Decision Support Systems 56 (2013) 140–147

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Exploring the effect of boundary objects on knowledge interaction

Eugenia Y. Huang [a,*], Travis K. Huang [b,1]

[a] Department of Management Information Systems, College of Commerce, National Chengchi University, 64, Sec. 2, ZhiNan Rd., Taipei 116, Taiwan, ROC
[b] Department of Information Management, Ling Tung University, 1, Ling Tung Rd., Taichung 408, Taiwan, ROC

ARTICLE INFO

Article history:
Received 4 December 2011
Received in revised form 2 November 2012
Accepted 21 May 2013
Available online 28 May 2013

Keywords:
Knowledge management
Efficiency
System analysis
Boundary objects
Knowledge interaction

ABSTRACT

This study attempts to tackle cross-boundary knowledge management problems by examining how knowledge can be generated efficiently. The subjects comprised 81 pairs of users and student analysts. To understand the similarities and differences among 81 records of knowledge interactions, a max–min model was employed to analyze project performance and calculate knowledge interaction efficiency. The analysis involved one output factor (project performance) and four input factors (frequencies of encountering four different types of boundary objects). Cluster analysis and the subsequent comparisons among the clusters suggest that the occurrence of metaphoric boundary objects is the key to good project performance in the context of software system analysis. This paper successfully demonstrates that observing knowledge interaction through the lens of boundary objects can be fruitful, and that some boundary objects are more important than others. However, the context-dependent nature of knowledge interaction mandates further studies in other contexts.

1. Introduction

Organizational performance is commonly linked to an organization's ability to manage knowledge effectively [22]. During the 1990s, knowledge management as a discipline was characterized by diverse foci with studies examining both within and across boundary phenomena [10,16,18,36,42]. Yet the increasing sophistication of professional specializations mandates a shift in focus toward cross-boundary knowledge management [2,23,25]. Organizations that desire efficient knowledge production need to establish an environment that facilitates ample opportunities for effective interactions among knowledge workers across boundaries [24,28,29]. Nickson and Zenger [29] stated that effective organizations should focus on the efficiency of alternative organizational forms when generating knowledge. Their emphasis was on producing knowledge efficiently, rather than merely exchanging it.

Because most innovation takes place along the boundaries between specializations [27], organizations tend to promote collaboration across multiple domains to trigger innovation. Knowledge workers' cross-boundary interactions facilitate cross-boundary knowledge exchange, transfer, and creation. Hence, organizations should not only provide appropriate ways for people to collaborate and accomplish tasks, but also pay attention to how interactions can be conducted efficiently.

As boundaries pose difficulties in knowledge flows, organizations should strive to reduce the influence of boundaries on multi-domain collaboration by either breaking them or, if they are difficult or impossible to eliminate, finding a way to communicate across them. This can be done via the boundary objects that can exist between boundaries, as suggested by Star and Griesemer [39]. These authors stressed that people should respect the different views arising from the many intersecting worlds of different actors. At these intersections, boundary objects emerge to facilitate existing knowledge exchange and new knowledge generation. According to Star and Griesemer, a boundary object is "an analytic concept of (those) scientific objects which both inhabit several intersecting social worlds and satisfy the informational requirements of each of them".

Star and Griesemer further explain boundary objects in the following statement:

> They are weakly structured in common use, and become strongly structured in individual-site use. These objects may be abstract or concrete. They have different meanings in different social worlds but their structure is common enough to more than one world to make them recognizable…

They claimed that "The creation and management of boundary objects is a key process in developing and maintaining coherence across intersecting social worlds". This coherence, which is made possible by the creation and management of boundary objects, is a necessary condition for efficient knowledge interaction. Thus, in this study we propose that knowledge interaction can be observed through the lens of boundary objects.

* Corresponding author. Tel.: +886 2 29387348.
E-mail address: huang.eugenia@gmail.com (E.Y. Huang).
[1] Tel.: +886 926117987.

0167-9236/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.dss.2013.05.012

When knowledge workers in different domains interact with one another, the resources involved in the interaction are not the knowledge workers themselves, but the forms of knowledge that they deploy. Hence, the interaction is termed a *knowledge interaction* (KI) [45], which is defined in this study as the knowledge transformation that occurs when actors interact. The term knowledge interaction is preferable to knowledge transformation, because when the latter term is used the emphasis is normally on processes and stages, whereas in this study attention is directed to the entities that can be observed during the transformation. As knowledge workers communicate, KIs occur and take different forms, similar to the interaction patterns discussed by Nonaka [30] or the processes discussed by Hedlund [20]. Nonaka identified four patterns of interaction between tacit and explicit knowledge–socialization, externalization, internalization, and combination–and modeled the pattern relationships as a spiral of knowledge. According to Hedlund, knowledge is transformed through eight processes that include articulation, internalization, reflection, extension, appropriation, dialog, expansion, and assimilation. Hedlund further stated that the quantity and quality of “dialog” and “reflection” are important determinants of the knowledge management approach needed and whether the prescribed knowledge management is effective. In this regard, if knowledge workers improve their “dialog” and “reflection” through the use of boundary objects, knowledge interaction efficiency is more likely to be enhanced.

With the development of information systems, organizations have gone to great lengths to fulfill explicit knowledge sharing [19]; however, technologies that can facilitate effective tacit knowledge sharing are only just emerging. Although some forms of tacit knowledge are being explicated for effective sharing, and are better understood, the central quality of tacit knowledge is inherently hard to explicate. In this regard, the focus of knowledge management has been shifting from information exchange models to social interaction management [38], as social interaction seems to provide a sharing solution for both explicit and tacit knowledge [11]. Further, organizations have noticed the importance of knowledge exchange across boundaries through interactions among people, technologies, and techniques [4]. At the international level, while investigating how members of global product-development organizations generate and sustain knowledge in their distributed operations, Orlikowski [33] emphasized the increasing importance of an organization's ability to operate effectively regardless of time, geography, politics, and culture. He referred to this as “distributed organizing”, the ability to manage knowledge interactions across boundaries to solve problems.

