Discovering KM Features of High-Performance Companies

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Abstract: - For purposes of reacting to an increasingly competitive business environment, many companies emphasize the importance of knowledge management (KM), thus, it is a worthwhile project to explore and learn about KM features of high-performance companies. Discovering and describing the critical KM features of high-performance companies is a qualitative analysis problem. To handle this kind of problem, the rough set approach is suitable because it embodies data-mining techniques which enable us to discover knowledge without rigorous statistical assumptions. This paper sets out to explore KM features of high-performance companies using the rough set approach. The results show that higher performing companies generally tend to be more explicit-oriented and less tacit-oriented. They also tend to consider the dimensions involved in the KM purpose and the factors crucial for success.

Key-words: - Explicit knowledge, Tacit knowledge, Knowledge management, Performance, Qualitative analysis, Rough sets

1 Introduction

Several studies from the literature [2][3][10][7][15]) have been devoted to discerning the relationships between knowledge management (KM) and corporate performance using traditional statistical methods. These studies have revealed that a specific KM style may result in better corporate performance. These KM studies are meaningful and helpful to us when selecting an appropriate style for implementation of KM activities. However, the desired outcome – better corporate performance – is not simply proportional to the amount of effort that firms invest in KM. It may also depend on the choice of KM strategies. Thus, adopting a cautious viewpoint is appropriate and, to be sure efforts are invested in the right direction, it is important that we first explore and discern the critical KM features – those which have contributed to the success of high-performance companies. After learning about various KM activities, and discovering those critical features, they can be imitated with more confidence and conviction.

Discovering these critical features is a qualitative analysis problem. To handle this kind of problem, we adopt the rough set approach which is a data-mining technique and do not require rigorous statistical assumptions. This approach differs from conventional data analysis which uses statistical inferential techniques. 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, and learning algorithms [17][11]. The RST is particularly useful for dealing with imprecise or vague concepts, and has been successfully applied in a variety of fields. Since the RST has these advantages with regard to qualitative analysis, it is suitable for solving the qualitative problem of discovering the critical features of KM.

2 The Conceptual Framework

In the knowledge economy, a key source of sustainable competitive advantage and consequent profitability is the way that a company creates and shares its knowledge [4]. Because knowledge is taking on such an important strategic role, larger and larger numbers of companies demand effective performance in the KM domain, and they aim to leverage and transform that knowledge into competitive advantages [16]. KM is a systematic management technique employed in the organizationally specified process of acquiring, organizing and communicating knowledge. There have been a number of frameworks developed to promote KM activities. According to Benbya et al.

[1], among the various different KM frameworks there are, in fact, 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.

To be sure, exploring and learning about KM features of high-performance companies is a worthwhile endeavor. At a minimum, meaningful KM features (see Figure. 1) involve the following: the purposes of KM, the degree of implementation of explicit-oriented KM, the degree of implementation of tacit-oriented KM, the main obstacles to implementation of KM, and the success factors in implementation of KM. Referring to [8], the purposes of KM range from improving KM activities (acquisition, sharing and usage of information) to improving performance, productivity and competitiveness; the main obstacles involve the lack of a sense of ownership of the problem, problems of organizational structure, lack of senior management commitment, *inter alia*; and the success factors include top management support, effective communication and knowledge sharing, etc. Choi & Lee [3] have provided useful measures for evaluating the explicit-oriented or tacit-oriented degree of implementing KM. With regard to measuring corporate performance, Bierly & Chakrabarti [2] note ROA and ROS are frequently used as the measures of financial performance. Corporate performance levels have been divided by one author into three classes according to the proportion: Bottom class 25%, Middle class 50%, and Top class 25% (Evans, 2004). This paper aims to explore KM features of the Top class (high-performance companies).

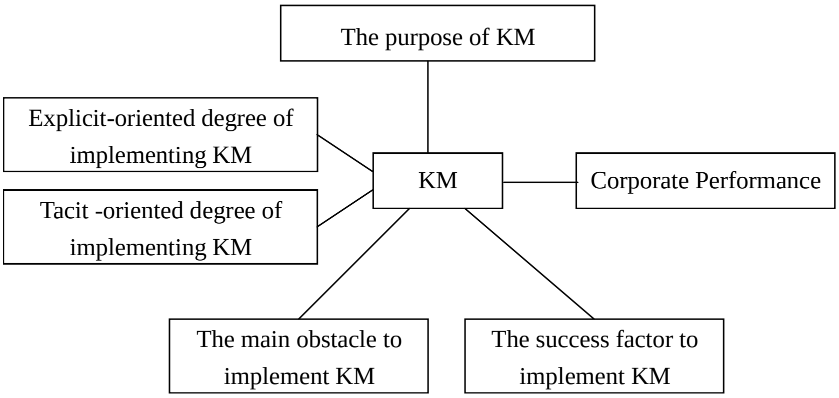

Fig. 1. The conceptual framework

3 The Basics of Rough Set Theory

The RST is a relatively new approach and very suitable for data reduction in qualitative analysis. In the rough set approach, any vague concept may be treated by choosing a pair of precise concepts that form the lower and upper approximation [13]. 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 [9].

