

# Exploring Critical Patterns between KM and Corporate Performances

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Several works have studied the relationships between knowledge management (KM) and corporate performances, using traditional statistical methods, and they declare that a specific KM style may result in better corporate performance. However, the outcome of having better corporate performance is not merely dependant on the effort invested in KM. This paper aims to explore the critical patterns between KM and corporate performances by using the rough set approach. The results show that higher performance companies stress the importance on both tacit and explicit knowledge, and consider that incentives and evaluations are the essentials to implementing KM.

**KeyWord** : Knowledge management ; Corporate performance ; Rough set theory.

## 1. Introduction

Knowledge has the ability to utilize information and to influence decisions (Watson, 1999), and has the capability to act effectively (Benbya et al., 2004). According to Liao (2003), knowledge is a very important resource for learning new things, solving problems, and creating core competences. Several works have studied the relationships between knowledge management (KM) and corporate performances using traditional statistical methods, and indicate that a specific KM style may result in better corporate performance (Bierly & Chakrabarti, 1996 ; Choi & Lee, 2003 ; Lee et al., 2005). These KM studies are meaningful and helpful to us when selecting a beneficial KM style to implement KM activities.

However, it is obvious that the outcome of having better corporate performance is not merely dependant on the effort invested in KM. Instead, we would rather hold a moderate viewpoint, and emphasize that it is more important to find out the critical patterns of such companies that implement KM and manifest better corporate performance. From the critical patterns, we can learn and imitate some KM activities with more confidence.

Finding out the critical patterns is a qualitative analysis problem. To handle this kind of problem, the rough set approach is based on data-mining techniques to discover knowledge without rigorous statistical assumptions, unlike a conventional data analysis which uses sta-

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tistical inferential technique (Goh & Law, 2003). The rough set theory (RST) was originally introduced by Pawlak in 1982 to help deal with problems such as inductive reasoning, automatic classification, pattern recognition, learning algorithms, etc. The RST is particularly useful for dealing with imprecise or vague concepts (Pawlak, 1997), and has been successfully applied in a variety of fields (Slowinski & Zopounidis, 1995 ; Dimitras, et al., 1999 ; Beynon & Peel, 2001 ; Goh & Law, 2003 ; Wang, 2003). Since the RST has these advantages in qualitative analysis, it is suitable for solving the qualitative problem of finding out the critical patterns.

Hence, this paper aims to explore the critical patterns between KM and corporate performances by using the rough set approach. The rest of this paper is organized as follows. In section 2, some of the prior literatures related to the relationships between KM and corporate performances are reviewed. In section 3, the basics of rough set theory are presented. In section 4, the research design and results are illustrated. Finally, based upon the findings of this research, conclusions and suggestions are depicted.

## 2. KM and Corporate Performances

Knowledge is a powerful resource of a competitive advantage, and is often expected to produce favorable performance. The concepts of KM and corporate performances are discussed below.

### 2.1 Concepts of the KM

In the knowledge economy, knowledge is the primary resource for competitiveness (Drucker, 1993) and is the new basis for wealth (Thurow, 1996). Further, a key source of sustainable competitive advantage and consequent profitability bases the way that a company creates and shares its knowledge (Desouza, 2003). Because knowledge is taking on an important strategic role (Zack, 1999 ; Desouza, 2003 ; Liao, 2003), numerous companies expect their KM to be performed effectively in order to leverage and transform that knowledge into competitive advantages.

There are some peculiar characteristics of knowledge. For example : it is intangible and difficult to measure, but sometimes increases through use (Wiig et al., 1997). In particular, Liao (2002) argues that it is necessary to update and share knowledge in order to conquer the problem of knowledge inertia. Trying better to understand the nature of knowledge is to categorize it (Roos & Roos, 1997). Although knowledge can be categorized into several types (Zack, 1999 ; Johannessen et al., 2001), the most frequently used distinction is tacit versus explicit knowledge (Roos & Roos, 1997). Explicit knowledge is based in data and is converted into information ; by contrast, tacit knowledge is based in practice and experience (Johannessen & Olsen, 2003). According to Nonaka and Konno (1998), explicit knowledge can be expressed in words and numbers ; whereas tacit knowledge includes subjective insights, intuitions, and hunches, is highly personal and hard to formalize. As Nonaka (1994)

indicates, organizational knowledge is created by a continuous dialogue between tacit and explicit knowledge.

There is increasing recognition that the competitive advantage of firms depends on their ability to create, transfer, utilize and protect difficult-to-imitate knowledge assets (Teece, 2000). In a knowledge economy, the core assets of the modern business enterprise are the knowledge assets including the intelligence, understanding, skills, and experience of its employees (Manville & Ober, 2003). Hence, organizations need to examine how they can better leverage knowledge assets for value creation (Massey et al., 2001). The knowledge asset is the main object for KM (Wilkins et al., 1997). According to Nonaka et al. (2000), knowledge assets are both the inputs and the outputs of the knowledge-creating process.

