J Inf Process Syst, Vol.13, No.6, pp.1496~1515, December 2017
https://doi.org/10.3745/JIPS.04.0050

ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

Combining Multi-Criteria Analysis with CBR for Medical Decision Support

Mansoul Abdelhak*,** and Atmani Baghdad***

Abstract
One of the most visible developments in Decision Support Systems (DSS) was the emergence of rule-based expert systems. Hence, despite their success in many sectors, developers of Medical Rule-Based Systems have met several critical problems. Firstly, the rules are related to a clearly stated subject. Secondly, a rule-based system can only learn by updating of its rule-base, since it requires explicit knowledge of the used domain. Solutions to these problems have been sought through improved techniques and tools, improved development paradigms, knowledge modeling languages and ontology, as well as advanced reasoning techniques such as case-based reasoning (CBR) which is well suited to provide decision support in the healthcare setting. However, using CBR reveals some drawbacks, mainly in its interrelated tasks: the retrieval and the adaptation. For the retrieval task, a major drawback raises when several similar cases are found and consequently several solutions. Hence, a choice for the best solution must be done. To overcome these limitations, numerous useful works related to the retrieval task were conducted with simple and convenient procedures or by combining CBR with other techniques. Through this paper, we provide a combining approach using the multi-criteria analysis (MCA) to help, the traditional retrieval task of CBR, in choosing the best solution. Afterwards, we integrate this approach in a decision model to support medical decision. We present, also, some preliminary results and suggestions to extend our approach.

Keywords
Case-Based Reasoning (CBR), Decision Support, Medical Diagnosis, Multi-Criteria Analysis (MCA), Multimodal Reasoning

1. Introduction

In recent years, the rule-based approach has been widely used for the development of decision aid systems in health science. Rule-based systems attempt to make a reasoning that leads to a disease identifying and/or propose a therapy. They appeared mostly in medicine and in various specialties. Only, recommended computer solutions (expert system) perform relatively well in many real applications and have some drawbacks. With a rule-based system, it's easy to express faithful and accurate knowledge with a fairly limited number of rules and when it involves using several features, the number of rules needed to find all possible combinations becomes very large and sometimes grows exponentially.

Manuscript received July 7, 2015; first revision November 8, 2016; second revision December 21, 2016; accepted March 4, 2017.
Corresponding Author: Mansoul Abdelhak (mansoul21@gmail.com)
* Dept. of Computer Science, University of Skikda, Algeria (mansoul21@gmail.com)
** LIO Laboratory, University of Oran 1 Ahmed Ben Bella, Algeria (mansoul21@gmail.com)
*** Dept. of Science, University of Oran 1 Ahmed Ben Bella, Algeria (atmani.baghdad@gmail.com)

Moreover, in medical decision support, it seems very awkward to express this knowledge (rules) mostly for decisive features, since a simple pathology involves more features to describe it. Moreover, the number of rules becomes so great for the expert who must supply the system with rules, and the task becomes so hard and difficult to translate medical knowledge or simple decisions into rules. Also, a system monitored by a rule-base established for solving particular problems, is generally not able to provide anything other than the consequents of the rules. So, a rule-based system cannot learn: its evolution can only be accomplished through an updating and reorganizing of its rules by an expert. Later, case-based reasoning (CBR) approach came out. It was appropriate in medical situations and widely applied to solve problems and support health care decision. However, it also presents some drawbacks in its two main tasks: the retrieval and the adaptation (reuse and revision) [1,2].

For the retrieval task, another major drawback emerges when the process finds several similar cases and consequently several solutions. Hence, a choice is required and involves looking for a strategy to choose the best solution. Thus, and as the two tasks are well-connected, several works have been conducted on the retrieval task using different strategies which deal with appropriate solutions aiming to impact positively the adaptation. These solutions have been widely studied in the literature. Firstly, by using simple methods as sequential calculation and non-sequential indexing, then by testing classification algorithms such as ID3 and Nearest Neighbor matching to experiment their performances. Clustering cases into prototypes was also used to avoid processing a huge cases' volume, but missing similar cases can occur and may lead to less strong decision due a large number of features. Combination of matching algorithms was also tried to help the retrieving to improve the CBR subtasks instead of using older techniques. In view of all that we have just underlined, it becomes imperative to review traditional processing's approaches, to propose new solutions based on new paradigms. Furthermore, nowadays it's well recognized that the therapy's decision related to each patient must take into account several criteria (drug risk, medication side effects, dosages, etc.). Moreover, the physician reasons when searching for a therapy as a system using old situations (cases) in order to propose a similar or a best therapy. These elements have been considered to develop new strategies by improving algorithms related to the main operations of CBR (retrieval, adaptation) or combining CBR with other techniques dealing with decisions such as multi-criteria analysis (MCA) or knowledge-based reasoning. This review sheds light on the new trends and new techniques that are capable of leading the research in this area in the next years [3-6].

