

Measuring Immaterial Capital for Organizations Using Multicriteria Reference Point Model

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ABSTRACT

The identification of crucial knowledge to be capitalized and especially crucial tacit knowledge is a complex process because knowledge cannot be measured quantitatively. In this paper, we propose a methodology based on multi-criteria decision aid for evaluating knowledge that needs to be capitalized using a non compensatory aggregation procedure based on reference point model. Our method allows taking into account the decision makers' preferences that can be different or even contradictory while exploiting and managing their multiple points of view to evaluate knowledge.

Keywords: Information and knowledge; Analysis of collective decision making; Conflict resolution

I. INTRODUCTION

The necessity to capitalize knowledge produced and used in firms has increased rapidly these last years. As said by Lee and Van den Steen (2010), “*know-how is a key resource for business, and know-how management is a potential lever for competitive advantage.*” Maintaining this capital is a powerful mean to improve the level of performance of the firm. In order to ~~create~~, preserve and share knowledge in firms, knowledge management has been occupying since the beginning of the nineties more and more important space within organizations. Thus, companies should invest in methods and tools in order to preserve knowledge especially those of tacit nature. Researchers in knowledge management (e.g., Davenport et al., 1998; Nonaka and Takeuchi, 1995; O’Learly, 1998; Sanchez, 1997; Schreiber et al., 2000) have been focusing on the problems of acquisition, preservation and transfer of knowledge. However, considering the large amount of knowledge to be preserved, the firm must first determine the specific knowledge that should be targeted by capitalization. We should indeed focus on only the so-called “crucial knowledge”, i.e. the risk of their loss and the cost of their (re)creation is considered to be important. In other words their contribution to reach the firm objectives is very important and their use duration is long (Saad et al., 2005).

Previous research works (Saad et al., 2005; Grundstein, 2000) also revealed the interest of the identification of crucial knowledge. Not enough works exist concerning the identification of knowledge on which it is necessary to capitalize (Grundstein, 2000; Tseng and Huang, 2005), thus, (Saad, 2009) have proposed a multicriteria methodology based on DRSA (Dominance-based Rough Set Approach) (Greco et al., 2001) to identify crucial knowledge in order to justify a situation where knowledge capitalization is advisable. The objective of this methodology is to elicit the preference of the decision makers. This method is supported by a decision support system called K-DSS (Saad et al., 2005; Saad and Chakhar, 2009). Moreover, because of the large amount of knowledge to analyze, the large number of decision makers involved in the assignments of knowledge, contradictory opinions that decision makers can have (that lead to inconsistencies in the shared knowledge base) and also usually hard delay constraints of projects, it is necessary to automate the resolution of conflicts between decision makers.

The aim of this paper is to propose a multicriteria procedure to evaluate immaterial capital principally knowledge using a non compensatory aggregation model to cope with inconsistency in decision rules in our decision support system.

The rest of the paper is structured as follows. Section 2 provides an overview on the related works. Section 3 presents the methodology used to identify knowledge to be capitalized. In section 4, we present the multicriteria procedure that we propose to evaluate knowledge. Section 5 summarizes our contribution.

II. RELATED WORKS

In this section, we describe three methods: GAMETH framework (Grundstein, 2000; Grundstein et al., 2006), the method proposed by Tseng and Huang (2005), and the method of identification of critical knowledge proposed in Ermine et al. (2006).

The main distinctive feature of these methods is related to the approaches used (i) to identify knowledge to be evaluated and (ii) to construct criteria and evaluate knowledge according to these criteria.

As for knowledge collection, we think that GAMETH framework proposed by Grundstein (2000) enables to study the area and to clarify the needs in knowledge required to deal with pertinent problems through the modeling and analysis of sensitive processes in the company. This approach involves all the actors participating in the area of the study. Tseng and Huang (2005) use the DELPHI method to collect the need in knowledge. The merit of this method is the fact that they are faster to apply than the one of GAMETH[®]. Further, DELPHI technique may be used remotely. Finally, the method proposed by Ermine et al. (2006) is evenly based on both a series of interviews with the leaders, and the study of strategic documents. This last approach assumes however that the leaders are able to identify the knowledge to evaluate.

