

Challenges in Capitalizing Knowledge in Innovative Product Design Process

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Abstract. Capitalizing on company's knowledge is increasingly being recognized in a private organizations environment since managing knowledge productivity is considered a source of competitive advantage. In this paper we present a generalization of GAMETH framework, that play an important role in identifying crucial knowledge used and created in innovative product design process. Thus, we have developed a method based on three phases. In the first phase, we have used GAMETH to identify the set of "reference knowledge". During the second phase, decision rules are inferred, through rough sets theory, from decision assignments provided by the decision maker(s). In the third phase, 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).

Keywords: Knowledge Capitalizing, crucial knowledge, Multi-criteria classification, Decision rules, Dominance Rough set approach.

1. INTRODUCTION

The knowledge created in innovative product design process has some characteristics. First, this knowledge is specific to the innovative product. It is mainly based on tacit knowledge [11] of the project experts gained from previous projects and they do not necessarily apply to the innovative product even if such experience is still important to search new concepts. Second, generally the lifetime of most knowledge used to develop the innovation product is very short because one part of knowledge is not validated in the innovative product project development or because the company's objectives change rapidly. In the automotive sector, capitalizing on

the knowledge used in design process, that is, locating, preserving, enhancing value and maintaining this knowledge is very complex [18]. It involves more and more heavy investments in order to convert unstructured tacit knowledge into explicit knowledge to be integrated in corporate memory defined as "Explicit, disembodied, persistent representation of knowledge and information in an organization" [2].

As resources of the company are limited, the automotive company must define accurately the knowledge to be integrated in the design process's corporate memory. In our case study, the goal is to propose a method to identify crucial knowledge in order to justify a situation where knowledge capitalization, specifically in the context of decision-making, is advisable.

The rest of the paper is organized as follows. Section 2 synthesizes the related research studies. Section 3 presents experimentations. Section 4 presents the methodology. In Section 5 we present the application of the methodology in the automotive French Company. Section 6 concludes the paper and presents our current and future work.

2. RESEARCH STUDIES

In literature, there are only few works that are interested in the identification of the knowledge on which preservation operation need to be conducted. Several authors, including [3] [5] [8] [9] [12] [25] consider crucial knowledge delimitation process as a hard operation.

The need for pertinent and crucial knowledge in any knowledge capitalizing operation has been proved by

several authors (e.g. [1] [2] [5] [6] [20]). Only few theoretical and empirical works are available in literature. Concerning knowledge collection, we think that the method proposed by [6] 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. Finally, the method proposed by [4] is evenly based on both a series of interviews with the leaders and, the study of strategic documents. These two last approaches suppose 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 permits us to remark that the methods proposed by [6] construct criteria intuitively. In turn, Tseng and Huang 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 important of each knowledge in respect to each problem. Finally, the average global 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.

3. EXPERIMENTATION

We carried experiments in order to show whether the decision rules resulting from the identification phase of crucial knowledge are effective. We considered a set of forty “Potential crucial knowledge” items and classified them in two classes: (1) “not crucial knowledge” (C_1) and (2) “crucial knowledge” (C_2).

| | DM1 | DM2 | DM3 | DM4 | AVERAGE |
|-----|------|------|------|-----|---------|
| C11 | 0,46 | 0,58 | 0,3 | 1 | 0,58 |
| C12 | 0,75 | 0,81 | 0,77 | 1 | 0,83 |

Table 1. Quality of approximation

The evaluation of each knowledge in this test set is carried with the help of the decision maker. Table1 reports the quality of approximation with respect to four individual decision rules corresponding to four decision makers (DM). The average 0,83 of Figure 1 shows that we have various results depending on the decision maker's preferences. In addition, the average of approximation quality of crucial knowledge (C_2) determine with GAMETH framework is 0, 83.