In this paper, we are exploring a new approach using cooperation between CBR and MCA to propose an available strategy at retrieval task which permit choosing the best solution from a set of solutions found by CBR. The main contribution is to tackle the drawbacks related to several similar cases and consequently several solutions. The solution choice is thus improved by an MCA process. We use a model based on cases, and instead of having several solutions proposed by the retrieval task, we improve the decision model with a MCA which chooses the best solution. Our objective is twofold: on the one hand, we have the easiness of a case-base's construction unlike an ordinary rule-base. On the other hand, we use the CBR-MCA combination to choose the best solution. Our main purpose is to provide an approach that can be achievable and operational, which may contribute to solve a medical situation within a given context, by a decision support. This medical situation is referred as 'problematic α' in decision aid theory [7].

The remainder of this paper is organized as follows: in Section 2, we give a survey of most important related works highlighting the use of case-based reasoning and multi-criteria analysis that have contributed to its evolution. In Section 3, we describe details regarding our approach. In Section 4, we present a descriptive framework which will be used for decision aid. In Section 5, we describe our experimentation and some preliminary results. In Section 6, we present a conclusion which summarizes the paper and point out some suggestions to extend our approach.

2. Related Works

CBR has attracted considerable research interest to support the decision. It was widely used in medical decision support systems [8]. Many researchers conducted a lot of studies to improve the retrieval task while others addressed other aspects of its use. Others have proposed also combining CBR with other techniques. Recently, a major trend seems to be the extending of CBR applications beyond the selection and recommendation of treatment towards the applicability of CBR to new reasoning tasks [1]. So, CBR becomes an attractive topic among the development of medical decision support systems. We highlight the following concerns.

2.1 Use of Case-Based Reasoning

Many studies concerning the CBR use in medical decision support were conducted. Marling et al. [9] presented an approach for the treatment of patients suffering from diabetes. Jha et al. [10] presented a study for diabetes detection and care. Song et al. [11] proposed a system for dose planning in radiotherapy for prostate cancer. De Paz et al. [12] presented a decision support system for the diagnosis of different types of cancer. Schwartz et al. [13] used also CBR to enhance care on insulin therapy. This is not an exhaustive list but it shows the diversity of the CBR use and underlines the interest in this approach to improve the patient care, by providing physicians with data processing tools for medical decision support.

2.2 Use of Multi-Criteria Analysis

With the redefinition of decision support that no longer considers the decision problem as an economic function to optimize, new concepts emerged, such as criterion, MCA and "problematics" as defined by Roy [7]. The multi-criteria aspect becomes a new development axis in medical decision support, particularly by the works of Belacel [14] who proposed a methodology using multi-criteria in medical diagnosis support. Belacel [14] used firstly a classification method which is based partly on fuzzy preference modeling and secondly a multi-criteria decision support. Shanbezadeh et al. [15] presented another interesting work in medicine. They used a modeling technique based on multi-criteria for quality evaluation of the asthma level. Van Valkenhoef et al. [16] proposed a new approach to build a multi-criteria support model that considers the evidence on the efficiency and unfavorable drug reactions. Erjaee et al. [17] proposed a specific method based on multi-criteria for an efficient decision of treatment for helicobacter pylori infection among children. Bouhana et al. [18] integrated CBR and the "AHP" multi-criteria method for itinerary search.

2.3 Use of Rule-Based Reasoning

The rule-based reasoning (RBR) has been used successfully in developing many rule-based systems. These systems use a rule-base, an inference engine and different interfaces which enable communication with its environment. These systems must make a reasoning that leads to a diagnostic strategy and/or proposed therapy. So, many systems appeared in many medical specialties. We mention below some of them:

De Dombal's system: it's an early rule-based decision system. It was developed for supporting the acute abdominal pain's diagnosis, based on analysis of the need for surgery [19]. INTERNIST I: it's a rule-based expert system designed for the diagnosis of complex problems in general internal medicine. It uses patient observations to deduce a list of compatible disease states [19]. MYCIN is one of the first expert systems made in the infectious diseases field. It's used for the identification of microorganisms that cause infections. It offers also a helpful medical aid by advising the physician on the choice of a suitable antibiotic for the treatment of a patient presenting a bacterial infection [19]. Another system EMYCIN (Essential MYCIN) developed in 1980 uses MYCIN's control structures. It's a domain independent framework and was used to build rule-based expert systems for diagnosis [19].

2.4 Use of Multimodal Reasoning

Multimodal reasoning is another way used to avoid the adaptation problem, mainly by combining the retrieval task with other reasoning strategies to provide decision support. The interest in multimodal approaches involving CBR has reached the medical areas. This is an issue of current concern in CBR research [20].

The first multimodal reasoning system in health care was CASEY. It integrated CBR with model-based reasoning (MBR) for heart failure diagnosis [21]. Li and Sun [22] combined MCA and CBR to improve a data mining process for diseases detection. Armaghan and Renaud [5] used also the combination CBR-MCA to study diabetes. Royes [23] used multi-criteria and CBR for strategic planning support. Araujo de Castro et al. [24] used a model based on MCA and CBR for diagnosis of Alzheimer's disease. Schmidt et al. [25] suggested clustering cases into prototypes and remove unnecessary ones to avoid an infinite growth of a case-base. The retrieval is only applied among these prototypes to simplify the adaptation task. Begum et al. [26] suggested a solution for the retrieval task using a three matching algorithms by combining different measures with fuzzy similarity. They also proposed another solution by using a reusability measure in addition to a constraints' check, and a scoring. This method gives the easiest case to the adaptation task. It was also used to propose a menu planer system based on CBR and RBR. Kumar et al. [19] used two distances (Weighted Euclidean, Mahalanobis) to perform a retrieval task and eliminate bad cases with an eliminating score. Bichindaritz and Marling [1] have used a combination of RBR and a model-based components. This strategy can't be seen as a solution for CBR drawbacks, but as an opportunity to improve CBR subtasks instead of using an older technique. Verma et al. [27] used integration of RBR and CBR to build a system to support decision making. A model was tested on real data in auto industry.

