Bridging Gaps in Organizational Knowledge - The Role of IT-Enabled Organizational Learning in Supply Chain Partnerships

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The Role of IT-Enabled Organizational Learning in Supply Chain Partnerships

Research-in-Progress

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Abstract

Supply chains have increasingly become an opportunity for firms to access complementary competencies and learn from other firms. To better understand the role of IT-enabled learning strategies in affecting the supply chain firms’ learning outcome, we use a computational simulation approach to model the IT tools used for intra- and inter-organizational learning. This research-in-progress builds on March’s (1991) organizational learning model and extends it to a supply chain context. The study will lay a foundation for theory building in IT-enabled inter-organizational learning and knowledge management.

Keywords: Organizational learning, interorganizational learning, knowledge management, knowledge management information technologies
Introduction

Supply chains have increasingly become an opportunity for firms to access complementary resources and learn from other firms (Larsson et al. 1998; Scott 2000). Prior research has shown that one of the important reasons why firms form supply chain relationships is to learn the specialized knowledge from each other (Scott 2000). Although knowledge resources play a strategic role in supply chain relationships, the impact of knowledge management (KM) strategies on supply chain performance has largely remained anecdotal. Furthermore, despite the studies examining the impact of the use of KM information technologies (IT) on firm performance (e.g., Alavi and Leidner 2001; Kane and Alavi 2007), little has been done to show how the use of KM IT in supply chain will impact the performance of a supply chain. Therefore, the purpose of this research is to understand the role of IT-enabled inter-organizational knowledge management strategies in affecting the knowledge outcome of supply chain firms.

This research views knowledge from the capability perspective that defines knowledge as justified belief that has potential to influence future actions (Alavi and Leidner 2001). The research question that we are interested in investigating lends itself to both empirical research methods and computational simulation research methods. However, because KM IT use in supply chain management remains largely anecdotal, and many ITs may not be readily identified as KM ITs by practitioners, using an empirical research approach may limit our ability to acquire an adequate sample size. Hence, we are going to use a computational simulation approach to model KM ITs and investigate the mechanisms through which KM ITs affect the supply chain’s and individual firm’s performance.

One seminal work of using simulation approach to study the impact of knowledge management and organizational learning on firms is March’s (1991) knowledge exploration and exploitation model. To study inter-organizational knowledge management phenomena, we extend March’s model to a dyad of firms that use IT-enabled learning mechanisms within and across firm boundaries.

We hope that this research can contribute to the literature in the following ways. First, the research will lay a foundation for theory building in IT-enabled inter-organizational KM. Second, using a simulation approach to model KM IT use in supply chains, we will extend the research on the impact of IT-enabled KM from a single organization (Kane and Alavi 2007) to an inter-organizational context so that the interaction effects of using KM IT by multiple firms can be examined.

In the next section, we highlight the important components in March’s (1991) original model of exploration and exploitation. We also review the extant research that builds on March (1991), with the purpose of extending the literature to consider inter-organizational knowledge management. In the third section, we describe how the intra- and inter-organizational learning using the IT-enabled knowledge management tools are modeled. Finally, we present preliminary results regarding the effects of the different types of IT tools on the firm’s knowledge outcome.

March’s (1991) Model and Its Extension

March (1991) studied the dynamics of knowledge exploration and exploitation in a single firm. Knowledge exploitation focuses on improving existing competence and knowledge exploration emphasizes finding new opportunities (March 1991). The three primary components in March’s model is an external reality, an organizational code representing the organization’s beliefs about reality, and individual knowledge representing the individual beliefs of reality. The organizational code refers to the rules, procedures, and norms that individuals use to guide their behavior. Exploitation occurs when individuals modify their beliefs to adapt to the organizational code. Hence, the exploitation process diffuses knowledge among individuals. Exploration, on the other hand, occurs when the organizational code is modified by the individuals whose beliefs better correspond with reality. The exploration process creates new knowledge in the organization. March (1991) observed the changes in the average knowledge level of individuals and in the knowledge level of the organizational code as a result of the mutual learning between the individuals and the organizational code. The results suggest that, although emphasizing exploitation strategies (than exploration strategies) can generate quick knowledge gains in the short run, a sole focus on exploitation can be detrimental to organizations in the long run. March’s model shows how to maintain a balance between the exploration and exploitation in order to achieve sustainable growth of individual knowledge and collective knowledge.

