A Max-Min Approach to the Output Evaluation of Knowledge Interaction

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Abstract

The concept of knowledge management has been flowering as information management matures. Nevertheless, up until now, more attention has been focused on knowledge management inside organizations and less on knowledge management across organizational boundaries. Attempting to fill this gap and address the problems of cross-boundary knowledge management, this research first identified key boundary objects in the context of knowledge management, and then studies how actors from different organizations interact through boundary objects. The result links the performance of collaborative acts to the frequency of boundary object encountering in the course of interaction. In this study, although the context is described with "actors" in mind, the unit of analysis is "knowledge" itself, rather than "actors," and the interaction is termed "knowledge interaction". Student assignments of information system projects serve as the cases of analysis. To analyze the performance of knowledge interactions, a max-min approach is applied, with one output factor, namely project performance, and four input factors, which are the frequencies of the encountering of four boundary objects. The result strongly suggests that identifying, creating, and facilitating useful boundary objects is the key to successful projects. Whether tacit knowledge is converted into explicit knowledge during the process is less important in achieving effective collaboration. Also, it is not always necessary to identify specific tacit knowledge in each organization.

1. Introduction

With globalization and organizational expansion, attention on knowledge management is gradually shifting from within a single organization to across multiple organizations. Orlikowski [15] observed how members of global product-development organizations generate and sustain knowledge in their distributed operations. She proposed the concept of "distributed organizing," which is the capability of operating effectively across the temporal, geographical, political, and cultural boundaries, a situation routinely encountered in global operations. The authors viewed this "distributed organizing" as the capability of creating new knowledge based on existing knowledge, with the intention of solving problems.

Organizational performance is commonly linked to its ability to manage knowledge well. Nickson and Zenger [12] stressed a viewpoint about effective organizations, one which focuses on the efficiency of alternative organizational forms in generating knowledge or capability. They divert the focus from the role of organizations in providing efficient knowledge exchange to their role in efficiently producing knowledge or capabilities. They argued that a problem's complexity influences the optimal method of solution search with the problem as the basic unit of analysis. From this problem-solving perspective, the important issues are what can improve the efficiency of collaboration across multiple organizations and how to enhance the efficiency of knowledge creation.

For collaborations across multiple organizations to be efficient and effective, the impact of boundaries should be reduced and the support of boundaries be greatly enhanced. Because boundaries always exist in multiple-domain collaboration, the choice is either to break them or to try to find a way to cross them. Star and Griesemer [20] stated that we should respect the different views arising from the many worlds of different actors at the points where the worlds of those actors intersect. In fact, they believe that it is unnecessary to break boundaries. Further, they pointed out that communication across multiple domains by means of boundary objects is an efficient way to reduce obstacles.

Interactions take place when knowledge actors in different organizations communicate with each other. Although actors are performing the interactions, the

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resources that are involved in the interaction are actually knowledge, and therefore the interaction is called a knowledge interaction.

Hedlund [10] proposed a model of knowledge categories and transformation processes in which eight processes are defined: articulation, internalization, reflection, extension, appropriation, dialogue, expansion, and assimilation. In other words, these transformation processes can be viewed as different kinds of knowledge interactions. Hedlund also pointed out that the quantity and quality of “dialogue” and “reflection” are important determinants of the type of knowledge management needed and whether the prescribed knowledge management is effective. For this reason, in effective interactions, “dialogue” and “reflection” play important roles which influence the efficiency of knowledge management as boundary objects function. They in fact can be regarded as additional kinds of boundary objects.

As new knowledge is generated from existing knowledge under knowledge interactions, whether the interactions are effective is crucial to new knowledge creation. Moreover, boundary objects are media of interactions and tightly coupled with the output performance, thus greatly influence the efficiency of knowledge interactions. This study first summarized types of boundary objects, and then applied a max-min methodology to measure the efficiency of each knowledge interaction. Our objective is to answer the question as to whether some types of boundary objects lead to more efficient knowledge interactions than others.