2.5 Use of Other Information Retrieval Techniques

Information retrieval is an important operation. It plays a key role in CBR and other reasoning methods. Recently, several techniques have been used in different fields such as medicine, image processing, linguistics, etc. These methods were implemented for improving the retrieval of information. We highlight the following developments:

Agarwal and Bedi [28] used a combined technique based on fusion of images to get more information and additional data that help in medical diagnosis. They apply this technique to medical images as another manner of retrieving information that helps to decision aid. Prabusankarlal et al. [29] used a combination of textural and morphological features for the detection and breast masses' diagnosis in ultrasound images. They used an SVM classifier to discriminate the tumors into benign or malignant. Vijayarajan et al. [30] used a combination of a domain ontology and semantics to improve information retrieval. A document and an image retrieval system were built to test the proposed technique. Moghadam and Keyvanpour [31] used stemming in information retrieval. In linguistics, stemming is the operation of reducing words to a more general form called the "stem". So, stemmers increase the speed of information retrieval and improve a retrieval operation of words. Kumar et al. [32] modified the Euclidean distance computed between the extracted orientation features of the sample and query images. They used this modification for a fingerprint matching system. Szelag et al. [33] considered the Dominance-based Rough Set Approach (DRSA) that is able to handle a monotonic relationship between objects, and a marginal similarity concerning single features. Thereafter, the marginal similarities are aggregated within induced decision rules. Malekpoor et al. [34] used a novel TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and CBR approach to capture the past experience and oncologists' expertise. Thereafter, inferred cases are evaluated using TOPSIS and a multi-criteria decision-making approach to prescribe an optimal dose plan for prostate cancer. Bouhana et al. [35] presented a novel information retrieval approach for personalized itinerary search in urban freight transport. The proposed approach is based on the integration of three techniques: CBR, choquet integral and ontology. Qi et al. [36] developed a new hybrid weighted mean method (HWM) for the CBR adaptation of similar cases. They used implicit knowledge hidden in similar case data to improve the performance of the classical weighted mean method (WM) by multiple similarity analysis (MSA), grey relation analysis (GRA) and inductive adaptability analysis (IAA). This method was implemented in mechanical design. Noori [37] used feature weighting for case retrieval and mixed it to a fuzzy AHP method to prioritize weighting methods. Wang et al. [38] used a hybrid similarity measure and a synthesis weight measure for retrieving cases. They applied this method in a computer numerical control turret to help designers achieving the goal of rapid design. Uddin et al. [39] presented a texture feature extraction technique. The extracted texture features of fault signals are used as inputs to a multi-class support vector machine (MCSVM) to classify each fault. This technique was used for fault induction motors' diagnosis.

3. The Proposed Approach

Our approach is based mainly on some concepts that we will explain first. Some of these concepts are given in a syntactic form aiming to meet the decision model's requirements, which is based on CBR and MCA.

(1) **The medical situation.** We are in a situation where the decision maker (physician) is in front of a diagnosis of a situation and will have to explore possible options (therapies) to choose the best

one. The medical situation that we advocate is characterized by: a more or less completely defined problem, an exhaustive survey of possible therapies and the existence of individual preferences for each therapy. The physician defines a pathological situation with two sets of clinical and paraclinical symptoms. The medical situation becomes a medical case composed of *m* descriptors having discrete or continuous values which are descriptive of the case and *p* descriptors giving the "diagnosis-therapy" considered. So, a medical case is a description with, a set of clinical symptoms such as blood, fever, weight loss, abdominal pain, etc., a set of paraclinical symptoms such as age, marital status, etc., and a description of possible therapies (solutions) which is a set of actions that are considered for the case being solved. The structure of the medical situation is defined as follows:

Medical situation= {Clinical symptoms, Paraclinical symptoms, Proposed Therapies}.

(2) **The medical case.** This medical situation will be assimilated to a medical case as follows:

[Medical_case]
[Clinical_symptom]
[C_symptom$_1$=C_value$_1$, …., C_ symptom$_u$=C_value$_u$]
[End_clinical_ symptom]
[Paraclinical_ symptom]
[P_symptom$_1$=P_value$_1$, ... ,P_symptom$_v$ =P_value$_v$]
[End_paraclinical_ symptom]
[Therapies]
[Therapy$_1$, …., Therapy$_w$]
[End_therapies]
[End_medical_case].

