

# Multicriteria Decision Aid Method for Knowledge Sharing

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**Abstract.** In a delicate field such as the medical one, the decision-making process is extremely important given the major impact it can have on the patient's life. Indeed, the dramatic effects that can cause an inadequate decision make it primordial to strengthen the knowledge on which this decision is based. Thus, sharing knowledge between the members of the medical staff turns out to be a promising alternative to fulfill our goal consisting in enriching the medical background of the medical staff members in order to enable them to make a conscientious decision. Hence, this work develops a theoretical method representing a recommendation system relying on a Multicriteria Decision Aid method as well as on filtering techniques such as the collaborative filtering and the knowledge-based filtering aiming at improving the tacit and explicit knowledge sharing within organizations.

**Keywords:** Knowledge sharing · Collaborative filtering · Knowledge-based filtering · DRSA

## 1 Introduction

In some domains, namely the medical one, it is very important to share and to seamlessly disseminate the set of knowledge either preserved within an organization memory or embodied in the staff medical's minds in order to enrich their individual and collective background. Such exchange process helps professionals make the right decisions in complex clinical circumstances. Thus, this paper aims to better the problem of "knowledge sharing" within organizations, and particularly within the Association of Protection of Motors Disabled of Sfax-Tunisia (APMDS). This association is characterized by a large number of stakeholders with various profiles and different natures (internal or external ones, permanents or trainers, volunteers or salaried...) and who are usually geographically dispersed, which leads to problems in knowledge transmission between them. In addition, the absence of such an interaction between the stakeholders stops the

knowledge development and limits it to the mind of each member. In fact, the knowledge within the APMDS is -always- at risk to be captured in the minds of its owners or therefore to be lost with their departure.

To overcome such a problem, this paper provides a theoretical method that targets the sharing of explicit knowledge preserved within an organizational memory and -also- the set of crucial but hardly explainable knowledge embodied in the human stakeholders' minds, called "tacit knowledge". This method is based on a recommendation system relying on a multicriteria decision aid approach and used as a sharing tool to provide the appropriate knowledge to a user needs. It plays the role of an intermediary between a transmitter who updates the system by the knowledge he possesses, and the receiver who accesses the system to seek knowledge that he needs. Yet, the knowledge sharing between the transmitter and the receiver does not require their physical presence. The method we propose relies mainly on the collaborative filtering technique based on DRSA (Dominance-based Rough Sets Approach) aiming at determining a set of users having tastes similar to the current user, called neighborhood. *A current user is the one for whom the recommendation system must provide an ordered list of knowledge meeting the needs he articulated in his query.* Moreover, to take into account the current user preferences, we have used the knowledge-based filtering technique to compare the current user query to the profile of knowledge already appreciated by his neighborhood. This study proposes reliable criteria to make multicriteria decisions about the knowledge "cruciality". Our aim, hence, is to help the medical staff members get the "appropriate" knowledge on the basis of which they can make the right decision.

This paper is organized as follows. Section two presents the background. Section three details our contribution. Section four illustrates the method by an example. Section five concludes the paper and underlines some future work.

## 2 Background

In this section, we present the DRSA method, the recommendation system and the knowledge sharing: Three concepts on which we have based our work.

### 2.1 Dominance-Based Rough Set Approach (DRSA)

DRSA method (Dominance-based Rough Set Approach) -developed by Greco [9]- is dedicated to the sorting problem in a *multicriteria decision aid* context. This is an extension of the rough sets theory to classify the reference actions within decision classes. This method allows the simultaneous consideration of criteria as well as of qualitative and quantitative attributes. The comparison of the actions is based on the dominance relation. Previous research has proposed the DRSA [9] to overcome the shortcomings of conventional rough sets theory [10] on multicriteria classification. The basic idea of DRSA is to replace the indiscernibility relation used in classical rough sets theory with the dominance relation, which is more appropriate for multicriteria decision-making. Moreover,

unlike the probability theory [12] and the fuzzy set theory [6] where the inclusion of inconsistency requires the determination of probabilities or membership degrees, the DRSA method requires no additional information about data, which prompted us to use it. According to the method DRSA, a data table is a 4-tuple  $S = \langle K, F, V, f \rangle$ , where  $K$  is a finite set of reference actions,  $F$  is a finite set of criteria,  $V = \cup_{g \in F} V_g$  is the set of possible values of criteria and  $f$  denote information function  $f: F \times K \longrightarrow V$  such that  $f(x, g) \in V_g, \forall x \in K, \forall g \in F$ .