When new knowledge is generated from existing knowledge domains during KIs, the effectiveness of the interactions is crucial to new knowledge creation. As boundary objects are the media of interactions, they greatly influence the workings of KIs and hence are tightly coupled with output performance. In the context of software system analysis, output performance is measured by the quality of the analysis report. If a high quality report is produced with fewer resources, we can infer that the KI seen during the course of the analyst–user communication is efficient. Although much research has been devoted to knowledge management, more attention has been focused on knowledge management inside organizations than across organizational boundaries. In an attempt to fill this gap and find ways to enhance cross-boundary knowledge management performance, this study approaches the KI performance issue from the perspective of efficiency, and formally calculates KI efficiency based on max–min models, with boundary objects as the input resource.

In this study, types of boundary objects are summarized, and the occurrences of each boundary object type are identified and counted using analyst journals and analyst–user communication recordings. These are the data of the max–min model input factors, whereas the output factor data are the system analysis report evaluations. Finally, max–min models are applied to calculate the maximum and minimum possible efficiency of each KI.

2. Literature review

During the interaction of knowledge workers from multiple domains, various types of boundary objects can be observed. In the following, categories of boundary object are reviewed and summarized. Then a max–min model is introduced, which is the basis for the evaluation of KI efficiencies in this paper.

2.1. Boundary objects

It is inevitable that cross-disciplinary collaboration takes place both inside and between organizations. If effective collaboration is desired, people who share a common goal must create common understandings, ensure reliability of communication across domains, and gather information that retains its integrity across time, space, and local contingencies. Further, the impact of the domain boundaries between disciplines should be reduced to improve cross-disciplinary collaboration performance.

Star and Griesemer [39] proposed the concept of “boundary objects”—objects adaptable to different viewpoints within domains and robust enough to maintain their identity across boundaries. As various subgroups in different domains must reconcile different meanings in order to collaborate successfully, they can use boundary objects as nexuses or bridges to aid cross-boundary communication. According to Star and Griesemer [39], using boundary objects could improve common representation and in turn increase the efficiency of communication between actors from different professional domains. In contrast, it is difficult to reach a common understanding in the absence of appropriate boundary objects, leading to a lesser chance of successful innovation [26]. The more an organization understands the nature of various boundary objects, the more likely it is that it will overcome existing barriers.

Star and Griesemer's work defines four boundary object categories: repositories, ideal types, coincident boundaries, and standardized forms. Collaboration success relies on the interaction of all parties, who need not only to share their own knowledge, but also to assess each other's knowledge during interactions. Cross-boundary knowledge interaction is a challenge because boundaries are shaped by gaps in party specialty and effective collaboration depends on overcoming this challenge.

Carlile [7] adopted Star and Griesemer's list of boundary objects in describing their use by individuals in observed settings and proposed three object categories–syntactic, semantic, and pragmatic–that support the parties working across such boundaries. In Carlile's classification of boundary objects, syntactic boundary objects map closely to Star and Griesemer's “repositories”, semantic boundary objects map to “standardized forms and methods”, and pragmatic boundary objects map to “ideal types” and “coincident boundaries”. Carlile [8] later examined knowledge management based on these three types of boundary objects and indicated the importance of clarifying knowledge worker relationships in order to manage knowledge effectively across boundaries.

Syntactic boundary objects refer to physical repositories, reports, databases, or libraries, whereas semantic boundary objects refer to standardized forms [7]. Since the term “pragmatic” was first proposed in Carlile's work, the essence of this type of object has been continually enriched by recognizing pragmatic boundary objects in empirical contexts. These include Gantt charts, milestone charts, PERT charts, and project timelines [44], which are used to achieve common schedules. They also include engineering design drawings and sketches [21], which are read by designers of different engineering disciplines to help them focus on their aspects of the representation. All of these visual artifacts were useful tools in achieving cross-boundary understanding.

The boundary object types described above are all explicit in nature. Tacit-type boundary objects seem to be missing, though several have been proposed. An example is described by Cook and Brown [13] in the “bread-making machine” case, in which the term “twisting stretch” is regarded as a “genre” and functions as a boundary object that straddles bread-making and machine-making domains. Additionally, Koskinen [26] emphasized the importance of vocabulary-based boundary objects, including figurative language and symbolism, in knowledge sharing within and between organizations' innovation processes. Koskinen called this boundary object type "metaphoric".

Further, Boland and Tenkasi [5] stated that an effective way to shape common belief, to achieve expectation, or to reach common cognition is by means of certain boundary objects that do not exist in any explicit form. Thus, we posit that expanding Carlile's categorization with the addition of metaphoric boundary objects is necessary. This category includes boundary objects such as figurative language and genres [13], symbolism [26], nonverbal expressions [32], and visionary objects [6]. In summary, boundary objects are the objects, whether explicit or tacit, that allow people in diverse groups to work together and enhance mutual understanding in the process [45].

Although context is described with "actors" in mind, the unit of analysis is knowledge interaction. However, knowledge may not be always beneficial to KIs; there are also poor interactions in which existing knowledge turns out to be a barrier [43]. This study posits that knowledge boundaries and boundary objects help to explain why knowledge is both a barrier to and a source of KIs. Further, while actors are in a knowledge interaction and communicating with each other, boundary objects are being generated without awareness. The existence of boundary objects is useful to both the assimilation and dissimilation of knowledge. However, because a party's existing knowledge may be dissimilar and their cognitive activities not uniform, identical boundary objects may have different effects. With the belief that some boundary objects are crucial to effective collaboration, this study investigates how these objects operate in each interaction and proposes an effective way for people to interact across multiple domains following the observation and max–min model analysis.