(3) **The multi-criteria problem.** It's the reviewing of possible therapies to solve the problem, the different criteria that are all determinants and the relevant weightings. Hence, our multi-criteria problem is defined as follows:

Multi-Criteria_Problem = MCP (T_p, C_k, W_t)
T= therapies=[therapy$_1$,therapy$_2$, ….., therapy$_p$]
C= criteria=[
[c_1, appreciation$_{11}$, appreciation$_{12}$, … , appreciation$_{1x}$]
…
[c_k, appreciation$_{k1}$, appreciation$_{k2}$, …, appreciation$_{kz}$]]
W= weighting therapies=[
[w_1, evaluation$_{11}$,evaluation$_{12}$,..,evaluation$_{1f}$]
...
[w_t, evaluation$_{t1}$,evaluation$_{t2}$,..,evaluation$_{th}$]].

(4) **The clinical reasoning process.** The clinical reasoning was resumed according to Pelaccia et al. [40] and Kassirer [41] as follows: "The clinical reasoning process is analytical (hypothetico-deductive models), non-analytical (recognition of similarity to a case already seen) or a combination of both. The analytical model is seen as a sequence of steps which contains, firstly, the generation of diagnostic's hypotheses, then the search for clinical information to confirm or invalidate the hypotheses. The clinical information collected can deduce new assumptions by itself. This process is performed until confirmation or elimination of the diagnosis. A non-analytical model is also seen as the recognition of a clinical situation stored in memory, which

matches up to clinical experience. This clinical experience contributes to generate hypotheses, but this interaction is not always positive, the recall of a clinical situation may sometimes disrupt an objective but can also complete analysis of the observed signs". We are based on a non-analytical model to study the physician when facing a pathological situation. In order to solve the situation, the physician often uses his proficiency and his memory to look for almost the same situations already seen. So, the reasoning process depends on the diagnosis of the current situation, his proficiency and the situations already faced. Thus, clinical reasoning involves different elements as referred to in Fig. 1, which are all determinants in the resolution of the clinical situation.

We are based on these two postulates (non-analytical model and case-based reasoning) to propose a decision support model. The following model (Fig. 2) shows the attainment of the best therapy.

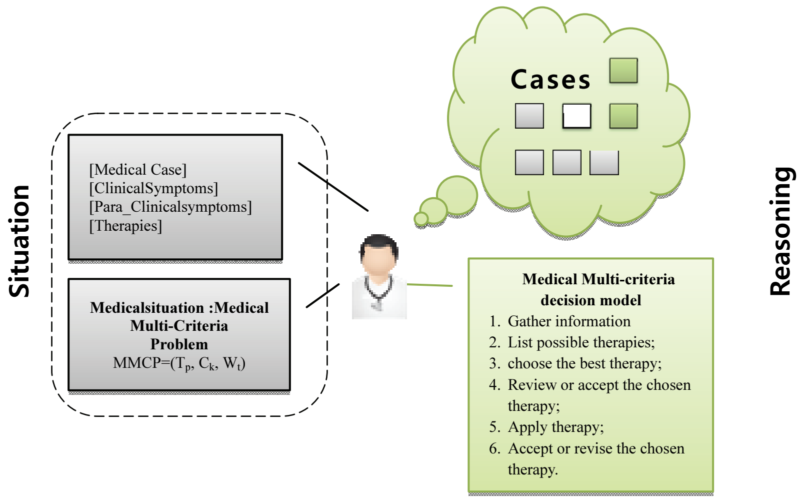

Fig. 1. Overview of the different elements involved by the physician reasoning.

(5) **The combination between CBR and MCA.** The use of CBR is very interesting in the medical domain, because the kernel of the reasoning process shows a strong similarity with the physician reasoning. In fact, the physician often tries to make the link between the case under diagnosis and cases already experienced in his practice and he follows the non-analytical model. Moreover, the physician is often helped by the medical knowledge he stores in his mind. This knowledge often refers to many domains: medical information, drug dosage, drug side effects, etc.

(6) **The proposed decision aid model.** The model we follow, stems from the situation described below: a more or less completely defined problem, a wide survey of possible actions (therapies) and the existence of individual preferences for each action. So, our approach is based on a typical situation and follows the non-analytical model of the clinical reasoning which is theoretically based on these hypotheses:

a) The physician has all the necessary information about the situation.
b) The physician knows the relevant criteria and all therapies with the consequences of each one, these criteria and therapies are weighted according to their importance.

c) The criteria listed are stable with weightings and don't change in time.
d) The physician chooses the therapy, which guarantees the most acceptable results.

