Chapter 7
Membership Reconfiguration in Knowledge Sharing Network: A Simulation Study

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Abstract The purpose of this study is to propose a new approach that minimizes the negative impacts of structural barriers to knowledge sharing in the current of knowledge sharing networks by dynamically reconfiguring communities of practice (CoP) memberships. For this purpose, we develop several propositions to determine source CoPs, destination CoPs, rearrangement candidates, and recipient candidates to regulate the process of reconfiguring collaboration networks of source CoPs and reconstructing networks of destination CoPs after reallocating members from source CoPs to destination CoPs. To test the validity and usefulness of the proposed approach, we simulate two reconfiguration strategies that are different in the sense whether or not the distribution of expertise levels of CoP members is considered to determine the destination CoP. Our experimental results confirm that the proposed approach with either strategy effectively decreases potential threats to collaboration among CoP members and improves the structural healthiness of knowledge sharing networks of departments and organization. In particular, the number of CoPs in which knowledge creating is more active than knowledge sharing is significantly increased while the number of inactive CoPs is decreased. We attribute this finding to the fact that both experts and non-experts members are more evenly distributed across CoPs through rearrangement and these experts with light collaboration burden post their knowledge and practical skills to help non-experts in their CoPs.

Keywords Knowledge sharing network • Communities of practice • Knowledge management system • Membership reconfiguration • Bottleneck impact score (BIS)

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7.1 Introduction

Recently, many organizations strive to integrate and maximize the use of knowledge and best practices embodied in the expertise of experts by operating knowledge management systems (KMS) (Fritz et al. 1998; Griffith et al. 2003). According to many studies, KMS not only enhances knowledge reuse but also stimulates innovative solutions by turning members' intellectual capital into knowledge resources that will improve the organization's capacity to cope with increased levels of competition and shortages of qualified knowledge workers (Janz and Prasarnphanich 2003; Von Krogh 1998). In particular, many practitioners and scholars are paying increasing attention to communities of practice (CoPs), an informal and spontaneous network of organizational members toward the common goal of sharing knowledge and best practices to solve problems (Brown and Duguid 1991; McDermott 1999). It is believed that CoPs help organizations not only inspire members to use their talents and best practices but also facilitate and revise new organizational strategies by allowing members to constantly exchange, validate, and refine multiple perspectives on work-related problems and issues (Lesser and Storck 2001; McDermott and Archibald 2010).

While CoPs are self-emerging and self-organizing networks in their nature, they are unlikely to be successful unless organizations cultivate environments in which members are strongly encouraged to share their knowledge by eliminating any structural bottlenecks or psychological barriers (Helms 2007; Helms et al. 2010; Lee et al. 2012). For this reason, it is not difficult to find formally and informally formed CoPs, and more organizations are interested in assessing the structural health of their CoPs to remove bottlenecks to employees' knowledge-sharing activities. One of the most well-known and successful treatments is to motivate organizational members by providing intrinsic and extrinsic (e.g., financial) rewards for actively engaging CoP members and CoPs (McDermott 1999). In this study, we like to boost knowledge sharing activities among CoP members by dynamically reconfiguring CoP memberships (i.e., reallocating members from a CoP (source CoP) to another CoP (destination CoP)) to minimize the negative impacts of loosely connected structure of CoP networks and any existing bottlenecks in the current CoP networks. Ideally these two methods—an organizational human resource management approach and a social network structural approach—can be combined to obtain optimal results.

As a prerequisite of our approach, the management teams should quantitatively diagnose whether any threats to knowledge management initiatives exist in their organizations and how serious they are. To this end, we rely on a bottleneck impact score (BIS) metric (Lee et al. 2012) that is a weighted sum of the pervasiveness of six bottlenecks in two possible barrier categories: master-apprenticeship relations and knowledge drain. Then we develop several propositions to determine ideal source and destination CoPs for reconfiguration and ideal candidates for reallocation in source CoPs. In addition, several other propositions are devised to regulate the process of reconstructing collaboration networks among remaining members in source CoPs and between new members and old members in destination CoPs.

We validate the effectiveness of our reconfiguration strategies by measuring the improvements of total sum of BISs. In terms of methodology, we combine a simulation approach and a social network analysis (SNA) based on real-world CoP datasets. Since the proposed approach continuously reconfigures the structure of knowledge sharing networks by dynamically reconfiguring CoP memberships to reduce master-apprenticeship relations and knowledge drain barriers, the resulting structure should have a decreased value of BIS metric and minimize the losses due to the business discontinuities caused by such risks.

This paper is organized as follows. In the following sections, we first briefly review several relevant studies that provide theoretical and empirical grounds for this study. Then we describe the framework of our KMS with important propositions to reconfigure collaboration networks among CoP members. Data pre-processing and simulation experimental setups are immediately followed. Experimental outcomes are presented and discussed in terms of BIS metric and improvement of structural changes in collaboration networks. Finally, we provide concluding remarks and suggestions for future research.