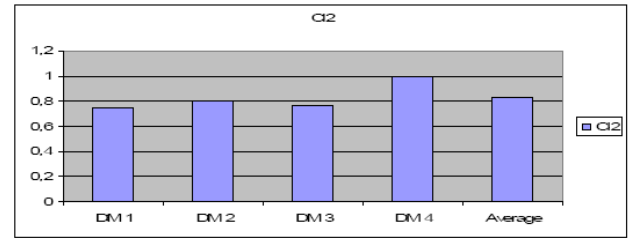


Figure 1. Approximation quality of crucial knowledge

4. METHODOLOGY

The methodology for crucial knowledge identification and evaluation is composed of three phases (Figure 2). A detailed description of it is available in [16].

Phase 1: Determining “Reference Knowledge”

The first phase is relative to constructive learning devoted to infer the preference model of the decision makers. Constructive learning, as opposite to descriptive learning, suppose that the preference model is not pre-existing but is interactively constructed by explicitly implying the decision maker. Practically, it consists in inferring, through the DRSA (Dominance-based Rough Set Approach) [4] method which is an extension of rough set theory [10] and which is devoted to multi-criteria sorting problems of a set of decision rules from some holistic information in terms of assignment examples provided by the decision makers. This set of rules may be used in the same project or in other similar or new projects. However, for similar or new projects an adaptation of the set of decision rules to the project under consideration often required. This phase includes also the identification, using GAMETH (Global Analysis METHodology) framework, of a set of “Reference crucial knowledge”.

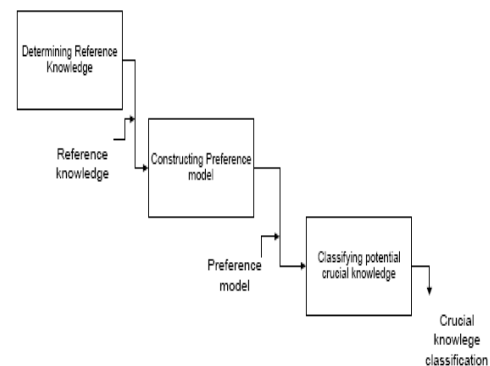


Figure 2. The methodology for crucial knowledge identification and evaluation

Phase 2: Constructing Preference model

The second phase includes the construct of preference model and the evaluation of knowledge with the respect to a convenient set of criteria [13]. Inspiring from the systemic approach of [7] and by using the bottom-up approach [15] [16], 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 its (re)creation; (ii) knowledge role family that are used to measure the contribution of the knowledge in the project objectives and (iii) use duration family that is devoted to measure the use duration of the knowledge basing on the company average and long term objectives. The criteria used to evaluate the “knowledge of reference” were constructed through a combination of the top-down and bottom-up approaches. The top-down approach was used to identify the indicators from which the criteria g_1, \dots, g_{15} are constructed. These indicators were defined basing on the theoretical research in knowledge engineering, strategic management and artificial intelligence domains and on the empirical studies conducted in the French car company see [23] for details.

To make the evaluation phase easier, we should analyze the “knowledge of reference”, i.e. identify the process where the knowledge is used, the person gathers it, the tacit level, production time and see if it is validate or not. To evaluate each knowledge K_i in respect to the each objective O_j , we have developed the computing model [21] [22]. The evaluation of knowledge in respecter 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 in respect to some complex criteria. To overcome this problem, complex criteria are decomposed into several more simple indicators. The 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 permitting to conjointly infer the decision rules. Two decision classes have been defined C11: “non crucial knowledge” and C12: “crucial knowledge”.

Phase 3: Classifying potential crucial knowledge

In the third phase, the decision maker use the preference models (decision rules) of the different stakeholders defined in the first phases to assign the new knowledge, called “potential crucial knowledge”, to the classes C11 or C12. More specifically, a multi-criteria 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 first phase. The term of “potential crucial knowledge” should be mapped to the concept of “potential action” as defined in the multi-

criteria decision-aid theory, that is, “real or virtual actions considered by at least one stakeholder as a temporally realistic one” [14]. “Potential crucial knowledge” is the knowledge that has been temporary, identified as crucial by at least one stakeholder. The generated “potential crucial knowledge” are analyzed and then evaluated against the criteria identified in the first phase. Then, they are assigned in one of two decision classes C11 or C12.