2. Literature review

2.1. Boundary objects

Scientific work requires collaboration which is carried out by diverse groups of actors of different disciplines. Those actors who share a common goal must create common understandings, ensure reliability of communication across domains, and gather information which retains its integrity across time, space, and local contingencies. Star and Griesemer [20] proposed the concept of “boundary objects,” which are adaptable to different viewpoints and robust enough to maintain identity across them, as a means of translating between different viewpoints. Boundary objects are therefore facilitators for communication between actors. They inhabit multiple worlds simultaneously and meet the demands of each of them. These objects mean different things in different worlds and might be simultaneously concrete and abstract, specific and general, conventionalized and customized. Actors must reconcile these different meanings to collaborate successfully. In Star and Griesemer’s work, four categories of boundary objects are defined: repositories, ideal types, coincident boundaries, and standardized forms. These four types of boundary objects are all explicit in nature. The “tacit” type of boundary object seems to be missing from Star and Griesemer’s work. An example of a tacit boundary object is described by Cook and Brown [8]. In the “machine design” case [13], genre is a kind of boundary object that straddled bread-making and machine-making. Another tacit type of boundary object is viewed as “organization’s memory” by Ackerman and Halverson [1].

Many different types of boundary objects are still unknown or less discussed. Koskinen [11] addressed the question of what role metaphoric boundary objects play in knowledge sharing within and between organizations’ innovation processes. He believed that the better an organization understands the nature of existing boundary objects, the more effectively it can take action to overcome existing barriers. In contrast, without the use of boundary objects, the possibility of arriving at common understandings is limited, and the opportunity to achieve a successful innovative process is reduced. Boundary objects can be artifacts, documents, and even vocabulary that can help people from multiple domains to build a shared understanding. Koskinen [11] focused on vocabulary-based boundary objects including figurative language and symbolism and dealt with the role of metaphors in the creation of boundary objects. He believed that a strengthened metaphoric boundary object will become better able to support the organization’s innovation process. In summary, boundary objects are those objects, whether explicit or tacit, which enhance mutual understanding and communication in the process.

2.2. Boundaries of knowledge management

Carlile [6] examined the management of knowledge across three knowledge boundaries: syntactic, semantic, and pragmatic. He pointed out the importance of clarifying the relationships between actors in order to manage knowledge effectively across boundaries. He observed that actors need to not only share their own knowledge, but also assess each other’s knowledge during interactions. Carlile [5] also adopted Star’s list of boundary objects in describing the uses of boundary objects by individuals in the settings that he observed. According to Star’s classification, there are four categories of boundary objects: repositories, ideal types, coincident boundaries, and standardized forms. In Carlile’s classification, there are three categories of boundary objects, namely, syntactic, semantic, and pragmatic.

Our study identifies more boundary objects and expands Carlile's categories to include a new metaphoric category. This new category includes boundary objects such as figurative language and symbolism (Koskinen, [11]), genres (Cook and Brown, [8]), nonverbal expressions (Nosek, [14]), and visionary objects (Briers and Chua, [4]). Table 1 shows the specific objects in each category.

Table 1. Categories of boundary objects and specific objects

Categories of boundary objects	Specific objects
Syntactic	Repositories
Semantic	Standardized forms and methods
Pragmatic	Objects, models, and maps
Metaphoric	Figurative language and symbolism, genres, non-verbal expressions, visionary objects