The criteria set  $F$  is divided into a set  $C$  of condition attributes and a decision attribute  $d$ . In a multicriteria classification, condition attributes are criteria. Furthermore, the decision attribute  $d$  makes a partition of  $K$  into a finite number of classes  $Cl = \{Cl_t; t \in T\}$ ,  $T = \{1..n\}$ . Each  $x \in K$  belongs to one and only one class  $Cl_t \in Cl$ . The classes from  $Cl$  are in a preference order following the increasing order of class indices, i.e. for all  $r, s \in T$ , such that  $r > s$ , the objects from  $Cl_r$  are preferred to the objects from  $Cl_s$ . Thus, the sets to be approximated are not particular classes but upward and downward unions of classes, thus:

$$Cl_t^{\leq} = \cup_{s \leq t} Cl_s, Cl_t^{\geq} = \cup_{s \geq t} Cl_s; t = 1..n$$

**Definition 1.** (*Dominance relation*) Let  $P \subseteq F$  be a subset of criteria. The dominance relation  $D_P$  associated with  $P$  is defined as follow:

$$\forall (x, y) \in K, x D_P y \Leftrightarrow f(x, g_j) \succcurlyeq f(y, g_j) \forall g_j \in P$$

With each object  $x \in K$ , are associated:

- a set of objects dominating  $x$ , called  $P$ -dominating set,  $D_P^+(x) = \{y \in K : y D_P x\}$  and;
- a set of objects dominated by  $x$ , called  $P$ -dominated set,  $D_P^-(x) = \{y \in K : x D_P y\}$ .

**Definition 2.** (*Lower approximation*) Lower approximation of unions of classes represents a certain knowledge provided by criteria  $P \subseteq F$ .

- $\underline{P}(Cl_t^{\geq}) = \{x \in K : D_P^+(x) \subseteq Cl_t^{\geq}, \forall t = 1..n\}$ : the set of all objects belonging to  $Cl_t^{\geq}$  without any ambiguity. It contains all objects whose  $P$ -dominating set is assigned with certainty to classes that are at least as good as  $Cl_t$ .
- $\underline{P}(Cl_t^{\leq}) = \{x \in K : D_P^-(x) \subseteq Cl_t^{\leq}, \forall t = 1..n\}$ : the set of all objects belonging to  $Cl_t^{\leq}$  without any ambiguity. It contains all objects whose  $P$ -dominated set is assigned with certainty to classes that are at most as good as  $Cl_t$ .

**Definition 3.** (*Boundary*) We call boundary of  $Cl_t$  the set of actions which are uncertainly classified in the decision class  $Cl_t$ . It is represented as follow:

- $Bn_p(Cl_t^{\geq}) = \bar{P}(Cl_t^{\geq}) - \underline{P}(Cl_t^{\geq})$ : set of all objects belonging to  $Cl_t^{\geq}$  with some ambiguity.
- $Bn_p(Cl_t^{\leq}) = \bar{P}(Cl_t^{\leq}) - \underline{P}(Cl_t^{\leq})$ : set of all objects belonging to  $Cl_t^{\leq}$  with some ambiguity.