7.2 Literature Review

7.2.1 Social Behavior Theories, Collaboration Climates, and Knowledge Sharing

Several social behavior theories–social exchange theory (Baum et al. 2001; Blau 1964; Molm 1997), expectancy theory (Vroom 1964; Wang and Strong 1996), public goods theory (Fulk et al. 2004; Marwell and Oliver 1993), and social capital theory (Deci 1971; Nahapiet and Ghoshal 1998; Nebus 2004; Putnam 1995)–are often adopted to understand and explain knowledge sharing behaviors of organizational members. Among those, public goods theory and social capital theory explain organizational members' conflicting perspectives on knowledge sharing activities under knowledge management including KMS and CoPs. First, public goods theory regards knowledge in pubic place such as KMS as one of public goods and raises the free-rider problem in that individuals who do not contributed to the creation of knowledge bases can benefit from accessing KMS (Fulk et al. 2004; Marwell and Oliver 1993) and hence some individuals may withhold tacit knowledge for themselves only (Bock et al. 2006; Deci 1971; Thorn and Connolly 1987; Venkatesh and Davis 2000). However, according to social capital theory, individuals may not want to be a free rider but, instead, they like to invest in social relations, the resources tied up in those connections, and the ability of securing benefits from those relationships (Borgatti and Foster 2003; Kilduff and Tsai 2003). Therefore, individuals want to build high social capital by not only reusing knowledge from the KMS but also contributing knowledge to it over time (Bock et al. 2008). Individuals with high social capital are willing to share various information across groups, engage in problem solving, and actively collaborate with others to get work done (Cross and Parker 2004; Dalkir 2005). Because of those organizational members' conflicting perspectives on knowledge sharing activities, many organizations has been faced with some barriers to reach success of knowledge management, and thus they have focused on cultivating organizational knowledge sharing climate which make organizational members follow social capital theory instead of public good theory.

Several studies identify collaboration climate in organizations as a critical success factor of knowledge sharing (Constant et al. 1996; Huber 2001; Orlikowski 1993). Scholars in cross-cultural research also argue that cultural factors such as group conformity and face saving in a Confucian society can directly affect intention to collaboration (Bang et al. 2000; Tuten and Urban 1999). For example, fair organizational practices build trust between members and lead employees to go beyond the call of duty to share their knowledge (Kim and Mauborgne 1997). Similarly, Al-Alawi et al. (2007) identify trust, communication, and rewards as critical organizational culture for successful knowledge sharing, and suggest to cultivate appropriate climates by arranging social events and outdoor discussions, providing sufficient information systems, and providing effective rewards. Individuals in innovative and pro-social work context are more likely to share new and creative ideas with each other and encourage a sense of collaboration among members (Kim and Lee 1995). Another research (Bock et al. 2005) recognizes a climate of trust, tolerance of failure, and pro-social norms as three organizational factors for successful knowledge sharing. According to Gupta (2008), employees with lower job-levels show higher integrity, respect, and trust than employees with higher job-levels such as executives, encouraging the need to cultivate knowledge sharing climate for employees with higher job-levels.

Interestingly, Hinds and Kiesler (1995) argue that technical workers (e.g., software engineers) rely extensively on lateral communication in CoPs because of the nature of the work they perform and the way they are organized. Similarly, Ahuja and Carley (1999) posit that non-routine tasks can be better performed through lateral communication and under the nonhierarchical coordination form, resulting in strongly tied network structure with active knowledge sharing activity among members. It is also shown that external factors such as institutional structures influence the salience of subjective norms (Bearden and Etzel 1982; Lee and Green 1991; Triandis 1972; Tse et al. 1988). For example, organizational incentive structures such as pay-for-performance compensation schemes can discourage knowledge sharing if employees believe that knowledge sharing will hinder their personal efforts to distinguish themselves relative to their coworkers (Huber 2001). Finally, collaborative climate seems to better in the small- to mid-size organization than in large organization, and in the private sector than in the public sector (Sveiby and Simons 2002).

7.2.2 Knowledge Sharing Bottlenecks and BIS Metric

As the importance of CoP has been emphasized, some researchers have suggested a diagnosis or an evaluation methodology for CoP activities (Botkin 1999; Lesser and Storck 2001; McDermott 1999; Wenger and Snyder 2000; Zhang and Watts 2008).

Since the first introduction of social network graph (Moreno 1934), the sociogram that contains actors as nodes and their relationships as links between the nodes, has been used to understand knowledge sharing activities. For example, Cross et al. (2000) employed SNA to visualize and understand the multitude of social relationships among members that can either facilitate or impede knowledge sharing. Specifically, they analyzed members' understanding of each other's knowledge to assess the overall cohesion of the group, and identified the core members and isolated members in the network like other studies (Cantner and Graf 2006; De Laat et al. 2007; Haythornthwaite 1996). In Bosua and Scheepers (2007), the Bosua-Scheepers Model (BSM) was introduced for an assessment of knowledge sharing activity assuming that efficient and effective knowledge sharing occurs only if current networks have an appropriate maturity and are supported by facilitating mechanisms such as email and online meetings. Finally, a recent study (Iyengar et al. 2011) showed that when low-status individuals are clustered around high-status individuals, they are more likely to engage in social dynamics than when their cluster is distantly separated from a densely connected core of high-status individuals.