In fact, one “potential crucial knowledge” is regarded as effectively crucial if there exists at least one decision rule within the rules base, whose premises are paired with the evaluation of this knowledge on the set of criteria.

The general form of a decision rule is:

If $g_j(k) \geq r_{g_j}; \forall j \in \{1, \dots, m\}$ 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

- $(r_{g_1}, \dots, r_{g_m}) \in V_{g_1} \times \dots \times V_{g_m}$ is the minimum performance of a knowledge k on the set of criteria.

5. CASE STUDY

The proposed methodology was conceived and validated in the French Car Company. More specifically, we have focalized on the depollution systems. The objective of the French car company is to transfer the knowledge developed in the depollution system for use with:

- Other types of vehicles
- Projects concerned with definition of the new depollution systems.

Phase 1: Determining “Reference crucial Knowledge”

To identify the “knowledge of reference”, we have applied GAMETH framework. This framework is composed of four steps. The first step is composed of four substeps. The first substep permits to define the organizational model of the depollution system project under study, i.e., define the study area, construct the organization chart and formalize the objectives in hierarchical form to help the decision makers identify sensitive processes. In the second substep we identify, with the help of the project responsible, the sensitive processes. Two sensitive processes are: “Choice of filter support” and “Design and methodology of supervisor calibration”. The third substep concerns the modeling and analysis of these processes as well as the study of “critical activities” associated with each process. In the last step we identify the sources of knowledge and their localization.

Phase 2: Constructing Preference model

Since our objective is to identify crucial knowledge, we have analyzed and characterize those knowledge that are mobilized in the different critical activities related to each sensitive process. We have often called to model the creation process of each of these knowledge. Table 2 illustrates the result of the in-depth analysis of the knowledge relative to “the choice of material”. To assure good choice of material, the filtration system needs to be efficient whatever the rolling system. The choice of the material includes the constraints relative of the engine working, implementation and storage of residue.

| Knowledge | Used in | Tacit/explicit dimensions | Production time | Validity |
|---|---|--|-----------------|------------------------------------|
| Knowledge relative to the choice of material structure” | Design and methodology relative to the calibration of filter reactivation | - 70% : Explicit (e.g. in technical documents) - 30% : explicitable | 2 years | Validated through experimentations |

Table 2. Analysis of the knowledge relative to “the choice of material”

Three sub-families of criteria where constructed : (i) knowledge vulnerability family including the eight criteria g_1, \dots, g_8 that are devoted to measure the risk of knowledge lost and the cost of its (re)creation; (ii) knowledge role family including the criteria g_9, \dots, g_{14} that are used to measure the contribution of the knowledge in the project objectives. The criteria g_9, \dots, g_{14} are specific to the depollution system project and should be replaced by other ones for other projects. These criteria correspond to the objectives in the contribution degree computing model and (iii) it use duration family including the criterion g_{15} that is devoted to measure the use duration of the knowledge basing on the company average and long term objectives.

Once criteria family is constructed, we need to evaluate each knowledge of reference in respect to all criteria. We have distinguished three family of criteria which permit to measure the vulnerability of the knowledge and implies criteria $\{g_1 : \text{complexity}, g_2 : \text{accessibility}, g_3 : \text{substituability}, g_4 : \text{validation type}, g_5 : \text{transferability}, g_6 : \text{rarity}, g_7 : \text{acquisition cost and } g_8 : \text{acquisition time}\}$; the role of each knowledge in each objective and implies criteria $g_9, g_{10}, g_{11}, g_{12}, g_{13}$ and g_{14} ; and use duration of each knowledge which implies criterion $\{g_{15} : \text{use duration}\}$.

