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

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This study investigates the effects of information technology (IT) on exploration and exploitation in organizational learning (OL). We use qualitative evidence from previously published case studies of a single organization to extend an earlier computational model of organizational learning (March 1991) by introducing IT-enabled learning mechanisms: communication technology (e-mail), knowledge repositories of best practices, and groupware. We find that each of these IT-enabled learning mechanisms enable capabilities that have a distinct effect on the exploration and exploitation learning dynamics in the organization. We also find that this effect is dependent on organizational and environmental conditions, as well as on the interaction effects between the various mechanisms when used in combination with one another. We explore the implications of our results for the use of IT to support organizational learning.

Key words: knowledge management; organizational learning; exploration; exploitation; simulation; groupware; knowledge repositories; knowledge portals; electronic communities of practice

The ability of organizations to learn and acquire knowledge has emerged as a key factor influencing organizational performance and survival (Argote et al. 2003, Grant 1996). Many organizations allocate dedicated resources to organizational learning (OL) and knowledge acquisition. Examples include research staff positions, research and development (R&D) departments, formal training programs, hiring employees with specialized knowledge, and the development and use of information technology (IT)-enabled learning support mechanisms. An emerging research area in the information systems (IS) field focuses on the application of advanced IT tools to support the underlying processes of knowledge sharing and organizational memory (Alavi and Leidner 2001, Sambamurthy and Subramani 2005, Robey et al. 2000).

A number of factors can influence how these IT-enabled learning mechanisms support OL. The characteristics of the mechanisms themselves, of the individuals who use those mechanisms, and of the organizational environment in which those mechanisms are used can each impact their influence. Little is understood about how the introduction of IT-enabled learning mechanisms into organizations influences complex OL processes. For instance, various IT-enabled learning mechanisms may each support distinct OL processes; but, they also may interact with one another to create different effects than when used alone. Individuals who use these IT-enabled learning mechanisms may have different learning characteristics than others who use the same mechanisms, leading certain individuals to benefit more from one type of mechanism than another type. The environmental context in which these tools are applied also may influence the way they can support OL in terms both of the organizational environment in which the mechanisms are applied and of the environment in which the organization operates.

In this manuscript, we explore the impact of IT on OL. More specifically, we use computer simulations, both individually and in combination, to investigate the impact of three types of IT-enabled learning mechanisms on learning processes: communication technology (e-mail), knowledge repositories (KRPs) of best practices, and groupware. We examine how different characteristics of the IT tools, the individuals using them, and the environment in which they are used each influences their impact. We rely on qualitative evidence and published accounts of a single organization as the basis for simulating these technologies and their associated capabilities. We then use findings of this case study to extend a previously published computational model of OL (March 1991).

Information Technology and Organizational Learning

Several organizational researchers have defined learning in terms of acquiring, retaining, and transferring knowledge at the individual and group levels (Huber 1991, Robey et al. 2000). We define *OL* as the dynamic process of creating new knowledge and transferring it to where it is needed and used, resulting in the creation of new knowledge for later transfer and use. Knowledge creation, transfer, and retention can be largely regarded as social processes involving communication, interaction,

collaboration, and discourse among organizational members. OL is related to the concept of knowledge management (KM), which is also primarily concerned with the organization's ability to create and transfer knowledge. KM, however, tends to emphasize the static stocks of knowledge held by an organization and the characteristics of that knowledge, rather than the dynamic processes through which knowledge is developed by organizations (Vera and Crossan 2002). Given their shared focus, natural points of comparison and commonality exist between OL and KM, particularly in the types of IT tools used. Nevertheless, since we are most interested in the use of IT to support dynamic knowledge creation processes, we have chosen to adopt the terminology of OL consistently throughout the paper.

We consider two forms of OL: exploration and exploitation. *Exploration* involves the development of new knowledge or replacing 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 knowledge (Larsson et al. 1998, March 1991, Smith and Zeithaml 1996). Previous literature has noted that IS can influence both exploration and exploitation in OL (Attewell 1992, Gray 2001, Pentland 1995). Missing from these investigations, however, are studies that systematically examine how organizations may use their IT-enabled learning mechanisms to affect the desired balance between exploration and exploitation in OL. Throughout the paper, we use the term *IT-enabled learning mechanisms* to refer to both the technologies themselves (e.g., e-mail, listservs) and the organizational capabilities and structures these technologies enable (e.g., an online community).

A number of important factors must be considered when assessing the influence of IT on OL. IT-enabled learning mechanisms are not applied generically to OL—rather, they are used in distinct ways to support learning processes. Certain mechanisms may enable different types of learning. For instance, KRPs may be better used for sharing structured or explicit knowledge, but communication technologies (e.g., e-mail, listservs) may be better suited for sharing unstructured or tacit knowledge (Goodman and Darr 1998). The effects of IT-enabled learning mechanisms on OL may also change over time. People may learn to use these tools to support OL more effectively (Carlson and Zmud 1999) or time may render some tools less effective as the amount of knowledge available through them becomes overwhelming for users (Hansen and Haas 2001). Understanding both the short- and long-term effects of different IT-enabled learning mechanisms on OL is important as organizations use these tools toward the attainment of various OL outcomes.

Most organizations, however, do not use only a single IT-enabled learning mechanism to support OL; instead, most use a combination of mechanisms (Goodman and Darr 1998, Vertegaal 2003). Because individual IT-enabled learning mechanisms have distinct influences on OL processes, using multiple mechanisms together to support OL may result in unpredictable outcomes. This combination of IT-enabled learning mechanisms may not involve a simple aggregation of their effects, since the relationship between different types of OL processes are non-linear and may involve significant interactions (Katila and Ahuja 2002). Furthermore, individuals often use IT-enabled learning mechanisms differently than intended by their designers. For instance, researchers have found that individuals used groupware systems to support OL in significantly different ways than their managers or the system designers intended (Orlikowski 1996), and these variations may increase as different systems are used in conjunction with one another.

Previous literature has provided mixed messages on the combined use of different IT-enabled learning mechanisms to support OL. The notion of balance between exploration and exploitation has been a consistent theme (March 1991, Teece et al. 1997, Weick 1992). It is generally believed that short- and long-term performances of organizations depend on achieving an effective balance between these two processes. Other researchers, however, have suggested that blending different types of IT-enabled learning mechanisms to support OL is detrimental, suggesting that organizations choose a single type of IT-enabled learning mechanism (Hansen et al. 1999). It is unclear how these seemingly contradictory prescriptions might be reconciled with one another or which prescription is preferable. Nevertheless, understanding whether and how to use IT-enabled learning mechanisms in conjunction with one another is a critical issue in OL.

The effects of IT-enabled learning mechanisms on OL can also be significantly influenced by the individuals who use them. Mechanisms might support individuals who have different learning capabilities in different ways. This effect might be complementary, IT enhancing learning capabilities that are already well developed in the individual. For instance, people who are more creative are better able than people who are less creative to leverage groupware to develop innovative ideas (Garfield et al. 2001). In contrast, this effect might be compensatory-IT augmenting underdeveloped individual learning capabilities. Faced with large volumes of information, individuals with limited memory may benefit significantly from knowledge repository technologies that enable them to compensate for this limitation. Understanding how different IT-enabled learning mechanisms are influenced by the learning characteristics of the individuals who use them may be an important factor in understanding their effect on OL.

The influence of particular IT-enabled learning mechanisms may also be dependent on organizational and environmental conditions. Organizational turnover, for instance, has been shown to be an important condition

for understanding OL, but its effect is somewhat paradoxical. Organizational turnover can result in the loss of key organizational knowledge because employees take their knowledge with them when they leave the organization, but it can also bring critical new knowledge to the organization through the contributions of new employees (Carley 1992, March 1991). IT-enabled mechanisms may have similar seemingly contradictory effects in relation to environmental conditions (Robey and Boudreau 1999). For instance, KRPs may preserve knowledge despite organizational turnover by retaining knowledge held by the individuals after they leave (Griffith 1999). By storing vast amounts of knowledge, however, repositories may also make the organization less sensitive to and aware of new knowledge, restricting the assimilation of new knowledge from the environment or the knowledge brought by new employees (Gill 1995). Understanding how IT-enabled learning mechanisms operate differently in both high- and low-turnover environments is a critical factor in determining how to use these mechanisms to support OL.