However, more relevant analyses in regard to diagnosing the structural healthiness in terms of knowledge networks in CoPs can be found in Lee et al. (2012) in which CoPs are classified into four types: knowledge sharing community (CoP^{SH}), knowledge storing community (CoP^{ST}), knowledge learning community (CoP^{LR}), and inactive community (CoP^{IA}). In short, CoPs categorized as CoP^{SH} perform active knowledge sharing activities in both creating and consuming, and CoP^{IA} includes CoPs whose knowledge creation and consumption activities are inactive. If a CoP is classified into neither CoP^{SH} nor CoP^{IA} and more interested in knowledge creating than consuming, then it is classified into CoP^{ST} while a CoP which has opposite trend is identified as CoP^{LR}. More importantly, they also investigate whether or not there are any structural weaknesses in knowledge networks by identifying the existence and seriousness of two major barriers, master-apprenticeship and knowledge drain barriers. According to Lee et al. (2012), the master-apprenticeship barrier includes four types of bottlenecks depending on the characteristics of the links between experts and non-experts. The first bottleneck (Bottleneck 1) addresses a case in which experts engage in knowledge transfer with too few non-experts (fewer than two), while the second (Bottleneck 2) refers to a case in which non-experts learn their best practices from too few experts (fewer than two). In the last two (Bottlenecks 3 and 4), experts engage in knowledge transfer with too many non-experts (more than four), and non-experts learn best practices from too many experts (more than four experts), respectively. In contrast, knowledge drain barrier recognizes knowledge drain risk that becomes an issue when experts who maintain few or none connections leave the organization (Bottleneck 5) or when organizational members who are not necessarily experts but who maintain high connectivity with others leave the organization (Bottleneck 6). Finally, they measure the pervasiveness of such bottlenecks using a bottleneck impact score (*BIS*) metric defined as $BIS = \sum_i BIS_i = \sum_i w_i \cdot p_i$ where w_i and p_i represent the relative priority and pervasiveness of the *ith* bottleneck, respectively. The same definitions of bottlenecks and *BIS* are adopted for this study.

Another relevant study (Kwon et al. 2007) investigated several ontological forms of network structures and evaluated the structural efficiency and stability embedded in each identified network under organizational downsizing through computer simulation. Particularly, they explored four ontological social network archetypes–random, small world, moderate scale free (MSF), and high scale free (or Barabasi)–and found that centralized coordination structures such as MSF and Barabasi are generally more resilient and facilitate better coordination to preserve a worker's efficiency and the stability of the network structure under a relatively small-scale workforce reduction. To this end, they proposed two alternative reconnecting mechanisms in the face of downsizing: "planned" or "unplanned" tactics (Ahuja and Carley 1999). In the case of "planned" tactics, the tasks performed by departed members prior to downsizing are reassigned to the remaining members with maximum capacity because that structural change is well designed, fully planned, and smoothly executed, while organizations randomly reassign disconnected wires to existing nodes in the case of "unplanned" tactics because they are not well prepared for workforce shrinkage. While their planned tactics are adopted in our study with minor changes to reconfigure collaboration networks in source CoPs, this study takes one step further by proposing tactics to create new connections of departed members from source CoPs with members in destination CoPs.

7.3 Framework of the Proposed KMS

7.3.1 Rearrangement Propositions of CoP Members

The proposed KMS is based on the fundamental assumption that dynamically rearranging redundant CoP members with high level of knowledge from highly performing CoPs (e.g., CoP^{SH}) to poorly performing CoPs (e.g., CoP^{IA}) improve the efficiency of knowledge sharing in both CoPs by (at least partially) eliminating existing bottlenecks. Note that while CoPs are characterized as informal and self-organizing, they can be nourished by strategically *seeding* active members who are willing to share their knowledge (Wenger and Snyder 2000). Ultimately, this improvement will result in the efficiency of bilateral communications and exchanges of knowledge and experiences among organizational members.

To this end, we posit several rearrangement propositions that regulate rearrangement process of CoP members across CoPs in this study. Note that these propositions were suggested to CoP management teams in Company P as a strategic approach to enhancing knowledge sharing activities and modified to reflect feedbacks in terms of organizational and technical feasibility.

For notation convenience, we denote a CoP where an expert or specialist member is selected for rearrangement purposes and a CoP where a new member is assigned into as source and destination CoP, respectively. We also denote CoP members in the destination CoP who are going to be connected with the rearrangement candidate from the Source CoP as recipient candidates.

The first set of propositions regulates the selection of the source CoP and the rearrangement candidate member within the source CoP, and we define them as follows:

Proposition 1-a *Selection Strategy of the Source CoP*. The ideal candidate for the source CoP is one of CoPs with the highest value of BIS_1 (i.e., where experts engage in knowledge transfer with too few non-experts) or BIS_4 (i.e., where non-experts learn best practices from too many experts).

Proposition 1-b *Selection Strategy of the Rearrangement Candidate in the Source CoP*. The ideal candidate for the rearrangement candidate is an expert or a specialist member who engage in knowledge transfer with too few non-experts. However, if the candidate is the only expert or specialist in the source CoP, then the member is not selected.

The reasoning behind for Proposition 1-b is that the members who perform core activity is one of the most critical ingredient for the growth of communities (Jones et al. 2004) and they can bring a broad span of influence in CoPs (Blyler and Coff 2003). It is believed that these seeding members rearranged into poorly performing CoPs are most likely to arouse knowledge sharing activities among members and, if successful, inactive members are likely to show herding behavior by imitating what active members are doing (Oh and Jeon 2007). Ultimately, the well-distributed *seeding* active members across CoPs may act as catalysts to build a favorable organizational climate for knowledge sharing.