2.3. Knowledge interaction

While the actors in a collaborative interaction, be they individuals or groups, are communicating with each other, boundary objects are also being generated. The existence of boundary objects themselves is useful to the assimilation and dissimilation of knowledge. Consider the collaboration between two organizations as an illustration of where boundary objects can be created. When collaboration occurs between organization A and organization B, the knowledge which will be used in the collaboration comes from three different sources (Figure 1). Two of these sources exist in organization A and organization B separately, and the third source is generated only from the interaction, at the point where the two organizations collaborate. Let the diamond shape in Figure 1 represent all the knowledge used during the collaboration. Then the diamond can be divided into three parts according to the sources of the knowledge. Part 1 represents the original knowledge from the actors in organization A, and Part 2 represents the original knowledge from the actors in organization B. Part 3 represents the new knowledge created during their interactions. It can be inferred that this new knowledge is generated by the actors from both organizations based on their existing knowledge, and that each boundary object generated bridges across these sources and functions as a carrier of one or more kinds of knowledge. However, identical boundary objects can have different effects on actors, because the actors' existing knowledge may not be similar and their cognitive activities are not uniform.

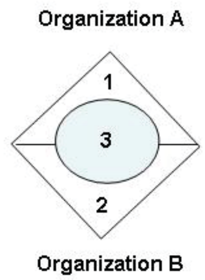

Figure 1. Three different sources of interorganizational knowledge

Our study focuses on identifying the relationship between the performance of collaborative interactions and the occurrence of various boundary objects.

Although the context is described with "actors" in mind, the unit of analysis is "knowledge" itself, rather than "actors." While actors interact with each other across boundaries, knowledge, rather than actors, is the source of knowledge interaction. Yet, knowledge may not be always beneficial to knowledge interactions; there are also poor interactions in which the actors' existing knowledge turns out to be the barrier of knowledge interaction. We posit that knowledge boundaries and boundary objects are helpful in explaining why knowledge is both a barrier to and a source of knowledge interactions, just what Carlile [5] insisted in his study. Therefore, in our study, we observe how boundary objects are in action in each interaction, with the belief that some boundary objects are crucial to effective collaboration, while others are not as crucial. Following the observation and Min-Max analysis, an effective way for actors to communicate across multiple organizations using boundary objects is proposed.

2.4. Max-min approach

Quite a few studies used standard DEA analysis, such as CCR and BBC, to evaluate efficiency in various contexts (Andersen and Petersen, [2]; Banker, Charnes and Cooper, [3]; Cooper, Park and Pastor, [9] ; Charnes, Cooper and Thrall, [7]; Saha and Ravisankar, [16] ; Sueyoshi, [21]; Sherman, [19] ; Shao, [18]). As the result is merely a number which represents the efficiency, the underlying belief of these studies obviously is that efficiency is a static value which is measured at a certain instance of time. The efficiency of each knowledge interaction (KI) in this study would have been precisely calculated, rather than bounded by maximum and minimum, from the inputs and outputs, if DEA analysis had been used. However, in practice, efficiency should be dynamic and it fluctuates within a range. Max-Min approach reasonably presents efficiency as a range rather than a number. In other words, Max-Min approach considers not only the best case but also the worst case.

In an assessment of various methodologies for evaluating project performance, Talluri and Narasimhan [24] proposed the max-min approach, of which the main concept was to measure the maximum and minimum performance of a vendor. A non-parametric statistical procedure referred to as the Krushkal-Wallis test is utilized in testing their hypotheses. Performance was based on a comparison with the ideal measurement standard set up by the buyer. Using max-min models, it is possible to determine two performance values for each vendor, namely max and min efficiency scores.

A model with too many indicators is never desirable. Therefore using input and output indicators to group KIs is unacceptable. By applying Max-Min approach in evaluating KIs, all values of input and output indicators are transformed into two values of efficiency, one being the upper bound and the other being the lower bound. All KIs are subsequently grouped into clusters according to the upper and lower bounds, namely the max-efficiency and min-efficiency. The performances of KIs in the same cluster are similar in the sense that the bounds, max-efficiency and min-efficiency, are approximately the same, relative to KIs in other clusters.

Besides ranking the performance of the vendors, Talluri and Narasimhan [24] also found the max-min approach helpful in determine clusters of vendors having the same properties. The vendors aggregated into the same cluster had a higher degree of homogeneity and were more likely to substitute for each other. They also suggested that whenever a buyer had to choose an alternative vendor to replace an existing vendor, it should first consider the vendors in the same cluster as the original vendor. In analogy, in our study, KIs in the same cluster deliver comparable performance with perhaps different patterns of BOs.