Another condition that may influence the effectiveness of particular IT-enabled learning mechanisms is environmental turbulence that leads to changing knowledge requirements for an organization. In some situations, the knowledge requirements of the organization are relatively stable. Certain industries such as construction or manufacturing experience relatively minor change in knowledge requirements over time. In other industries, the knowledge requirements are highly turbulent. The biotechnology industry, for instance, experiences relatively significant changes in both the core knowledge and the means of obtaining that knowledge (Enriquez et al. 2002). Organizations in turbulent environments need to accommodate radical changes in knowledge requirements. Certain IT-enabled learning mechanisms may function better under different levels of environmental turbulence. Understanding how different IT-enabled learning mechanisms function under both internal and external environmental conditions such as organizational turnover and environmental turbulence may be critical for understanding their influence on OL.

Research Method and Setting

To explore the effects of IT on exploration and exploitation, we replicate and extend a computational model of OL developed by March (1991). Building on 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 exploration and exploitation framework (Benner 2002, Lee and Lee 2003), but surprisingly lit-

tle work has extended the original model on which the theory of exploration and exploitation was based.

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 and executed, followed by analysis of the program's output (Carley 1995). These models represent theoretical abstractions of real-world organizations and focus on simulating general organizational principles and processes. Comparing and contrasting ideal type models yield results that 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 dynamic and nonlinear processes over time. Within a model, the researcher can vary the parameters of the simulation to assess the effects of various manipulations on specific processes and their outcomes. Because of the control the researcher enjoys over the research environment, computer simulations have often been called "virtual experiments" (Prietula et al. 1998).

Because computational modeling is a theoretical abstraction and simplification of reality, the researcher can use empirical observation to inform the development and implementation of model parameters and their values. Recent research has combined qualitative case study with computational modeling to develop an effective research method that is likely greater than the sum of its parts (Rudolph and Repenning 2002, Sastry 1997). Qualitative evidence provides rich insight into organizational processes, and this insight can be effectively used to develop the computational model. Computational modeling formalizes the observations made as a result of the qualitative analysis, extending and manipulating these results in ways that would be difficult to obtain through qualitative observation alone.

To extend March's (1991) model to account for the introduction of IT into OL, we rely on a series of published case studies of a single organization (Alavi et al. 2005, Gongla and Rizzuto 2001, Huang 1998, Mack et al. 2001). The company studied will be known in this paper by the pseudonym Company Z. Company Z relies heavily on, and is regarded as a worldwide leader in, applying IT tools inside its organization. In addition to using published accounts, we were granted access to the primary qualitative interview data collected by some of these researchers (Alavi et al. 2005), providing us with rich insight regarding the role of IT tools in learning processes for this organization.[1] The interview data were coded by both of the researchers independently, and the results were compared and reconciled to provide greater reliability. The results were then placed in a content-analytic summary to facilitate analysis and provide a data structure on which to base our extensions to the model (Miles and Huberman 1994).

Company Z uses three types of IT to support OL, which are roughly equivalent to general classes of IT-enabled learning mechanisms identified elsewhere in the IS literature. First, Company Z has developed a robust system for knowledge storage and retrieval using disparate *knowledge repositories and portals* (KRP) which provide efficient access to the contents of these repositories. Knowledge repositories have been regarded by IS researchers as the cornerstone of OL initiatives (Argyres 1999, El Sawy and Bowles 1997). Second, Company Z uses groupware (in form of a combination of communication technology and KRPs) to create a secure learning environment, known as virtual *team rooms* (TRs), in which project teams can share and discuss engagement-specific knowledge with one another. IS researchers have investigated the role of similar types of groupware to support team-level learning in this way (Dennis et al. 1988, Orlikowski 1996). Third, Company Z relies heavily on communication technologies (e-mail and instant messaging) to connect employees who share common interests and expertise from across the globe into *electronic communities of practice* (ECOPs). These ECOPs have drawn considerable interest from researchers in recent years (Ahuja and Carley 1999, Wasko and Faraj 2005). Further details regarding how Company Z uses these IT-enabled learning mechanisms to support OL can be found in Table 1.

Replicating March's Model

March (1991) constructed a computational model of an organization to explore how different factors influenced the nature and effectiveness of learning. March's model of OL is parsimonious, comprising three primary components: (1) an external reality (reflecting what the knowledge or beliefs of the organization should be), (2) an organizational code representing the organization's 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). See Appendix A for a detailed description of March's original model.

March (1991) 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. (However, the equilibrium value may actually differ from reality.) March found that higher individual learning rates and higher learning rates by the code resulted in quicker convergence of knowledge levels to equilibrium (exploitation). March also found that slower individual learning rates accounted for many of the higher equilibrium levels, especially when coupled with fast code learning. This result occurred because slow individual learning extended heterogeneity of the individuals' knowledge, therefore disallowing premature convergence of the organizational code to lower knowledge equilibria (exploration). Thus, the rapid diffusion of knowledge may not necessarily be a desirable organizational characteristic if the level of knowledge matters more than quicker resolutions of individual heterogeneity.

March (1991) also extended this basic model to account for the effects of organizational turnover and environmental turbulence. To simulate turnover, March allowed the possibility for any given individual's knowledge to revert to an initial random state according to a set probability, representing the replacement of one individual with another. To simulate environmental turbulence, March introduced the possibility of the knowledge dimensions of reality to change according to a different parameter. March found that organizational turnover and environmental turbulence each had a detrimental effect on average knowledge levels in the population, although in certain situations these environmental conditions had a positive effect on the code knowledge by introducing an additional exploratory effect into the learning processes. We first replicated these models and validated our efforts by comparing these results with March's.

Extending the Model

Using Company Z as a guide, we modified March's (1991) model in three primary ways to account for the introduction of IT in OL. First, we made baseline modifications to his original model—modeling learning between individuals and project teams—to more closely replicate the organizational conditions represented by Company Z and most contemporary organizations. Second, we modeled the three types of IT-enabled learning mechanisms used by Company Z to support OL—KRP, TRs, and ECOP. KRP uses KRPs to store and make valuable knowledge available across the organization, TR uses a combination of IT tools to support OL at a local level, and ECOP use communication technologies to transfer knowledge between individuals. Third, we modeled a number of different possible configurations of these tools. These different configurations also enabled us to isolate the particular features of each tool, helping us to understand how these tools are used in conjunction with one another and permitting a greater degree of generalization of our findings beyond Company Z. Table 2 illustrates and describes our extensions in relation to March's (1991) original model.

Baseline Extensions. We first modified March's (1991) model in two key ways—modeling learning between individuals and modeling project teams in the population—to facilitate our later introduction of IT-enabled learning mechanisms to support OL.

First, we extended March's (1991) model to allow individuals to learn from one another. Although March did not permit learning between individuals in his original model, he explicitly addressed this characteristic of his model and introduced the possibility for individuals to interact with one another (p. 75). A long and robust

Table 1   Summary of IT-Enabled Learning Mechanisms Used by Company Z and Implemented in Simulation

IT-enabled learning mechanism	General observations from case study	Examples from case study evidence	Model specifications
KRP	1. Employees contribute knowledge to repositories maintained by project teams. 2. Contributed knowledge is vetted by subject matter experts within the team. 3. Access knowledge through portal that aggregates and organizes the knowledge. 4. Employees noted that KRPs often became out of date, since no formal procedures to remove knowledge once contributed.	1. "The repositories are independently organized, each one of them. There are some standard things that they have to have in there, but then each team can apply its own categorization to it." 2. "An important part of this is content evaluation. We do not put anything on the repository that is not vetted by the subject matter experts. All content in the repository has been reviewed for quality." 3. "It is basically a huge database that ties together all these other databases. You can get to it through the Intranet and you can go on and do a search like a megasearch, where you can search all the different databases." 4. "Now with the knowledge in the repositories we have a whole lot of noise and nobody has the time to search it all. It takes a lot of effort to get what you want at times."	1. Each project team (t) maintains independent repository. 2. Individual knowledge is compared to those with above-average knowledge levels in team. Only tuples matching the majority are contributed to KRP. 3. Knowledge portal synthesizes knowledge in each repository into single vector. The individual searches portals to assemble Φ_{KRP}-group of vectors from which individual learns. 4. Once knowledge contributed to a repository, remains in repository for duration of simulation.
TRs	1. TR used primarily to support learning within a project team. Password protected to exclude nonteam members.	1. "The process to set up a TR is fairly easy. It's a really helpful way to coordinate project-specific knowledge because you don't have to worry about sanitizing knowledge." "Because we know the room is secure, we can challenge each other in there and get a sense of what is really contributed."	1. Φ_{TR}-group assembled only from members of project team (t).
ECOP	1. ECOP assembled on the basis of shared interests among employees. 2. Employees learn from a subnetwork of individuals within the ECOP. 3. ECOP reported as relatively lean channel compared to other tools.	1. "The membership of the community is voluntary. Members have a 'day job'. …it is the passion for the knowledge domain that motivates people to participate [in these communities]. Members are willing to spend personal time on that." 2. "People typically rely on people they have a previous relationship with…for example, if they've worked together before. They simply trust the responses more if they know the people. The higher [the] level of trust, also the more quickly people will respond." 3. "In the tools used for ECOP, knowledge sharing can be limited because there's not very much you can actually say on a particular subject. It's small in that respect. If you want more on a particular subject, then you would rely on other tools like the [knowledge repository]."	1. Individuals randomly assigned to one of four interest groups at beginning of simulation. 2. Individuals assemble subnetwork of other employees based on whether or not individuals shared interest parameter. 3. Exchange only limited portion ($R_{ct} = 0.33, 0.20$) of knowledge vector via ECOP.

