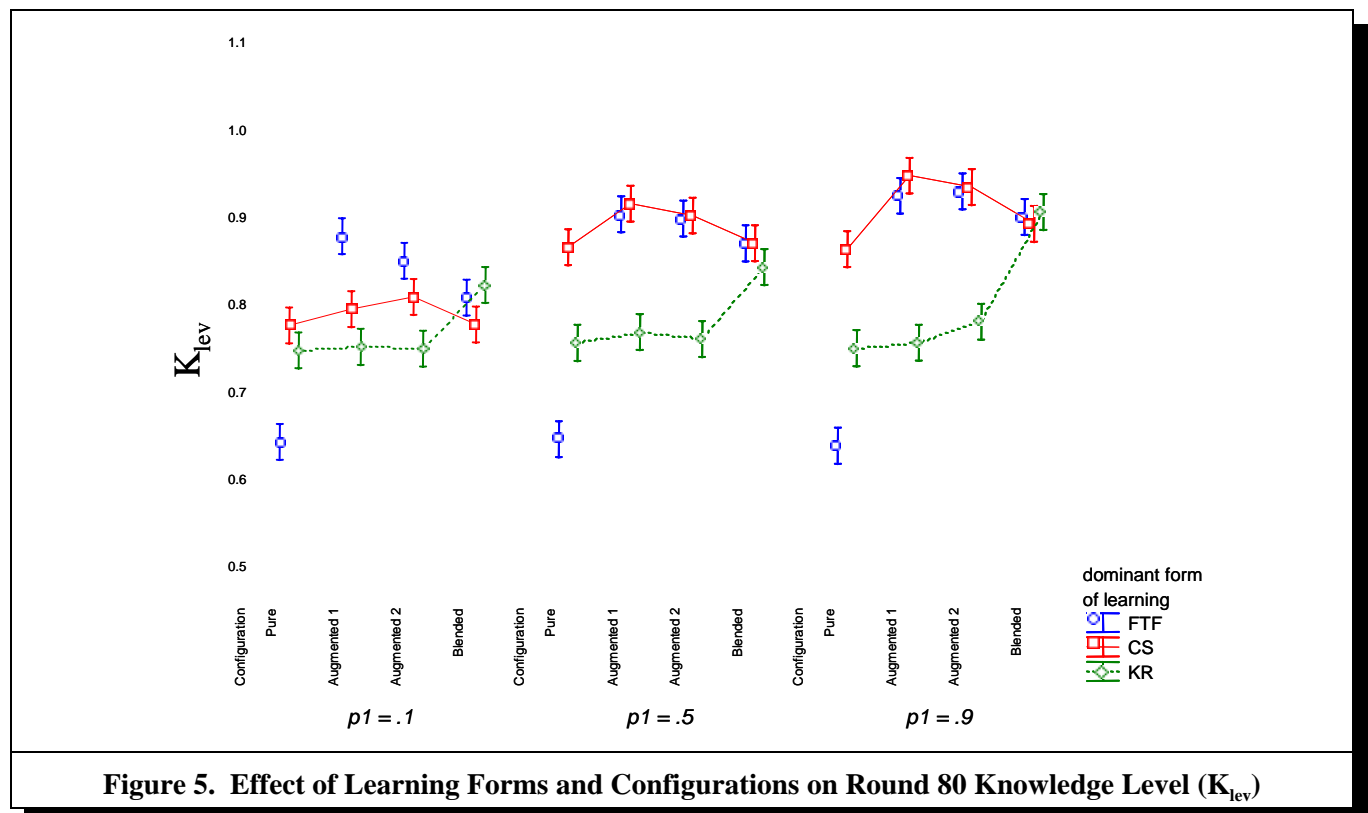


Figure 5. Effect of Learning Forms and Configurations on Round 80 Knowledge Level ( $K_{lev}$ )

## Discussion

This study investigates the effects of IT on exploration and exploitation in organizational learning. We effected it by extending an earlier computational model of organizational learning (March 1991) and by introducing learning between individuals in an organization through three distinct mechanisms: face-to-face exchange, communication support technologies, and as mediated through knowledge repositories. We found that each of these mechanisms has a distinct effect upon the exploration and exploitation dynamics in organizational learning, and we conclude that organizations that cultivate a robust IT infrastructure can enable agile learning in which exploratory or exploitative influences are introduced depending on organizational learning goals.

### *Enhancing Exploration*

The study suggests that the deployment of certain IT capabilities (communication support) can enhance *exploration* processes. Having found little difference in CS network size or structure concerning organizational performance, our results seem to indicate that CS cultivates diversity of knowledge within the population. March (1991) noted that it was the preservation of knowledge variance within the population that accounted for the exploratory influences in learning.