2.5. A max-min approach to the evaluation of knowledge interaction outputs

The max-min approach proposed by Talluri and Narasimhan [24] was used to evaluate the performance of vendors in a supply chain. This approach has also been proven to be an effective tool for evaluating two-way factors, the output factors and input factors (Talluri, [22]; Talluri and Baker, [23]; Sarkis and Talluri, [17]). Our study calls for a composite model of two-way factors to evaluate the performance of knowledge interactions. All values derived from each KI are either output factors or input factors.

First, the max-min approach is used to evaluate the performance for each knowledge interaction. All KIs are aggregated into clusters according to their performance. Then a relationship between the performance and the input factors are drawn.

Taking the management of knowledge interaction as an optimization problem, the objective of a highly efficient knowledge interaction involves maximizing the ratio of the weighted sum of outputs to the weighted sum of inputs. This optimization is subject to some constraints.. For example, the weighted sum of outputs does not exceed the weighted sum of inputs, and that the weights are not negative.

This optimization problem is formulated as follows.

$$\max \frac{\sum_{r=1}^{v} a_r y_{r_p}}{\sum_{s=1}^{u} b_s x_{s_p}}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{v} a_r y_{r^*}}{\sum_{s=1}^{u} b_s x_{s^*}} = 1,$$

$$\frac{\sum_{r=1}^{v} a_r y_{r_i}}{\sum_{s=1}^{u} b_s x_{s_i}} \le 1 \quad \forall i,$$

$$a_r, b_s \ge 0 \quad \forall r, s,$$

The formulation aims to calculate the maximum, which corresponds to the efficiency in the best scenario. However, the worst case scenario is also crucial to organizational decision making. In other words, both maximum and minimum values matter. The max-min approach is based on this belief and is expressed in the following two models.

Model (1)

$$\max \sum_{r=1}^{v} a_r y_{r_p}$$

$$\text{s.t.} \quad \sum_{s=1}^{u} b_s x_{s_p} = 1$$

$$\sum_{r=1}^{v} a_r y_{r^*} - \sum_{s=1}^{u} b_s x_{s^*} = 0,$$

$$\sum_{r=1}^{v} a_r y_{r_i} - \sum_{s=1}^{u} b_s x_{s_i} \le 0 \quad \forall i,$$

$$a_r, b_s \ge 0 \quad \forall r, s,$$

Model (2)

$$\min \sum_{r=1}^{v} a_r y_{r_p}$$

s.t. model (1) constraints are satisfied.

p: the KI being evaluated
a_r: the weight given to the *r*th output
b_s: the weight given to the *s*th input
v: the number of KI evaluation outputs
u: the number of KI evaluation inputs
y_{ri}: the value of the *r*th output for the *i*th KI
x_{si}: the value of the *s*th input for the *i*th KI
y_{r*}: the best value for the *r*th output across all KI
x_{s*}: the best value for the *s*th input across all KI

Since knowledge interactions take organizational resources to carry out, it is desirable for organizations to contain the amount of resource (or effort). Models (1) and (2) capture the objective of knowing the range of performance of each KI while containing the effort or resource.

The max efficiency of each KI is determined by Model 1, and the min efficiency of each KI is determined by Model 2 with the constraints in Model 1. It is necessary to further discuss their relative performance. Interactions with similar properties are aggregated into the same cluster. Knowledge interactions in the same cluster can be viewed as priority replacement solutions for one another, and exhibit approximately similar efficiency, defined as the performance of KI divided by the input efforts made by the organization.