**Definition 4.** (*Quality of approximation*) It is the quality of classification performed by a decision maker for a given decision class with respect to the set of criteria  $P \subseteq F$ . It is defined as the ratio between the number of  $P$ -correctly classified objects and the number of all the objects in the data sample set. It can be written as:

$$\gamma_P = \frac{|K - (\cup_{t=1...n} Bn_p(Cl_t^{\leq})) \cup (\cup_{t=1...n} Bn_p(Cl_t^{\geq}))|}{|K|}$$

**Definition 5.** (*Core*) For a given set of decision examples, it is possible to determine which criteria are relevant for the approximation of the attribution made by the decision maker agent. We call such subsets of relevant criteria, the “reducts” and we call their intersection, the “Core”. Otherwise, for each minimal subset of criteria  $P \subseteq F$  such as  $\gamma_P(Cl) = \gamma_F(Cl)$ ,  $P$  is called a reduct of  $F$ . A decision table can contain several reducts and their intersection set is the “Core”.

The DRSA method deals with the problem of the decision maker hesitation when assigning knowledge within a decision class which produces an uncertain assignment. In fact, DRSA method distinguishes between two sets of assignment: the certain assignments which represent the “Lower approximation” and the uncertain or ambiguous ones that represent the “Boundary”. Thus, knowing his boundary, a decision-maker has always the possibility of revising his uncertain assignments in order to clear his Boundary and make the right decisions.

The concepts defined by the DRSA method will be used as inputs and outputs to develop the filtering techniques of the recommendation system in order to ensure knowledge sharing between the different system’s users.

## 2.2 Recommendation System

According to [3], the recommendation system *is a software tool that has the effect of guiding users in a personalized way to interesting or useful objects in a large space of possible options*. In literature, several filtering techniques have been proposed to define a recommendation system, namely the collaborative filtering [8], the hybrid filtering [3], the knowledge-based filtering [4], etc. In our medical context, as we search the diversity and the novelty of knowledge, we have chosen the “collaborative filtering technique” [8] to take into account the opinions of all the users. We have also used the “knowledge-based filtering” [4] as a way of comparing the user query with the knowledge profile.

- *Collaborative Filtering* [8]: It is one of the earliest and most promising recommendation techniques. It provides recommendations by applying the matching principle that puts together users with similar interests. This filtering technique predicts items that can be appreciated by the current user, on the basis of opinions (ratings) expressed by other people for the same items. It defines a neighborhood for each user: it is the set of users who “liked” items that have already been appreciated by the current user. It takes as input the user’s profile and the data on the community. It -then- applies a similarity function to determine the neighborhood so as to provide a list of recommendations.

- *Knowledge-based Filtering* [4]: It applies inferences on a set of items to find a particular one that must meet a specific need of a current user. This technique takes as input the user profile and the characteristics of all items. The conversational process of knowledge based recommendation always respects the following steps: the current user starts by specifying his requirements. Then, the system compares these requirements with the characteristics of the existing items to find those that meet the current user's requirements. Finally, the system will recommend an ordered list of the resulting items.

### 2.3 Knowledge Sharing

According to [5], *knowledge sharing is both a process of transmission and of absorption (use)*. In literature, many studies have focused on the issue of knowledge sharing within organizations. Some of them proposed theoretical models that bring a conceptual framework for several knowledge sharing processes where the most popular are the SECI model [11] and the BOISOT I-space KM model [2].

**SECI Model** [11]: The SECI (Socialization, Externalization, Combination, Internalization) model focuses on the creation and the transformation of knowledge. Organizations create and use knowledge through series of conversions:

- Socialization: the transformation from a tacit knowledge related to only one person to a set of tacit knowledge related to a group of people.
- Externalization: the transformation of tacit knowledge to an explicit one among individuals within a group. It requires a structuring effort to express tacit knowledge in a comprehensive form for the others.
- Combination: the process of creating new forms of explicit knowledge from the existing one.
- Internalization: the process of understanding and absorbing explicit knowledge into tacit knowledge held by the individual.

The SECI model describes the conversion of knowledge into a dynamic mode. It is based on the transformation of the tacit knowledge into an explicit one.