Further, KM is a systemic way to manage knowledge in the organizationally specified process of acquiring, organizing and communicating knowledge (Benbya et al., 2004). According to Kamara et al. (2002), KM is the organizational optimization of knowledge to achieve enhanced performance through the use of various tools, processes, methods and techniques. KM and related strategy concepts are promoted as important components for organizations to survive (Martensson, 2000). There have been numbers of frameworks developed to promote the KM activities. Most KM frameworks can be classified as prescriptive, descriptive, or a combination of the two (Rubenstein-Montano et al., 2001). According to Benbya et al. (2004), those different frameworks have many similarities : they are often articulated in four phases where the first one is a “create” phase, while the last phase concerns the ability to share and use knowledge.

## **2.2 The Relationships between KM and Corporate Performances**

Although numerous creditable works are devoted to the study of how to build a KM strategy and execute the KM successfully (Grant, 1991 ; Jordan & Jones, 1997 ; Hansen et al., 1999 ; Zack, 1999 ; Massey et al., 2001 ; Maier & Remus, 2003 ; Campos & Sanchez, 2003), few of those link up KM implementation with its performance. In fact, many managers are facing difficulties in demonstrating positive effects of KM to their companies. If they can not clearly verify the benefit of KM efforts, the KM implementation may not go forward. Hence, how to display the performance of KM is becoming an important issue.

There are some special works that have studied the relationship between KM styles and corporate performance. For example, Bierly and Chakrabarti (1996) cluster companies into four groups with different knowledge strategies, and indicate that the “Innovator” and “Explorer” groups tend to be more profitable than the “Exploiter” and “Loner” groups. Moreover, Choi and Lee (2003) conduct an investigation of KM styles and their effect on corporate performance in a non-financial perspective, and state that the dynamic style of KM results in higher performance. In addition, Lee et al. (2005) propose a knowledge management performance index (KMPI) for assessing the performance of KM at a point in time, and declare that the KMPI can represent the efficiency of the knowledge circulation process. Those works (Bierly & Chakrabarti, 1996 ; Choi & Lee, 2003 ; Lee et al., 2005) have some

similarities, such as: (1) the implementation of different KM styles may result in distinct performances; (2) a good KM style produces a higher corporate performance; (3) statistical analysis techniques are used as the research methods; and (4) their findings imply that a specific KM style is a better choice.

Certainly, different corporate performances among firms may be partly or mainly a result of varied KM styles. But, the same KM styles do not surely produce equal corporate performances. Hence, we would rather stress a loose way that if a company has higher corporate performance, then its KM practices are worth emulating. For this reason, we stress the importance of exploring the critical patterns regarding the KM of higher performance companies.

### 3. The Basics of Rough Set Theory

The RST is a relatively new approach and good at data reduction in qualitative analysis. In the Rough Set approach, any vague concept is characterized by pair of precise concepts that forms the lower and upper approximation (Pawlak, 1997). Using the lower and upper approximation of a set, the accuracy and the quality of approximation can be defined, and the knowledge hidden in the data table may be discovered and expressed in the form of decision rules (Mi et al., 2004). Those wishing to learn more details of the theory can refer to Pawlak (1982; 1984). The basic concepts of rough set theory and the analytical procedure of data analysis are discussed as follows.

#### 3.1 Information System and Decision Table

Rough set-based data analysis starts from a data table called an information system which contains data about objects of interest characterized in terms of some attributes or features (Pawlak, 2002). An information system is used to construct the approximation space. The information system can be viewed as an application such that each object is described by a set of attributes (Pawlak, 1997).

According to Pawlak (1984, 1997), an information system is defined as the quadruple  $S = (U, Q, V, \rho)$ , where the universe  $U$  is a finite set of objects, the  $Q$  is a finite set of attributes, the  $V = \bigcup_{q \in Q} V_q$  is the set of values of attributes and  $V_q$  is the domain of the attribute  $q$ ;  $\rho: U \times Q \rightarrow V$  is a description function such that  $\rho(x, q) \in V_q$  for every  $q \in Q, x \in U$ .

The decision table describes decisions in terms of conditions that must be satisfied in order to carry out the decision specified in the decision table (Pawlak, 2002). An information system can be seen as the decision table in the form of  $S = (U, CUD, \rho)$  in which  $C \cup D = Q$  means that condition attributes  $C$  and decision attributes  $D$  are two disjoint classes of attributes (Greco et al., 2002). Condition attributes can be regarded as descriptive parameters while decision attributes can be viewed as classification parameters. Through analyzing the decision table, valuable decision rules can be extracted.

### 3.2 Covering Index and the Analytical Procedure

Except the approximation accuracy, the classification quality, and the classification accuracy, the Covering Index (CI) is a rather valuable way to evaluate the quality of the decision rule (Wu et al., 2005). Let  $P \subseteq Q$  and  $Y \subseteq U$ , the  $P$ -lower approximation of  $Y$ , denoted by  $\underline{PY} = \bigcup X \{X \in P^* \text{ and } X \subseteq Y\}$ ; and the  $P$ -upper approximation of  $Y$ , denoted by  $\overline{PY} = \bigcup X \{X \in P^* \text{ and } X \cap Y \neq \emptyset\}$ . According to Pawlak (1984, 1997), in order to measure the approximation accuracy  $\mu_P(Y)$  of the set  $Y$  by  $P$  in  $S$ , we can use  $\mu_P(Y) = \text{card}(\underline{PY}) / \text{card}(\overline{PY})$ , in which  $0 \leq \mu_P(Y) \leq 1$ ; the  $Y$  is definable by  $P$  in  $S$  if  $\mu_P(Y) = 1$ , whereas the  $Y$  is not definable by  $P$  in  $S$  if  $\mu_P(Y) < 1$ .