Rough sets-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 [12]. 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. According to [14], 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: these are conditions that must be satisfied in order to carry out the particular decision specified in the decision table [12]. An information system can be seen as a decision table in the form of $S=(U,C\bigcup D,\rho)$, in which $C\bigcup D=Q$ means that condition attributes C and decision attributes D are two disjoint classes of attributes [6]. By analyzing the decision table, we can extract valuable decision rules.

Except the approximation accuracy, classification quality, and classification accuracy, the Covering Index (CI) is, on the whole, a valuable way to evaluate the quality of the decision rule. Importantly, the CI represents a ratio which indicates how many objects there are with the same attribute value matching the decision class, in contrast with how many objects there are belonging to the same decision class. Let the decision attributes D be a singleton $D=\{d\}$, the $d-$elementary sets are denoted by $Y_i \in \{Y_1, Y_2, \ldots, Y_m\}$ called the decision classes of the classification. Let the condition attribute $A \subseteq C$ and its domain V_{a_j} of the attribute $a_j \in A$. Then, the CI can be expressed as $\mathrm{CI}(V_{a_j}, Y_i) = card(V_{a_j} \wedge Y_i) / card(Y_i)$, where the "$\wedge$" is the operator of conjunction. For the analysis of the decision table, we recommend the following three-step analytical procedure: (1) calculate the classification quality and accuracy; (2) find the core attribute; and (3) evaluate the decision rule and CI.

4 Research Design and Results

For this study, a questionnaire was developed, based on the rough set approach, whose purpose was to collect data in the form of expert judgments. The study was conducted in two stages. In the first stage, the content of the questionnaire was determined and confirmed through an intensive literature review and significant discussions with six experts. The questionnaire contains two portions: one portion is devoted to basic information about the respondents, while the other portion is the series of questions about the topic issue. The series of questions consists of five questions about the constitution of the condition attributes, including: (1) The purposes of knowledge management, (2) The degree of implementation of explicit-oriented knowledge management, (3) The degree of implementation of tacit-oriented knowledge management, (4) The main obstacles to implementation of knowledge management, and (5) The success factors in implementation of knowledge management

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, the first question was as follows: "Regarding the purpose of knowledge management, which of the following answers reflects the situation for your company?" In the answer portion, these options as the attribute values 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.

The first, fourth, and fifth questions about purposes, main obstacles, and the success factors in implementing KM refer to M. Martensson [8] who provides an in-depth review in terms of KM issues and suggests some critical elements that must be considered in implementing KM. The second and third questions about KM styles cite Choi and Lee[3] 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 proposed by Bierly and Chakrabarti [2] who note that ROA and ROS are frequently used as measures of financial performance. Furthermore, following the method of dividing objects into three groups proposed by J.R. Evans [5], respondent companies are divided into three classes according to the following proportions: Bottom 25%, Middle 50%, and Top 25%.

Of high-tech companies in Hsinchu Science Park (HSP), there are nearly 112 which 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, representing a response rate of 57.1% i.e. more than half the listed companies of HSP. The respondents came from the following industry categories: 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.

The implementation of data analysis was performed through the suggested three-step analytical procedure with the help of software called ROSE (Rough Sets Data Explorer). ROSE is a type of software that implements basic elements of the rough set theory and rule discovery techniques. Commonly, it is necessary to build the decision table before proceeding to data analysis. 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 five condition attributes and their values are denoted as follows: $V_{\text{Purpose}} = \{A,B,C,D,E\}$, $V_{\text{Explicit}} = \{F,G,H,I\}$, $V_{\text{Tacit}} = \{J,K,L,M\}$, $V_{\text{Obstacle}} = \{N,O,P,Q,R,S\}$, and $V_{\text{Success}} = \{T,U,V,W,X,Y,Z\}$.

Step 1: Calculating the classification quality and accuracy. According to the analysis results, the classification accuracy of ROS (0.88) was superior to that of ROA (0.83), and also the classification quality of ROS (0.94) was superior to that of ROA (0.91). This implies that using ROS is superior to using ROA for exploring the critical relationship patterns between KM and corporate performance in this study. Furthermore, each decision class is describable with a high degree of accuracy (0.88) when using ROS. 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 an attribute. The analysis results using the RST obtained only one reduct of attributes: {Purpose, Explicit, Tacit, Obstacle, Success}, and five core attributes: {Purpose}, {Explicit}, {Tacit}, {Obstacle}, and {Success}. This implies that all the condition attributes are significant and it is not appropriate to omit any one of them in this case.