2.2. Max–min models

Within data envelopment analysis (DEA) literature, a variety of extensions to the basic DEA models, such as CCR, BCC, ADD, and SBM models, have been developed to evaluate efficiency in various contexts [3,9,15,34,37,40]. As the result is merely a number that represents the relative efficiency using multiple inputs to produce multiple outputs, the underlying belief of these studies is that efficiency is a static value measured at a certain instance of time. By applying DEA analysis, the efficiency of decision-making units (DMUs) is calculated precisely. However, in practice, efficiency should be dynamic and should fluctuate within a range. To resolve this conflict between fluctuating efficiency and fixed values, several models based on DEA were developed to overcome the problem of the single time evaluation of DMUs, such as network DEA [17], a hierarchical model [14], and max–min models [41].

In an assessment of various methodologies for evaluating production efficiency, Talluri and Narasimhan [41] proposed the max–min approach to measure the maximum and minimum efficiency of a vendor in a supply chain. Efficiency was based on a comparison with the ideal measurement standard set up by the buyer. Using a max–min model, it is possible to determine two efficiency values for each vendor (maximum and minimum efficiency scores). In other words, max–min models consider not only the best case but also the worst case—they reasonably present efficiency as a range rather than a fixed number.

DMUs can be subsequently divided into clusters according to the upper and lower bounds (maximum and minimum efficiency). The efficiencies of DMUs in the same cluster are similar in the sense that the bounds (maximum and minimum efficiency) are approximately the same. Max–min models not only rank vendor efficiency, but also help determine clusters of vendors that have the same properties. Vendors aggregated into the same cluster have a higher degree of homogeneity and are more likely to substitute for each other. When choosing an alternative vendor to replace an existing one, a buyer should first consider the vendors in the same cluster as the original vendor.

Although max–min models were first used to evaluate vendor efficiency, they were proven effective in evaluating DMUs in different contexts [1,35]. In this study, max–min models were applied to evaluate DMUs (namely, KIs), and all values of input and output factors were transformed into two efficiency values (upper and lower bounds).

This study adopts max–min models and proposes the optimization problem formulated in the following equations. Taking the efficiency measurement of KI as an optimization problem, the objective of a highly efficient KI is to maximize the ratio of the weighted sum of outputs to the weighted sum of inputs. This optimization is subject to some constraints: the weighted sum of outputs does not exceed the weighted sum of inputs, and the weights are not negative. Expressed in mathematical form, this optimization is as follows:

$$\begin{aligned}
&\max \frac{\sum_{r=1}^{v} a_r y_{r_p}}{\sum_{s=1}^{u} b_s x_{s_p}}\\
&\text{s.t.} \frac{\sum_{r=1}^{v} a_r y_{r^*}}{\sum_{s=1}^{u} b_s x_{s^*}} = 1,\\
&\frac{\sum_{r=1}^{v} a_r y_{r_i}}{\sum_{s=1}^{u} b_s x_{s_i}} \le 1 \forall i,\\
&a_r, b_s \ge 0 \forall r, s,
\end{aligned}$$

p	the KI being evaluated
a_r	the weight given to the rth output
b_s	the weight given to the sth input
v	the number of KI evaluation outputs
u	the number of KI evaluation inputs
y_{r^*}	the best value for the rth output across all KIs
x_{s^*}	the best value for the sth input across all KIs
y_{r_i}	the value of the rth output for the ith KI
x_{s_i}	the value of the sth input for the ith KI

As maximizing a ratio is equivalent to maximizing the numerator while minimizing the denominator, the above optimization formulation can be split into two parts:

$$\begin{aligned}
&\max \sum_{r=1}^{v} a_r y_{r_p}\\
&\text{s.t.} \sum_{s=1}^{u} b_s x_{s_p} = 1\\
&\sum_{r=1}^{v} a_r y_{r^*} - \sum_{s=1}^{u} b_s x_{s^*} = 0,\\
&\sum_{r=1}^{v} a_r y_{r_i} - \sum_{s=1}^{u} b_s x_{s_i} \le 0 \ \ \forall i,\\
&a_r, b_s \ge 0 \ \ \forall r, s,
\end{aligned} \qquad \text{Model 1}$$

$$\min \sum_{r=1}^{v} a_r y_{r_p}. \qquad \text{Model 2}$$

s.t. Model 1 constraints are satisfied.

The maximum efficiency of each KI is determined by Model 1, and the minimum efficiency of each KI is determined by Model 2, with the same constraints seen in Model 1. Max–min models were independent of measurement units. In the next section, max–min models were applied to evaluate the efficiency for each KI. KIs were then aggregated into clusters according to their efficiencies, revealing a relationship between the outcome performance and input factors.

3. Method and results

3.1. Experimental design

During the development of an information system, systems analysts usually take the initiative to interact with end-users to identify relevant system requirements. In this study, we tracked 81 such knowledge interactions between systems analysts and end-users during the system requirement identification process. The subjects comprised 81 end-users and 81 senior college students; the student analysts were recruited from various sessions of the same IT project course, and the end-users were the persons in small and medium enterprises (SMEs) that the student analysts interacted with. As part of the course requirement, each student analyst collaborated with an end-user to carry out an IS requirement analysis project in the end-user's organization.

Student analysts were required to consider both front-end and back-end office operations and to innovate with a full understanding of the organization's operation. This was a semester-long project, an adequate time scale for an analyst/end-user collaboration. The project report included a written document of the proposed information system requirements with a website design as the user interface. During the collaboration, each analyst recorded all conversations and kept a journal detailing the interactions. Performance was determined by evaluating the quality of the analysis report, including its completeness and innovativeness.

In this study, KIs between student analysts and end-users were observed. Although the approximation of a school project context to a real-world context is always a concern, a school project context is probably more feasible; finding 81 similar cases in a real-world context would be unlikely. To lessen the concern, it may be worth pointing out that most senior IS students (from which our samples were drawn) engage in IT outsourcing tasks right after graduation. Each has the ability to act as an IT specialist for IT implementation projects; hence, their lack of experience is maybe the only concern.