Note also that we only consider master-apprentice bottlenecks in the selection process of the source CoP and the rearrangement candidate mainly because knowledge drain bottlenecks cannot be directly controlled by rearrangement strategies. However, both master-apprenticeship bottlenecks and knowledge drain bottlenecks are fully considered when the outcome of rearrangement strategy is estimated in terms of *BIS* to accurately estimate the structural risk of CoP network based on all identifiable bottlenecks.

Once the source CoP and the rearrangement candidate are selected, it is necessary to determine the destination CoP and recipient candidates so that the rearrangement candidate can be reconfigured with recipient candidates in the destination CoP to maximize the impact of rearrangement strategy. To this end, another set of propositions regulates main and supplemental strategy to select the ideal destination CoP and the recipient candidate. These propositions are formally specified as follows:

Proposition 2-a *Main Selection Strategy of the Destination CoP*. The destination CoP must belong to the same department of the source CoP and should not be one of CoPs that the rearrangement candidate has a membership.

Proposition 2-b *Supplemental Selection Strategy of the Destination CoP*. Among CoPs that satisfies the requirement specified in Proposition 2-a, the ideal candidate for the destination CoP is one of CoPs with the highest value of BIS_2 (i.e., non-experts learn best practices from too few experts) or BIS_3 (i.e., where experts engage in knowledge transfer with too many non-experts).

Proposition 2-c *Selection Strategy of the Recipient Candidate in the Destination CoP*. The ideal candidate for the recipient candidate is an expert (or a specialist member) who most actively engages in knowledge transfer with (and possibly overwhelmed by) non-experts.

The reasoning behind Proposition 2-a is that when a rearrangement candidate moves to the destination CoP in a different department (e.g., Iron & Steel department to Staff department), she is most likely to remain inactive mainly because she has not accumulated knowledge and experiences relevant and useful to members in another department. In addition, reallocating a member into another CoP in the same department is likely to remove unnecessary times to adapt to other members and their communication patterns in other departments. Another special case to remind is that a rearrangement candidate engages in both the source CoP and the destination CoP because an employee can participate in multiple CoPs. In this case, CoPs that already include the candidate as a member cannot be selected as a destination CoP. To complete a rearrangement strategy of the rearrangement candidate from the source CoP to the destination CoP, it is necessary to first reconfigure network connections that the rearrangement candidate has maintained with other members in the source CoP. To this end, we present two propositions as follows:

Proposition 3-a *Main Reconfiguration Strategy in the Source CoP* (Fig. 7.1): When a member in the source CoP is reallocated to the destination CoP, her collaboration relationships are reconfigured to other remaining members with the most

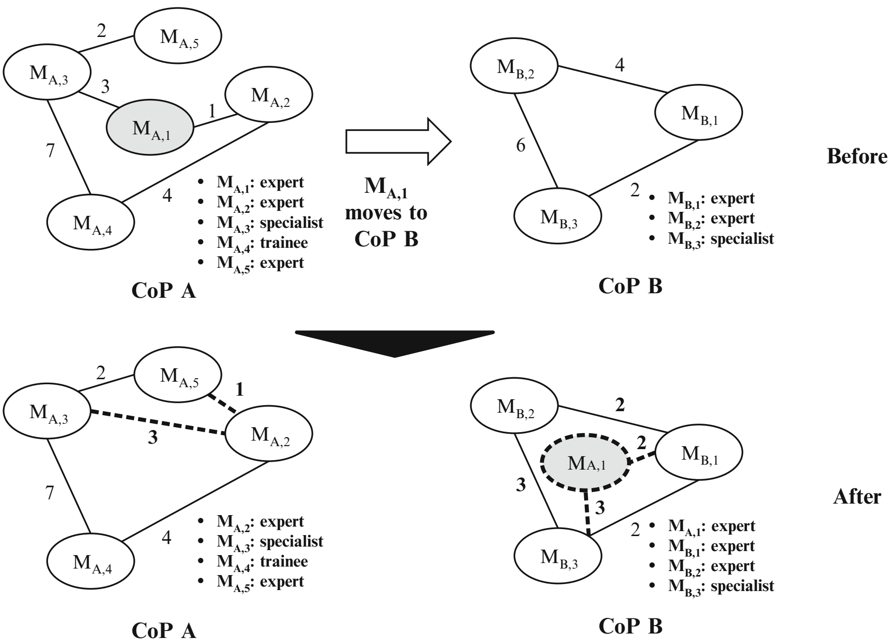

Fig. 7.1 Reconnection and reconfiguration strategy in source and destination CoPs

active involvement in knowledge sharing in the source CoP. Members with the same or higher expertise level are preferred to members with lower expertise level.

For example, in Fig. 7.1, when an expert member $M_{A,1}$ in CoP A is reassigned to CoP B, her connections with $M_{A,3}$ (weight 3) and $M_{A,2}$ (weight 1) are reassigned to $M_{A,2}$ who has the maximum knowledge-processing capacity (total weight 4) among experts in CoP A mainly because the tasks performed by departed member tend to be reassigned to the remaining members with maximum performance capacity (Kwon et al. 2007). To prevent the loss of the total amount of CoP activity, a new direct relationship between $M_{A,3}$ and $M_{A,2}$ is assumed to take a weight of 3, a larger weight of $M_{A,1}$ because $M_{A,3}$ is not an expert but a specialist. However, a new direct connection between $M_{A,5}$ and $M_{A,2}$ is created with a weight of 1 (a smaller weight because $M_{A,5}$ is also an expert like $M_{A,2}$) to restore to-be-lost direct connection between $M_{A,1}$ and $M_{A,2}$. When there are few remaining members with the same expertise level or no members with the same expertise level in the source CoP, however, it is necessary to randomly break the tie and select a member with the same expertise level or randomly select a member with lower expertise level to reconfigure connections of the rearrangement candidate. To this end, we posit the following proposition.