Notes. We model three approaches at Company Z. (1) Knowledge repositories (KRPs), which are our more formal, explicit tools for sharing knowledge (2) TRs, which are a very unstructured environment in which team members share with one another, and (3) electronic communities of practice (ECOP), which involve people from many different teams all living under one roof.

research stream examines how individuals learn directly from one another in interpersonal settings (Borgatti and Foster 2003), and OL literature has used similar sorts of models that embed learning between individuals (Chang and Harrington 2005). Since learning is operationalized within March's simulation 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 found in the model.

When seeking to learn from other individuals, people tend to look for knowledge from those they perceive as having superior knowledge (Perry-Smith and Shalley 2003). For consistency, we sought to implement individual learning in ways as similar as possible to the original model. The algorithms for individual learning are replicated from March's (1991) original model, in which the code assembles knowledgeable individuals from which to learn. In our case, though, we substitute the individual learning parameter for the OL

Table 2 Illustration and Description of Extended Model

Callouts:

- **TR** Learn only from individuals with same team number
- **KL** Percent of individual/code knowledge dimensions match reality
- **KRP** Team members contribute to KRP at team level. Knowledge synthesized across repositories through portal for dissemination across population and stored for use in later rounds.
- **ECOP** Learn from network of others based on same interest number.
- **Φ-group** All eligible sources with higher KL (here, Φ-group for code = individuals with KL > 0.47)

Knowledge dimension #	Team number	Interest number	1	2	3	4	5	6	7	...	25	26	27	28	29	30		KL
Reality			1	1	−1	1	1	−1	1	...	−1	1	1	−1	1	1		
Code			1	1	−1	1	1	−1	1	...	1	−1	−1	1	−1	−1		0.47
Individual 1	1	1	1	1	−1	1	1	−1	1	...	−1	1	1	−1	1	1		1.0
Individual 2	1	2	0	1	−1	1	1	−1	1	...	−1	1	1	−1	1	1		0.97
Individual 3	1	3	0	0	−1	1	1	−1	1	...	−1	1	1	−1	1	1		0.93
...																		...
Individual n	5	2	−1	−1	0	−1	0	1	0	...	−1	1	1	−1	1	1		0.50
...																		...
Individual 98	10	2	−1	−1	0	−1	−1	0	−1	...	0	−1	0	1	1	1		0.07
Individual 99	10	3	−1	−1	0	−1	−1	0	−1	...	0	−1	0	1	0	1		0.03
Individual 100	10	4	−1	−1	0	−1	−1	0	−1	...	0	−1	0	1	0	−1		0

KRP boxes:

- 1 0 −1 ... 1 1 / 1 1 0 ... 0 −1 (KRP for Group 1)
- −1 0 −1 ... 0 1 (KRP for Group 5)
- 1 0 −1 ... 1 1 / 1 1 0 ... 0 −1 (KRP for Group 10)

Note. KL = knowledge level.

parameter. Thus, when a given individual seeks to learn from others in the population, that individual assembles a group of knowledgeable individuals (Φ-group) from which to learn (Fang et al. 2006). When assembling the Φ-group, an individual cannot know which knowledge that another individual or source possesses may be valuable (i.e., the same as reality), but the individual simply knows and chooses to learn from particular individuals or nonhuman repositories that are generally more knowledgeable. Parameter specifications were chosen for the three IT-enabled learning mechanisms so that the number of available sources from which an individual could assemble the Φ-group was approximately equal for each. Controlling for the number of knowledge sources allowed us to focus on how the particular features of each mechanism influenced outcomes.

Second, employees in most large organizations are not uniformly distributed, but rather are organized into some form of organizational structure. Company Z is no exception. These organizational structures can influence the nature and effectiveness of OL and also how IT is used to enhance it (Carley 1992, Siggelkow and Rivkin 2005). Given the team-based structure preferred by Company Z, we organized the population into a simple team-based structure consisting of an equal number of identically sized and configured teams. This relatively simple structural form was chosen to maintain simplicity in the model (Taber and Timpone 1996), while permitting us to capture ways in which the use of IT-enabled learning mechanisms may be influenced by these organizational structures. At the beginning of the simulation,

we partitioned the population into 10 distinct project teams (*t*) of 10 individuals each. Each individual was placed in one project team and remained a member of that team throughout the duration of the simulation. The number of teams into which the population was partitioned was based on trial simulations conducted during the initial construction of the model. We experimented with various team sizes ($n = 2, 5, 10, 25, 50$) and found that all but the largest and smallest teams performed relatively consistently with one another. Thus, we chose a middle value ($n = 10$) on which to base the remainder of our extensions.

Knowledge Repositories and Portals. A combination of technology and processes governed how KRPs were used by Company Z to support OL. Individuals contributed to KRPs at the team level. Through the process of repackaging knowledge to be made more relevant to others in the organization, subject matter experts vetted the repackaged knowledge to ensure its quality and applicability. The knowledge portal then provided powerful tools to search and access the knowledge held in the disparate team-level repositories across the organization. Once knowledge was added to the repository, no formal procedures were established to remove outdated knowledge. Although recognized by users as having notable limitations, this practice characterized the way Company Z used KRP.

These features were implemented into our simulation. The process of using the KRP for knowledge sharing involved three stages: (1) individuals contributing KRPs,

(2) synthesizing knowledge, and (3) portals disseminating knowledge. First, individuals contribute their existing knowledge to the repository maintained by their team (t). This knowledge is vetted by team members by comparing an individual's knowledge to that of the most knowledgeable members of the team (those with knowledge levels above the group average) that represented the subject matter experts. Only those knowledge dimensions that matched the majority values of this group of knowledgeable individuals were included in the KRP. The KRP retains all knowledge contributed to it for the remainder of the simulation. Second, each repository maintained by a project team (t) synthesizes the knowledge it contains to produce a single knowledge vector. At the beginning of each round, the repository aggregates all of the knowledge contributed to it and selects a majority value for each knowledge dimension. These values become the knowledge vector for the repository. This knowledge vector is compared to reality, and the knowledge level for the repository is determined. Third, the knowledge portal disseminates the knowledge by allowing individuals to search knowledge held in each of the independent repositories maintained by teams across the organization. When individuals access knowledge through the knowledge portal, they search the repositories by assembling a Φ_{KRP}-group of those repositories that have knowledge levels that are higher than the individual's level. The individual then adopts the knowledge contained within these repositories according to a similar selection algorithm implemented for each of the other forms of learning used in the simulation.

Therefore, when learning via KRP, individuals contribute knowledge to the KRP by (1) identifying which members of the team have a higher knowledge level than the individual (subject matter experts) and (2) contributing to the team-level repository only those dimensions of the knowledge vector that match the majority value of these subject matter experts (vetting knowledge). Each team-level repository synthesizes all of the knowledge contained within it, contributed in this and previous rounds, into a single vector. Individuals adopt knowledge from the KRP by (3) assessing which of the knowledge vectors in the team-level repositories has a higher knowledge level than the individual (Φ_{KRP}-group), and (4), for each dimension of the knowledge vector, adopting the majority value of the Φ_{KRP}-group of repositories according to a given probability set by the individual learning parameter ($p1$).

Team Rooms. Company Z used both knowledge repository and communication technologies to support learning within a given project team, restricting learning in TR to occur only within the project team. In our simulation, when individuals choose to learn via TR, they assemble their superior group (Φ_{TR}-group) and learn only from the individuals who have been assigned to the same project team (t). Learning in TR is thus confined to

a local scope, compared to the other tools, which permit a wider exchange of knowledge.

When learning via TR, individuals (1) assess which of all individuals in the project team (t) have a higher knowledge level than the individual (Φ_{TR}-group), and (2) for each dimension of the knowledge vector, adopt the majority value of the Φ_{TR}-group according a given probability set by the individual learning parameter ($p1$).