The following five steps were used to conduct the analysis via max–min models, and the data used in each step are described here in detail:

Step 1 Codify each knowledge interaction

First, all KIs were evaluated according to input and output indicators. In this study, the output factor values were derived from project performance, and the input factor values were the percentages of the relative frequency of occurrence of the four boundary object types (syntactic, semantic, pragmatic, and metaphoric). Performance was considered an output because it represents the fruitage of KI. All types of boundary objects were treated as inputs, which are either preexistent and identified, or are created during KI, thus form the resource pool for KI output. Based on the convention of max–min models, higher values of outputs and lower values of inputs are desirable characteristics because they represent higher efficiency.

According to the classification of boundary objects in Table 1, the values of four input factors were codified from analyst journals and conversation recordings by the course instructor and randomly checked by an outside evaluator. The evaluation was done by observing the relative frequency of occurrence of syntactic, semantic, pragmatic, and metaphoric boundary objects, respectively. The output factor values were the scores given to each analysis report. The values provided by two evaluators were highly correlated (.783, .721, .690, .700, and .867 for syntactic, semantic, pragmatic, and metaphoric boundary objects and the performance, respectively), and the differences were statistically insignificant based on a paired-sample t-test ($t = 2.058$, 1.246, 1.964, 1.809, and .380, respectively; d.f. = 9). Hence, the values produced by the two independent evaluators had a high degree of conformity, and there is little doubt that this evaluation was objective. After codification, the values for four input factors and one output factor of all 81 KIs were summarized and are shown in Table 2.

Table 1
Type and description of boundary objects.

Type	Description
Syntactic	Ordered "piles" of objects indexed in a standardized way [39]
	Physical repositories, reports, databases, or libraries [7]
Semantic	Standardized forms and methods such as objects devised as methods of common communication across dispersed work groups [7,39]
Pragmatic	Objects, models and maps that have the same boundaries but different internal content [39]
	Objects such as a diagram, an atlas or other descriptive element that does not in fact accurately give the details of any one locality or thing [39]
	Gantt charts, milestone charts, PERT charts, project timelines [44]
	Design drawings and sketches [21]
Metaphoric	Vocabulary-based boundary objects include figurative language and symbolism, diffused rapidly throughout the company [26,32]
	Conceptual objects that can evoke similar emotive and affective responses [6]
	Genres [13], visionary objects [6], nonverbal expressions [32]

Step 2 Confirm boundary objects construct

The relationship between input and output factors should be confirmed. This is an important step of testing the validity of input–factor measurement before proceeding to the actual calculation of maximum and minimum efficiencies. In order to be sure that the input factors were measuring different boundary objects, there should not be a high degree of collinearity among them. Further, a multiple regression should indicate that a high percentage of output variance is explained by the input factors.

As shown in Table 3, all VIF values were much less than 10, indicating a low degree of collinearity among input factors. The relationship between input and output factors is also confirmed, as all regression coefficients were statistically significant, with more than 60% of the output variance explained by the inputs. Hence, the measurement of input factors was valid.

Step 3 Apply max–min models

In the third step, the input and output factor values of each KI were fed into the maximum and minimum efficiency calculations (Fig. 1).

In practice, organizations would like to maximize output and minimize input—that is, to use the minimum amount of resources to attain maximum benefit. In this study, the output factor was the project performance and the input factors were the relative frequency of occurrence of four boundary object categories. The objective was to achieve higher project performance under the constraint of limited resources, which in our case were the efforts to sustain various boundary object categories. In other words, each factor had its target value, which was either the maximum or minimum of all KIs. In the case of the output factor, the target value was the maximum, whereas input factors targeted the minimum values. As indicated by the asterisks in Table 1, the target value was 98 for project performance, 40 for syntactic boundary objects, 30 for semantic and pragmatic boundary objects, and 20 for metaphoric boundary objects.

Model 1 was run 81 times to calculate the maximum efficiency for all 81 KIs. The results are shown in Fig. 1: KI 34 achieved the highest efficiency of 0.95, followed by KI 7, KI 14, KI 50, KI 3, KI 17, KI 54, KI 63, KI 1, and KI 65 with scores of 0.93, 0.92, 0.92, 0.91, 0.89, 0.89, 0.89, 0.875, and 0.87, respectively. These scores represent the maximum efficiencies achievable by each KI when evaluated against the target values of input factors. In calculating these scores, Model 1 selected factor weights for four input factors that optimized the performance of the KI while maintaining the target efficiency at 1. Hence, in a sense, Model 1

Table 2
Input and output values of each KI.