Our analysis of these approaches at the level of criteria construction and knowledge evaluation allows us to remark that the methods proposed by Ermine et al. (2006) and Grundstein et al. (2006) construct criteria intuitively. In turn, Tseng and Huang (2005) propose to compute the average score of each attribute of the knowledge as a function of the evaluations provided by each analyst. Then, the analyst evaluates the importance of knowledge in respect to each problem. Finally, the global average is computed for each analyst. One limitation of this method is that the scales used are quantitative. However, due to the imprecise nature of the knowledge, qualitative scales are preferred. Furthermore, additive aggregation and in particular weighted sums are already frequently used in compensatory logic since they are simple to manipulate. However, they are often inefficient when it comes to aggregate qualitative parameters that have only ordinal significance.

Brigui-Chtioui and Saad (2011) propose a multicriteria approach based on a weighted sum. It is well-known that the weighted sum, which is the simplest multicriteria aggregation model, suffers from several drawbacks. First, it requires the specification of weights which are difficult to obtain and to interpret. This is all the more important that slight variations on these weights may change dramatically the choice of the best solution. This is partly due to the fact that the weighted sum is a totally compensatory aggregation model. In our context, a very bad value on a criterion can be compensated by a series of good values on other criteria that represent a given knowledge. Such knowledge could obtain a weighted sum similar to knowledge with rather good scores on all criteria, while in many cases, the latter would be preferred. This suggests the use of non-compensatory or partially compensatory aggregation models. Finally, it can be shown that some of the non-dominated solutions, called non-supported, cannot be obtained as the best solution using the weighted sum for any possible choice of weights. This is a very severe drawback since these non-supported solutions, whose potential interest is the same as the other non-dominated solutions, are rejected only for technical reasons.

The contribution of this paper is to evaluate knowledge with a procedure based on a non compensatory multicriteria model called reference point model (Brigui-Chtioui and Pinson, 2010). Our method takes into account the preferences of decision makers which can be different or even contradictory while exploiting and managing their multiple points of view to evaluate knowledge.

III. METHODOLOGY

The methodology proposed by Saad (2009) for crucial knowledge identification and evaluation is composed of three phases.

A. Phase 1: Determining “Reference Crucial Knowledge”

The first phase is relative to constructive learning devoted to infer the preference model of the decision makers. Constructive learning, in contrast to descriptive learning, assumes that the preference model is not pre-existing but is interactively constructed by explicitly involving the decision maker. Practically, it consists in inferring a set of decision rules from some holistic information in terms of assignment examples provided by the decision makers. This is done through the DRSA (Greco et al., 2001) method which is devoted to multi-criteria sorting problems. The set of rules may be used in the same project, a similar project or a new one. However, for similar or new projects an adaptation of the set of decision rules to the project under consideration is often required. This phase includes also the identification, of a set of reference crucial knowledge.

The construction of the “Reference Crucial Knowledge” is based on the identification and the analysis of sensitive processes to determine the need of knowledge necessary to solve problems related to these sensitive processes. More precisely, the approach used contains three steps. First, we identify the sensitive processes with a group of decision makers. These processes will be the object of an in-depth analysis. Indeed, we believe that the analysis of the processes is not achievable in the short term. Our method is based on a heuristic approach to identify these sensitive processes. The second step consists, on the one hand, in modeling sensitive processes identified and on the other hand, in analyzing critical activities associated to each sensitive process. The third step consists of clarifying and locating the knowledge needed to solve relevant problems. This analysis leads to the identification of two types of knowledge: missing knowledge and poorly mastered knowledge. In addition, it provides information for the identification of knowledge that can be crucial such as the knowledge owned by a unique expert.

B. Phase 2: Constructing Preference Model

The second phase includes the construction of preference model and the evaluation of knowledge with the respect to a convenient set of criteria. Three sub-families of criteria were constructed: (i) knowledge vulnerability family that are devoted to measure the risk of knowledge lost and the cost of their (re)creation; (ii) knowledge role family that are used to measure the contribution of the knowledge to reach the project objectives. Each criterion of this family corresponds to an objective; and (iii) knowledge use duration family that aims at measuring the duration of using the knowledge based on the company average and long term objectives.

Based on the reasoning of the actors and the constraints relative to the nature of the scale (ordinal scale), we have developed an algorithm for maximizing the degree of the minimal contribution of knowledge to each objective. The proposed method includes two steps:

Step 1: For each project we list all possible paths (knowledge→ Process→ Project) and then we identify, for each project, the path that maximizes the minimal degree of contribution of knowledge to each project.