**BOISOT I-Space KM Model** [2]: In Boisot's scheme, knowledge assets can be located within a dimensional space defined by three axes: from "uncodified" to "codified", from "concrete" to "abstract" and from "undiffused" to "diffused". Thus, knowledge is structured, understood and shared via three steps:

- Codification: The process of transformation of knowledge into a tangible and an explicit form (code, documents...) in order to be communicated more widely and at a low cost.
- Abstraction: Recently codified knowledge is more adapted to the context in which it is applied.
- Diffusion: New knowledge is shared with a target population in a codified and an abstract form.

Despite the importance of the knowledge sharing process, authors are limited to propose theoretical models without provide automated tools.

### 3 Recommendation System Based DRSA to Support the Organizational Knowledge Sharing

The aim of the APMDS (Association of Protection of Motors Disabled of Sfax-Tunisia) is to make an early medical management of children with cerebral palsy. It consists of *improving the monitoring and the evaluation of the early support of young children with cerebral palsy*. So, this care process is made by a succession of several actions in the form of medical and paramedical monitoring as well as of early assessment of these children. For each child, this care process takes as input a maximum of medical knowledge and generates a new set of knowledge that should be explained for other care processes. This new knowledge will be either preserved in documents or embodied in the minds of these stakeholders. However, due to the fact that stakeholders are often busy or geographically dispersed, the transmission of such knowledge is missing which prevents its reuse. Thus, our objective is to enhance the knowledge sharing process in order to prevent its loss and -so- to enrich the background of the medical staff.

In this section we present the main axes on which our recommendation system is based. First, we define a theoretical set of criteria to be used as inputs for the DRSA approach. Then, we introduce our knowledge sharing method.

#### 3.1 Knowledge Evaluation Criteria

In order to identify a meaningful set of evaluation criteria, we have conducted a literary review. In our proposed method, these criteria will be applied as inputs to the DRSA method. Seven theoretical criteria have been identified:

- $g_1$ = Accessibility [11]: Denotes the extent to which knowledge is available, or easily and quickly retrievable.
- $g_2$ = Specificity [11]: Denotes the degree to which knowledge is dependent on many different contexts of use.
- $g_3$ = Codifiability [11]: Denotes the degree to which knowledge could be articulated in documents and software.
- $g_4$ = Timeliness [15]: Denotes how far knowledge is sufficiently up-to-date. It can be related to the time when knowledge is created, stored and accessed.
- $g_5$ = Completeness [15]: Denotes the extent to which knowledge is not missing and is of sufficient breadth and depth for the task at hand.
- $g_6$ = Relevancy [15]: Denotes the extent to which knowledge is applicable.
- $g_7$ = Accuracy [14]: Denotes how correct and error-free knowledge is.

To develop our method, we should validate these criteria using the constructive approach of Belton and Pictet [1]. In fact, successive meetings with the APMDS experts, each one separately, have to be organized. Each meeting shall

be equipped with this theoretical criteria list and each expert can accept it without any modification, delete some criteria or add some others that do not exist but that he considers relevant. After each meeting this list will be updated. The meetings will be made in an iterative manner with all the decision makers (APMDSs experts) until reaching a collaborative list that satisfies all of them.

**Preferences Table:** According to DRSA [9], each knowledge  $K_i \in K$  must to be evaluated on the basis of each criterion  $g_j \in F$ . The set of all identified knowledge, all identified criteria and all evaluations has to be collected in a matrix called *Preferences table* (see Fig. 1). This table is fulfilled by a “man study” and domain experts after a thorough study on the field. It is *common* to all decision-makers supposed to use the system.

To clarify the concepts of criterion and evaluation, we cite the example of the criterion  $g_1$  that describes the knowledge accessibility level and that is already validated on our application field (APMDS). The evaluations of a knowledge  $K_i$  on the criterion  $g_1$  can have three values which are:  $V_{i,1} = 1 = \text{easy}$ ,  $2 = \text{medium}$ ,  $3 = \text{difficult}$ . Thus, the value  $f(K_1, g_1) = V_{1,1} = 1$  means that the knowledge  $K_1$  is easily accessible. To explain the concepts of tacit ( $K_1$ ) and explicit ( $K_2$ ) medical knowledge we give a reduced set of validated knowledge:

- $K_1$  = Experiential expertise on the research of abnormal movements;
- $K_2$  = Prescriptive knowledge on the assessment of intellectual level.