The paradigm of knowledge exploitation and exploration has lent itself to guiding the conceptualization of organizational innovation behaviors in numerous managerial contexts, such as the context of high-tech innovations.
(Lee et al. 2003), the context of IT use by small suppliers (Subramani 2004), and the context of interorganizational learning (Holmqvist 2004). However, those studies do not directly build on March’s original computational model. To the best of our knowledge, there is surprisingly scarce research extending the original model proposed by March (1991). It is only recently that Kane and Alavi (2007) and Bray and Prietula (2007) have extended March’s simulation model to account for the effect of organizational structure and IT-enabled mechanisms in organizational learning.

Kane and Alavi (2007) studied the effect of IT-enabled learning mechanisms on exploration and exploitation. Three types of IT-enabled learning mechanisms used in a single organization were modeled: the group-based learning technologies, such as team rooms; the individual learning technologies, such as email and instant messaging; and the organizational portals that were used to store and disseminate organizational-wide knowledge. Kane and Alavi (2007) demonstrated both the main effects and the interaction effects of the three IT-enabled learning mechanisms on the average individual knowledge level in an organization. Bray and Prietula (2007) extended March’s model to study the effect of organizational hierarchies and the use of knowledge management systems (KMS) on the average employee knowledge level. The KMS modeled in Bray and Preitula (2007) plays the similar role as the organizational code in March (1991).

Research Setting and Model

In order to extend the computational models of organizational learning to the inter-organizational context, we take into consideration not only the learning of individuals from the same firms but also the learning by individuals from the partnering firm in the supply chain. Because IT has become a prominent contributor to organizational learning and knowledge management, we model IT-enabled learning mechanisms that can facilitate learning on both the individual level and the organizational level\(^1\). Based on the findings and reports from the literature (Kane and Alavi 2007; Parise and Sasson 2002; Peli and Booteboom 1997; Scott 2000), we identified four IT-enabled learning mechanisms that the individuals working in a supply chain can utilize. The four mechanisms are internal Electronic Communication Networks (ECN), external ECN, Company Knowledge Repositories and Portals (CompKRP), and Supply Chain Knowledge Repositories and Portals (SCKRP).

IT used in ECNs includes e-mail, instant messaging, chat rooms, and social network software. Those ITs facilitate the interactions between individuals in order to achieve the goals of creating and transferring knowledge. KRP refer to the information systems that are used by firms to store and disseminate firm knowledge. The four learning mechanisms can be described by two characteristics: the source of knowledge (internal or external to the firm) made available by the learning mechanisms and whether the learning mechanisms facilitate the learning from human or from IT artifacts. Table 1 presents the categorization of the four IT-enabled learning mechanisms.

<table>
<thead>
<tr>
<th>Type of Learning Source</th>
<th>Scope of Learning Source</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Firm</td>
</tr>
<tr>
<td>Human</td>
<td>Internal Electronic Communication Networks (ECN)</td>
</tr>
<tr>
<td>Information Systems</td>
<td>Company Knowledge Repositories and Portals (CompKRP)</td>
</tr>
</tbody>
</table>

\(^1\) We assume that individuals learn from others or from organizational knowledge repositories while organizations learn from the individuals.


Model setup

We create a hypothetical supply chain that consists of a dyadic relationship between firm X and firm Y. Firm X and Y face a universal reality that is composed of $m$ dimensions. Consistent with March (1991), each reality dimension assumes a value of either 1 or -1. The reality modeled in this research should be a reality that is relevant to the supply chain partnership between firm X and firm Y. The reality dimensions that do not concern the supply chain partnership (e.g., outsourcing payroll IT within the firms) are not considered as part of the reality.

We assume that firm X and firm Y each focuses on their own core competencies and the two firms can complement each other’s core competencies by learning from their partners. For example, in a supply chain between a retailer and a manufacturer, the retailer may have superior knowledge on the merchandising, marketing, customer service, purchasing, and inventory management domains of reality, while the manufacturer is superior at the research and development, product design, order management, logistics, and manufacturing domains of reality; the retailer can gain knowledge about how the manufacturer conducts order management through their interactions. In terms of the model, we use different knowledge domains in reality to represent the two firms’ core competencies. The number of firm X’s core competency knowledge dimensions is $m_{core_{x}}$, and the number of firm Y’s core competency knowledge dimensions is $m_{core_{y}}$. We assume that there is no overlapping of core competency knowledge dimensions between firm X and firm Y, i.e., $m_{core_{x}} + m_{core_{y}} = m$.