In addition, let  $\ddot{Y}$  be the classification of  $U$  by  $P$ , the subsets  $Y_i = \{Y_1, Y_2, \dots, Y_n\}$  are the classes of the classification  $\ddot{Y}$ , the  $P$ -lower approximation of  $\ddot{Y}$  is denoted as  $\underline{P}\ddot{Y}$ , and the  $P$ -upper approximation of  $\ddot{Y}$  is denoted as  $\overline{P}\ddot{Y}$ . Then, the classification quality  $\eta_P(\ddot{Y})$  by  $P$  can be measured by  $\eta_P(\ddot{Y}) = \frac{\sum_{i=1}^n \text{card}(\underline{PY}_i)}{\text{card}(U)}$ . As to the classification accuracy  $\beta_P(\ddot{Y})$  by  $P$ , it can be measured by  $\beta_P(\ddot{Y}) = \frac{\sum_{i=1}^n \text{card}(\underline{PY}_i)}{\sum_{i=1}^n \text{card}(\overline{PY}_i)}$ .

Importantly, the CI represents a ratio which indicates how many objects with the same attribute value matching the decision class contrast with how many objects belonging to the same decision class. Let the decision attributes  $D$  be a singleton  $D = \{d\}$ , the  $d$ -elementary sets are denoted by  $Y_i \in \{Y_1, Y_2, \dots, Y_m\}$  and called the decision classes of the classification. Let the condition attribute  $A \subseteq C$  and its domain  $V_{aj}$  of the attribute  $a_j \in A$ . Then, the CI can be expressed as  $\text{CI}(V_{aj}, Y_i) = \text{card}(V_{aj} \wedge Y_i) / \text{card}(Y_i)$ , where the " $\wedge$ " is the operator of conjunction.

For the analysis of the decision table, there are some main steps put forward by Walczak and Massart (1999). Similarly, we recommend the three-step analytical procedure: (1) calculating the classification quality and accuracy; (2) finding the core attribute; and (3) evaluating the decision rule and CI.

## 4. Research Design and Results

The survey design, sampling, data analysis, and discussions are presented as follows.

### 4.1 Survey Design

For this study, a questionnaire was developed based on the rough set approach to collect data of expert judgments. The study was conducted with two stages. In the first stage, the content of the questionnaire was confirmed through an intensive literature review and significant discussions with six experts. The questionnaire contains two portions: one portion is the basic information about the respondents, and the other portion is the serial questions about the topic issue. In the topic issue portion, the respondents were asked to indicate which condition attribute value is the most important for each condition attribute. For example, one question was as follows: "Regarding the purpose of knowledge management, which of the following answer can reflect the situation for your company?" In answer, these options

were available : (A) To improve effective acquisition, sharing and usage of information ; (B) To reduce research costs and delays ; (C) To improve decision making and to capture best practices ; (D) To become a more innovative organization ; and (E) To improve performance, productivity and competitiveness.

As shown in the Appendix, the first, fourth, and fifth questions about purposes, main obstacles, and the success factors in implementing KM refer to Martensson (2000) who provides an in-depth review in terms of KM issues and suggests some critical elements that must be considered in implementing KM, such as : support from top management, communication, creativity, culture and people, sharing knowledge, incentives, and evaluation. The second and third questions about KM styles cite Choi and Lee (2003) who provide ways to measure the explicit-oriented degree and the tacit-oriented degree of KM styles.

All five questions are used as the condition attributes ; moreover, the answers to these questions are called the condition attribute values (alphabetic symbols from A to Z) for rough set analysis. In addition, the Return on Assets (ROA) and the Return on Sales (ROS) are used as decision attributes for measuring corporate performance, this idea is brought up by Bierly and Chakrabarti (1996) who note ROA and ROS are frequently used as the measures of financial performance. Furthermore, following the method of dividing objects into three groups proposed by Evans (2004), respondent companies are divided into three groups by the proportion : bottom 25%, middle 50%, and top 25%.

## 4.2 Sampling

In Taiwan, the premier science-based industrial park is the Hsinchu Science Park (HSP), introduced in 1980. The HSP performs as a powerful tractor tugging economic growth, and has greatly contributed to the development of Taiwan's high-tech industries. In particular, numerous enterprises in HSP are representative of the high-technology industry of Taiwan. Business fields in HSP are categorized into six segments : Integrated Circuits, Computers and Peripherals, Telecommunications, Optoelectronics, Precision Machinery, and Biotechnology.