Electronic Communities of Practice. The case studies of Company Z revealed that ECOP were organized along particular interest groups and involved individuals learning from a subnetwork of employees within the ECOP. In terms of our simulation parameters, individuals were randomly assigned to have one of four general interests that represent those topics around which the ECOP are organized. Individuals assemble a subnetwork of others from which to learn within the ECOP according to a set probability ($p_i = 0.25$). Although individuals cannot belong to more than one ECOP in our simulation, we did introduce the possibility for individuals to learn from other individuals in the population according to another probability ($p_{ni} = 0.02$) to represent the permeable boundaries between the ECOP that were accounted for in the case studies. Parameter values were varied somewhat and results were robust with respect to these variations ($p_i = 0.35, 0.25, 0.15$; $p_{ni} = 0.01, 0.02, 0.03$). We also imposed alternative network structures on these ECOP. These had no significant influence on the results of our simulation, so we chose a simple random network structure.

ECOP members also claimed that communication technologies used as the basis for ECOP are regarded as a relatively lean learning mechanism when compared to other mechanisms. We sought to model this characteristic of communication technologies by specifying that individuals could only exchange a portion of their knowledge dimensions with others when using communication technologies for learning. If the interest parameter defines who an individual can learn from using ECOP, the mechanism richness parameter governs what can be learned via these channels. In a given period, the individual randomly selects a portion of the code to learn from the Φ_{ECOP}-group. Since the reputation and credentials of individuals in a network of practice are not limited by the communication medium, this channel leanness did not affect the formation of the Φ_{ECOP}-group. Individual knowledge levels are still based on the entire individual knowledge, even though only a portion is exchanged.

It is interesting to note that respondents perceived the tools used to support ECOP as a lean mechanism but did not so perceive the others, such as KRP and TR. It may be that ECOP enables types of knowledge sharing in practice other than the other IT-enabled learning mechanisms. This difference could affect the amount and type of knowledge exchanged through a given mechanism.

TR were used to augment face-to-face relationships, and this inherent multiplexity may have provided significant contextual information when used in practice. The KRP also contained a high volume and variety of knowledge (including multimedia), perhaps also lending itself to perceptions of greater richness. TR and KRP are able to provide a considerable amount of background information in ways that ECOP does not. Furthermore, knowledge in the KRP was repackaged for consumption by a more general audience (e.g., project-specific information was removed, keywords added, key points synthesized, etc.) and thus the KRP was explicitly and intentionally made more lean. Employees may perceive this synthesized knowledge differently. ECOP, in contrast, enabled people with common interests and knowledge to exchange knowledge regarding relatively specific and deep issues, without the benefit of significant contextual or shared background knowledge. The main differences may be that the former two spaces are used to share codified materials while the ECOP is used to ask or discuss highly tacit questions and issues. Each technology provides affordance to different types of knowledge sharing. This difference would account for the variance in perceptions of richness for each mechanism.

In sum, when learning via ECOP individuals (1) identify individuals that belong to their ECOP subnetwork, (2) assess which of these individuals have a higher knowledge level than the individual (Φ_{ECOP}-group), (3) select a portion (R_{ct}) of the knowledge vector to learn from the Φ-group, and (4) for each dimension of the knowledge vector, adopt the majority value of the Φ_{ECOP}-group according a given probability established by the individual learning parameter ($p1$).

Combining IT-Enabled Learning Mechanisms for OL. Company Z uses all three IT-enabled learning mechanisms to support OL. Once we modeled the three mechanisms in the simulated organization, we varied the degree to which the organization used each for learning. This variation enabled us to isolate the distinct features of each, as well as examine how they function in combination with one another.

We implemented these variations through a series of probabilities to represent the likelihood that an individual will choose one of the three learning forms in a given round. At the beginning of a given round of knowledge exchange, each individual chooses to use one of these mechanisms, according to probabilities established at the beginning of the simulation. The choice of an IT-enabled learning mechanism in one round does not influence the choice of other mechanisms in further rounds. At the beginning of the simulation, one mechanism was identified as the dominant tool and was selected by members of the population according to a particular probability (p_d). The other mechanisms were identified as secondary tools, 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 on one form of learning. In the *augmented* configurations ($p_d = 0.8$, $p_s = 0.1$; $p_d = 0.6$, $p_s = 0.2$), the organization preferred a particular technology but augmented it with each of the other forms of learning. In the *blended* configuration ($p_d = 0.33$, $p_s = 0.33$), the organization used each of the forms equally. These configurations were modeled to test both the main and the interaction effects for each form of learning.

Evaluating Computational Models. Several criteria have been forwarded to evaluate the validity and contribution of computational models (Taber and Timpone 1996, Burton and Obel 1995). First, choices regarding model parameters should be grounded in existing theory or empirical observation, or both, to ensure that the model captures and simulates the critical features of reality in appropriate ways. Table 1 shows our model parameters and the empirical observations on which they are based. Second, parameters must be subjected to sensitivity analyses in which they are varied within a given range to ensure that the results of the model do not stem from arbitrary choices by the researcher during model construction. Table 3 details our parameter values and the sensitivity analyses conducted. Third, computational models should be made as simple as possible to isolate the most important theoretical features being analyzed and to minimize extraneous influence. (Appendix B contains a flowchart of our programming logic.) Fourth, results of the model should have face validity, but should also provide new and interesting insights not immediately obvious during model construction. These implications are addressed in our results section and our discussion section.

Results

The simulation was executed 30 times for each set of parameter specifications. Each of the conditions was systematically analyzed and evaluated. Once values and parameters included for sensitivity analysis were determined to have no significant effect on model outcomes, they were discarded. On completing specification analysis, we focused on a few primary areas of interest for detailed analysis. We focused most intently on the most interesting, surprising, and important outcomes of our model: exploration and exploitation characteristics of specific IT-enabled learning mechanisms individually and in combination, the influence of individual learning rates on particular mechanisms, and the influence of the mechanisms under different environmental conditions. Following March (1991), we examined the effects of parameter variation on average population knowledge level (K_{pop}), code knowledge level (K_{code}), and knowledge variance in the population (K_{var}). Also consistent

Table 3 Parameter Values and Sensitivity Analysis

Parameter	Values used in final model	Additional values included for sensitivity analysis	Values reported by March (1991)
Dominant tool	TR, ECOP, KRP		
Tool configuration ($p_d/p_{s1}/p_{s2}$)	100/0/0, 80/10/10, 60/20/20, 33/33/33	80/0/20, 80/20/0	
Individual learning rate (p_1)	0.1, 0.5, 0.9	0.3, 0.7	0.1–0.9
OL rate (p_2)	1	0.1, 0.3, 0.5, 0.7, 0.9	0.1–0.9
Turnover (p_3)	0, 0.1, 0.3	0.2, 0.5, 0.9	0.1, 0.9
Turbulence (p_4)	0, 0.01, 0.03	0.01, 0.02, 0.04, 0.05, 0.1	0.02
Mechanism richness (R_{ct})	0.2, 0.33	0.1, 0.5, 1	
Number of teams (t)	10	2, 5, 20, 50	
ECOP structure	Random network	Core-periphery structure	
Probability of including those with shared interest in ECOP subnetwork (p_i)	0.25	0.15, 0.35	
Probability of including those not with shared interest in ECOP subnetwork (p_{ni})	0.02	0.01, 0.03	

with March, we look at these outcomes in terms of both short-term dynamics (Rounds 1–30) and long-term equilibrium (Round 80).

The value of computer simulation as a research methodology rests less on the actual results obtained and more on the process of understanding and explaining why the model operates in the way it does. Therefore, in addition to presenting the results, we also seek to understand why our model behaves as it does. If an examination of our simulation results can uncover the causal mechanisms behind them, the simulation provides results that can both inform real-world situations and generalize these findings into less-studied domains of IT and OL.

Exploration and Exploitation. The first observation from our simulation is that, when examined alone, different IT-enabled learning mechanisms appear to have different effects on exploration and exploitation processes in organizations. Figure 1 demonstrates the effects of IT-enabled learning mechanisms on the knowledge level of the average population. Both KRP and TR yield similar learning patterns: very rapid short-term performance benefits that tend to plateau within the first few rounds of the simulation. March (1991) labeled these patterns exploitation, and our simulation suggests that these tools tend to have an exploitatory effect on OL. Conversely, knowledge levels under ECOP 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 Round 15, then continuing to improve. March labeled this pattern exploration, and our simulation suggests that ECOP has an exploratory effect on OL.