Proposition 3-b *Supplemental Reconfiguration Strategy in the Source CoP*: When Proposition 3-a is not applicable for any reasons, collaboration relationships of the rearrangement candidate are reconfigured to other randomly chosen remaining members with the same (preferred) or lower expertise level in the source CoP while keeping the total knowledge sharing activities constant in the source CoP.

Note that while the total number of connections in the source CoP remain at approximately same level, connections of remaining members vary as knowledge activities of the departing member are reassigned. Therefore, it is possible that the *BIS* of the source CoP increases or decreases after reconfiguration. Once the process of disconnecting and reconnecting of collaboration relationships among remaining members in the source CoP is completed, the process of making connections between the rearrangement candidate from the source CoP and members in the destination CoP begins. This process is regulated by the following proposition:

Proposition 4 *Reconnection Strategy in the Destination CoP* (Fig. 7.1): The rearrangement candidate from the source CoP takes a half of the collaboration relationships of the member with the most active knowledge sharing activities in the destination CoP.

The reconnection of collaboration relationships in the destination CoP (CoP B) based on the proposition 3 is graphically illustrated by two figures in the right of Fig. 7.1. According to this proposition, when an expert member $M_{A,1}$ from the source CoP, she takes a half of $M_{B,2}$'s collaboration relationships before rearrangement because $M_{B,2}$ performs the maximum level of knowledge sharing activities. In particular, the collaboration relationship of $M_{B,2}$ with $M_{B,3}$ has a weight of 6. Then, when $M_{A,1}$ is connected to $M_{B,3}$, the original weight of a collaboration relationship between $M_{B,2}$ and $M_{B,3}$ is reduced to a half (i.e., 3) and the lost weight is distributed to the new direct connection made between $M_{A,1}$ and $M_{B,3}$ (weight of 3). The relationship of $M_{B,2}$ with $M_{B,1}$ is also reconnected similarly. $M_{A,1}$ makes a new connection with $M_{B,1}$ by taking a half (i.e., 2) of the original weight of a collaboration relationship between $M_{B,2}$ and $M_{B,1}$.

Note that the direction of knowledge flow between members is not specified in Fig. 7.1 mainly to avoid unnecessarily complicated presentation of our reconnection and reconfiguration propositions. However, this study explicitly considers the flow directions of collaborations (both in- and out-degree) in the process of implementing reconnection and reconfiguration strategies in the following sections to realistically model knowledge sharing processes with knowledge creation and knowledge consumption.

7.3.2 Knowledge Sharing Data Sets

To show the improvement of knowledge sharing activities among CoPs members by reconfiguring CoP memberships, we start with real CoP activity data sets from Company P that currently supports 1,600 CoPs, with a total number of CoP participants of about 89,000 employees. The data sets used in this study is a sampled data sets that contain the knowledge sharing activities of 3,730 employees (representing 4,414 members because 568 employees, or 15.2 %, engage in more than one CoP) across 59 CoPs from four departments: Iron & Steel (I01–I14), Maintenance (M01–M15), Rolling (R01–R14), and Staff (S01–S16). To obtain reliable and representative information, we sample about the same number of CoPs (between 14 and 16) and a similar number of members from each department (910 members from Staff to 1,296 members from Rolling). Each CoP has an average of about 7.48 employees, and each employee creates 4.4 messages and consumes 72.2 messages. The total number of members is 4,414 with 838 experts (e.g., executive, VP, senior managers), 1,584 specialists (e.g., junior managers), and 1,992 trainees (e.g., new employees). For further analysis, CoP members are first classified into four categories—$Member^{CO}$ (core player, 5.7 %), $Member^{CR}$ (knowledge creator, 7.7 %) and $Member^{CS}$ (knowledge consumer, 15.6 %), $Member^{IA}$ (inactive player, 71.0 %)—based on the information captured in knowledge transfer matrix. Then, 59 CoPs are classified into four types: knowledge sharing community (CoP^{SH}, 10.2 %), knowledge storing community (CoP^{ST}, 1.7 %), knowledge learning community (CoP^{LR}, 28.8 %), and inactive community (CoP^{IA}, 59.3 %). For detailed descriptions of member types, CoP types, and classification schemes, the readers are advised to refer to Lee et al. (2012).

In our study, the pervasiveness of the *ith* bottleneck is measured as the proportion of members who actually cause the *ith* bottleneck out of all members who can cause it (e.g., all experts and specialists) while the relative priorities (w_i) of the *ith* bottleneck are based on subjective assessments on the importance of each bottleneck from two experts. The derived relative normalized priorities of the bottleneck categories and types are summarized in Table 7.1.