As mentioned earlier, the evaluations of “knowledge of reference” in respect to criteria g_1, g_2, \dots, g_8 are provided by the decision makers. For example, in respect to criterion complexity, the knowledge “relative to different characteristics that exist between depollution system command law and the other CMM command laws” is considered as “very complex” since this knowledge depends on several other knowledge related to the law of EGR (Exhaust Gaz Recirculation) command, the law of CAN (Controller Area Network) command, the law of

gearbox command, to the injection system and to the law of depollution system command.

To infer rules, we have constructed four decision tables containing the evaluations of 34 “knowledge of reference” in respect to 15 and to the assignment examples provided by four decision makers.

We present in Table 3 an extract from the decision table concerning the assignment of three knowledge of reference”.

| K_i | g_1 | g_2 | g_3 | g_4 | g_5 | g_6 | g_7 | g_8 | g_9 | g_{10} | g_{11} | g_{12} | g_{13} | g_{14} | g_{15} | Decision |
|----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|----------|----------|----------|----------|----------|----------|----------|
| K_8 | 2 | 2 | 3 | 3 | 1 | 2 | 4 | 4 | 5 | 2 | 4 | 5 | 5 | 5 | 2 | 1 |
| K_9 | 3 | 3 | 2 | 2 | 3 | 3 | 4 | 4 | 4 | 2 | 4 | 4 | 3 | 4 | 2 | 1 |
| K_{16} | 2 | 3 | 3 | 2 | 2 | 2 | 3 | 4 | 5 | 2 | 5 | 5 | 5 | 2 | 2 | 2 |

Table 3. An extraction from the decision table for one decision maker

First, each decision maker selects the decision rules. We have applied the DOMLEM algorithm, proposed in DRSA [10] method to infer rules permitting to characterize knowledge assigned to classes C11 and C12. The set of decision rules identified by decision maker r permit to establish Table 4. The result obtained are traduced 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. To illustrate the incoherence, we consider the assignment of a given decision maker r . Initially, decision maker r assigns $K_{11}, K_{14}, K_{15}, K_{16}$ and K_{21} simultaneity to C11 and C12. Thus, we have called this decision maker to carefully reconsider the evaluation of each of these knowledge. Concerning knowledge K_{11} and K_{15} , the decision maker mentioned that hesitated when he assigned these knowledge. For knowledge K_{14}, K_{16} and K_{21} , there is no remark and we do not modify his/her assignment. We have reviewed with all the decision makers that have provided inconsistent decision rules and that are ready to modify his/her assignment examples. Once each decision makers chooses the decision rules relatives to different assignment examples, we determine, jointly with the decision makers, a subset of decision rules that permit to evaluate the crucial knowledge. Three examples of jointly selected decision rules follows (expressed in mathematical form):

| Decision Class | F-lower approximation | F-upper approximation | F-Boundaries of sets C11 and C12 | Approximation quality |
|---------------------------------------|---|---|----------------------------------|-----------------------|
| C11 : "at most non crucial knowledge" | K1, K2, K8, K9, K17, K23, K28 | K1, K2, K8, K9, K11, K14, K15, K16, K17, K21, K23, K28 | K11, K14, K15, K16, K21 | 0.58 |
| C12 : "at least crucial knowledge" | K3, K4, K5, K6, K7, K10, K12, K13, K18, K19, K20, K22, K24, K25, K26, K27, K29, K30, K31, K32, K33, K34 | K3, K4 K5 K6 K7 K10 K11 K12 K13 K14 K15 K16 K18 K19 K20 K21 K22, K24, K25 K26 K27 K29 K30 K31 K32 K33 K34 | K11, K14, K15, K16, K21 | 0.81 |