KI no.	Input 1	Input 2	Input 3	Input 4	Output	KI no.	Input 1	Input 2	Input 3	Input 4	Output
KI 1	40*	30*	70	40	86	KI 41	40*	30*	70	40	69
KI 2	40*	50	30*	20*	64	KI 42	40*	50	30*	20*	68
KI 3	60	50	50	20*	90	KI 43	40*	30*	30*	20*	65
KI 4	40*	30*	50	20*	84	KI 44	60	30*	50	20*	74
KI 5	100	50	100	40	98*	KI 45	40*	30*	30*	20*	61
KI 6	60	70	50	40	98*	KI 46	40*	50	30*	40	74
KI 7	40*	30*	70	20*	92	KI 47	40*	50	30*	20*	66
KI 8	40*	30*	50	20*	69	KI 48	40*	30*	50	20*	61
KI 9	60	30*	30*	20*	64	KI 49	40*	30*	50	20*	78
KI 10	60	30*	50	20*	70	KI 50	60	70	30*	60	90
KI 11	40*	50	50	40	83	KI 51	60	30*	30*	20*	69
KI 12	60	30*	50	20*	65	KI 52	40*	50	50	40	77
KI 13	60	30*	50	40	74	KI 53	60	30*	30*	20*	64
KI 14	60	30*	50	40	90	KI 54	40*	50	30*	60	87
KI 15	40*	50	50	40	83	KI 55	40*	50	50	20*	78
KI 16	40*	30*	30*	20*	69	KI 56	40*	50	50	40	64
KI 17	60	50	50	20*	87	KI 57	40*	30*	30*	40	73
KI 18	60	70	70	60	98*	KI 58	40*	30*	30*	20*	66
KI 19	40*	50	50	20*	70	KI 59	80	50	30*	20*	72
KI 20	60	30*	50	20*	77	KI 60	40*	50	50	20*	83
KI 21	40*	30*	50	40	84	KI 61	40*	70	30*	20*	70
KI 22	40*	30*	70	40	75	KI 62	40*	50	50	20*	72
KI 23	60	50	30*	40	70	KI 63	40*	100	50	40	87
KI 24	40*	30*	50	20*	65	KI 64	40*	50	70	60	82
KI 25	60	30*	50	20*	78	KI 65	40*	30*	70	40	85
KI 26	60	30*	50	20*	69	KI 66	40*	30*	30*	20*	61
KI 27	40*	50	30*	20*	64	KI 67	40*	50	50	20*	76
KI 28	80	90	70	100	98*	KI 68	40*	30*	30*	40	68
KI 29	60	50	30*	40	82	KI 69	40*	70	50	20*	85
KI 30	40*	30*	70	20*	74	KI 70	40*	30*	50	20*	71
KI 31	40*	30*	30*	20*	64	KI 71	40*	50	70	20*	77
KI 32	40*	50	30*	20*	63	KI 72	40*	50	30*	20*	64
KI 33	40*	50	50	20*	71	KI 73	40*	30*	50	20*	60
KI 34	80	50	50	20*	93	KI 74	40*	70	50	20*	75
KI 35	60	50	70	20*	75	KI 75	60	30*	50	20*	85
KI 36	40*	30*	30*	20*	63	KI 76	60	70	50	20*	82
KI 37	40*	30*	50	20*	72	KI 77	40*	50	50	20*	69
KI 38	60	70	50	20*	79	KI 78	40*	50	30*	20*	63
KI 39	80	90	70	40	90	KI 79	40*	30*	50	40	69
KI 40	60	50	70	40	94	KI 80	60	70	50	20*	75
						KI 81	60	50	50	20*	82

Note: *Target value, Input 1: Syntactic B. O., Input 2: Semantic B. O., Input 3: Pragmatic B. O., Input 4: Metaphoric B. O., Output: Project performance.

is a generous formulation that emphasizes the strengths of each KI.

Careful consideration in the decision process involved the estimation of both maximum and minimum efficiency. The calculation of minimum efficiency followed Model 2. As in Fig. 1, when compared with minimum efficiency, KI 16 performed the best out of 81 KIs with a score of 0.7, followed by KI 58, KI 43, KI 31, KI 36, KI 66, KI 3, KI 17, KI 75, and KI 4 with scores of 0.655, 0.65, 0.645, 0.62, 0.55, 0.53, 0.52, and 0.51, respectively. Contrary to Model 1, Model 2 can be referred to as a selfish model that searches for factor weights which represent the worst-case scenario for each KI while maintaining the target efficiency score at 1. Hence, it emphasizes the weaknesses of each KI.

Models 1 and 2 were applied to acquire the maximum and minimum efficiency values of each KI, which are illustrated in Fig. 1.

Step 4 Cluster KIs

In the fourth step, KIs were clustered according to their proximity measured by max and min efficiencies, through a K-means algorithm. Eighty-one KIs were grouped into four clusters. The centers of these clusters are listed in Table 4, and the KI numbers in each of the four clusters are 22, 51, 6, and 2, respectively. Table 4 also shows the mean and standard deviation of five factors, namely, four types of boundary objects and the project performance of each cluster.

KIs in the same cluster exhibited similar maximum and minimum efficiencies, where efficiency was defined as KI output divided by the efforts made by the organization, and can be viewed as priority replacement solutions for each other.

Step 5 Analyze results

The distribution of maximum and minimum efficiencies is plotted and shown in Fig. 2. Clearly, clusters 1 and 2 together enclose most KIs, whereas cluster 3 only has six KIs and cluster 4 has two. This plot illustrates the degree of homogeneity among the 81 KIs. In other words, KIs in the same cluster showed a higher degree of homogeneity than those in different clusters. Taking clusters 3 and 4 as examples, the degree of homogeneity between KI 28 and KI 39 was greater than that

Table 3
Results of the regression analysis.

Input factors	Output factor: project performance	
	Coefficients	VIF
Syntactic B. O.	.290***	1.140
Semantic B. O.	.268***	1.014
Pragmatic B. O.	.354***	1.151
Metaphoric B. O.	.362***	1.123
F = 31.959***, R^2 = .624, Adj-R^2 = .605		

* $p < .05$.
** $p < .01$.
*** $p < .001$.

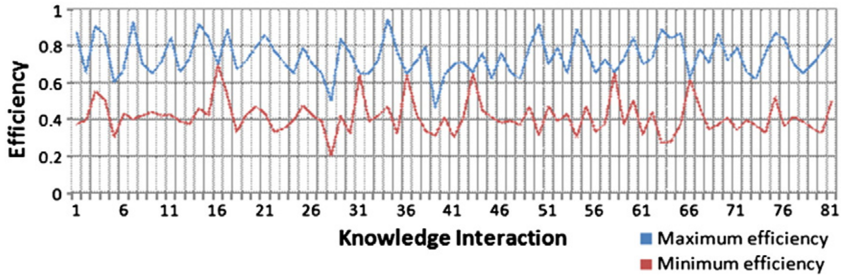

Fig. 1. Maximum and minimum efficiency of each KI.

Table 4
Cluster center and five factors of each cluster.