3. Measurement design and results

3.1. Measurement Design

To observe collaborative knowledge interactions between two individuals from different organizations, the interactions between 86 students, who were undergraduates in their fourth year, in various sessions of the same IT Project course and the organizations for which they were designing and implementing the information systems were tracked in the experiment. As part of the course requirement, each student acted as an IT specialist for an IT implementation project in an actual organization. Each student collaborated with an individual in that organization to carry out the project. The project scale was adequate for a student and an individual in an organization. For example, one of the students helped a bakery to set up a web site to promote the products. During the collaboration, each student kept a journal detailing the interactions and recorded all conversations. At the end of semester, each presented the outcome. Performance was measured based on the outcome according to output factors.

The knowledge interactions between organizations and college IS-major seniors were investigated. Since these seniors are quite well trained in information system development, the interactions are nearly similar to the interorganizational interactions such as in the IT outsourcing cases. In fact, most students would be engaging in IT outsourcing tasks right after graduation; they all have the abilities to act as IT specialists for IT implementation projects. Hence, their lack of experience is the only concern. Although the interactions are not exactly between two businesses, the setting in this study reasonably approximates that of two businesses. Studying knowledge interactions as closely as this study is very difficult in the context of two actual businesses, if not entirely impossible.

Four input factors were codified by the instructor based on the student journals and recordings of conversations. The relative frequencies of occurrence of syntactic boundary objects, semantic boundary objects, pragmatic boundary objects, and metaphoric boundary objects were noted by the instructor to be used as the values of the input factors. All values were assessed by the instructor who has tremendous experience in IT projects and has taught the same course for seven years and earned high regards. Thus there is little doubt of whether the evaluation is objective. Furthermore, the quality levels of these four BOs are not of particular concern, since the course has been taught for seven years with excellent evaluation. Resources and support could be accessed by all students equally. Hence, possible variances in the quality for these four BOs are effectively controlled.

In the analysis, the values of the output factors are derived from the project performance, and the values of the input factors are the percentage of the relative frequencies of occurrence of the four types of boundary objects. Performance is considered as an output, because it represents the fruitage of the knowledge interaction. All types of boundary objects are treated as inputs, since they represent the efforts which each knowledge interaction generates in the process. Based on our model convention, higher values of outputs and lower values of inputs indicate desirable characteristics, i.e. higher efficiency.

3.2. Results

To make the illustration of the methodology concise and to simplify the visualization of the figure presented later, this study randomly chose ten out of the 86 KIs as recorded by 86 students, and applied the max-min methodology to the ten chosen KIs. These ten records were mutually exclusive. The input and output factors of each KI, shown in Table 2, were fed into the calculations of max and min efficiencies.

The objective of this study is less in proving a theory than in probing into the working of BOs in KIs.

For the former, calculating all 86 records may be necessary. However, for the purpose of demonstrating the analysis and concluding that some boundary objects are more important than others, the use of 10 records should be adequate. Further, in practice, organizations may have less chance to compare 86 KIs, but more likely to come across the need to compare 10 KIs.

Organizations desire to maximize output, while minimizing input; for example, to use minimum resources to acquire maximum benefits. In this study, the output factor is the performance, and the input factors are the relative occurrence frequencies of four categories of boundary objects. The objective is to achieve higher performance in each KI under the constraint of limited resources, which in our case, are the efforts to sustain various categories of boundary objects. In other words, each factor has its target value, which is either the maximum or minimum out of all ten KIs; in the case of output factor, the target value is the maximum, while the input factors, the minimum. These target values are shown in Table 2 in bold and summarized under the heading "Target," which are 97 for performance, 20 for syntactic boundary objects, 30 for semantic and pragmatic boundary objects, and 10 for metaphoric boundary objects.

Model 1 is run ten times to calculate the maximum efficiency scores for all ten KIs. The results are shown in Table 3: KI 3 achieved the highest efficiency score of 0.958 followed by KI 2, KI 5, KI 1, KI 9, KI 10, KI 8, KI 6, KI 4 and KI 7, with scores of 0.927, 0.865, 0.804, 0.804, 0.734, 0.68, 0.625, 0.5 and 0.427, respectively. These scores represent the maximum efficiencies achievable by each of the KI when evaluated against the target values of input factors. In calculating these scores, Model 1 selects factor weights for four input factors that optimize the performance of the KI, while maintaining the target efficiency score at 1. Thus, in a sense Model 1 is a generous formulation that emphasizes on the strengths of each KI.