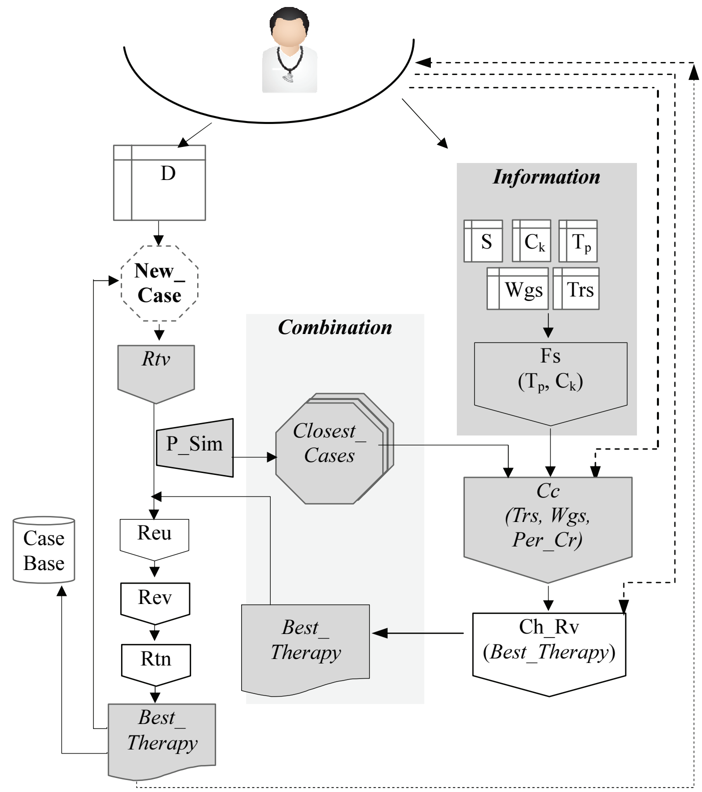

Fig. 2. Overview of the proposed decision model.

D: Diagnosis
P_Sim: Perform Similarity
Rtv: Retrieve similar cases
Reu: Reuse a suggested solution
Rev: Revise or adapt the solution
Rtn: Retain the new solution
S: Subject
C_k: *k* Criterion
Wgs: Weights
T_p: *p* Therapies
Trs: Thresholds
Fs (T_p, C_k):Formulation_of_subject (*p* Therapy , *k* Criteria)
Cc (Trs, Wgs, Per_Cr): Conception (Thresholds, Weights, Performance_Criteria)
Ch_Rv(Best_ Therapy): Choice_Revise(Best_Therapy)

So, to search for a solution (therapy), we must follow a convenient decision scheme that can be easily assimilated to a medical multi-criteria decision model as follows:

1. Gather information about the medical situation.
2. Consider a list of possible therapies.
3. Evaluate and choose the best therapy.
4. Revise (if possible) or accept the chosen therapy.

This model will be handled by a multi-criteria analysis as shown in Fig. 2.

4. Architecture and Implementation of the Framework

4.1 The Considered Medical Domain: Contraceptive Method Choice

We have previously considered working on family planning to guide the system's setup and allow clearly defining our application domain, and performing well the information step of the proposed decision model. Family planning is conducted by different contraception methods [42,43], including:

- Long-acting reversible contraception, such as an implant, or an intra-uterine device.
- Hormonal contraception, such as contraceptive pills.
- Barriers methods, such as condoms and diaphragms.
- Fertility awareness.
- Emergency contraception.
- Permanent contraception, such as vasectomy and tubal ligation.

4.2 The System Architecture

We propose an interactive medical decision support system, defined as a complete process which includes a set of relevant elements and routines in order to ensure the main functions and help making appropriate decisions. A description of the model is illustrated in Fig. 3 which shows schematically a system that integrates all the processes from the information acquisition about the decision subject till the final decision.

(a) Definition of the Medical Situation

It's the understanding and perception of the situation (diagnosis). The physician marks out the situation context, defines the decision objectives (goals), identifies the decision actor(s) and proposes therapies T_p that are considered for the present medical situation. Afterwards, he notes criteria C_k and their relevant weightings W_t (of therapies). In fact, this procedure is common to the two axes of the decision process: CBR and MCA. This procedure includes defining the new case for CBR and defining also the medical multi-criteria problem. So, the physician defines his medical situation with clinical (C_s) and paraclinical (P_s) symptoms. Then, he proposes possible therapies (Pr_Trs) that are considered for the present patient and which are based on several criteria that are all determinant. At this step of the definition of the medical situation, the C_s and P_s symptoms contribute to build the new case **NC** (C_s, P_s, Ø) with an empty set of therapies. Considering our medical context (contraception method choice) a medical case will be created. It will have the following structure:

[Medical_case]
[Clinical_symptom]
[End_Clinical_ symptom]
[Paraclinical_ symptom]
[Wife's age=$value_1$]
[Wife's education=$value_2$]
[Husband's education=$value_3$]
[Number of children ever born=$value_4$]
[Wife's religion=$value_5$]
[Wife's now working?=$value_6$]

[Husband's occupation=value$_7$]
[Standard-of-living index=value$_8$]
[Media exposure =value$_9$]
[End_Paraclinical_ symptom]
[Therapies]
[]
[End_Therapies]
[End_medical_case]

The part two of this procedure contains in part, the beginning of the MCA Process (Step A), which is the Multi-criteria Information (MCI). It leads to the definition of the Medical Multi-Criteria Problem (MMCP): MMCP (T_p,C_k,W_t), where T_p=Therapies, C_k=Criteria,W_t=Weightings (of therapies).