		Cluster 1 n = 22	Cluster 2 n = 51	Cluster 3 n = 6	Cluster 4 n = 2
Cluster center	Max. efficiency	.87	.70	.65	.48
	Min. efficiency	.40	.40	.65	.26
Project performance	Mean	88.68	75.94	68.33	98.00
	S. D.	4.745	9.092	2.582	5.657
Syntactic B. O.	Mean	50.00	48.63	40	80
	S. D.	11.952	12.809	0	0
Semantic B. O.	Mean	48.64	43.33	30	46.5
	S. D.	18.592	13.064	0	61.518
Pragmatic B. O.	Mean	51.82	45.88	30	70
	S. D.	12.203	14.721	0	0
Metaphoric B. O.	Mean	33.64	25.49	20	70
	S. D.	14.325	9.862	0	42.426

between KI 28 and KI 16, and the degree of homogeneity between KI 43 and KI 66 was greater than that between KI 43 and KI 39. As a result, compared with KI 16, KI 39 was a better alternative solution to KI 28, and compared with KI 39, KI 66 was a better alternative solution to KI 43.

The cluster centers show that both the maximum and minimum efficiencies of cluster 3 were higher than those of cluster 4. As for clusters 1 and 2, their minimum efficiencies were about the same; only their maximum efficiencies set them apart. If efficiency is the primary concern, the KIs in cluster 1 were more desirable than those in cluster 2, because the KIs in cluster 1 achieved better efficiency than those in cluster 2 in the best scenario (maximum efficiency) whereas the KIs in both clusters showed little difference in the worst scenario (minimum efficiency).

Although efficiency is an important aspect to organizations, project performance is also a focal point. Ideally, excellent project performance would be achieved along with high efficiency.

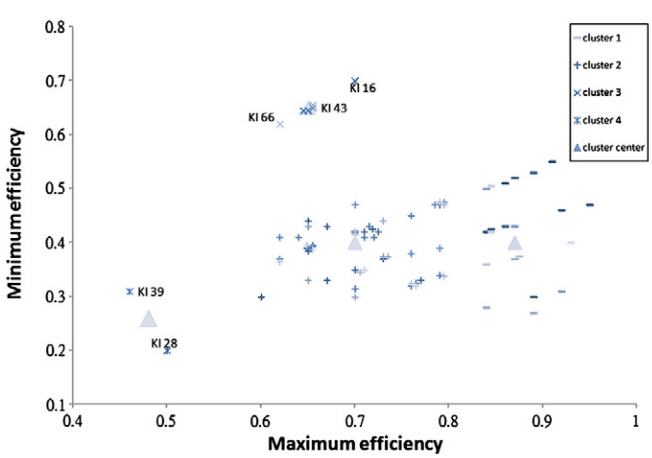

Fig. 2. Clusters of KIs.

Because exceptional project performance sometimes arrive to the detriment of efficiency, it is necessary to further examine the inter-cluster differences in the five factors, including project performance and the frequencies of occurrence of the four boundary object types.

Because most KIs were clustered in clusters 1 and 2, with only a few in clusters 3 and 4, only the comparison between clusters 1 and 2 was statistically meaningful and could provide sufficient statistical power. The comparison was conducted by applying a *t*-test, and the results are shown in Table 5. In terms of actual project performance, KIs in cluster 1 (mean = 88.68) outperformed those in cluster 2 (mean = 75.94) on average. It is clear that metaphoric boundary objects occurred more frequently on average in a cluster 1 KI (mean = 33.64) than in a cluster 2 KI (mean = 25.49). In addition, because syntactic, semantic, and pragmatic boundary objects were insignificant in setting these two clusters apart, metaphoric boundary objects were probably the key to good project performance.

The noted importance of metaphoric boundary objects is quite interesting. Recall that in this study, project performance is determined by the completeness and innovativeness of the analysis report; analysts were expected not only to automate but also to innovate the process. Perhaps, to innovate the process, the necessary boundary objects have to go beyond explicit artifacts.

Table 5
Intergroup comparisons between cluster 1 and cluster 2.

Factors	*t* value	Results
Project performance	t = 6.202***	cluster 1 > cluster 2
Syntactic B. O.	t = .428	Not significant
Semantic B. O.	t = 1.394	Not significant
Pragmatic B. O.	t = 1.659	Not significant
Metaphoric B. O.	t = 2.430*	cluster 1 > cluster 2

* p < .05.
** p < .01.
*** p < .001.

Thus, boundary objects such as genres, symbolism and visionary objects are necessary for communicating on a higher level view of the key processes and objectives, and looking into where goals are unmet.

Syntactic, semantic, and pragmatic boundary objects are all explicit in nature. These objects may be essential to running a business, and trained analysts would certainly ask to have access to them in order to get a quick glimpse of the operation; hence, they are not easily missed, unless the operation is complicated, which is highly unlikely for SMEs. This is one possible explanation, and it has to do with the context of this study. Future research can investigate different contexts for comparison.

For a handful of data in clusters 3 and 4, any tests involving these clusters would not have adequate statistical power. To avoid missing out on valuable insights, inter-cluster comparisons were still attempted via t-test. However, readers are cautioned that concrete comparisons should anchor on adequate amounts of data, and this presumption did not hold for the current data. For this reason, neither the t values nor the p values are reported here, though they were significant.

First, the average project performance (mean = 68.33) of KIs in cluster 3 was the poorest among all. These KIs also demonstrated the least occurrence of all four boundary object types (mean = 40, 30, 30, 20), as can be seen clearly in Table 4. Interestingly, KIs in cluster 3 did not exhibit the worst efficiencies, whether in terms of minimum or maximum efficiency. Obviously, neither low inputs nor low output led to low efficiency; instead, they displayed moderate efficiencies. In contrast, the KIs in cluster 4 attained the highest project performance (mean = 98) but suffered low efficiencies (max = .48, min = .26). The above observations concerning clusters 3 and 4 imply that cluster 3 spent the least amount of resources, resulting in the worst project performance, whereas cluster 4 achieved the best project performance with the most resources, which in our study comprised boundary object occurrences. Consequently, we can nearly deduce that the KIs in cluster 4 probably spent tremendous amounts of effort creating boundary objects, thereby affecting their efficiencies. KIs in clusters 3 and 4 possibly represent scarce cases of worst and best project performance, and hence both clusters contain only handful of KIs. Therefore, to confirm the above speculations, further effort of finding and observing extreme cases is necessary.