The next step in the decision process involves the estimation of the minimum efficiency scores, by using Model 2. As in the third row of Table 3, when compared by minimum efficiency, again, KI 2 performs the best out of ten KIs, with a score of 0.309, followed by KI 8, KI 7, KI 9, KI 3, KI 5, KI 1, KI 10, KI 6 and KI 4, with scores of 0.302, 0.285, 0.268, 0.239, 0.216, 0.201, 0.195, 0.187 and 0.167, respectively. Contrary to Model 1, Model 2 can be referred to as a selfish model that searches for factor weights that represent the worst case scenario for each of the KI, while maintaining the target efficiency score at 1. Thus, it emphasis the weaknesses of each of the KI.

Concisely, Model 1 and Model 2 were applied to acquire values of the max and min efficiencies of each KI, which are summarized in Table 3.

A distribution diagram of the max and min scores are plotted and shown in Figure 2. This diagram illustrates the distribution of the degree of homogeneity among KIs. For example, the degree of homogeneity between KI 2 and KI 3 is greater than that between KI 2 and KI 9, and the degree of homogeneity between KI 5 and KI 1 is greater than that between KI 5 and KI 10. As a result, compared with KI 9, KI 3 is a better alternative solution to KI 2; compared with KI 10, KI 8 is a better alternative solution to KI 5.

By using K-means algorithm, the KIs were clustered according to their proximity, measured by max-efficiency and min-efficiency. Ten KIs are grouped into six clusters, with some clusters containing only one KI. The center of such cluster is exactly the KI itself, as indicated in Table 4.

As shown in Figure 2, KI 2 and KI 3 are clustered in group 1, and KI 1, KI 5, KI 9 and KI 10 in group 2. KI 4, KI 6, KI 7 and KI 8 each forms a group by itself. Clearly, the average efficiency of group 1 is significantly better than group 2. A comparison of the boundary objects between these two groups offers a valuable implication as to how organizations can improve knowledge interactions by better managing the key boundary objects. Of course, boundary objects which are effective in one knowledge interaction may be ineffective in another knowledge interaction. Hence, this study does not intend to generalize the result from a sample of ten records. Rather, it attempts to demonstrate the evaluation of interorganizational knowledge interactions through boundary objects. In the following, group1 and group2 are taken as examples to illustrate the findings.

Figure 3 shows the effectiveness of each type of boundary objects. The average values of five factors in group 1 and group 2 convey the relationship between the performance and the types of boundary objects. When the scores of semantic and syntactic boundary objects decreased, the performance of knowledge interaction increased. Whereas, when the scores of pragmatic and metaphoric boundary objects increased, the performance of knowledge interaction also increased. This finding is of vital importance. It can mean that organizations should set a higher priority in exerting effort to maintain pragmatic and metaphoric boundary objects, if efficient knowledge interactions are desired. Unfortunately, currently more efforts are put into enhancing semantic and syntactic boundary objects, and less efforts into pragmatic and metaphoric ones (Carlile, [6]). However, this is only a proposition suggested by the comparison of the KIs in groups 1 and 2. The confirmation would require a large sample.