According to Table 7.1, the knowledge drain bottleneck is twice as important as the master-apprenticeship bottleneck (0.667 vs. 0.333) in determining the capacity of the *BIS* metric. In addition, while two bottlenecks in the knowledge drain category

Table 7.1 Relative weights of six bottlenecks

Bottleneck category priority		Bottleneck type priority		Relative priority
Master-apprenticeship	0.333	Bottleneck 1	0.597	0.199
		Bottleneck 2	0.214	0.071
		Bottleneck 3	0.101	0.034
		Bottleneck 4	0.088	0.029
		Total	1.000	0.333
Knowledge drain	0.667	Bottleneck 5	0.500	0.333
		Bottleneck 6	0.500	0.333
		Total	1.000	0.667

Source: Lee et al. (2012)

(i.e., Bottlenecks 5 and 6) are equally important, Bottleneck 1 is considered most important, followed by Bottlenecks 2, 3, and 4 in the master-apprenticeship category. Finally, multiplying the bottleneck category priority by the bottleneck type priority establishes the relative priority of each bottleneck. Examining the relative priority values, we find that Bottlenecks 5 and 6 (0.333 for each) are the most important, followed by Bottlenecks 1 (0.199) and 2 (0.071). While relative weights in Table 7.1 are subjective and could be different with different decision makers' preferences, our general analysis framework is still applicable and obtained managerial insights will be useful.

Using relative weights in Table 7.1, we compute the values of *BIS* of 59 CoPs to measure how serious each (and aggregated) bottleneck is and present them in Table 7.2. One notable fact is that the values of *BIS* of CoPs in different departments and even in the same department are very different. For example, we note that CoPs in Staff department have the highest value of *BIS* on average and the CoP with the highest *BIS* in Staff department is S14 and its *BIS* value is about 3.5 times higher than that of S01 (0.559 vs. 0.155). We believe that by dynamically reconfiguring CoP memberships within the same department, the organization may evenly distribute active participants of collaboration network across CoPs and eliminate bottlenecks associated with CoP members who have to respond to so many requests from non-experts. This will ultimately improve the organizational knowledge sharing climate (Constant et al. 1996; Huber 2001; Orlikowski 1993) and employees' intention to share their knowledge (Ardichvili et al. 2003; Bock et al. 2005).

7.3.3 Simulation Experiments Setups

We adopt a computer simulation method as a principal analysis tool to test the effectiveness of the proposed system with propositions to decrease the total sum of *BIS* in the organization. Note that simulation method offers great flexibility and robustness to gain insights into the real-world situation by testing various scenarios in an artificially created and controlled environment (Starbuck 2004; Kwon et al. 2007).

Table 7.2 BIS of 59 CoPs

CoP ID	BIS	CoP ID	BIS	CoP ID	BIS	CoP ID	BIS
I01	0.245	M01	0.227	R01	0.349	S01	0.155
I02	0.395	M02	0.369	R02	0.456	S02	0.297
I03	0.227	M03	0.229	R03	0.212	S03	0.436
I04	0.356	M04	0.320	R04	0.219	S04	0.350
I05	0.248	M05	0.237	R05	0.327	S05	0.329
I06	0.259	M06	0.451	R06	0.275	S06	0.481
I07	0.274	M07	0.283	R07	0.366	S07	0.395
I08	0.322	M08	0.379	R08	0.266	S08	0.492
I09	0.274	M09	0.366	R09	0.268	S09	0.374
I10	0.241	M10	0.318	R10	0.255	S10	0.221
I11	0.258	M11	0.350	R11	0.451	S11	0.438
I12	0.283	M12	0.186	R12	0.360	S12	0.548
I13	0.362	M13	0.371	R13	0.246	S13	0.302
I14	0.342	M14	0.392	R14	0.272	S14	0.559
–	–	M15	0.229	–	–	S15	0.529
–	–	–	–	–	–	S16	0.520
Avg. BIS	0.292	Avg. BIS	0.314	Avg. BIS	0.309	Avg. BIS	0.402

```
BIS_cur:=Calculate the total sum of BIS;
while (iteration):
        CoP_source:=select source CoP;
        Member_move:=select Member;
        CoP_destination:=select destination CoP;
        move Member_move from CoP_source to CoP_destination;
        BIS_new:=calculate the new total sum of BIS;
        If (BIS_new < BIS_cur):    // improved
                BIS_cur:=BIS_new;
        else:                                // not improved
                Cancel the movement and restore original network;
        end if;
end while;
```

Fig. 7.2 Pseudo code

We carry out simulations with two different strategies to determine the destination CoP in addition to general propositions in previous section. These strategies are different in the sense whether it considers the distribution of expertise levels of CoP members in the selection process of the destination CoP (Strategy B) or not (Strategy A). In other words, the ultimate goal of Strategy B is to evenly distribute experts across CoPs to catalyze an organizational knowledge sharing climate that will boost employees' willingness to share their knowledge (Ardichvili et al. 2003; Bock et al. 2005). We present the pseudo code of rearrangement process in Fig. 7.2.

7.4 Experimental Results: BIS Improvement and Network Structure

7.4.1 Comparison of BIS Improvements and CoP Types Distribution

We carry out simulations with 5,000 iterations for each strategy and measure the improvement of *BIS* (= $(BIS_{old}–BIS_{new})/BIS_{old}$) over iterations as CoP members are rearranged and collaboration networks are reconfigured. We graphically present such information in Fig. 7.3.