4. Conclusions

Investigating knowledge interactions and testing relationships based on large amounts of data have been challenging tasks in knowledge management research. This study strived to overcome this difficulty by analyzing numerous system analysis projects of a similar scope, scale and complexity. A large amount of data was made available by conducting the research in a software analysis course setting, in which independent teams executed similar projects and the project performances could be compared objectively. However, due to an uneven distribution of KIs amongst clusters, clusters 3 and 4 did not have sufficient data to support certain reasoning. Nevertheless, speculative reasoning was attempted based on the scarce data in order to avoid missing out on valuable insights. Readers are reminded that relevant inferences are subject to confirmations of future research with adequate amounts of data.

Knowledge interaction is a very complicated and inherently context-dependent phenomenon [12]. Therefore, the purpose of this study is not to suggest that metaphoric boundary objects are the key to good performance in all situations. Rather, it intends to demonstrate that observing knowledge interaction through the lens of boundary objects can be fruitful, and that some boundary objects are more important than others. As to which boundary objects are more important, we must stress their context-dependent nature. Coincidentally, although the importance of metaphoric boundary objects has been emphasized in various renowned articles [13,30,31] in the contexts of bread-making machine design, flute-making practice, and paper path design for copiers and printers, our study also confirmed the importance of metaphoric boundary objects in the context of software system analysis.

Carlile [8] pointed out that in knowledge management research, more effort has been put into understanding the roles of syntactic and semantic boundary objects than on advancing the understanding of pragmatic and metaphoric boundary objects. This study effectively showed the importance of metaphoric boundary objects in software system analysis activities, which are increasingly frequent and tightly coupled with business infrastructure and applications.

Although an optimization model was used in this study to measure the best and worst scenario efficiencies of each KI, our focus was by no means only on KI efficiency. Searching for ways to achieve good performance with high efficiency, analysis results stressed both efficiency and actual project performance. In our study's setting, answers pointed to an emphasis on metaphoric boundary objects. Although there did not seem to be a dilemma between efficiency and actual performance, we would not rule out the possibility that striking a balance between efficiency and performance may be necessary in other contexts. When it comes to such a decision, insights of varying importance of boundary objects would prove to be very valuable.

Acknowledgment

This research was partially funded by National Science Council, Taiwan, ROC under contract number NSC 96–2416-H-004–044.

References

[1] N. Aissaoui, M. Haouari, E. Hassini, Supplier selection and order lot sizing modeling: a review, Computers and Operations Research 34 (12) (2007) 3516–3540.
[2] S. Bandyopadhyay, P. Pathak, Knowledge sharing and cooperation in outsourcing projects: a game theoretic analysis, Decision Support Systems 43 (2) (2007) 349–358.
[3] R.D. Banker, A. Charnes, W.W. Cooper, Some models for estimating technical and scale efficiencies in data envelopment analysis, Management Science 30 (9) (1984) 1078–1092.
[4] G.D. Bhatt, Knowledge management in organizations: examining the interaction between technologies, techniques, and people, Journal of Knowledge Management 5 (1) (2003) 68–75.
[5] R.J. Boland, R.V. Tenkasi, Perspective making and perspective taking in communities of knowing, Organization Sciences 6 (4) (1995) 350–372.
[6] M. Briers, W.F. Chua, The role of actor-networks and boundary objects in management accounting change: a field study of an implementation of activity-based costing, Accounting, Organizations and Society 26 (3) (2001) 237–269.
[7] P.R. Carlile, A pragmatic view of knowledge and boundaries: boundary objects in new product development, Organization Science 13 (4) (2002) 442–455.
[8] P.R. Carlile, Transferring, translating, and transforming: an integrative framework for managing knowledge across boundaries, Organization Science 15 (5) (2004) 555–568.
[9] A. Charnes, W.W. Cooper, R.M. Thrall, A structure for classifying and characterizing efficiency and inefficiency in data envelopment analysis, Journal of Productivity Analysis 2 (3) (1991) 197–237.
[10] A.N.K. Chen, T.M. Edgington, Assessing value in organizational knowledge creation: considerations for knowledge workers, MIS Quarterly 29 (2) (2005) 279–309.
[11] S.Y. Choi, Y.S. Kang, H. Lee, The effects of socio-technical enablers on knowledge sharing: an exploratory examination, Journal of Information Science 34 (5) (2008) 742–754.
[12] A.Y.K. Chua, D.H. Goh, Untying the knot of knowledge management measurement: a study of six public service agencies in Singapore, Journal of Information Science 34 (3) (2008) 259–274.
[13] S.D.N. Cook, J.S. Brown, Bridging epistemologies: the generative dance between organizational knowledge and organizational knowing, Organization Science 10 (4) (1999) 381–400.
[14] W.D. Cook, R.H. Green, Evaluating power plant efficiency: a hierarchical model, Computers and Operations Research 32 (4) (2005) 813–823.
[15] W.W. Cooper, K.S. Park, J.T. Pastor, RAM: a range adjusted measure of inefficiencies for use with additive models, and relations to other models and measures in DEA, Journal of Productivity Analysis 11 (1) (1999) 5–42.
[16] H.R. Ekbia, N. Hara, The quality of evidence in knowledge management research: practitioner versus scholarly literature, Journal of Information Science 34 (1) (2008) 110–126.