Table 4. Approximation qualitative decision maker r

Rule 1: If $g_3(k) \geq 3 \wedge g_6(k) \geq 2 \wedge g_9(k) \geq 5 \wedge g_{15}(k) \geq 2$

Then $x \in \geq C1$

Rule 2: If $g_3(k) \geq 2 \wedge g_6(k) \geq 2 \wedge g_{12}(k) \geq 4 \wedge g_{15}(k) \geq 2$

Then $x \in \geq C1$

Rule 3: If $g_1(k) \geq 3 \wedge g_3(k) \geq 2 \wedge g_8(k) \geq 4 \wedge g_{15}(k) \geq 2$

Then $x \in C1 \geq$

In the system, Rule 2 is traduced as follows:

IF K_i . Substitutable –Level is "at least weak"

and

K_i . Rarity-Level is "at least rare"

and

K_i . Competitivity is "at least high"

and

K_i .use-duration is at least "average"

THEN K_i is at least in C12

This rule means that a piece of knowledge K_i is considered crucial (i.e. K_i belongs to the class of at least crucial C12), if it is difficult to replace it, it is scares, have an important impact on commercial position of the company and also has convenient use duration.

Phase 3: Classifying potential crucial knowledge

In this phase, the system use decision rules defined in the first step to assign new "potential crucial knowledge" to either C11 or C12. Those assigned to C12 are the crucial ones that need to be capitalized on.

1) Step1. Definition of a "potential crucial knowledge" set: First, we have identified, with the help of the stakeholder, the decision makers implied in this second phase. There are 6 implied decision makers. These are the ones that have participated to phase one plus the responsible on the cooperation with another automobile constructor company. With all these decision makers, we have first retained all the knowledge that are supposed potentially crucial and then we have combined some ones (that they find very detailed) and removed/added some

another ones. The final list is obtained after individuals discussion with the different decision makers and validated through emails with all of them. The choice of the set is facilitated by the analysis of process and activities performed during the definition of knowledge of reference process.

2) Step2. In-depth analysis of "potential crucial knowledge": we have applied for each "potential crucial knowledge" the same process as applied in step 2 of phase 1.

3) Step 3.Evaluation of "potential crucial knowledge": We have evaluated all potential crucial knowledge in respect to all criteria constructed in step 3 of phase 1. The obtained performance table contains the evaluation of each "potential crucial knowledge" in respect to criteria related to:

- The vulnerability of knowledge (i.e $g_1, g_2, g_3, g_4, g_5, g_6, g_7, g_8$);
- The role of knowledge for each objective (i.e. $g_9, g_{10}, g_{11}, g_{12}, g_{13}, g_{14}$); and
- Use duration (i.e g_{15})

4) Step 4. Application of decision rules:

We have used the performance table containing the evaluation of different knowledge of reference as input in this phase. Thus, it will be required only one rule (that characterize knowledge required a capitalizing operation) is verified to conclude that the knowledge is crucial.

6. CONCLUSION

In this paper we have presented a generalized method to make GAMETH usable for any complex project. We have developed a novel methodology that constructs the set of "crucial knowledge". This methodology consists of three phases. During the first phase, decision rules are inferred, through rough sets theory, from decision assignments provided by the decision maker(s). It includes the identification of a set of "reference knowledge" and its evaluation with respect to a convenient set of criteria. In the second phase, 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).

Several points related to the methodology itself need to be investigated. The contribution degrees model should take into account evolution of different industrial projects concerned by the capitalization operation. For example, during our experiences at automobile company, some data relative to the use of a chemical substance in the DE POLLUTION system were qualified as very important by the actors, and hence the corresponding knowledge were computed as important by the model. Eight months later, this substance is not used any more in

the project. One possible solution to tackle this problem is to use robustness analysis [14]. More precisely, this type of uncertainty may be modeled in terms of scenarios corresponding to the possible combinations of different values attributed by each actor to the contribution of each knowledge to each objective.

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