Overall, both strategies significantly improve the healthiness of collaboration networks in terms of BIS value. To our surprise, however, Strategy A results in greater improvement (18 %) than Strategy B (10 %). We partially attribute this finding to the fact that Strategy A makes it possible to assign more rearrangement candidates into destination CoPs during the fixed iteration because it does not enforce any extra eligibility requirements on destination CoPs while Strategy B searches for destination CoPs that satisfy an additional distribution requirement of experts. In particular, Strategy B does not make further improvement in terms of *BIS* values after the iteration of 3,500, indicating that there is no available destination CoPs. Interestingly, Strategy B makes steeper improvement at early iterations (up to 255 iterations) mainly because it heuristically finds better fitting destination CoPs for chosen rearrangement candidates.

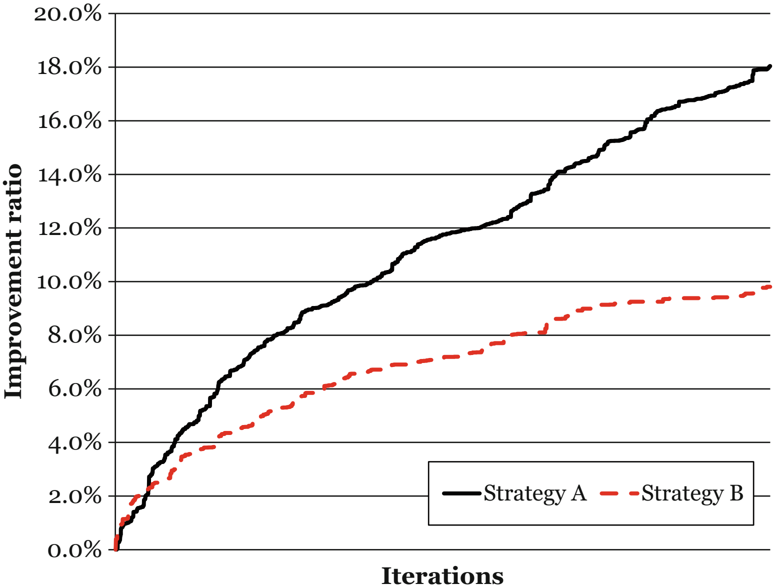

Fig. 7.3 Improvement of BIS values by strategy A & B

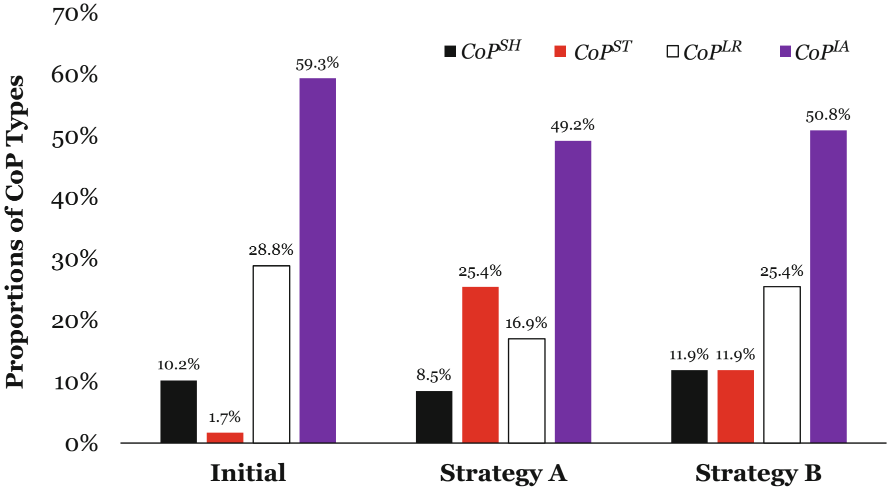

Fig. 7.4 Proportions of CoP types

The effectiveness of Strategy A and B is also compared in terms of the proportions of each CoP types. According to Fig. 7.4, both Strategy A and B significantly increase the proportion of CoP^{ST} type (from 1.69 % to 25.42 % and 11.86 %, respectively) and also significantly decrease the proportion of CoP^{IA} type (from 59.32 % to 49.15 % and 50.85 %, respectively). Therefore, both strategies greatly improve the structural healthiness of collaboration networks with the organization. One of major differences between two strategies come from the fact that Strategy A results in a much higher proportion of CoP^{ST} than (25.42 % vs. 11.86 %) Strategy B while it results in a much lower proportion of CoP^{LR} than Strategy B (16.95 % vs. 25.42 %). Therefore, we can conclude that the major improvement of BIS value via Strategy A over Strategy B is due to the significantly increased proportion of CoP^{ST} type. However, we also note that Strategy A slightly decrease the proportion of CoP^{SH}, insinuating a possible negative impact over a long-term period.

7.4.2 *Improvement of Collaboration Network Structures*

To illustrate the improvement of structural healthiness, we graphically show the change of the network structure of an exemplar CoP, S05 in Fig. 7.5 in which triangle, rectangle, and circle represents expert, specialist, and trainee, respectively. This CoP was one of inactive CoPs in which eight members were orphaned without connections to other members, indicating that few experts were connected with too many non-experts and many experts and specialists (two experts and five specialists) were not fully utilized. However, after the reconfiguration of its collaboration networks via either Strategy A or Strategy B, all members except two are now connected to other members and the loads of few experts with heavy loads are nicely spread out