The number of employees in firm X is $n_x$ and the number of employees in firm Y is $n_y$. Each individual in a firm holds beliefs (knowledge) on $m$ dimensions, corresponding to the $m$ dimensions of reality. Following March, each dimension of individual beliefs is assumed to take a value of 1, 0, or -1. If an individual’s belief is 0 for a particular dimension of reality, it means that the individual does not have any knowledge on that dimension. This way of coding the individual knowledge allows us to model the state where an individual has correct knowledge, no knowledge or wrong knowledge on a certain dimension of reality. The individual knowledge level (KL) is determined by the proportion of reality that is correctly represented by individual beliefs. For example, if reality has 60 dimensions ($m = 60$) and 30 of an individual’s knowledge dimensions match that of reality, that individual has a knowledge level of 0.50. In order to reflect complementary relationship between supply chain partners, at the beginning of each simulation, we make sure that the average knowledge level of all individuals on the firm’s core competency knowledge dimensions is higher than that on the firm’s non-core competency knowledge dimensions.

We organize the individuals in each firm into a simple group structure consisting of equal sized groups. A group is similar to the notion of a functional team or a department in organizational hierarchies. We further assume that an individual belongs to one and only one group. Hence, we divide the $n_x$ individuals in Firm X into $d_x$ mutually exclusive groups and divide the $n_y$ individuals in Firm Y into $d_y$ mutually exclusive groups.

Each group focuses on a number of knowledge dimensions within the firm’s core competency knowledge domain. We consider those knowledge dimensions as the group’s internal focus domain (IFD). For example, each of the customer services, purchasing, and merchandising groups in a retailing company has their own IFD. In terms of our model parameters, each of the $d_x$ groups in firm X focuses on a subset of the $m_{core_{x}}$ dimensions, while each of the $d_y$ groups in Firm Y focuses on a subset of the $m_{core_{y}}$ dimensions. We allow the different groups in the same firm to have knowledge overlaps. For example, if one group in Firm X focuses on the internal focus domain $IFD_{d1} = \{1, 3, 4, 5, 6, 13, 14\}$ (the numbers in the braces are knowledge dimension numbers) and the other group in the same firm focuses on internal focus domain $IFD_{d2} = \{1, 2, 3, 8, 9, 10, 11\}$, the dimensions that both groups cover are dimensions 1 and 3.

We further assume that a group does not only focus on the knowledge within the firm’s core competency domain, but also focuses, to some extent, on the knowledge dimensions that fall in the partnering firm’s core competency domain. For example, employees working in the marketing department in a fashion-clothing retailing company may pay special attention to the knowledge about product design that is part of the core competency domain of a vendor company. Although the marketing group in the retailing company may not be an expert in the area of product design, this group of employees has better knowledge in the design area than the other employees working in same
company. We refer to the knowledge dimensions that do not fall into a firm’s core competency domain, but are familiar to a group in the firm as the group’s external focus domain (EFD).

The number of knowledge dimensions in a group’s IFD is determined by \( k_{internal, x} \) (\( k_{internal, y} \)) - the percentage of firm X’s (firm Y’s) core competency that a group specializes on. Similarly, the number of knowledge dimensions in a group’s EFD is determined by \( k_{external, x} \) (\( k_{external, y} \)) - the percentage of firm X’s (firm Y’s) non-core competency that a group is familiar with. We assume that each group in the same firm has equal amount of knowledge, thus equal \( k_{internal} \) or \( k_{external} \), but on different knowledge dimensions. For instance, each group in Firm X focuses on 30% of the firm’s core competency domain. The number of knowledge dimensions in the internal focus domain for a group in Firm X is calculated as \( k_{internal, x} \times m_{core, x} \); the number of knowledge dimensions in the external focus domain for a group in Firm X is \( k_{external, x} \times m_{core, y} \).

Other than the function groups within each firm, we also allow the individuals to join one of the f supply chain-wide interest groups. An interest group consists of individuals who share similar job interests from the same firm or from the supply chain partnering firm. We model the interest groups in this way because work-related interactions not only occur within a group but also across groups, and even across firms.

**IT-enabled KM mechanisms**

Given the setup of the supply chain, this section explains how we model the use of the four types of IT-enabled KM mechanisms – CompKRP, SCKRP, internal ECN and external ECN for internal or external learning.

![Figure 1. Model Illustration](image)

**CompKRP**

CompKRP is modeled as a knowledge vector that has \( m \) dimensions, with each dimension corresponding to a dimension in reality. Firm X and firm Y have their own CompKRP; individuals from one firm do not have access to the CompKRP in the other firm. CompKRP accumulates knowledge contributed by domain expert employees and
disseminates the knowledge to all employees in the firm. Individuals learn from CompKRP according to the internal learning probability \( p_1 \) and CompKRP is updated by experts according to the internal contribution probability \( p_2 \). The detailed mechanisms of how CompKRP works are described as follows.