Our results suggest that the ability of CS to provide access to *more* sources of knowledge is not as important as the fact that it provides *different* sources of knowledge. CS helps maintain heterogeneity in knowledge *content*. Since CS operates via relatively lean media, only a portion of an individual's knowledge is shared in any given exchange. Previous research has uniformly pointed to this characteristic as a limitation of CS, but our model reveals it might be potentially advantageous for organizations over time. By exchanging only a portion of knowledge between two individuals, knowledge heterogeneity is maintained and can be drawn upon in later exchanges. Thus, CS inherently moderates the speed of learning within the population while introducing exploratory characteristics. For this reason, fast learning organizations appear to be able to leverage CS most effectively: the *exploitative* learning characteristics of the population are balanced by the *exploratory* characteristics of the medium to result in higher overall performance. Conversely, CS can under perform other learning forms in slow learning organizations, due to an overemphasis on exploratory forces, and result in lower overall performance in the short run.

### *Enhancing Exploitation*

Our model indicated that some other technological tools (represented in this simulation in the form of KR for the development of best-practices repositories) tend to enhance knowledge *exploitation* by maximizing short-term gains at the expense of long-term performance. Because of the inherent ability of knowledge repositories to collect and to process large volumes of codified knowledge, combined with their ability to provide online access to the collected knowledge, KR can quickly reduce knowledge variance across the organization. This characteristic results in enhanced short-term learning as the necessary knowledge is widely and uniformly disseminated across the organizational population. Nevertheless, since knowledge variance within the population is reduced just as rapidly, there remain few alternative knowledge sources from which to learn once these immediate gains are realized.

The process by which the KR homogenize knowledge appears to "crowd out" the knowledge heterogeneity cultivated by CS and FTF learning forms or the heterogeneity arising from the slow learning conditions inherent to the organization (Benner 2002). Simulations in which KR were the dominant form of learning appeared relatively unaffected by the introduction of CS and FTF forms of learning, whereas the latter forms were impacted fairly significantly by the inclusion of the KR (see Figure 4). These results further suggest that judicious use of KR is perhaps most effective for organizational learning. Apparently, using some KR goes a long way, and even a minimal inclusion of KR has a considerable impact upon variance reduction in the population. Organizations seeking to augment their learning processes with KR might do so with a relatively small investment and implementation. Conversely, the influence of KR tends to offer decreasing marginal benefits beyond a certain point.

### *Blending Exploration and Exploitation*

Since CS and KR have different effects upon the dynamics of exploration and exploitation in organizational learning, our results also seem to suggest that they can be combined to optimize learning within an organization. This recommendation draws upon recent work that suggests exploration and exploitation are not in actuality a tradeoff with one another, but the result of distinct forces acting within and upon the organization (Katila and Ahuja 2002). Although the underlying drivers of exploration and exploitation are both grounded in knowledge variance within the population, as March originally asserted, this variance can be manipulated using distinct IT capabilities in conjunction with one another. Our results show that a combination of organizational

learning mechanisms consistently outperforms any single mechanism of learning used independently. These results suggest that a portfolio that employs each of the available learning forms to some degree would be a more effective learning strategy than that of organizations that rely only on a single form of organizational learning.

Although the exploration–exploitation balance can be manipulated using more traditional managerial initiatives, these changes in learning dynamics can be attained through IT-enabled capabilities without resorting to more radical and disruptive methods such as turnover (Carley 1992), altering existing organizational culture (Harrison and Carroll 1991), or the recruiting of employees with a particular mix of learning capabilities (March 1991). Organizations with robust IT infrastructure in place can manipulate the exploration–exploitation balance simply by choosing to cultivate organizational learning using particular IT-supported capabilities or by disseminating knowledge through particular channels.

## Limitations and Conclusion

Like all research, this paper and the methodology upon which it is based are not without their limitations. Most significantly, simulation is a simplified representation of a real-world environment, and simplification always introduces limitations. One always risks oversimplifying a given process (e.g., knowledge represented in 30 discrete tuples), and certain environmental characteristics can only be estimated, such as the geographical barriers between face-to-face groups. We have sought to mitigate these limitations by extending a well-established and highly-regarded computational model and by grounding each of our extensions in mainstream information systems theory and research. Alongside these limitations, however, are certain benefits of simulation over other research approaches, namely the ability to analyze dynamic processes over time and the ability to exercise significant control over the environment. We believe that the benefits provided by our methodology outweigh its limitations, and we further believe that this paper makes contributions unlikely to be arrived at through other research methods. Nevertheless, the insights presented in this simulation—as in all simplifications of reality for research purposes—must be corroborated by other methods. The results of this computer simulation can and should be augmented by further empirical research, and these findings are only one small part of the cumulative research tradition involving exploration and exploitation in organizations. The findings of this study are offered as general insights into the tradeoffs between exploration and exploitation processes that result from various forms and combinations of IT deployments in organizations. As such, they provide guidelines for future research as well as for the application of technology to support organizational learning.

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