[17] R. Fare, S. Grosskopf, Network DEA, Socio-Economic Planning Sciences 34 (1) (2000) 35–49.
[18] Z. Guo, J. Sheffield, A paradigmatic and methodological examination of knowledge management research: 2000 to 2004, Decision Support Systems 44 (3) (2008) 673–688.
[19] W. He, K.-K. Wei, What drives continued knowledge sharing? An investigation of knowledge-contribution and -seeking beliefs, Decision Support Systems 46 (2009) 826–838.
[20] G. Hedlund, A model of knowledge management and the N-form corporation, Strategic Management Journal 15 (1994) 73–90.
[21] K. Henderson, Flexible sketches and inflexible data bases, Science, Technology, and Human Values 16 (4) (1991) 448–473.
[22] Y.H. Huang, S.C.T. Chou, G.H. Tzeng, Knowledge management adoption and assessment for SMEs by a novel MCDM approach, Decision Support Systems 51 (2011) 270–291.
[23] W.H. Hung, C.F. Ho, J.J. Jou, K.H. Kung, Relationship bonding for a better knowledge transfer climate: an ERP implementation, Decision Support Systems 52 (2) (2012) 406–414.
[24] A. Jashapara, Moving beyond tacit and explicit distinctions: a realist theory of organizational knowledge, Journal of Information Science 33 (6) (2007) 752–766.
[25] C. Kimble, C. Grenier, K. Goglio-Primard, Innovation and knowledge sharing across professional boundaries: political interplay between boundary objects and brokers, International Journal of Information Management 30 (5) (2010) 437–444.
[26] K.U. Koskinen, Metaphoric boundary objects as co-ordinating mechanisms in the knowledge sharing of innovation processes, European Journal of Innovation Management 8 (3) (2005) 323–335.
[27] D. Leonard-Barton, D. Leonard, Well Springs of Knowledge: Building and Sustaining the Sources of Innovation, Harvard Business School Press, Boston, 1998, pp. 91–135.
[28] D.R. Liu, C.H. Lai, Knowledge group-based knowledge flows for sharing task knowledge, Decision Support Systems 50 (2011) 370–386.
[29] J.A. Nickson, T.R. Zenger, A knowledge-based theory of the firm: the problem-solving perspective, Organization Science 15 (6) (2004) 617–632.
[30] I. Nonaka, A dynamic theory of organizational knowledge creation, Organization Science 5 (1) (1994) 14–35.
[31] I. Nonaka, H. Takeuchi, The Knowledge Creating Company, Oxford University Press, New York, 1995, pp. 95–123.
[32] J.T. Nosek, Group cognition as a basis for supporting group knowledge creation and sharing, Journal of Knowledge Management 8 (4) (2004) 54–64.
[33] W.J. Orlikowski, Knowing in practice: enacting a collective capability in distributed organizing, Organization Science 13 (3) (2002) 249–273.
[34] A. Saha, T.S. Ravisankar, Rating of Indian commercial banks: a DEA approach, European Journal of Operational Research 124 (1) (2000) 187–203.
[35] J. Sarkis, S. Talluri, Performance based clustering for benchmarking of US airports, Transportation Research Part A: Policy and Practice 38 (5) (2004) 329–346.
[36] G. Schiuma, Managing knowledge for business performance improvement, Journal of Knowledge Management 16 (4) (2012) 515–522.
[37] B.B.M. Shao, Technical efficiency analysis of information technology investments, Information Management 39 (5) (2002) 391–401.
[38] S.W. Smoliar, Interaction management: The next (and necessary) step beyond knowledge management, Business Process Management Journal 9 (3) (2003) 337–353.
[39] S.L. Star, J.R. Griesemer, Institutional ecology, "translations", and boundary objects: amateurs and professionals in Berkeley's museum of vertebrate zoology, 1907–39, Social Studies of Science 19 (3) (1989) 387–420.
[40] T. Sueyoshi, Tariff structure of Japanese electric power companies: an empirical analysis using DEA, European Journal of Operational Research 118 (2) (1999) 350–374.
[41] S. Talluri, R. Narasimhan, Vendor evaluation with performance variability: a max–min approach, European Journal of Operational Research 146 (3) (2003) 543–552.
[42] P.L. Teh, C.C. Yong, Knowledge sharing in IS personnel: organizational behavior's perspective, The Journal of Computer Information Systems 51 (4) (2011) 11–21.
[43] A. Willem, H. Scarbrough, M. Buelens, Impact of coherent versus multiple identities on knowledge integration, Journal of Information Science 34 (3) (2008) 370–386.
[44] E.K. Yakura, Charting time: timelines as temporal boundary objects, Academy of Management Journal 45 (5) (2002) 956–970.
[45] Travis K. Huang, Eugenia Y. Huang, A Max-Min Approach to the Output Evaluation of Knowledge Interaction, Proceedings of 42nd Annual Hawaii International Conference on System Sciences (HICSS), Hawaii, USA, 2009.

Eugenia Y. Huang is Distinguished Professor of MIS at College of Commerce, National Chengchi University, Taiwan. Her research and teaching interests are in Internet-enabled changes in business and society, with emphases on e-commerce and knowledge management. She holds a Ph.D. in Electrical Engineering from Northeastern University, an M.S. in Electrical Engineering from the University of Michigan, and an M.S. in Physics from Northwestern University. Her earlier career was with MIT Lincoln Laboratory, MITRE Corporation, and AT&T Bell Laboratories. Her research appears in Communications of the ACM, Computers in Human Behavior, Computers & Education, Industrial Management and Data Systems, and Journal of Computer Information Systems. She is Associate Editor of Management Review and a charter member of the Association for Information Systems. Eugenia Y. Huang is the corresponding author and can be contacted at: huang.eugenia@gmail.com.

Travis K. Huang is Assistant Professor of IM at College of Information, Ling Tung University, Taiwan. He holds a Ph.D. in Management Information Systems from National Chengchi University, and an M.S. in Management Information Systems from National Changhua University of Education. His research interests include knowledge management, E-learning, information systems implementation, and information security. His research appears or is forthcoming in such journals as Decision Support Systems, Computers & Education, Behaviour & Information Technology, Journal of Computer Information Systems, and Journal of Theoretical and Applied Information Technology.