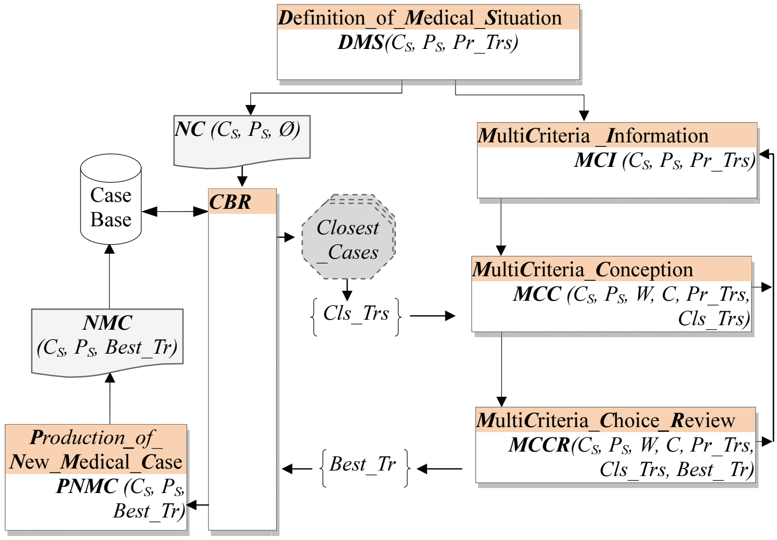

Fig. 3. Combination between CBR and MCA.

NC (C_S, P_S, Ø): New_Case (Clinical symptoms, Paraclinical symptoms, Therapies= {Ø})
DMS(C_S, P_S, Pr_Trs): Definition_of_Medical_Situation(Clinical symptoms, Paraclinical symptoms, Proposed Therapies)
MCI(C_S, P_S, Pr_Trs): MultiCriteria _Information (Clinical symptoms, Paraclinical symptoms, Proposed Therapies)
MCC(C_S, P_S, W, C, Pr_Trs, Cls_Trs): MultiCriteria_Conception(Clinical symptoms, Paraclinical symptoms, Weightings, Criteria, Proposed Therapies, Closest Therapies)
MCCR(C_S, P_S, W, C, Pr_Trs, Cls_Trs, Best_Tr): MultiCriteria_Choice_Review(Clinical symptoms, Paraclinical symptoms, Weightings, Criteria, Proposed Therapies, Closest Therapies, Best_Therapy)
PNMC(C_S, P_S,Best_Tr): Production_of_New_Medical_Case(Clinical symptoms, Paraclinical symptoms, Best_Therapy)
NMC(C_S, P_S, Best_Tr): New_Medical_Case (Clinical symptoms, Paraclinical symptoms, Best_Therapy)

(b) CBR Process

This process has a main task: the matching. It's the search for the *n* closest cases of the proposed case by using a similarity measure. We used the *k-nn* method for the simpleness of its implementation. The process will select closest or similar cases from the case-base, and will extract the initial closest therapies (Cls_Trs) that have been considered for the *n* similar cases. These initial closest therapies are sent to MCA process to filter out the best therapy (Best_tr). At this step, the physician:

- assigns the value k for k-nn method;
- launches the CBR process which will be handled by the following pseudo algorithm.

Pseudo algorithm: CBR_Process

```
1:  Input:Cls_Trs ← Ø
2:  NC (Cs, Ps, Ø)
3:  Initialize k
4:  Retrieve(NC, Closest_Cases) using k-nn
5:  If  Closest_Cases≠Ø then
    For each  Current_Case  in Closest_Cases
    For  i=1 to n
        {Cls_Trs←Cls_Trs∪Current_Case (Case, therapyi)}
    Endfor
    Endfor
      Else
        Cls_Trs← Ø
    EndIf
6:  Call MCA_Process(Cls_Trs)
7:  Reuse(Best_ Tr)
8:  Revise(Best_Tr)
9:  Retain(Best_Tr, result)
10: If result = "yes" then
        NMC(Cs, Ps, Best_Tr)= PNMC (Cs, Ps,  Best_Tr)
      Else
        NMC(Ø, Ø, Ø)
      Endif
11: Output: NMC(Cs, Ps, Best_Tr)
```

Cls_Trs: Closest Therapies PNMC: Production_of_New_Medical_Case
NMC: New_Medical_Case NC: New_Case

(c) Multi-Criteria Process

A set of closest therapies (Cls_Trs) is received from the CBR process to join it to the physician's proposed therapies (Pr_Trs). The physician has already proposed them, when defining the medical situation as described below (4.2.a). In fact, the multi-criteria process has already begun with the definition of the medical situation (Step A) and it continues processing, that is why we continue its explanation from Step B. This process will be handled as follows:

Step A: Multi-Criteria Information

This step was already launched by the physician (4.2.a). He has only to proceed successively step B and C.

Step B: Multi-Criteria Conception

At this step, the physician:

- Identifies and proposes all possible and appropriate therapies (Pr_Trs).
- Identifies the criteria for therapies' evaluation.
- Assigns the criteria weightings.
- Assigns the thresholds.
- Evaluates therapies according to criteria.

Once, the medical multi-criteria problem defined, the physician will decide the convenient multi-criteria method to use. So, Electre I is applied. It allows solving multi-criteria "problematic α", known as "choice problematic", by identifying the subset (as small as possible) of actions offering the best possible aggregation [7,44], i.e., the best solution [44,45]. This step begins by the following pseudo algorithm which will propose the best therapy (Best_Tr).

Pseudo algorithm: MCA_Process

```
1: Input: Cls_Trs, Pr_Trs
2: Cls_Trs ← Cls_Trs∪{Pr_Trs}
3: Defines Therapies, Criteria
   Assigns criterias' weightings
   Assigns Thresholds
   Construction of Evaluation_Matrix
4: Electre-I (Cls_Trs, Performance_Table)
5: Best_Tr ← Choice()
6: Accept_or_refuse(Best_Tr)
7: If accept = "yes"  then
       Transmit Best_Tr to CBR_Process
   Else
       Review any step: 3 or 4 or 5
   Endif
8: Return to CBR_Process
```

Step C. Multi-criteria Choice/Review.