Step 2: We use the graph obtained in the first step to identify the complete path from the knowledge to each objective. We enumerate all possible paths and then we select the one that maximizes the degree of minimal contribution.

To compute the contribution degrees of each knowledge K_i to each objective O_j three algorithms are provided:

$$\text{Max}_{p \in P} \text{Min}_{e \in P} \text{Min}_{d \in D} v^d(e). \quad (1)$$

$$\text{Max}_{p \in P} \text{Min}_{e \in P} \text{Median}_{d \in D} v^d(e). \quad (2)$$

$$\text{Max}_{p \in P} \text{Min}_{e \in P} \text{Max}_{d \in D} v^d(e). \quad (3)$$

where P is the set of paths from K_i to O_j ; p is a path from P ; $D = \{d_1, \dots, d_r\}$ is the set of decision makers; and $V^d(e)$ is the evaluation of e to decision maker d .

The evaluation of knowledge with respect to criteria of families (i) and (iii) are normally provided by the decision maker. However, in practice the decision makers may show some difficulty in directly evaluating knowledge due to the complexity of some criteria. To overcome this problem, complex criteria are decomposed into several more simple indicators so that decision makers can easily evaluate these indicators.

Once all knowledge items are evaluated with respect to all criteria, the next step is an iterative procedure aiming at jointly infers the decision rules. Two decision classes have been defined C11: “non crucial knowledge” and C12: “crucial knowledge”. This procedure is based on DRSA. This procedure is composed of four steps:

Step 1: Individual assignment

The first step assigns, with the help of each decision-maker, a set of knowledge items called “Reference Crucial Knowledge” in the decision classes C11 and C12. The decision table contains, in addition to the columns related to vulnerability, contribution degree and use duration criteria, as many columns as decision makers ($D_1, D_2 \dots D_n$). Once the whole decision table is generated, it will be used as the input of the second step.

Step 2: Generation of individual decision rules

The second step infers decision rules for each assignment sample determined in the previous step. The obtained results are translated to the form of approximation quality which allows verifying the presence of inconsistencies in the decision rules:

$$\gamma_F = \frac{\text{card}(A - (\bigcup_{t=1, \dots, n} Bn_F(CI_t^{\geq}))}{\text{card}(A)} \quad (4)$$

We have applied the DOMLEM algorithm (Greco et al., 2001), proposed in DRSA method to infer rules permitting to characterize knowledge assigned to classes C11 and C12. The obtained results are transformed in the form of approximation quality, and permitted us to verify the presence of inconsistencies in the decision rules. These

rules are deduced from the comparison of information related to the assignment examples intuitively provided by each decision maker, and the assignment generated by the algorithm.

Step 3: Suppression of inconsistencies in individual decision rules

The third step modifies sample assignments or evaluations in collaboration with the concerned decision-maker when inconsistencies are detected in the decision rule base. Thus, we ask this decision maker to carefully reconsider the evaluation of knowledge.

Step 4: Generation of collective decision rules

In the last step we determine decision rules that are collectively accepted. Thus, based on the multicriteria procedure (cf. § 4) we have determined a collective decision rules used to identify the crucial knowledge.

C. Phase 3: Classifying “Potential Crucial Knowledge”

In the third phase, the decision maker uses the preference models (collectively decision rules) of the different decision makers defined in the second phase to assign the new knowledge which is called “Potential Crucial Knowledge”, to the classes C11 or C12. The results are stored in a performance table.

More specifically, a multicriteria classification of “Potential Crucial Knowledge” is performed on the basis of the decision rules that have been collectively identified by the decision maker(s) in the second phase. The term of “Potential Crucial Knowledge” refers to the knowledge that has been temporarily identified as crucial by at least one decision maker. The generated “Potential Crucial Knowledge” are analyzed and then evaluated against the criteria identified in the second phase. Then, they are assigned in one between the two decision classes C11 or C12. One potential crucial knowledge is considered as effectively crucial if there exists at least one decision rule within the rule base, whose premises are paired with the evaluation of this knowledge on the set of criteria. The general form of a decision rule is:

$$\text{If } g_j(k) \geq rg_j ; \forall j \in \{1, \dots, m\} \text{ then } k \in C12$$

where g_1, \dots, g_m is a family of m criteria; $g_j(k)$ is the performance of the knowledge k on criterion g_j ; $(rg_1, \dots, rg_m) \in \mathbb{V}g_1 \times \dots \times \mathbb{V}g_m$ is the minimum performance of a knowledge k on the set of criteria.