Of high-tech companies in HSP, there are 112 are listed in the Taiwan Stock Exchange. We targeted these listed companies of HSP for this research. At the beginning of July 2006, we mailed the questionnaire to general managers of those 112 listed companies of HSP. By August 2006, in total, 64 valid responses were obtained with a response rate of 57.1% which covered more than half the listed companies of HSP. The respondents came from such industry categories as : Integrated Circuits (20), Computers and Peripherals (12), Telecommunications (8), Optoelectronics (16), and other (8) ; the majority of respondents were from the Integrated Circuits industry and the Optoelectronics industry.

## 4.3 Data Analysis

The implementation of data analysis is performed through our suggested three-step analytical procedure with the help of software called ROSE (Rough Sets Data Explorer). ROSE is

**Table 1 The decision table**

Object	ROA	ROS	Purpose	Explicit	Tacit	Obstacle	Success	Object	ROA	ROS	Purpose	Explicit	Tacit	Obstacle	Success
1	1	1	C	G	L	P	Z	33	2	2	E	G	L	P	T
2	1	1	E	H	L	S	Z	34	2	2	D	I	L	N	Z
3	1	1	A	G	L	R	W	35	2	2	E	I	M	P	T
4	1	1	E	G	L	S	U	36	2	2	E	I	L	R	W
5	1	1	A	F	J	N	X	37	2	2	C	H	J	R	Y
6	1	1	C	F	L	Q	Y	38	2	2	C	H	L	N	U
7	2	1	E	H	L	O	Z	39	2	2	A	I	L	R	U
8	2	1	E	F	L	R	Y	40	2	2	A	I	L	P	X
9	1	1	E	G	J	R	Z	41	2	2	A	G	M	R	W
10	1	1	E	G	J	R	Z	42	2	2	B	F	J	Q	T
11	1	1	A	I	L	P	X	43	2	2	A	I	M	P	X
12	2	1	A	G	J	R	T	44	2	2	A	I	J	Q	T
13	1	1	A	I	M	R	W	45	2	2	C	I	L	P	X
14	2	1	A	G	J	R	U	46	2	2	E	H	L	N	T
15	2	1	A	H	J	P	X	47	3	2	E	F	J	Q	Z
16	2	1	E	G	L	Q	Z	48	3	2	E	I	L	Q	W
17	2	2	C	I	J	P	Z	49	3	3	A	H	L	Q	X
18	2	2	A	G	L	Q	T	50	3	3	E	G	J	R	U
19	2	2	A	I	L	R	W	51	2	3	E	I	J	R	V
20	2	2	E	G	L	P	T	52	3	3	E	G	J	P	U
21	1	2	A	I	L	P	Z	53	3	3	D	H	J	N	X
22	1	2	A	G	K	R	X	54	3	3	A	G	M	R	W
23	1	2	E	G	J	N	U	55	3	3	C	I	J	N	T
24	2	2	D	I	J	Q	T	56	3	3	D	I	J	R	U
25	2	2	A	I	L	R	W	57	2	3	A	I	L	Q	U
26	2	2	A	H	J	R	T	58	3	3	A	I	J	N	W
27	1	2	A	I	L	Q	W	59	3	3	E	F	J	R	Z
28	1	2	A	I	L	R	U	60	3	3	E	G	J	P	X
29	1	2	A	I	J	R	X	61	3	3	A	I	L	Q	T
30	2	2	E	I	L	P	W	62	3	3	E	I	J	Q	V
31	2	2	E	G	J	R	X	63	3	3	D	I	L	P	T
32	2	2	A	I	L	P	T	64	3	3	E	H	L	N	U

software that implements basic elements of the rough set theory and rule discovery techniques. Before the data analysis, it is necessary to construct the decision table. As shown in Table 1, the decision table contains 64 records characterized by two decision attributes (ROA, and ROS) and five condition attributes (“Purpose”, “Explicit”, “Tacit”, “Obstacle”, and “Success”). Further, these attributes and their values are denoted as follows :

$V_{ROA} = \{1, 2, 3\}$ ,  $V_{ROS} = \{1, 2, 3\}$ ,  $V_{Purpose} = \{A, B, C, D, E\}$ ,  $V_{Explicit} = \{F, G, H, I\}$ ,  $V_{Tacit} = \{J, K, L, M\}$ ,  $V_{Obstacle} = \{N, O, P, Q, R, S\}$ , and  $V_{Success} = \{T, U, V, W, X, Y, Z\}$ .



**Table 2 Classification quality and accuracy**

Class number	Number of objects	Lower approx.	Upper approx.	Accuracy	Quality
ROA				0.8286	0.9063
1	16	14	18	0.7778	
2	32	29	35	0.8286	
3	16	15	17	0.8824	
ROS				0.8824	0.9375
1	16	15	17	0.8824	
2	32	30	34	0.8824	
3	16	15	17	0.8824	

Step 1 : Calculating the classification quality and accuracy.