Table 2. Input and output values of each KI

	KI 1	KI 2	KI 3	KI 4	KI 5	KI 6	KI 7	KI 8	KI 9	KI 10	Target
Output (performance)	78	90	93	**97**	84	91	83	88	78	95	97
Input1 (syntactic)	50	40	**20**	40	80	30	40	50	60	30	20
Input2 (semantic)	**30**	**30**	70	70	40	70	90	60	80	90	30
Input3 (pragmatic)	**30**	**30**	50	60	30	60	70	40	50	40	30
Input4 (metaphoric)	40	30	40	60	20	50	20	30	**10**	50	10

Table 3. Max and min efficiency of each KI

Efficiency	KI 1	KI 2	KI 3	KI 4	KI 5	KI 6	KI 7	KI 8	KI 9	KI 10
(a) Max. eff.	0.804	0.927	0.958	0.5	0.865	0.625	0.427	0.68	0.804	0.734
(b) Min. eff.	0.201	0.309	0.239	0.167	0.216	0.187	0.285	0.302	0.268	0.195
(a) - (b)	0.603	0.618	0.719	0.333	0.649	0.438	0.142	0.378	0.536	0.539

Table 4. Cluster centers by K-means algorithm

	Cluster					
	1	2	3	4	5	6
Max. eff.	0.943	0.802	0.427	0.5	0.68	0.625
Min. eff.	0.274	0.220	0.285	0.167	0.302	0.187
Number of KIs in each cluster	2	4	1	1	1	1
located on			KI 7	KI 4	KI 8	KI 6