IV. MULTICRITERIA PROCEDURE

As we said before in the real organization where projects are complex, it is very difficult to use a constructive approach like the approach proposed by Belton and Pictet (1997) to solve conflicts between decision makers and determine collective decision rules. We propose in this phase to evaluate knowledge based on a multicriteria model and to compare them according to a preference relation.

Before presenting our multicriteria reference point model, we start by proposing some preliminary useful notations:

Let p be the number of criteria. $D = D_1 \times \dots \times D_p$, the decision space where D_j is the domain of values for attribute j ($j = 1, \dots, p$); $C = C_1 \times \dots \times C_p$ the criterion space; v_j , the value function defined from D_j to $C_j = [0; 100]$ that corresponds to attribute j .

Let $x = (x_1 \times \dots \times x_p) \in D$ denotes knowledge. $k = (k_1 \times \dots \times k_p) \in C$, where $k_j = v_j(x_j)$ denotes the knowledge evaluated on all criteria, $j = 1, \dots, p$.

Definition 1. Classification. A classification α is represented by a triplet $\langle a_i, k, c \rangle$ where a_i represents the decision maker, k denotes the classified knowledge and c the class.

Definition 2. Conflict. A conflict is detected iff: $\exists \alpha \langle a_i, k, c \rangle$ and $\beta \langle a_j, k, c' \rangle / c \neq c'$.

Definition 3. Consistency. It exists Consistency iff $\forall \alpha \langle a_i, k, c \rangle$ and $\beta \langle a_j, k, c' \rangle$, *No Conflict*.

A. Preference Model

Our preference model is based on two reference points: (1) The *aspiration point*, denoted by $a = (a_1 \times \dots \times a_p)$ whose coordinates $a_j = v_j(dv_j)$ are aspiration levels, where $dv_j \in D_j$ is the optimal value on criterion j . The aspiration point is kept private during the classification process. (2) The *reservation point*, denoted by $r = (r_1 \times \dots \times r_p)$ whose coordinates $r_j = v_j(mv_j)$ are reservation levels, where $mv_j \in D_j$ is the minimal value required on criterion j .

B. Aggregation Model

The aggregation model determines the utility associated with a given knowledge classification according to an aspiration point. It is defined by the deviation from the aspiration point. This deviation measures the maximum difference between aspiration levels and knowledge classification values on each criterion. The model computes the differences between the aspiration value and the knowledge value on each criterion and keeps the greatest one. The max function is chosen to insure that a bad score on a criterion cannot be compensated by good scores on other criteria. Equation (5) gives the utility of a knowledge classification α . It measures the maximum of the differences $(a_j - \alpha_j)$ between a knowledge classification α and the aspiration point a on each criterion j .

$$U_a(\alpha) = \max_{j=1, \dots, p} (a_j - \alpha_j) \quad (5)$$

The preference relation based on the utility presented above is given by Equation (6).

$$\alpha \succ \beta \Leftrightarrow U_a(\alpha) < U_a(\beta) \quad (6)$$

The classification criteria used to evaluate knowledge classifications are:

- $NAg(\alpha)$: the number of decision makers establishing α
- $\gamma(A(\alpha))$: the approximation quality of the decision maker establishing α .
- R_α : the number of rules conducting to establish α .
- $\partial(R_\alpha)$: the average of the rules strength in R_α .

V. CONCLUSION

In the literature, there are few works dedicated to the evaluation of knowledge to be capitalized. Identification of knowledge to assess seems poorly explained in the majority of previous methods; however, this identification is an important issue itself. The method we propose is based on the multicriteria reference point model that addresses the compensatory model shortcomings. This approach leads to an efficient solution for all decision makers since it helps them to work together in order to identify crucial knowledge. The decision based on reference point model reflects well the decision makers' preferences that may be different or even conflicting. The multicriteria decision also incorporates a degree of subjectivity in the assessment of knowledge relative to the objectives of the company, because it takes into account the different evaluations given by decision makers. These assessments are used to calculate a multicriteria utility corresponding to each knowledge. Our achievement is about building a *satisfactory* decision and not an *objective* decision even if optimal.

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