The system selects the possible therapies and propose them to the physician. Then, the physician conduct an assesssement according to his degree of satisfaction and he will decide whether to take into account what it has been proposed and validate the solution which will be considered for the new case. For the revision operation, it will be assimilated to the task "revise or adapt the solution" of the CBR process because it don't need any factual data but simply physician evaluation. So, the physician may review the situation if he considers that the proposed therapy doesn't satisfy him by allowing coming back to a previous step A or B of MCA process to any reformulation that he considers necessary to well define his problem or revise his case.

5. Experimentation

Experiments are conducted on an interactive system developed with Java and have an interconnection module to JCOLIBRI framework [46]. It's based upon the model described by the diagram presented in Fig. 2. We use JCOLIBRI to build the case-base and all the relative operations of the CBR engine. Then, the MCA continue processing to make decision support that will be returned to the CBR engine to improve the decision support and conclude the process. The final objective of the whole process is to target the best therapy decision, associated to each new case given as input.

5.1 Family Planning and Preventing Pregnancy Related Health Risks in Women

"Family planning allows individuals and couples to anticipate and attain their desired number of children and the spacing and timing of their births. It's achieved through use of contraceptive methods and the treatment of involuntary infertility. A woman's ability to space and limit her pregnancies has a direct impact on her health and well-being as well as on the outcome of each pregnancy, etc. Family planning can avoid risk of health problems and death from early childbearing, etc. It's well recognized that women who have more than four children are at increased risk of maternal mortality, etc." [42]. "Family planning can reduce the risk of unintended pregnancies among women living with HIV which causes fewer infected babies and fewer infant deaths" [47]. In order to improve the health and human reproduction that several research works are conducted, including developing decision support plans for birth planning [48,49], others are designed to evaluate whether computerized clinical decision support can increase primary care providers' (PCPs') provision of family planning [43]. A study tends to show that couples who space their births 3 to 5 years apart increase their children's chances of survival, and mothers are more likely to survive, too, according to new research [50]. More studies tend to show that spacing of pregnancies through family planning can improve health of women and children [51]. Other studies are trying to find a possible link between contraception and the kinds of deaths [43].

5.2 Data Description

We project to use Contraceptive Method Choice Data which is a subset of the 1987 National Indonesia Contraceptive Prevalence Survey [52]. The samples are married women who were either not pregnant or do not know if they were at the time of interview. This data contains information about current contraceptive method choice of a woman (No-use method, Long-term method or Short-term method) based on her demographic and socio-economic characteristics. Fig. 4 gives an overview of the data set sample.

38,1,3,2,1,0,3,3,1,1
37,2,3,7,1,1,3,4,0,2
22,4,4,1,1,1,1,2,0,2
34,3,4,4,1,1,1,3,0,3
40,4,4,4,1,1,1,4,0,3

Fig. 4. Overview of the Contraceptive Method Choice Data Set sample [52].

Each married woman is described by a set of ten descriptors, the last of which, containing the used contraception method. The Contraceptive Method Choice Data Set sample is described by [52]:

1. Wife's age	(numerical)	
2. Wife's education	(categorical)	1=low, 2, 3, 4=high
3. Husband's education	(categorical)	1=low, 2, 3, 4=high
4. Number of children ever born	(numerical)	
5. Wife's religion	(binary)	0=Non-Islam, 1=Islam
6. Wife's now working?	(binary)	0=Yes, 1=No
7. Husband's occupation	(categorical)	1, 2, 3, 4
8. Standard-of-living index	(categorical)	1=low, 2, 3, 4=high
9. Media exposure	(binary)	0=Good, 1=Not good
10. Contraceptive method used	(class)	1="No-use method" 2="Long-term method" 3="Short-term method"

5.3 Construction of the Case-Base Ω_N and Partial Case-Bases

For the purposes of our experimentation, we transformed the Contraceptive Method Choice Data Set sample into a case-base named Ω_N. It contains *n* cases ω_i, $\Omega=\{\omega_1, \omega_2, \ldots, \omega_n\}$ where each case is made up of the set $X_1, X_2, ,..,X_9$, called descriptive attributes. Then, we associate a target attribute Y corresponding to the contraceptive method used, which has values in the set Y= {1, 2, 3}, where 1="No-use method", 2="Long-term method" and 3="Short-term method".

Table 1 shows the case-base attributes and Table 2 shows some cases of the Contraceptive Method Choice Case-Base, labeled ω_i.

After construction of the case-base Ω_N, there is a splitting, on used contraceptive method, into a learning case-base Ω_A (60% of Ω_N) and a testing case-base Ω_T (40% of Ω_N). Table 3 shows the partial case-bases.