(1) **Domain experts contribute to CompKRP.** In the beginning of the simulation, CompKRP starts with neutral beliefs on all the knowledge dimensions. Domain experts are defined as the individuals who work in a group and have higher KL on the group’s focus domains (both IFD and EFD) than the CompKRP. Domain experts can only update the CompKRP knowledge dimensions that fall into their IFD and EFD, not all \( m \) knowledge dimensions. At each period, the probability that a domain expert contributes to a particular knowledge dimension in CompKRP is \( p_2 \). The probability that each dimension is updated is independent. When the knowledge value on a particular knowledge dimension in CompKRP is the same as the dominant belief among the domain experts, the knowledge value in CompKRP remains unchanged. When the knowledge value in CompKRP differs from the dominant expert belief, whether the value in CompKRP will be changed depends on the agreement among the experts and \( p_2 \). Specifically, the chance that the knowledge value in CompKRP remains unchanged at the end of the period is \((1 - p_2)^t\) (\( t \) is the difference between the number of experts who hold different belief than CompKRP and the number of experts who hold the same belief as CompKRP).

(2) **Individuals learn from CompKRP.** Individuals adopt the values in CompKRP according to a learning probability \( p_1 \). At each period, there is the chance of \( p_1 \) that the individual’s belief on a particular knowledge dimension changes to the non-zero value in CompKRP. (Zero values in CompKRP do not affect individual beliefs.)

**SCKRP**

The SCKRP stores knowledge in \( m \) dimensions, with each dimension corresponding to a dimension in reality. Unlike the CompKRP, which is an intra-organizational knowledge management system, the SCKRP is inter-organizational and, therefore, individuals from both firms can contributed to it and learn from it. Domain experts from either firm update the knowledge dimensions that fall into their IFD. The SCKRP also disseminates knowledge to all the individuals in the supply chain. Next, we describe the mechanisms in which the SCKRP works.

(1) **Domain experts contribute to the SCKRP.** The simulation begins with a SCKRP characterized by neutral beliefs on all dimensions. In the context of the SCKRP, domain experts are defined as the individuals whose knowledge in IFD matches better with reality than the SCKRP. Unlike in the CompKRP, the domain experts for the SCKRP are selected based on the individuals’ KL on IFD only (not IFD and EFD). At each period, domain experts contribute a particular knowledge dimension of the IFD in the SCKRP according to the external contribution probability \( q_2 \). The probability that each dimension is updated is independent. When a knowledge value in the SCKRP is the same as the majority of expert belief, the knowledge value remains unchanged. When a knowledge value in the SCKRP differs from the majority of expert belief, the probability that the knowledge value in the SCKRP remains unchanged at the end of a round is \((1 - q_2)^t\) (\( t \) is the number of experts whose belief differs from the SCKRP minus the number of experts who agree with the SCKRP).

(2) **Individuals learn from the SCKRP.** The SCKRP not only draws expertise from firm X and firm Y, it also allows each firm’s expertise to be disseminated in the supply chain. Whether an individual will adopt the SCKRP’s knowledge value on a particular dimension is determined by the external learning probability \( q_1 \).

**ECN**

Individuals in the supply chain learn from each other through an ECN. An ECN allows individuals to discuss businesses, ask questions, or to exchange ideas. Each employee’s ECN comprises two types of individuals: the ones working in the same function group as the employee and the ones belonging to the same interest group as the employee. Furthermore, an employee’s interest group may include individuals from the same firm as well as those from the supply chain’s partnering firm. We call the ECN in which individuals come from the same firm as the employee’s internal ECN, and we call the ECN in which individuals come from the partnering firm as the employee’s external ECN.
(1) Internal ECN. An employee’s internal ECN consists of individuals from the employee’s functional group and the individuals who are outside of the functional group but sharing the same interest group with the employee. When learning from the internal ECN, the employee first assembles a subnetwork of the individuals in the internal ECN to learn from, according to a probability of \( b \). Once the subnetwork of internal ECN is assembled, the employee assesses which of these individuals have higher knowledge levels on all knowledge dimensions than the employee herself – the expert group in the ECN subnetwork. Finally, the individual adopts the majority value of the expert group on a particular knowledge dimension according to the internal learning probability \( p_{1} \).