March (1991) argued that these exploration and exploitation effects are driven by the heterogeneity of knowledge in the population. Figure 2, which demonstrates the effect of each mechanism on knowledge

variance within the population, supports this interpretation. KRP results in rapid reduction in knowledge variance within the first two rounds, virtually eliminating the knowledge variance in the population by about Round 5. ECOP initially introduces an increase in knowledge variance, followed by a gradual reduction in variance in successive rounds. Although the variance appears to be continually and steadily decreasing with the ECOP, an examination of knowledge variance at Round 80 (not shown) demonstrates that ECOP will never entirely eliminate knowledge variance within the population ($K_{var} = 0.02$). TR seem to maintain a fairly consistent degree of variance within the population across all rounds. Further analysis demonstrates that this variance exists across rather than within the project teams. Requisite knowledge variance exists within the population, but the organization lacks the means to get the knowledge to the individuals who can benefit from it. Thus, consistent with March, exploitation tools are characterized by a rapid homogenization of knowledge, whereas exploration tools tend to preserve the heterogeneity of knowledge longer in the process.

Combining Mechanisms. Figure 1 also demonstrates the results of combining IT-enabled learning mechanisms on average population knowledge levels. TR demonstrate the most substantial effect of blending mechanisms. When other tools are combined with TR, this configuration avoids the knowledge plateau characteristic of exploitation, continuing to improve average population knowledge levels into later rounds and to outperform predominantly exploration tools (ECOP-dominant) in the long run. We do not see the same marked improvements, however, when other tools are blended with KRP. KRP appears to perform largely the same regardless of the particular blend of IT-enabled learning mechanisms. All the simulations in which KRP was dominant ($p_d = 1, 0.8, 0.6$) performed nearly

Figure 1 **The Effect of IT-Enabled Learning Mechanisms on Knowledge Levels** (K_{pop}, Round 1–30, $p_1 = 0.5$, $R_{ct} = 0.33$)
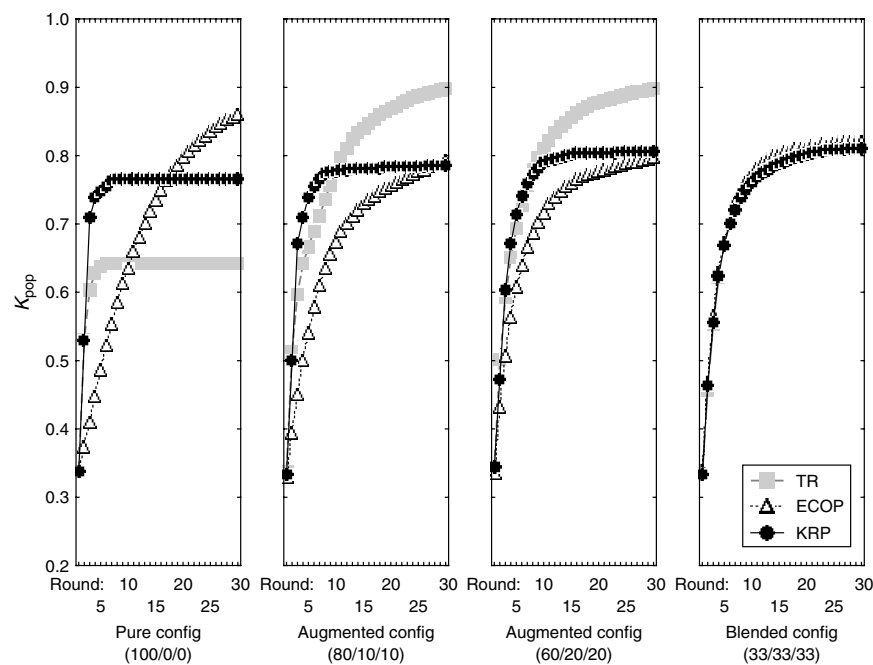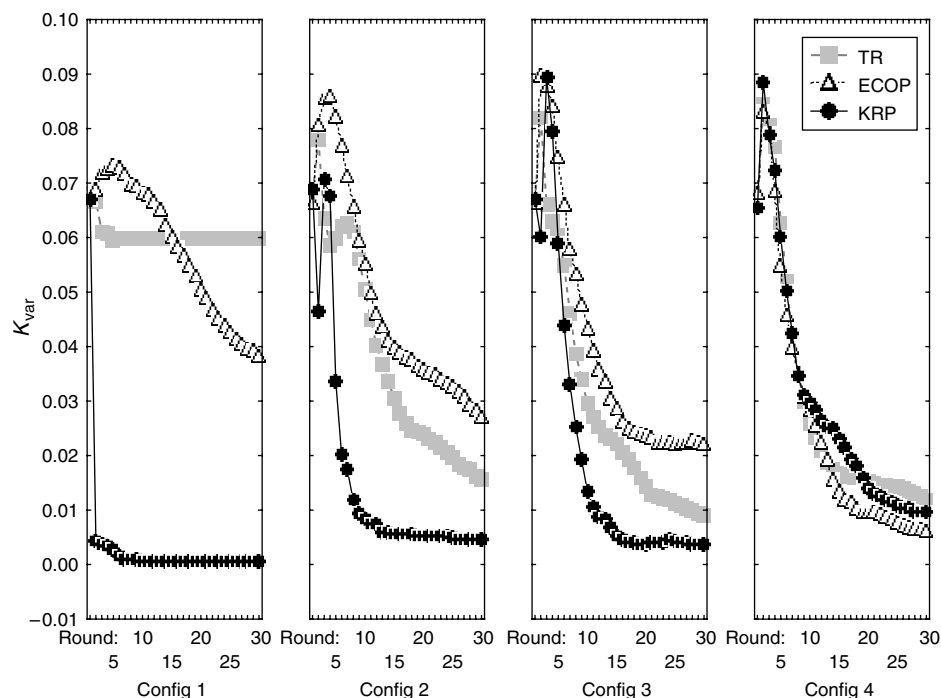

Note. Config = configuration.

equally with one another, except for the blended configuration in which all three tools were used equally. ECOP behaves still differently when other mechanisms are added. In these cases, the blending of mechanisms tends to have a detrimental effect on overall knowledge levels. This effect is only marginal in relation to average population knowledge level (Figure 1), but becomes

more dramatic in relation to levels of knowledge held by the organizational code (Figure 3).

One key to understanding how blending IT-enabled learning mechanisms promotes or reduces knowledge heterogeneity can be explained by the knowledge transformation cycle identified by Carlile and Rentibish (2003). This cycle involves three stages: individuals

Figure 2 **The Effect of IT-Enabled Learning Mechanisms on Knowledge Variance** (K_{var}, Round 1–30, $p_1 = 0.5$, $R_{ct} = 0.33$)

Note. Config = configuration.

Figure 3 The Effect of Combining IT-Enabled Learning
Mechanisms on Knowledge Levels (K_{pop}, Round 80,
$p_1 = 0.9$, $R_{ct} = 0.2$)
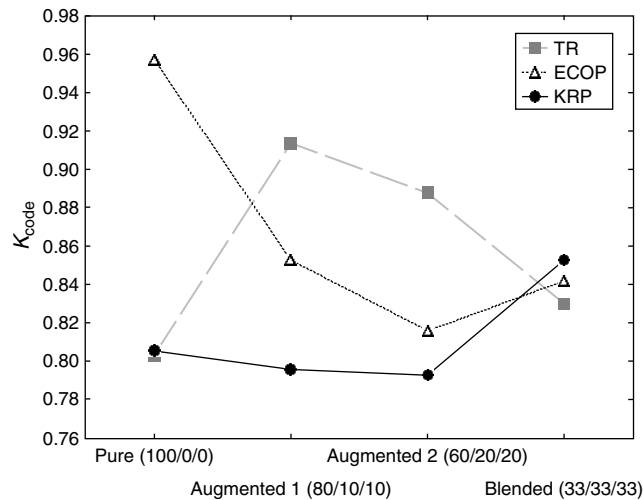
(1) accessing knowledge, (2) transforming that knowledge according to their own experience (and their experience is in turn transformed by that knowledge), and then (3) contributing the transformed knowledge for later use or for use by others in the organization. Our results support their framework, but also extend it by suggesting differences between closed and open knowledge transformation cycles. In a *closed transformation cycle*, all individuals have access to the same knowledge, which then transforms and is transformed by the same population, and finally, is contributed back to common IT-enabled learning mechanisms for access by the entire population in the future. As this knowledge transformation cycle repeats itself in successive rounds, knowledge converges quickly and exploitation occurs. In an *open transformation cycle*, individuals have different sources of and recipients for knowledge. Individuals draw knowledge from heterogeneous sources, combine it with their own knowledge in personalized ways, and then transfer that knowledge to a heterogeneous set of recipients, who will repeat the cycle in later rounds. As individuals continue to draw on and contribute to diverse knowledge sources, knowledge converges more slowly, resulting in exploration.