Based on this common preferences tables, each decision maker must build its own *decision table*.

**Decision Table:** In this work, two decision classes are identified: the class  $Cl_1$  containing knowledge classified as “not crucial” and the class  $Cl_2$  containing the one classified as “Crucial”. We note *that knowledge is classified as crucial if it is relevant and necessary to solve problems related to a given objective of the organization*. Each decision maker has to classify the set of knowledge and so to complete the column D by “1” if knowledge is not crucial and by “2” if it is (See Fig. 1). By adding the column D to the preferences table, the latter will be called a *decision table* that concerns a *specific* decision maker (see Fig. 1). Each decision maker has two possibilities to complete his column D: he can classify knowledge either on the basis of the preferences table or without considering theses evaluations but - only- according to his experience.

**DRSA Application:** In this paper we developed a Java program to run DRSA method. This program takes as input the decision table of a unique decision maker. In the preferences table, we have fixed a sample of thirty-four knowledge, called references knowledge. The “Calculate” button (see Fig. 1) displays the Boundary, the Core and the quality of approximation of the decision maker. The lower approximation of the class  $Cl_2$  is the difference between the Boundary and all knowledge classified in  $Cl_2$ . More details on these steps are available in [13]. Figure 1 shows the results of executing the DRSA method on the data related to the Decision Maker 3 (DM3). Results are as follows:

- DM3's Boundary =  $B = \{K_3, K_{10}, K_{13}, K_{14}, K_{15}, K_{20}, K_{23}, K_{24}\}; |B| = 8$ .
- Knowledge that is classified by DM3 in  $Cl_2 = K = \{K_3, K_4, K_5, K_6, K_7, K_8, K_{10}, K_{12}, K_{13}, K_{15}, K_{16}, K_{18}, K_{19}, K_{20}, K_{21}, K_{22}, K_{24}, K_{26}, K_{27}, K_{29}, K_{30}, K_{31}, K_{32}, K_{33}, K_{34}\}; |K| = 25$ .
- Lower approximation =  $LA = K - B = \{K_4, K_5, K_6, K_7, K_8, K_{12}, K_{16}, K_{18}, K_{19}, K_{21}, K_{22}, K_{26}, K_{27}, K_{29}, K_{30}, K_{31}, K_{32}, K_{33}, K_{34}\}; |LA| = 19$ .
- Approximation quality of DM3 =  $\frac{|LA|}{|K|} = 0.76$
- DM3's Core =  $\{g_1, g_2, g_3, g_4, g_6, g_7\}$ : DM3 classifies knowledge as "Crucial" because it is easily accessible ( $g_1$ ), specific ( $g_2$ ), easily codifiable ( $g_3$ ), up-to-date ( $g_4$ ), relevant ( $g_6$ ) and accurate ( $g_7$ ), without giving importance to whether it is complete or not, so ( $g_5$ ) cannot belong to his core.

### 3.2 Theoretical Method of Explicit and Tacit Knowledge Sharing

The knowledge sharing process that we define is based on a recommendation system (RS) and distinguishes between explicit and tacit knowledge. The RS plays the role of an intermediary between the knowledge transmitter and the knowledge receiver. It takes as inputs the *current decision maker (CDM) query* and the *decision tables of all the system decision makers (DMs)*. At the first use of the RS, each decision maker (DM) must register: he has to enter his personal information and -then- to complete the "column D" about all knowledge classifications. Upon the second use, the DM can use the RS only by submitting his query. This method is based on two steps: applying the collaborative filtering based on DRSA to find a *neighborhood* for the CDM and then using the knowledge based filtering to consider the CDM needs.