As shown in Table 2, the classification accuracy of ROS (0.8824) is superior to that of ROA (0.8286), and also the classification quality of ROS (0.9375) is superior to that of ROA (0.9063). This means that using ROS is better than using ROA for exploring the critical patterns between KM and corporate performances in this study. When using ROS, each decision class is well describable with high accuracy of 0.8824. This is to say that all three decision classes of ROS are characterized exactly by those data in the decision table. Therefore, the following analysis merely focuses on ROS.

Step 2 : Finding the core of attribute.

As a result, we obtained one reduction of attribute and five core attributes. The reduction is {Purpose, Explicit, Tacit, Obstacle, Success} ; and these five core attributes are {Purpose}, {Explicit}, {Tacit}, {Obstacle}, and {Success}. This implies that all the condition attributes are significant and it is not favorable to omit any one of those in this case.

Step 3 : Evaluating the decision rule and CI.

The most important step of data analysis is to generate decision rules. As a result, 27 rules are created as shown in Table 3. For decisions class 1, obviously the rule 2={F, G, H, L, Y, Z}

**Table 3 The decision rule and covering index**

Rule 1.	(Explicit = I) & (Tacit = M) & (Obstacle = R) => (ROS = 1) ; 6.25%.
Rule 2.	(Explicit in {G, F, H}) & (Tacit = L) & (Success in {Z, Y}) => (ROS = 1) ; 37.50%.
Rule 3.	(Explicit = G) & (Tacit in {L, J}) & (Obstacle in {S, R}) & (Success in {Z, W, T}) => (ROS = 1) ; 25.00%.
Rule 4.	(Explicit = F) & (Success in {U, X}) => (ROS = 1) ; 6.25%.
Rule 5.	(Obstacle = S) => (ROS = 1) ; 12.50%.
Rule 6.	(Purpose = A) & (Explicit in {H, G}) & (Tacit = J) & (Success in {U, X}) => (ROS = 1) ; 12.50%.



- Rule 7. (Explicit = I) & (Tacit = L) & (Success in {Z, W}) => (ROS = 2) ; 25.00%.
- Rule 8. (Purpose in {E, B}) & (Success = T) => (ROS = 2) ; 15.63%.
- Rule 9. (Tacit = J) & (Obstacle = Q) & (Success in {T, X, U, Y, Z}) => (ROS = 2) ; 12.50%.
- Rule 10. (Obstacle = R) & (Success = X) => (ROS = 2) ; 9.38%.
- Rule 11. (Explicit = G) & (Obstacle = N) => (ROS = 2) ; 3.13%.
- Rule 12. (Purpose in {C, A}) & (Explicit in {G, H}) & (Obstacle in {Q, N}) & (Success in {T, U}) => (ROS = 2) ; 6.25%.
- Rule 13. (Purpose = C) & (Explicit in {I, H}) & (Obstacle in {R, P}) => (ROS = 2) ; 9.38%.
- Rule 14. (Tacit = M) & (Success = X) => (ROS = 2) ; 3.13%.
- Rule 15. (Purpose = A) & (Explicit in {H, I}) & (Obstacle in {R, P}) & (Success in {T, U}) => (ROS = 2) ; 12.50%.
- Rule 16. (Obstacle in {Q, P}) & (Success in {V, U}) => (ROS = 3) ; 18.75%.
- Rule 17. (Tacit = J) & (Success in {V, W}) => (ROS = 3) ; 18.75%.
- Rule 18. (Purpose = D) & (Obstacle in {R, P}) => (ROS = 3) ; 12.50%.
- Rule 19. (Explicit in {H, I}) & (Obstacle in {N, Q}) & (Success = X) => (ROS = 3) ; 12.50%.
- Rule 20. (Purpose in {E, C}) & (Tacit = J) & (Success = T) => (ROS = 3) ; 6.25%.
- Rule 21. (Purpose = E) & (Explicit = H) & (Success in {U, X}) => (ROS = 3) ; 6.25%.
- Rule 22. (Purpose = E) & (Obstacle in {P, R}) & (Success = U) => (ROS = 3) ; 12.50%.
- Rule 23. (Purpose = E) & (Tacit = J) & (Obstacle = P) => (ROS = 3) ; 12.50%.
- Rule 24. (Explicit in {I, F}) & (Tacit = L) & (Obstacle in {Q, R}) & (Success in {Z, T}) => (ROS = 3) ; 6.25%.
- Rule 25. (Explicit = F) & (Tacit = J) & (Obstacle = R) => (ROS = 3) ; 6.25%.
- Rule 26. (Purpose = A) & (Explicit = I) & (Tacit = L) & (Success = X) => (ROS = 1) OR (ROS = 2) ; 100.00%.
- Rule 27. (Explicit = G) & (Tacit = M) => (ROS = 2) OR (ROS = 3) ; 100.00%.
- 

holds the highest CI of 37.50%. Similarly, for decisions classes 2, the rule 7={I, L, W, Z} holds the highest CI of 25.00%. As for decisions classes 3, both the rule 16={Q, P, V, U} and the rule 17={J, V, W} hold the higher CI of 18.75%. The rule 17 is better than the rule 16 because its length is shorter. Additionally, the rule 26={A, I, L, X} can classify objects into class 1 or 2 with high CI of 100%, and the rule 27={G, M} can classify objects into class 2 or 3 with a great CI of 100%.