This difference between the closed and open knowledge transformation cycle is clearest in our simulation when we examine the effects of combining IT-enabled learning mechanisms with one another. We observe a strong positive effect of adding other mechanisms to TR, but we observe little if any benefit to adding other tools to KRP. This difference can be traced to the type of knowledge these additional tools bring to the exploitation process. In the case of TR, additional IT-enabled learning mechanisms bring new knowledge to the exploitation process. As the TR continues to rapidly synthesize and disseminate knowledge, additional tools infuse this process with knowledge from other parts of the organization. The closed knowledge transformation cycle, in which the source and recipient of knowledge are the same, is broken by adding a new knowledge source independent from any learning that occurs within the team. The resulting learning curve begins to demonstrate some characteristics of exploration—slightly underperforming other exploitation processes (KRP) in the short term and then surpassing its knowledge as the KRP plateaus (Figure 1).

Adding other IT-enabled learning mechanisms to the KRP has little, if any, effect on the exploitation process. In this case, the additional tools do not add new knowledge to the closed knowledge transformation cycle and offer little to no additional benefit to the OL processes, since the entire population (or a subset of that population) remains both the source and recipient in the knowledge transformation cycle. Additional IT mechanisms circulate existing knowledge through the population differently, but this process adds little value as the KRP continues to homogenize the knowledge across the organization. Figure 2 supports this interpretation, since the population knowledge variance follows nearly the same pattern and rate of reduction under pure KRP conditions as when KRP is blended with other tools. Therefore, adding more IT-enabled learning mechanisms in this circumstance does not benefit the organization.

Concurrent use of ECOP with other IT-enabled learning mechanisms demonstrates still different effects from either condition observed in the exploitation tools. The overall results of ECOP degrade when other tools are added to the process (Figure 3). The knowledge heterogeneity cultivated by the ECOP is easily affected by the introduction of exploitation tools that are used to reduce that variance. As knowledge exploitation tools are added to the learning process, they provide a common source of homogenous knowledge that erodes the knowledge variance on which the exploration tools rely for later gains. March (1991) and other researchers (Benner 2002) have previously noted this tendency for exploitation to dominate and crowd out exploration. It is interesting to note that the open knowledge transformation cycle in which individuals learn differently from one another across the population results in similar outcomes, as when March introduced heterogeneous learning rates into the population of his simulation (pp. 76–77). We are able to recreate his results by modeling IT-enabled structures to introduce these heterogeneous learning rates, rather than relying on an inherent feature of the population of employees. Since we controlled for and conducted sensitivity analyses on the size of the network in relation to specific IT tools, our results support this interpretation. ECOP provides access to different sources of knowledge, not simply more of them, a finding consistent with previous studies of information networks (Constant et al. 1996).
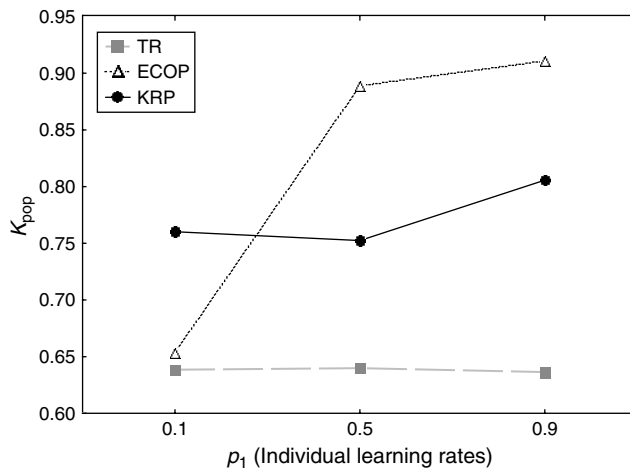
Individual Learning Rates. Figure 4 compares the effect of individual learning rates on the performance of IT. The learning rate influences the performance of the IT-enabled learning mechanisms somewhat differently. ECOP is significantly influenced by variation in the individual learning rate, yielding significantly higher results under high learning rates ($p_1 = 0.9$) than under low rates ($p_1 = 0.1$). In contrast, KRP and TR appear less influenced by individual learning rates, performing relatively similarly across all learning rates. Mechanisms that promote exploitation tend to be robust in light of changes to individual learning values in the population. Using these mechanisms, high learning rates demonstrate roughly the same outcomes as low learning rates (Figure 4).

March (1991) found that high learning rates were the key sources of exploitation in his original model. Using ECOP, high learning rates ($p_1 = 0.9$) perform consistently and substantially better than low learning rates ($p_1 = 0.1$). In our simulation, high learning rates (exploitation) combined with IT-enabled learning mechanisms that promote knowledge heterogeneity (exploration) lead to a blend of forces that results in performance superior to other mechanisms under similar conditions. In contrast, when ECOP operates under conditions of slow learning, the exploratory forces of slow learning redouble the exploratory tendencies of ECOP, resulting in inadequate exploitation and inferior outcomes when compared to other mechanisms under similar conditions.

Since the refined and homogeneous common knowledge synthesized by the closed knowledge transformation cycle is the primary source of learning in exploitation, it matters little whether individuals quickly or slowly adopt knowledge through the exploitation tools. All individuals (the team for TR and the population for KRP) simultaneously transform and are transformed by the same knowledge. Knowledge will, therefore, ultimately converge to the same levels regardless of learning rates. In a
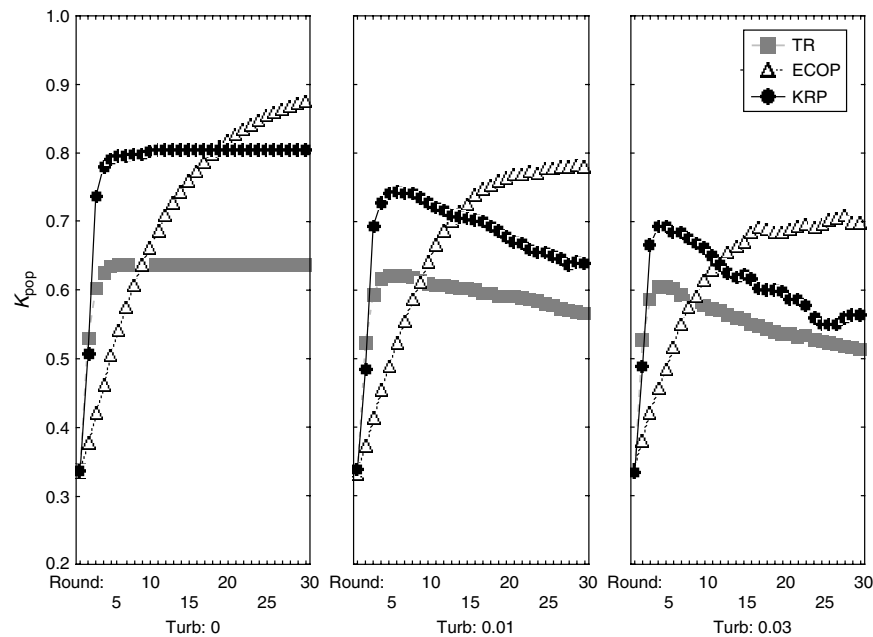
closed knowledge transformation cycle, slower learning does not provide more opportunity for knowledge heterogeneity to exist in the population.

Organizational Turnover. In his original model, March (1991) found that the introduction of both organizational turnover and environmental turbulence enhanced the knowledge level of the organizational code by introducing an exploratory influence, but consistently deteriorated average knowledge levels in the population. We find in our simulation that IT-enabled learning mechanisms behave differently in relation to the negative effects of these environmental influences found in March's original model.

First, March (1991) found that organizational turnover decreased overall equilibrium knowledge levels in the population by shortening the tenure of the individuals within the organization and providing these individuals with less opportunity to learn from others and to refine their knowledge (p. 79). Our simulation of IT-enabled learning mechanisms in the population showed that certain mechanisms were less susceptible than others to negative first-order effects of turnover in the population when compared to other mechanisms in the short term. Figure 5 displays the effect of organizational turnover on average population knowledge level at Round 80. ECOP is radically affected by the introduction of organizational turnover. This effect is strong. Under conditions of no turnover ($p_3 = 0$), ECOP outperforms other mechanisms. This performance drops under increasing turnover, underperforming all tools with only moderate turnover ($p_3 = 0.2$). ECOP performance continues to deteriorate more rapidly than other mechanisms under still higher turnover. Although average population knowledge levels of exploitatory tools (KRP and TR) are still negatively affected by organizational turnover, they are less affected than ECOP, even under relatively high levels of
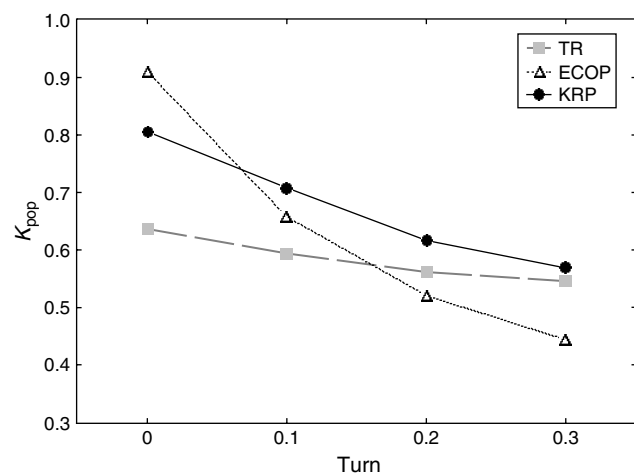
Figure 6   The Effect of IT-Enabled Learning Mechanisms Under Environmental Turbulence (K_{pop}, Round 1–30, $p_1 = 0.9$, $r_{ct} = 0.2$)

turnover ($p_3 = 0.3$). TRs are the most resistant to high turnover levels.