Step 3: Evaluating the decision rule and CI. The most important step in data analysis is to generate decision rules. As a result, two approximate rules were generated as shown in Table 1. Rule 1 (Purpose = A, Explicit = I, Tacit = L, Success = X) enables us to classify records into the Top or Middle class with the CI value of 100%. This means that the Top or Middle class of ROS can be identified according to whether "the KM purpose is to improve effective acquisition, sharing and usage of information", "knowledge is shared through codified forms like manuals or documents", "informal dialogues and meetings are used for knowledge sharing", and "the success factor to implement KM is sharing knowledge". Rule 2 (Explicit = G, Tacit = M) enables us to classify records into the Middle or Bottom class with the CI value of 100%. This means that the Middle or Bottom class of ROS can be identified according to whether "knowledge can be acquired easily through formal documents and manuals", and "knowledge is acquired by one-to-one mentoring in my company".

Table 1 Approximate rules

Rule 1. (Purpose = A) & (Explicit = I) & (Tacit = L) & (Success = X) => Top or Middle class (CI= 100.00%) ; (A) To improve effective acquisition, sharing and usage of information; (I) Knowledge is shared through codified forms like manuals or documents; (L) Informal dialogues and meetings are used for knowledge sharing; (X) Sharing knowledge.
Rule 2. (Explicit = G) & (Tacit = M) => Middle or Bottom class (CI= 100.00%); (G) Knowledge can be acquired easily through formal documents and manuals (M) Knowledge is acquired by one-to-one mentoring in my company.

5 Conclusions

As stated at the outset, the aim of this study was to explore KM features of high-performance companies. From the study results, several valuable implications can be derived for KM implementation. As shown in Figure 2, there are obvious differences between the Top or Middle class and the Middle or Bottom class. For example, the Middle or Bottom class focuses on the explicit-oriented degree and the tacit-oriented degree of implementing knowledge management, whereas the Top or Middle class highlights not only the explicit-oriented degree and the tacit-oriented degree but also the KM purpose and the success factor. This means that the higher performing company (the Top or Middle class) considers more dimensions related to KM implementation, ranging from the explicit-oriented degree or tacit-oriented degree to the linkage of KM purpose and the success factor.

Furthermore, with regard to the explicit-oriented degree of implementing KM, in the Top or Middle class it is emphasized that knowledge is shared through codified forms like manuals or documents, whereas the Middle or Bottom class stresses that knowledge can be acquired easily through formal documents and manuals. This reveals that the Top or Middle class is extremely explicit-oriented and is inclined to transform documents into explicit knowledge. With regard to the tacit-oriented degree of implementing KM, the Top or Middle class emphasizes that informal dialogues and meetings are used for knowledge sharing whereas the Middle or Bottom class stresses that knowledge "is acquired by one-to-one mentoring in my company". This implies that the higher performing company is less tacit-oriented. On the whole, the results show that higher performing companies generally tend to be more explicit-oriented and less tacit-oriented.

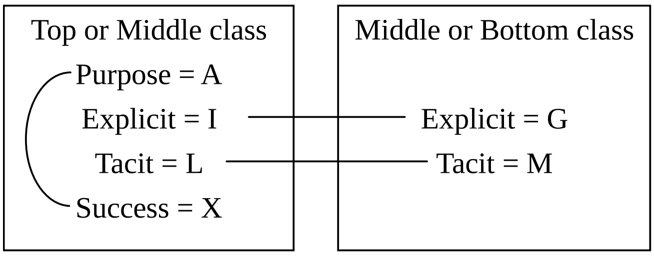

Fig. 2. KM features of different classes

This study has successfully discovered certain KM features of high-performance companies. The results of this study indicate that the higher performing company tends to be substantially explicit-oriented, less tacit-oriented, and, in considering the dimensions involved, includes the KM purpose and the success factor. It is hoped that these findings can be useful in the process of developing more formal theories; the proposed analytical procedure can effectively handle any issue where there is an advantage in reducing a complex and multi-attribute problem, exploring and delineating some valuable patterns, and mining the minimal sets of significant elements.

Previous studies are helpful to us in the effort to select an appropriate style for implementation of KM activities. This study, however can serve as a meaningful complementary study, emphasizing the practical perspective. Although this study has some limitations, for instance, the fact that the results might be different if respondent companies were divided into more or less than three groups, it does reveal some important practical aspects of knowledge management in high-performance companies.

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