#### 4.4 Discussions

From the results of the empirical study, we can acquire several valuable implications for KM implementation. For example, focusing on the Top group, the rule 2 implies that the 37.50% of the Top group have significant patterns in the KM implementation, such as : (F) Knowledge is well codified in my company ; (G) Knowledge can be acquired easily through formal documents and manuals ; (H) Results of projects and meetings are well documented ; (L) Informal dialogues and meetings are used for knowledge sharing ; (Y) Incentives ; and (Z) Evaluation.

**Table 4 The KM profile of the 37.5% Top group**


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The explicit-oriented degree of implementing KM ?

- (F) Knowledge is well codified in my company ;
- (G) Knowledge can be acquired easily through formal documents and manuals ;
- (H) Results of projects and meetings are well documented ;
- (I) Knowledge is shared through codified forms like manuals or documents.

The tacit-oriented degree of implementing KM ?

- (J) My knowledge can be easily acquired from experts and co-workers ;
- (K) It is easy to get face-to-face advises from experts ;
- (L) Informal dialogues and meetings are used for knowledge sharing ;
- (M) Knowledge is acquired by one-to-one mentoring in my company.

The success factor to implement knowledge management ?

- (T) Support from top management ;
  - (U) Communication ;
  - (V) Creativity ;
  - (W) Culture and people ;
  - (X) Sharing knowledge ;
  - (Y) Incentives ;
  - (Z) Evaluation.
- 

The findings can be summarized as shown in Table 4 entitled “The KM profile of the 37.5% Top group”. The Table 4 reveals that 37.50% of the Top group stress the importance of not only explicit knowledge but also tacit knowledge, such as : (1) from explicit knowledge perspective, knowledge is well codified and can be easily acquired through formal documents, even results of projects and meetings are well documented in their companies ; and (2) from tacit knowledge perspective, informal dialogues and meetings are used for knowledge sharing in their companies. Consequently, this fact reveals that those of the Top group would not stick to a specific KM style in practice because both explicit knowledge and tacit knowledge are indispensable to enrich corporate knowledge. Additionally, they consider that incentives and evaluations are the essentials for a successful KM implementation.

This study has obtained some meaningful facts, but it has the limitation of that the sample size is small and lacks great statistical significance. However, the above findings reflect the situation that several Taiwan high-tech companies in HSP, concerning how they think about KM styles and important elements for the KM implementation in practice.

## 5. Conclusions

Many people believe that knowledge can help us to enhance competitive advantage, and thereby achieve favorable performance. Previous works have made a creditable contribution

to the issue of the relationships between KM and corporate performances, but there is still room for enrichment. First, they declare that a specific KM style may result in better corporate performance. However, the outcome of having better corporate performance is not merely dependant on the effort invested in KM, and even the same KM style does not surely produce equal corporate performance. Hence, we would rather highlight the importance of exploring the critical patterns concerning the KM activities of higher performance companies.

Secondly, their findings are based on the statistical analysis techniques with rigorous statistical assumptions. In contrast to classical statistical techniques, the strength of RST is that it requires no statistical assumptions. In particular, the RST can directly analyze the original data without any additional information ; it discovers important hidden meanings behind data ; decision rules obtained from the rough set approach are based on the facts of real examples ; moreover, the analysis results from the rough set approach are easy to understand straight away without redundant interpretations. Additionally, in nature, the RST seems to be more adequate for dealing with the qualitative problem.

For the above reasons, this paper aims to explore the critical patterns between KM and corporate performances, using the rough set approach. When conducting this study, we targeted listed companies in HSP. According to the results of the empirical study, we are able to derive many implications. For example, using ROS is better than using ROA for exploring the critical patterns in this study. Focusing on the Top group of ROS, 37.5% higher performance companies have significant patterns in KM implementation, such as : knowledge is well codified, and can be acquired easily through formal documents and manuals ; results of projects and meetings are well documented ; informal dialogues and meetings are used for knowledge sharing ; and incentives and evaluations are regarded as the important success factors to implement KM.

The results of this study are satisfactory, and provide different insights into the relationship between KM and corporate performances. Previous works are helpful to us in selecting a beneficial KM style to implement KM activities, whereas our work can serve as a meaningful complementary study emphasizing the practical perspective. However, our study still has some limitations. For example, the results may be different if respondent companies are divided into more or less than three groups. Nevertheless, our findings can be useful for developing more formal theories, and our suggested analytical procedure can effectively handle any issue of reducing a complex and multi-attribute problem and exploring some valuable patterns and mining the minimal sets of significant elements.

#### References

- Benbya, H., Passiante, G. & Belbaly, N. A. (2004). Corporate portal : a tool for knowledge management synchronization. *International Journal of Information Management*, 24 (3), 201-220.
- Beynon, M. J. & Peel, M. J. (2001). Variable precision rough set theory and data discretisation : an application to corporate failure prediction. *Omega*, *International Journal of Management Science*, 29 (6), 561-576.
- Bierly, P. & Chakrabarti, A. (1996). Generic knowledge strategies in the US pharmaceutical industry. *Strategic Management Journal*, 17 (4), 123-135.