Exploratory tools are more susceptible to the effects of organizational turnover as a result of the open knowledge transformation cycle. As new individuals enter the organization, the exploratory tools do not afford them the opportunity to quickly assimilate organizational knowledge from a single source. Each new individual is forced to learn "from scratch" by assembling knowledge from their ECOP network. Each must determine which knowledge is valuable in a given reality without the benefit of knowledge improvements made by the organization prior to his arrival. It takes the individual many rounds to accumulate, assess, and accept organizational knowledge, even if the individual is a fast learner. In the meantime, more employees are turning over, continuing to lower the overall knowledge levels of the organization, and leaving less valuable knowledge in the population available for learning in later rounds. As the rate of turnover increases, the ECOP becomes a less effective tool for OL because it simply cannot process knowledge faster than it is being lost via turnover.

The rapid homogenization of organizational knowledge permits mechanisms that promote exploitation to better resist the impact of organizational turnover. Because the closed knowledge transformation cycle enables only a single available source from which to learn, exploitation tools homogenize the knowledge held by new individuals to that of the population more rapidly. These exploitation mechanisms also limit the degree to which new knowledge brought via turnover disseminates to the rest of the population. Whether due to the subject matter experts (KRP) or to the locally

defined scope of the Φ_{TR}-group, new individual knowledge is weighed against that of an established set of local experts. Only knowledge that approximates local perceptions of existing organizational knowledge is considered for learning in successive rounds. Thus, by limiting the sources of knowledge on which individuals can rely, exploitation tools resist the effects of turnover by ensuring that individuals with new knowledge are quickly brought into line with organizational expectations.

Environmental Turbulence. March (1991) simulated environmental turbulence by allowing the dimensions of reality to change according to a particular probability ($p_4 = 0.02$) and found that there was also an inevitable deterioration of average population knowledge within the organization (p. 80). March found that his simulation resisted the degrading effects of environmental turbulence only by introducing new knowledge through organizational turnover. We found that certain IT-enabled learning mechanisms were more susceptible than other mechanisms to the environmental effects of turbulence (Figure 6). Knowledge exploitation tools exhibited a susceptibility of environmental turbulence similar to March's original model, rapidly converging to equilibrium knowledge and then slowly deteriorating as the knowledge held in these technologies became irrelevant with changing reality. ECOP, however, demonstrated considerable resistance to these effects. Even under conditions of environmental turbulence higher than March's original model ($p_4 = 0.03$), knowledge continues to improve throughout the early rounds of the simulation and does not demonstrate the degradation observed in the knowledge exploitation tools.

Because ECOP cultivates and preserves knowledge heterogeneity in later rounds of the simulation, it

performs better than exploitatory mechanisms in high-turbulence situations. The population still possesses relevant knowledge to adapt to a changing reality under environmental turbulence. As reality changes, individuals who possess different knowledge that is now more (or less) relevant in relation to the new reality are readily identified by the population, and Φ-groups are updated accordingly. Through this process, the organization can reevaluate the value of the knowledge possessed by individuals. Average population knowledge levels can continue to improve in the face of a changing reality and generally resist environmental turbulence relatively better than other mechanisms.

Exploitation mechanisms do not perform well in the face of environmental turbulence. The rapid and uniform homogenization of knowledge makes it difficult for alternative knowledge to exist within the population. Thus, the organization has little knowledge resources with which to adapt to a changing reality. As reality changes sufficiently from the state to which the organizational knowledge has been optimized, reality becomes less and less relevant to the knowledge that the organization has accumulated. As March (1991) noted, knowledge improvements devolve toward random chance that reality will change to match what had previously been established as organizational knowledge—which is a situation analogous to the proverbial stopped clock being right twice per day.

Discussion

A direct quantitative comparison between our extended model and March's (1991) original is difficult, because many of the baseline changes required to implement our extensions affect the interpretation of model dynamics (e.g., introducing learning between individuals). Nevertheless, we can make some qualitative comparisons of the original model with our extended model that enhance our understanding of the results. One observation is that our model provides further evidence to support March's assertion that knowledge heterogeneity is the source of exploration and exploitation dynamics. We find that the same fundamental mechanism that drove March's model also drives ours. March, however, attributed most of the difference between organizations to differences in the employees themselves (e.g., individual learning rates). We found that IT-enabled learning mechanisms by which individuals learn also significantly influence the exploration and exploitation balance in firms and should not be overlooked in future examinations of OL.

Another comparison between our model and March's (1991) can be made in examining the general influence of individual learning rates on overall knowledge levels. In March's model, higher learning rates generally decrease the overall knowledge levels of the organization (p. 76), but in our model of IT-enabled learning mechanisms, higher learning rates either have no effect or increase the overall knowledge levels of the organization

(Figure 4). Comparing our results with March's on this point suggests that IT-enabled learning mechanisms may be effective in some types of organizations (i.e., with fast learners) but may be ineffective or even detrimental in other types of organizations (i.e., with slow learners). Combined with our other results demonstrating the relative performance differences between IT-enabled learning mechanisms under various environmental conditions, our results suggest that if the right IT-enabled learning mechanisms are used for learning under the right environmental and organizational conditions, they can have a considerable benefit for OL. If an organization uses the wrong type of IT-enabled learning mechanisms given environmental and organizational conditions, however, those mechanisms can be severely detrimental to OL. Thus, IT can be a double-edged sword in relation to OL—either helping or hindering learning.

This work provides some initial insights on which IT-enabled learning mechanisms should be used under given conditions (if at all). First, IT-enabled learning mechanisms have different effects on exploration and exploitation processes. Managers would be well advised to consider their short- and long-term learning goals when selecting the IT tools to make available to their employees. Certain tools (KRP and TR) tend to promote exploitation by reducing knowledge heterogeneity, leading to improved results for the short term and lower results for the long term. Other tools (such as ECOP) cultivate exploration by preserving knowledge heterogeneity, resulting in better long-term results, but may be less effective leveraging knowledge in the short-term. IT tools should be selected to support OL with these knowledge goals in mind.

Second, this research has implications for how organizations can select and combine IT-enabled learning mechanisms. Previous research offers somewhat contradictory prescriptions, some suggesting that a combination of mechanisms should prove superior (March 1991), while others advocate a limited combination of different IT-enabled learning mechanisms in conjunction with one another (Hansen et al. 1999). Our results suggest that each of these seemingly contradictory prescriptions can be valid under particular conditions. Organizations that primarily pursue a knowledge exploitation strategy would be advised to augment their exploitation tools with exploration tools, particularly if those tools can bring new knowledge to the knowledge transformation cycle. Augmenting knowledge exploitation tools with other mechanisms appears to have considerable potential for improvement with very little downside risk. We also find some support, however, for the position that organizations choosing an exploration strategy through IT-enabled learning mechanisms such as ECOP might be advised not to augment these ECOP with other IT-based mechanisms. These strategies thrive on an ability to cultivate knowledge heterogeneity within a population, providing

greater opportunity for future learning and holding up well under conditions of environmental turbulence. Introducing additional IT-enabled learning mechanisms to the organization, particularly those that promote knowledge homogenization, can erode the benefits of ECOP. In this case, a pure strategy may prove advisable.