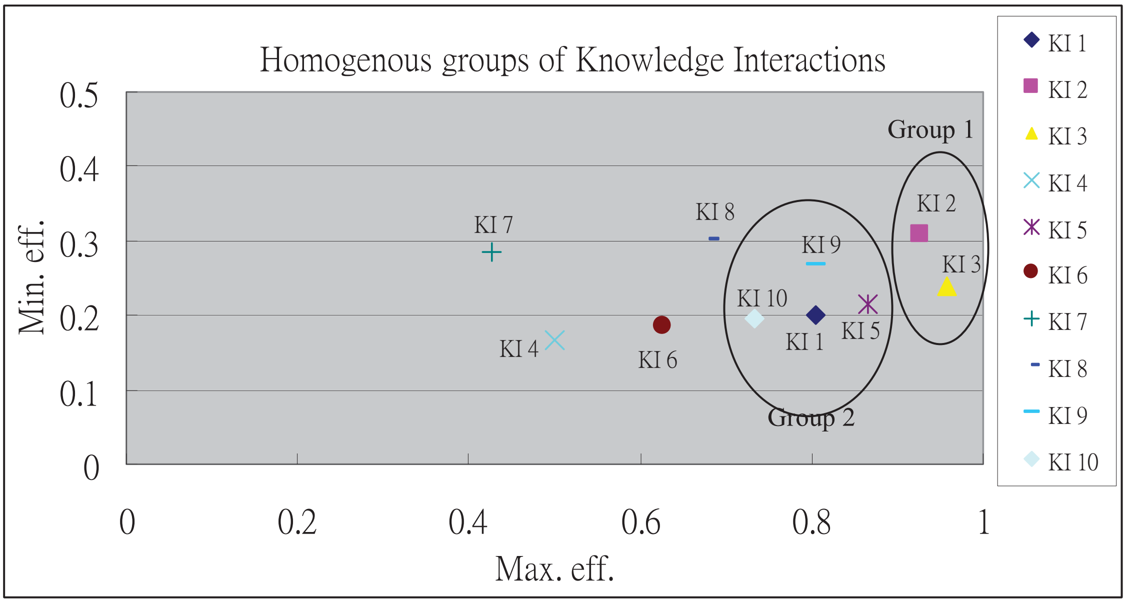

Figure 2. Homogenous groups of knowledge interactions

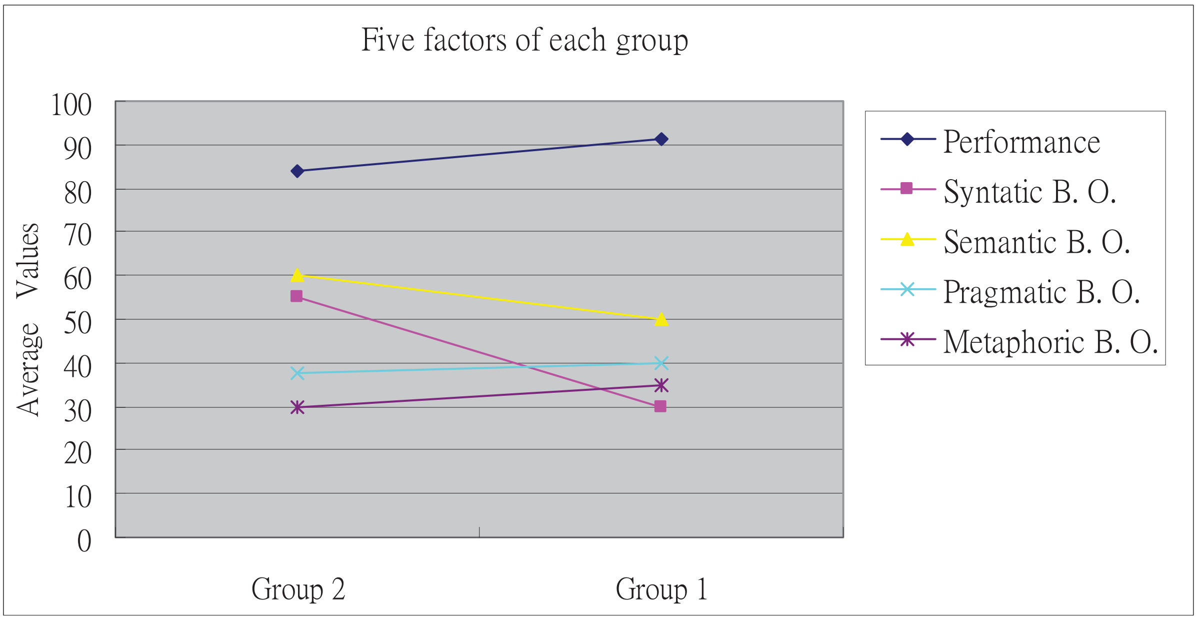

Figure 3. Five factors of each group

This is an ongoing research. As qualitative data analysis tends to be extremely time-consuming, at the present stage interesting results is already possible with 10 KIs. With all 86 KIs, the similar conclusion that some boundary objects are more important than other would be reached. However, as to which types of boundary objects are more important, we might see variations. Other explanatory variables to address the variations and enrich the model would be expected to be brought in for future research.

Even though this study could not validate the theory, it presented an interesting methodology to evaluate knowledge interaction. Possible relationships are inferred, but statistically confirm the relationship is not possible with a qualitative research such as this one, even with a large sample.

4. Conclusions

This research applied a max-min method to evaluate the performance of knowledge interactions between two individuals from different organizations. By means of the max-min approach, knowledge interactions with better performance were clearly distinguished from those with worse performance using criteria selected by the researchers. This method not only is capable of identifying better-performing knowledge interactions, but also assigns weightings to each category of boundary objects when optimizing the performance. The weightings represent the relative importance of different categories of boundary objects.

Based on the sample, the efficiency of knowledge interaction increased as the scores of semantic and syntactic boundary objects decreased; whereas the efficiency increased as the scores of pragmatic and metaphoric boundary objects increased. The result of this study strongly suggests that organizations should pay more attention to the more important types of boundary objects and ponder on how to better maintain them.

Note that the objective of the analysis is not to conclude whether increasing or decreasing knowledge interactions is positive for organizations. Rather, it focuses on the relationships between the types of boundary objects and the efficiency of knowledge interaction.

Although boundary objects are the only set of criteria in this study, they by no means are the only possible set of criteria. In fact, a diversification of criteria would likely offer different insights. It is therefore recommended that alternative criteria that best suit the context in interest be developed in the future. The evaluation of the project performance in this study is quite reasonably done by one person, because it is quite common that all student projects are graded by the instructor of the course. However, if a more objective evaluation is required depending on the research context, qualified evaluators can be teamed up to grade the performance. This arrangement can be considered for future research.

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