- Campos, E. B. & Sanchez, M. P. S. (2003). Knowledge management in the emerging strategic business process : Information, complexity and imagination. *Journal of Knowledge Management*, 7 (2), 5-13.
- Choi, B. & Lee, H. (2003). An empirical investigation of KM styles and their effect on corporate performance. *Information & Management*, 40 (5), 403-417.
- Desouza, K. C. (2003). Strategic contributions of game rooms to knowledge management : some preliminary insights. *Information & Management*, 41 (1), 63-74.
- Dimitras, A. I., Slowinski, R., Susmaga, R. & Zopounidis, C. (1999). Business failure prediction using rough sets. *European Journal of Operational Research*, 114 (2), 263-280.
- Doumpos, M. & Zopounidis, C. (2002). Rough Sets and Multivariate Statistical Classification : A Simulation Study. *Computational Economics*, 19 (3), 287-301.
- Drucker, P. F. (1993). *Post-Capitalist Society*. New York : HarperBusiness.
- Dubois, D. & Prade, H. (1992). Putting rough sets and fuzzy sets together. In : Slowinski, R. (Ed). *Intelligent Decision Support : Handbook of Applications and Advances of the Rough Sets Theory*. Dordrecht : Kluwer Academic Publishers, pp. 203-232.
- Evans, J. R. (2004). An exploratory study of performance measurement systems and relationships with performance results. *Journal of Operations Management* 22 (3), 219-232.
- Goh, C. & Law, R. (2003). Incorporating the rough sets theory into travel demand analysis. *Tourism Management*, 24 (5), 511-517.
- Grant, R. M. (1991). The resource-based theory of competitive advantage : implications for strategy formulation. *California Management Review*, 30 (3), 114-35.
- Greco, S., Matarazzo, B. & Slowinski, R. (2002). Rough sets methodology for sorting problems in presence of multiple attributes and criteria. *European Journal of Operational Research*, 138 (2), 247-259.
- Hansen, M. T., Nohria, N. & Tierney, T. (1999). What's your strategy for managing knowledge ? *Harvard Business Review*, 77 (2), 106-126.
- Johannessen, J. A., Olaisen, J. & Olsen, B. (2001). Mismanagement of tacit knowledge : the importance of tacit knowledge, the danger of information technology, and what to do about it. *International Journal of Information Management*, 21 (1), 3-20.
- Johannessen, J. A. & Olsen, B. (2003). Knowledge management and sustainable competitive advantages : The impact of dynamic contextual training. *International Journal of Information Management*, 23 (4), 277-289.
- Jordan, J. & Jones, P. (1997). Assessing your company's knowledge management style. *Long Range Planning*, 30 (3), 392-398.
- Kamara, J. M., Anumba, C. J. & Carrillo, P. M. (2002). A CLEVER approach to selecting a knowledge management strategy. *International Journal of Project Management*, 20 (3), 205-211.
- Krusinska, E., Slowinski, R. & Stefanowski, J. (1992). Discriminative versus rough set approach to vague data analysis. *Applied Stochastic Models and Data Analysis*, 8 (1), 43-56.
- Lee, K. C., Lee, S. & Kang, I. W. (2005). KMPI : measuring knowledge management performance. *Information & Management*, 42 (3), 469-482.
- Liao, S. H. (2002). Problem solving and knowledge inertia. *Expert Systems with Applications*, 22 (1), 21-31.
- Liao, S. H. (2003). Knowledge management technologies and applications-literature review from 1995 to 2002. *Expert Systems with Applications*, 25 (2), 155-164.
- Maier, R. & Remus, U. (2003). Implementing process-oriented knowledge management strategies. *Journal of Knowledge Management*, 7 (4), 62-74.
- Manville, B. & Ober, J. (2003). Beyond Empowerment : Building a Company of Citizens. *Harvard Business Review*, 68 (4), 79-93.
- Martensson, M. (2000). A critical review of knowledge management as a management tool. *Journal of Knowledge Management*, 4 (3), 204-216.
- Massey, A. P., Montoya-Weiss, M. M. & Holcom, K. (2001). Re-engineering the customer relationship : leveraging knowledge assets at IBM. *Decision Support Systems*, 32 (2), 155-170.
- Mi, J. S., Wu, W. Z. & Zhang, W. X. (2004). Approaches to knowledge reduction based on variable precision rough set model. *Information Sciences*, 159 (3-4), 255-272.
- Nonaka, I. (1994). A Dynamic Theory of Organizational Knowledge Creation. *Organization Science*, 5 (1), 14-37.
- Nonaka, I. & Konno, N. (1998). The concept of "ba" : Building a foundation for knowledge creation. *California Management Review*, 40 (3), 40-54.
- Nonaka, I., Toyama, R. & Konno, N. (2000). SECI, Ba and Leadership : a Unified Model of Dynamic Knowledge Creation. *Long Range Planning*, 33 (1), 5-34.
- Pawlak, Z. (1984). Rough Classification. *International Journal of Man-Machine Studies*, 20 (5), 469-483.