(2) External ECN. An employee’s external ECN consists of the individuals from the supply chain partner’s firm who are from the same interest group with the employee. Similar to the steps involved in learning from internal ECN, when learning from external ECN, the employee first assembles a subnetwork of her external ECN, according to the probability of \( b \). Next, the employee identifies the experts who have higher knowledge levels on all knowledge dimensions. Finally, the employee adopts the majority value of the expert group on a particular knowledge dimension according to the external learning probability \( q_{1} \).

Combining the Learning Mechanisms

Because of the wide availability of communication technologies, such as E-mail, we allow everyone to assemble their internal or external ECN. We also allow all individuals in firm X and firm Y to access the knowledge management system – KRP and SCKRP.

We vary the degree to which the firms use each learning mechanism. In each period, we determine an individual’s chance to use one of the four learning mechanisms through the combination of two probabilities - the probability of choosing the external learning mode \( p_{\text{externalLearning}} \) and the probability of choosing the KRP learning mode \( p_{\text{KRPLearning}} \). \( p_{\text{KRPLearning}} \) determines whether an individual will choose to learn from an external knowledge source or from an internal knowledge source, and \( p_{\text{KRPLearning}} \) determines whether the individual will learn from human knowledge source or KRP. The choices of a learning mechanism in different periods are independent.

Experiment and preliminary results

We use C# to implement a computer simulation of the IT-enabled learning in a supply chain. Because March’s (1991) original model can be considered as a special case of our model when the external learning probabilities in our model are set to zeroes, we first validated our simulation model by replicating the results in March (1991).

As an initial step in investigating the effects of different learning mechanisms on interorganizational learning, we modeled two firms with the symmetric knowledge structure and symmetric organizational structure, i.e., two firms with equal number of core competency knowledge dimensions, equal number of employees, and equal number of groups. The parameter values used in the experiment are shown in Table 2. We also assume that the propensities for knowledge learning and contributing in two organizations are the same (\( p_{1x} = p_{1y} \); \( p_{2x} = p_{2y} \); \( q_{1x} = q_{1y} \); \( q_{2x} = q_{2y} \)).

<table>
<thead>
<tr>
<th>Table 2. Parameter Values Used in the Experiment</th>
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<tbody>
<tr>
<td>Number of employees (( n ))</td>
</tr>
<tr>
<td>Number of functional groups (( d ))</td>
</tr>
<tr>
<td>Number of core competency Knowledge dimensions (( m_{\text{core}} ))</td>
</tr>
<tr>
<td>% of knowledge dimensions in IFD (( k_{\text{internal}} ))</td>
</tr>
<tr>
<td>% of knowledge dimensions in EFD (( k_{\text{external}} ))</td>
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</table>
In the first experiment, we modeled a supply chain partnership with high internal and external individual contributing probabilities (p2 and q2) and moderate internal and external individual learning probability (p1 and q1) in both firms. This set of parameters indicates a collaborative type of partnership because both firms have a high propensity to share knowledge with each other. We tested the effects of learning using only the ECN and learning using only the KRP on the average employee knowledge level in the supply chain firms. We chose to focus on the average employee knowledge level as the outcome variable because it is an indicator of a firm’s fundamental knowledge competency. The objective of this experiment is to investigate which learning mechanism can help the firms reap greater benefits of collaborating with supply chain partners. We ran the simulation for 80 periods and made 10 replications. The result of the simulation is displayed in Figure 2. Because the two firms are symmetric, we only show the average knowledge level for Firm X. Firm Y’s result should be similar. The result indicates that using the ECN allows the average employee knowledge level to rise steadily and to reach a high level (nearly 100%) eventually. On the other hand, when only the KRP was used, the average knowledge level increased quickly in the first few periods but settled at a plateau with a level much lower than in the case of the ECN. An interesting implication of this result for supply chains is that in situations requiring quicker dissemination of expertise, the structured knowledge portals seem to be more effective while for greater levels of expertise to be disseminated, the free-form community learning seems more appropriate.

![Figure 2. Effects of using ECN or KRP on the Average Employee Knowledge Levels in Firm X (p1 = 0.5; p2 = 1; q1 = 0.5; q2 = 1 for employees in Firm X and Firm Y)](image)

**Conclusion**

We plan to conduct our simulations with varying probabilities for learning and contributing, both to test the robustness of our model and to identify how the opportunities available to individuals to learn from different sources can have an impact on the supply chain knowledge level. We will also extend our experiment to asymmetric supply chain partnerships (asymmetric in organizational structure and in knowledge structure) to study the consequences of
such asymmetries on supply chain learning. The complete results of our simulation experiments and our conclusions will be presented at the conference.

References