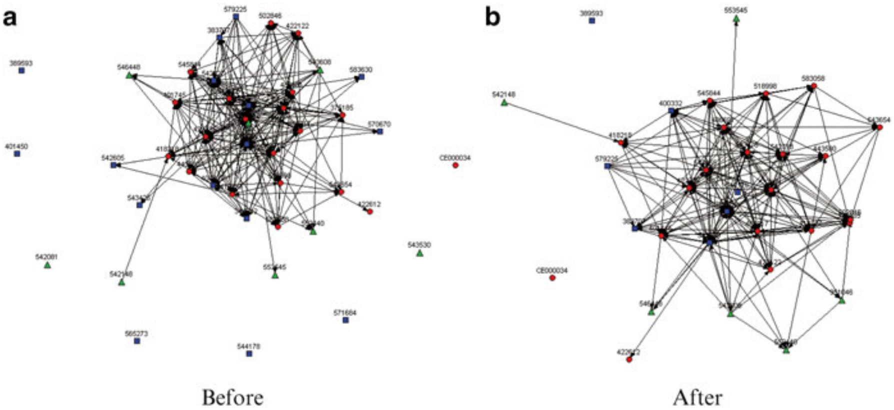

Fig. 7.5 Network structures of S05 before and after reconfiguration

to other experts or specialists. There are no experts without active connections to other members. Overall, the new collaboration network structure of S05 shows the typical pattern of CoP^{ST} and its *BIS* is improved by 45 % and 15 % for Strategy A (from 0.329 to 0.180) and Strategy B (from 0.329 to 0.281), respectively.

One final note in regard to the comparison of Strategy A and B is that while Strategy A results in a greater improvement in terms of *BIS* value than Strategy B, Strategy B is likely to provide a solution that reflects the desired distribution of three CoP member types. To this end, we present the proportions of member types in CoPs of Rolling department. According to Table 7.3, the proportions of experts show an extremely distorted distribution (between 1 % and 33 %) across CoPs in Strategy A induced networks, while the corresponding distribution in Strategy B induced networks is much more balanced (between 9 % and 34 %). Specialists (18–67 % vs. 21–62 %) and trainees (14–81 % vs. 16–63 %) across CoPs in Strategy B induced networks are also more evenly distributed than in Strategy A induced networks. Note that well-balanced distributions of experts and specialists are likely to arouse collaborative environments because they are ones who can create and share knowledge, and hence lead CoPs to a higher level of knowledge sharing activities from a long-term perspective. However, Strategy A is still useful in the sense that it presents an upper bound of *BIS* improvement when balanced distributions of human experts are not considered at all.

7.5 Conclusion

This study simulates two reconfiguration strategies to modify the structure of collaboration networks established among 4,414 members in 59 CoPs and reports that the proposed approach effectively decreases potential threats to knowledge sharing and improves the structural healthiness of knowledge sharing networks when it is measured by *BIS*. Specifically, the number of knowledge storing CoPs is

Table 7.3 Distributions of expertise levels of CoPs in rolling department

	Proportions with strategy A			Proportions with strategy B		
CoP ID	Expert	Specialist	Trainee	Expert	Specialist	Trainee
R01	18 %	46 %	36 %	12 %	44 %	44 %
R02	23 %	45 %	32 %	11 %	46 %	43 %
R03	20 %	40 %	40 %	13 %	38 %	48 %
R04	13 %	30 %	57 %	11 %	33 %	56 %
R05	10 %	27 %	63 %	14 %	46 %	40 %
R06	18 %	***67 %***	**14 %**	22 %	***62 %***	**16 %**
R07	19 %	49 %	32 %	***34 %***	33 %	33 %
R08	13 %	27 %	60 %	11 %	33 %	56 %
R09	**1 %**	**18 %**	***81 %***	**9 %**	36 %	55 %
R10	15 %	64 %	21 %	11 %	46 %	43 %
R11	5 %	43 %	51 %	26 %	33 %	40 %
R12	22 %	53 %	25 %	26 %	36 %	38 %
R13	8 %	38 %	54 %	11 %	42 %	48 %
R14	***33 %***	33 %	33 %	16 %	**21 %**	***63 %***

significantly increased while the number of inactive CoPs is decreased. Another important structural improvement is that expert members with an appropriate amount of collaboration burden are evenly distributed across CoPs, making it possible for each CoP to further transform into a full-fledged CoP with a sufficient number of experts from whom trainees may learn. Overall, the proposed approach helps organizations by eliminating structural bottlenecks and evenly distributing both experienced and unexperienced members.

Findings from this research contribute to knowledge sharing and management community in the sense that we quantitatively measure the seriousness of barriers to knowledge sharing activities in CoPs and demonstrate the impact of reconfiguration strategies by linking current activity data sets collected from real CoPs to simulated future outcomes. Practitioners may benefit from adopting the proposed approach not only to improve the current structural healthiness of knowledge networks in CoPs for a short-term period but also to establish a stable structure of organizational collaboration networks toward active knowledge sharing for a long-term period with no needs to change their current IT infrastructure, rewards incentives, or organizational hierarchy.

While the proposed system bears methodological contributions and presents several managerial insights, it is limited in the sense that reconfiguration strategies do not consider other important individual psychological factors or organizational cultures that may affect members' motivations to share their implicit and explicit knowledge through collaboration networks and regulate reconfiguration propositions. Therefore, in our follow-up research, we intend to extend the current research to compare the effectiveness and usefulness of the proposed approach within two completely different organizational cultures (e.g., vertical or horizontal organizational culture). Another possible future research is to develop a new methodology with reconfiguration propositions and measure the synergy effects when two or more intimate members are allowed to move at the same time.

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