- Pawlak, Z. (2002). Rough sets, decision algorithms and Bayes' theorem. *European Journal of Operational Research*, 136 (1), 181-189.
- Pawlak, Z. (1997). Rough Sets. In : Lin, T. Y. & Cercone, N. (Eds.). *Rough Sets and Data Mining : Analysis for Imprecise Data*. Norwell, MA : Kluwer Academic Publishers.
- Pawlak, Z. (1982). Rough sets. *International Journal of Computer and Information Science*, 11 (5), 341-356.
- Roos, R. & Roos, J. (1997). Measuring your company's intellectual performance. *Long Range Planning*, 30 (3), 413-26.
- Rubenstein-Montano, B., Liebowitz, J., Buchwalter, J., McCaw, D., Newman, B. & Rebeck, K. (The Knowledge Management Methodology Team) (2001). A systems thinking framework for knowledge management. *Decision Support Systems*, 31 (1), 5-16.
- Skowron, A. & Grzymala-Busse, J. W. (1993). From the rough set theory to the evidence theory. In : Fedrizzi, M., Kacprzyk, J., Yager, R. R. (Eds.). *Advances in the Dempster-Shafer Theory of Evidence*. New York : John Wiley & Sons, pp. 295-305.
- Slowinski, R. & Zopounidis, C. (1995). Application of the rough set approach to evaluation of bankruptcy risk. *International Journal of Intelligent Systems in Accounting, Finance and Management*, 4 (1), 27-41.
- Tay, F. E. H. & Shen, L. (2002). Economic and financial prediction using rough sets model. *European Journal of Operational Research*, 141 (3), 641-659.
- Teece, D. J. (2000). *Strategies for Managing Knowledge Assets : the Role of Firm Structure and Industrial Context*. *Long Range Planning*, 33 (1), 35-54.
- Thurow, L. C. (1996). *The Future of Capitalism : How Today's Economic Forces Shape Tomorrow's World*. New York : William Morrow & Co.
- Walczak, B. & Massart, D. (1999). Rough sets theory. *Chemometrics and Intelligent Laboratory Systems*, 47 (1), 1-16.
- Wang, Y. F. (2003). Mining stock price using fuzzy rough set system. *Expert Systems with Applications*, 24 (1), 13-23.
- Watson, R. (1999). *Data management : Databases and organizations* (2nd ed). New York : John Wiley.
- Wiig, K. M., Hoog, R. D. & Spek, R. V. D. (1997). Supporting Knowledge Management : A Selection of Methods and Techniques. *Expert Systems with Applications*, 13 (1), 15-27.
- Wilkins, J., Van Wegen, B. & De Hoog, R. (1997). Understanding and Valuing Knowledge Assets : Overview and Method. *Expert Systems with Application*, 13 (1), 55-72.
- Wu, W. W., Lee, Y. T. & Tzeng, G. H. (2005). Simplifying the manager competency model by using the rough set approach. In *Proceedings of The Tenth International Conference on Rough Sets, Fuzzy Sets, Data Mining, and Granular Computing (RSFDGrC2005)*, Canada : Regina.
- Zack, M. H. (1999). Developing a knowledge strategy. *California Management Review*, 41 (3), 125-145.

## Appendix

Condition attributes and decision attributes

### Condition attributes :

1. The purpose of knowledge management ?
  - (A) To improve effective acquisition, sharing and usage of information ;
  - (B) To reduce research costs and delays ;
  - (C) To improve decision making and to capture best practices ;
  - (D) To become a more innovative organization ;
  - (E) To improve performance, productivity and competitiveness.
  
2. The explicit-oriented degree of implementing knowledge management ?
  - (F) Knowledge is well codified in my company ;
  - (G) Knowledge can be acquired easily through formal documents and manuals ;
  - (H) Results of projects and meetings are well documented ;
  - (I) Knowledge is shared through codified forms like manuals or documents ;
  
3. The tacit-oriented degree of implementing knowledge management ?
  - (J) My knowledge can be easily acquired from experts and co-workers ;
  - (K) It is easy to get face-to-face advises from experts ;
  - (L) Informal dialogues and meetings are used for knowledge sharing ;
  - (M) Knowledge is acquired by one-to-one mentoring in my company.

4. The main obstacle to implement knowledge management ?

- (N) Lack of ownership of the problem ;
- (O) Lack of time ;
- (P) Lack of organizational structure ;
- (Q) Lack of senior management commitment ;
- (R) Lack of rewards and recognition ;
- (S) An emphasis on individuals rather than on teamwork.

5. The success factor to implement knowledge management ?

- (T) Support from top management ;
- (U) communication ;
- (V) Creativity ;
- (W) Culture and people ;
- (X) Sharing knowledge ;
- (Y) Incentives ;
- (Z) Evaluation.

**Decision attributes:**

1. Return on Assets (ROA)

- (1) Top ; (2) Middle ; (3) Bottom.

2. Return on Sales (ROS)

- (1) Top ; (2) Middle ; (3) Bottom.