**Collaborative Filtering Technique Based on DRSA:** The collaborative filtering objective is to define a *collection of system DMs having the same taste as the CDM in the past*, called neighborhood. This technique takes as input the set of all decision tables to calculate a *similarity measure* that we define, in our method, using the parameters of *Lower approximation* and *Core* provided by the DRSA method. In fact, two DMs are similar if they classified the same knowledge with certainty as crucial for the same reasons: some knowledge belongs to their Lower approximation (LA) and sometimes they shared the same Core criteria. Based on this idea, our method is based on two selections:

- At the first selection, for each DM we will compute the set of intersection between his LA and that of the CDM. Then, DMs will be ordered in a decreasing way according to the size of the intersection set found.

List 1: **CDM's neighborhood based LA** =  $\{DM_1 \dots DM_n; \text{ such as } \forall i \in \{1..n\} \mid LA(DM_i) \cap LA(CDM) \geq |LA(DM_{i+1}) \cap LA(CDM)|\}$   
 where n is the number of DMs who have at least a knowledge that belongs both to their LA and to that of the CDM.



- The second selection is applied to customize the results of the first list. In fact, if two or more DMs of List 1 have the same size of the set of intersection between their LA and that of the CDM, they will be ordered according to the intersection of their Core and that of the CDM:

List 2: **CDM's neighborhood based LA & Core** =  $\{DM_1...DM_n; \text{ such as } \forall i \in \{1..n\} (|LA(DM_i) \cap LA(CDM)| \geq |LA(DM_{i+1}) \cap LA(CDM)| \vee (|LA(DM_i) \cap LA(CDM)| = |LA(DM_{i+1}) \cap LA(CDM)| \wedge |Core(DM_i) \cap Core(CDM)| \geq |Core(DM_{i+1}) \cap Core(CDM)|) \}$

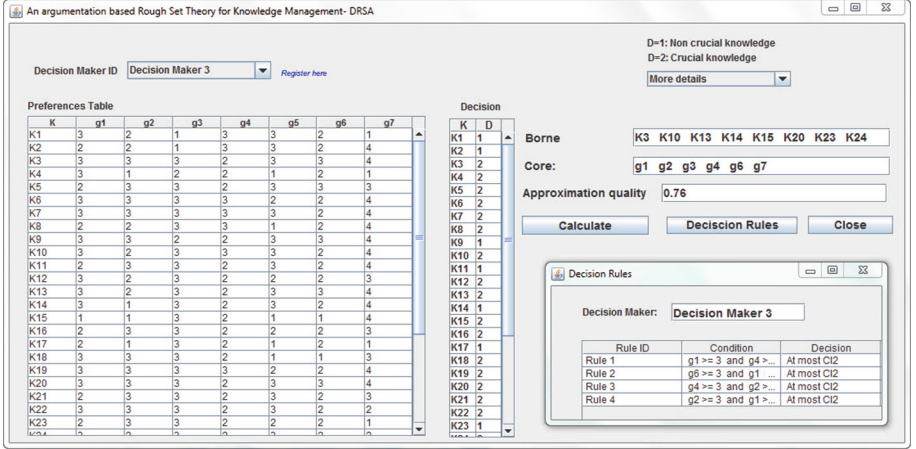


Fig. 1. Decision Table provided by a unique user

**Knowledge-Based Filtering Technique:** Once the final selective neighborhood (List 2) is determined, the RS gathers all the knowledge that is already appreciated by this neighborhood but not yet seen by the CDM. However, the set of obtained Knowledge may not entirely match the CDM needs. To do so, we apply the knowledge-based filtering to compare the CDM's query with the resulting knowledge metadata in order to recommend only those that satisfy the query. To analyze DMs' queries we have been based on the medical ontology proposed in [7].

Thus, this new recommended knowledge set can construct and enrich the knowledge background of the current user and help him make a right and a revised decision that should be -then- classified by the CDM as crucial or not.

As we already mentioned, our model treats both the explicit and the tacit knowledge. The recommendations must, thus, depend on the knowledge's nature:

- *If the recommended knowledge is explicit:* the system provides the list of obtained knowledge. Then, the user must interpret each of them and transform it into a new explicit knowledge (combination) or into a tacit knowledge (internalization).