Third, this research offers considerable insight regarding how to use IT-enabled learning mechanisms under particular environmental conditions. Our results suggest that organizations can use IT to compensate for the effects of turnover and turbulence, without necessarily resorting to more radical organizational solutions such as forced turnover. Thus, an effective portfolio of IT-enabled learning mechanisms might give the organization the opportunity to respond to various environmental conditions, and the organization would be well advised to develop its learning mechanisms with these environmental conditions in mind. For instance, we observed that ECOP performed well under conditions of low organizational turnover, but that these relative benefits rapidly deteriorated as turnover increased. In comparison, results of TR and KRP are relatively stable in the face of various rates of turnover. Thus, organizations that typically experience a high degree of turnover or variable turnover rates might cultivate IT-enabled learning mechanisms that function better under these conditions. These mechanisms function not only by preserving the valuable knowledge for later use by the organization, but also by assimilating new employees quickly into the organization and imparting on them the relevant knowledge to address the environmental conditions. In contrast, organizations that experience substantial environmental turbulence would benefit from exploration mechanisms that preserve knowledge heterogeneity in the population. These tools better retain essential divergent knowledge in the organization that provides a knowledge base from which to effectively respond to inevitable changes in future knowledge requirements.

Limitations. Like all research, this study has limitations. Most significantly, simulation is a simplified representation of a real-world environment. All simplification of real-world phenomena for research purposes involves drawbacks. One risks oversimplifying a given process (e.g., knowledge represented in 30 discrete dimensions) and idealizing imperfect processes (e.g., individuals identifying those with superior knowledge). We have sought to mitigate these limitations by extending an established and highly regarded computational model (March 1991) and by grounding our extensions to this model using previously published case studies in a single organizational setting. Nevertheless, other organizations may use different IT-enabled learning mechanisms or use the same technologies to support different learning structures not simulated here. Furthermore, our model suggests that the ECOP strategy consistently outperforms a number of other approaches and may seem to be the logical default mechanism. Although some researchers have suggested that ECOP is, in fact, the superior OL mechanism (Cross and Baird 2000), it is important to recognize that we model some important and common conditions where ECOP is not superior (e.g., high turnover, low individual learning rates) that must be considered when introducing IT to support OL.

Summary. This study investigates the effects of IT on exploration and exploitation in OL. We relied on qualitative case evidence in a single organization to extend an earlier computational model of OL (March 1991) by introducing learning between individuals in an organization through three distinct IT-enabled learning mechanisms: KRPs, TRs, and ECOPs. We found that each of these mechanisms has a distinct effect on the exploration and exploitation dynamics in OL. We further found that how these tools are blended together, the environmental conditions under which they operate, and the characteristics of the individuals who use the tools all influence the impact of IT-enabled learning mechanisms on OL in terms of the exploration or exploitation dynamics.

Understanding how various IT-enabled learning mechanisms support OL when used in different combinations and under particular environmental conditions can help us better grasp their effect on exploration and exploitation dynamics. The results from computer simulation can also help extend our understanding of under-researched areas such as unintended effects of IT in OL.

Acknowledgments

Appendix A. Description of March's Original Model

Reality is modeled as a single external vector of 30 integers, where each integer i presents an orthogonal and independent element of reality, consisting of 1 or -1. The organizational code is similarly modeled as a single vector of beliefs, and each element of the vector 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 individual in the simulation (100 individuals), each vector representing an organizational member. Consistent with March's (1991) original model (p. 75), the number of individuals simulated in the organization had little qualitative influence on model outcomes.

Both organizational and individual knowledge change via learning, and learning is represented in this model as specific interactions between the individuals and the code occurring over 80 periods (iterations). Each period, every individual will alter any given belief to conform to that of the organizational code with some probability ($p1$), reflecting the learning rate of individuals in the organization. Likewise, the organizational code will also alter any given belief based on the dominant belief of a knowledgeable group of individuals, hereafter called the Φ-group, based on a factor that reflects the learning rate of

Appendix B.   Simulation Flowchart
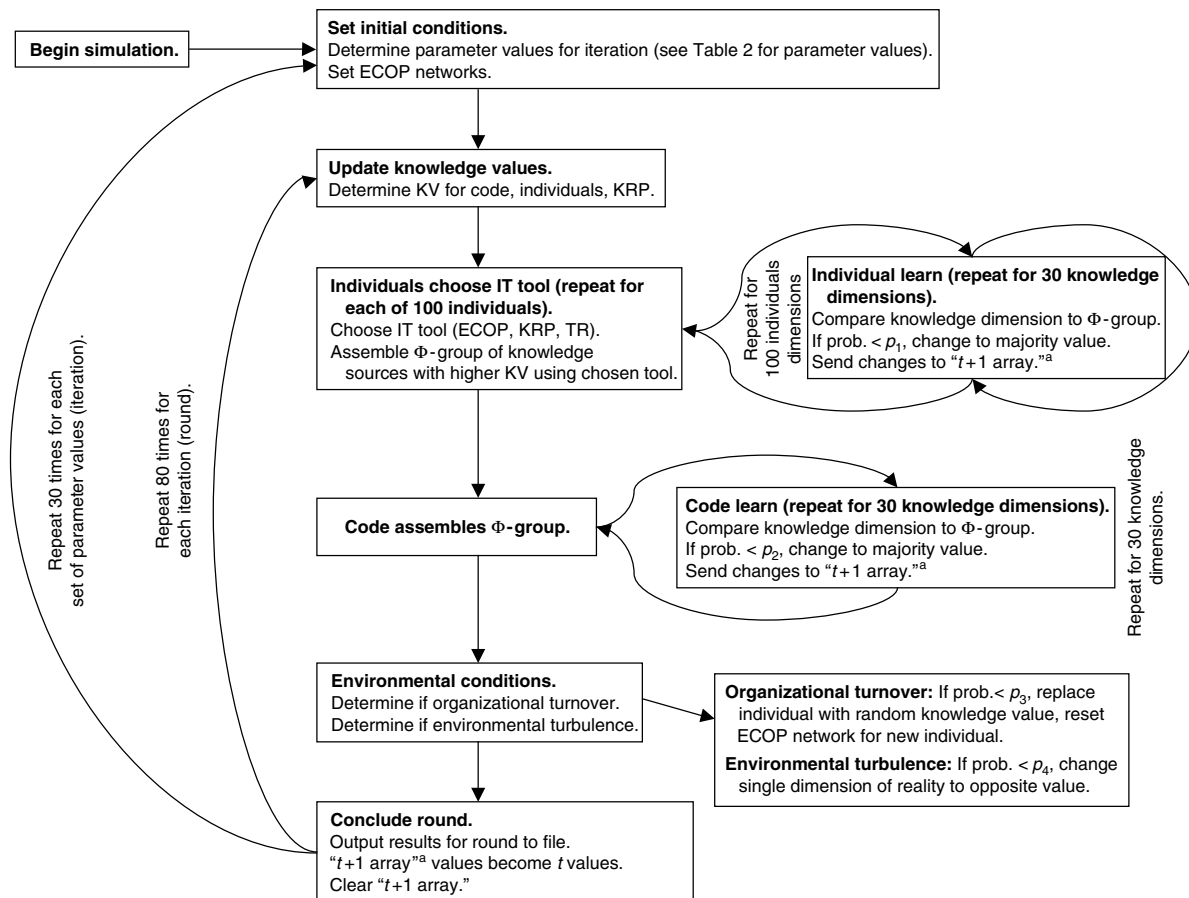
[a] $t + 1$ array: All changes in individual and code knowledge are first recorded in the "$t + 1$ array," then simultaneously updated at the end of the round.

the code ($p2$). This Φ-group is defined as all those individuals who have a higher knowledge level than the code.

The knowledge level is the proportion of reality correctly represented by either the organizational code or an individual. If 10 of an individual's 30 knowledge dimensions match that of reality, that individual has a knowledge level of 0.33; if 15 of 30 knowledge dimensions match reality, the individual's knowledge level is 0.5; and if there is a perfect match between an individual's knowledge and reality, the individual has a knowledge level of 1.0. Neither the code nor the individuals directly observe reality, but reality influences learning by defining the Φ-group of individuals in the organization with valuable knowledge. The code can identify which individuals have knowledge that more closely approximates reality in aggregate, but it cannot assess which elements of an individual's knowledge vector match reality and which do not.

Endnote

[1] We obtained data from semistructured telephone interviews with 20 employees of Company Z at various locations and hierarchical positions. Each employee interviewed had been with the company from between 6 months to 17 years and included such job titles as consultant, program manager, senior consultant, vice president of industry program, project manager, and managing associate. The interviews lasted 45 to 75 minutes each. Each informant was asked to describe the specific IT-enabled learning mechanisms that were provided by Company Z. They were also asked to describe the impact of these mechanisms on themselves, their coworkers, and the organization as a whole. Next, each informant was asked to describe any resistance or impediments to the use of these mechanisms that she might have noticed in her business unit. The same interviewer, using identical data collection protocols, conducted all the interviews in Company Z.

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