- *If the recommended knowledge is tacit:* this knowledge is usually difficult to be articulated or shared. It is generally transferred through face-to-face interactions between persons who hold it. In this case, the recommendation system recommends to the current user the profiles of the stakeholders holding the desired knowledge. It proposes thus- a list of possible meetings according to the stakeholders' availability. If, following a meeting, the tacit knowledge remains difficult to be articulated, it is still held in the DMs' minds (Socialization). Otherwise, it will be transformed into an explicit one (Externalization).

## 4 Illustrative example

This example treats a reduced set of five DMs and thirty-four references knowledge. According to their decision tables that are given as inputs to the DRSA method, our program calculated the Lower approximation (LA) and the Core of all DMs (see Table 1). The two last columns contain -respectively- the *LA* and the *Core* intersection sets between each DM and the CDM (Celine).

**Table 1.** DRSA results for the recommendation system users

DM	LowerApproximation (LA)	Core (Co)	DM3'LA $\cap$ DM'LA	DM3'Co $\cap$ DM'Co
<b>Jean</b>	$K_1, K_4, K_6, K_7, K_8, K_{11}, K_{24}, K_{26}, K_{28}, K_{29}, K_{30}, K_{31}, K_{32}$	$g_1, g_2, g_3, g_4, g_6, g_7$	$K_4, K_6, K_7, K_8, K_{24}, K_{26}, K_{29}, K_{30}, K_{31}, K_{32}$	$g_1, g_2, g_3, g_4, g_6, g_7$
<b>Mark</b>	$K_2, K_3, K_4, K_5, K_7, K_8, K_9, K_{10}, K_{11}, K_{12}, K_{14}, K_{16}, K_{20}, K_{23}, K_{31}, K_{32}, K_{33}$	$g_1, g_2, g_4, g_5, g_7$	$K_3, K_4, K_5, K_7, K_8, K_{10}, K_{12}, K_{16}, K_{20}, K_{31}, K_{32}, K_{33}$	$g_1, g_2, g_4, g_7$
<b>Celine (DM3)</b>	$K_3, K_4, K_5, K_6, K_7, K_8, K_{10}, K_{12}, K_{13}, K_{15}, K_{16}, K_{18}, K_{19}, K_{20}, K_{21}, K_{22}, K_{24}, K_{26}, K_{27}, K_{29}, K_{30}, K_{31}, K_{32}, K_{33}, K_{34}$	$g_1, g_2, g_3, g_4, g_6, g_7$	$K_3, K_4, K_5, K_6, K_7, K_8, K_{10}, K_{12}, K_{13}, K_{15}, K_{16}, K_{18}, K_{19}, K_{20}, K_{21}, K_{22}, K_{24}, K_{26}, K_{27}, K_{29}, K_{30}, K_{31}, K_{32}, K_{33}, K_{34}$	$g_1, g_2, g_3, g_4, g_6, g_7$
<b>Abdel</b>	$K_3, K_4, K_6, K_8, K_{10}, K_{11}, K_{15}, K_{16}, K_{17}, K_{19}, K_{22}, K_{24}, K_{26}, K_{27}, K_{30}, K_{33}$	$g_2, g_3, g_4, g_5, g_6$	$K_3, K_4, K_8, K_{10}, K_{15}, K_{16}, K_{19}, K_{22}, K_{24}, K_{26}, K_{27}, K_{30}, K_{33}$	$g_2, g_3, g_4, g_6$
<b>Paul</b>	$K_1, K_2, K_5, K_6, K_8, K_9, K_{11}, K_{12}, K_{13}, K_{15}, K_{21}, K_{24}, K_{27}, K_{28}, K_{30}, K_{31}, K_{34}$	$g_1, g_2, g_4, g_6, g_7$	$K_5, K_6, K_8, K_{12}, K_{13}, K_{15}, K_{21}, K_{24}, K_{27}, K_{30}, K_{31}, K_{34}$	$g_1, g_2, g_4, g_6, g_7$

Table 2 details the first table. Its last column contains the new knowledge that has already been appreciated by the DMs. So, our RS runs as follow:

- Applying the Collaborative filtering based Lower Approximation: we get an ordered list of decision-makers according to the size of the intersection set of their lower approximations and that of the current decision-maker. So:

The first selection = List 1 =  $\{Abdel, Mark, Paul, Jean\}$ ;

- Applying the Collaborative filtering based Core: The first ordered list (List 1) must be ordered according to the size of the intersection set of the decision makers' Core and that of the current decision-maker. So:

The second selection = List 2 =  $\{Abdel, Paul, Mark, Jean\}$ ;

- Generating the knowledge list that have been appreciated by the decision-makers in List 2 respecting their order:

List 3 =  $\{K_{43}, K_{46}, K_{52}, K_{46}, K_{47}, K_{51}, K_{43}, K_{48}, K_{50}, K_{46}\}$ ;

- Removing redundancy in List 3:

List 4 =  $\{K_{43}, K_{46}, K_{52}, K_{47}, K_{51}, K_{48}, K_{50}\}$ ;

- Using Knowledge-based Filtering: This step is based on the matching between the knowledge metadata and the current DM query. If we suppose that the metadata available on knowledge are  $\langle \text{Knowledge holder, Knowledge domain, Knowledge user} \rangle$ . So, descriptions that we have on the List 4's knowledge are:
  - $K_{43} = \langle \text{Dr Elene, Pediatrics Neurology, Child} \rangle$
  - $K_{46} = \langle \text{Pr Layla, Physical therapy, Both} \rangle$
  - $K_{52} = \langle \text{Dr Marylene, Speech therapy, Both} \rangle$
  - $K_{47} = \langle \text{Dr Agnes, Neurology, Adult} \rangle$
  - $K_{51} = \langle \text{Pr Florence, Pediatrics Neurology, Child} \rangle$
  - $K_{48} = \langle \text{Pr Pierre, Speech therapy, Adult} \rangle$
  - $K_{50} = \langle \text{Dr Mathieu, Pediatrics Neurology, Child} \rangle$

**Table 2.** A summary for decision-makers results compared to those of (DM3)

Decision maker (DM)	$ DM3'LA \cap DM'LA $	$ DM3'Co \cap DM'Co $	Knowledge appreciated by DM
Jean	10	6	$K_{46}$
Mark	12	4	$K_{43}, K_{48}, K_{50}$
Abdel	13	4	$K_{43}, K_{46}, K_{52}$
Paul	12	5	$K_{46}, K_{47}, K_{51}$

We suppose, now, that the query submitted by Celine (DM3) is as follow: ***How to examine the cranial nerves of a child?***. Thus, if we consider the medical ontology proposed by [7], we find that the “cranial nerves exam” is a process in the pediatric Neurology domain that concerns children. Therefore, our system should recommend to Celine only the ordered list of knowledge whose “domain” is that of Pediatrics Neurology and whose “user” is the child.

**Final recommended List** =  $\{K_{43}, K_{51}, K_{50}\}$

Finally, the current user (Celine) has to evaluate the three recommended knowledge. She has just to say if any one was “Crucial” or “not crucial”.

## 5 Conclusion

In this paper, we have proposed a theoretical method of organizational knowledge sharing based on a recommendation system that relies on a multicriteria decision aid method to improve the explicit and tacit knowledge sharing processes. We relied on the collaborative filtering based-DRSA to identify the current decision maker's neighborhood, and the knowledge-based filtering to match the current decision maker's query with the knowledge profile. In order to implement the DRSA method, we proposed a set of evaluation criteria. Our goal is to improve the knowledge sharing among the medical staff to help them consolidate their decisions in complex clinical circumstances. Our future work will be, thus, to validate our method on a medical field that is of the APMDS. We will, first, involve the experts of this association in order to validate the evaluation criteria. Then, we will exploit the mobile learning methods and the Web 2.0 technology such as the social networks or the forums to organize meetings between the system users and to enhance the tacit knowledge transfer. Finally, we will have to implement our automated recommendation system for knowledge sharing.

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