Table 1. Case-base attributes

	Label
X_1	Wife's age
X_2	Wife's education
X_3	Husband's education
X_4	Number of children ever born
X_5	Wife's religion
X_6	Wife's now working
X_7	Husband's occupation
X_8	Standard-of-living index
X_9	Media exposure
Y	Contraceptive method used

Table 2. Ω_N

ω	$X_1(\omega)$	$X_2(\omega)$	$X_3(\omega)$	$X_4(\omega)$	$X_5(\omega)$	$X_6(\omega)$	$X_7(\omega)$	$X_8(\omega)$	$X_9(\omega)$	Y (ω)
ω_1	38	1	3	2	1	0	3	3	1	1
…										
ω_4	37	2	3	7	1	1	3	4	0	2
…										
ω_9	26	2	4	3	1	1	3	4	0	3
….										

Table 3. Partial case-bases Ω_A, Ω_T, Ω_0, Ω_1, Ω_2

Case-base Ω_N	Ω_A Learning case-base 60%	Ω_T Testing case-base 40%	Ω_0 women didn't use any method	Ω_1 women used long-term method	Ω_2 women used short-term method
1473	884	589	1214	106	153

5.4 Experimentation

Experiments are conducted on an interactive system which allows the physician entering his data through an interface, which permits also launching successively the following steps 1, 2, 3:

Step 1. Definition of the medical situation

This procedure is shared between CBR and MCA. The entered data are partly distributed between CBR and MCA processes. Hence, the physician checks, the clinical and the paraclinical symptoms (C_S, P_S). These symptoms contribute to create partially the new case: NC (C_S, P_S, Ø). Also, this procedure initiates the MCA process (step: Multi-Criteria Information, MCI (C_S, P_S, Pr_Trs)).

Step 2. CBR process

At this step, the physician:

- Assigns the value of *k* for the *k-nn* method.
- Initiates the CBR process described above (4.2.b).

Step 3. Multi-criteria process

The physician:

- Assigns the different parameters shown in Table 4: therapies, criteria, weightings.
- Evaluates therapies according to these criteria (Performance_Table).
- Initiates the MCA process described above (4.2.c).

Table 4. Therapies, criteria and weightings

Therapy (T)	Criteria (C)	Weightings (W)
No-use method	Side effects	Many
Long-term method	Efficacy	No
Short-term method	Duration	Not at all
		Efficient
		Inefficient
		Long
		Reduced

5.5 Evaluation of Results

To assess the effectiveness and verify the scalability of the proposed approach, experiments were carried out with two techniques. We use the conditional structure (1) to compare each case presented to the system respectively stemming from the physician's testing case-base Ω_P or the internal testing case-base Ω_T. Each case presented to the system is compared with the cases in learning case-base Ω_A to verify its matching. At last, we calculate the rates (%) of good matching and mismatching. These rates represent the number of cases truly identified ("No-use method", "Long-term method" or "Short-term method") and also wrongly identified in the case-base Ω_A.

$$\begin{array}{l} \forall\, \omega_i \in \Omega_P \ \text{ or } \ \omega_i \in \Omega_T \\ \quad \text{and} \\ \quad \forall\, \omega_j \in \Omega_A \end{array} \left\{ \begin{array}{l} \text{if } \ Y(X(\omega_i)) = Y(X(\omega_j)) \text{ then good matching} \\ \text{else} \quad \text{mismatch} \end{array} \right. \tag{1}$$

1st technique: cases introduced by the physician (Ω_P) and verified on learning case-base Ω_A.

We have introduced values to define 12 cases which are assumed to be "No-use method", 12 cases with the hypothesis "Long-term method" and 12 cases with the hypothesis "Short-term method". Each case presented by the physician is compared with cases in the learning case-base Ω_A.

2nd technique: cases selected from testing case-base (Ω_T) and verified on learning case-base Ω_A.

We considered 12 cases taken randomly from the testing case-base Ω_T without any hypothesis of diagnosis. A comparison is done for each case coming from Ω_T with cases of the learning case-base Ω_A.

Table 5. Results for the experimentation

	Cases in each testing case-base	Type of method used in testing case-base	Cases in Ω_A	Good matching (%)				Mismatch (%) on overall testing values of k
				k=4	k=7	k=12	k=15	
1st technique	12		884					
		No-use		66	75	58	58	≈ 36
		Long-term		50	66	66	66	≈ 38
		Short-term		58	58	75	75	≈ 34
2nd technique	12		884					
		No-use		58	66	75	66	≈ 34
		Long-term		66	58	66	66	≈ 36
		Short-term		58	58	66	58	≈ 40

The results in Table 5 show, that the good matching's rate is more than the average, which demonstrate that our approach makes a good matching of contraceptive method as shown previously. We can notice for example with "No-use method", when $k \geq 7$ and also for "Short-term method" with 75% of good matching. We can also notice, that the rate of correct matching (similar diagnosis) is relatively high (>58%) for our approach. So, as compared to the average, these results show that our approach identify with a high percentage a case which has "No-use method", "Long-term method" or "Short-term method" as declared in testing case-base Ω_T or Ω_P. As well as for mismatching which indicates how accurately our approach identifies wrongly contraceptive methods?. In Table 5, we note a mismatching less than 40 %. Hence, we can say: according to the two techniques, the results indicate how accurately our approach don't identify correctly the contraceptive method or how often is the comparison test false. Our approach gives a result less than 40%, on overall testing values, which is relatively an interesting percentage.

6. Conclusion and Future Trends

We have initiated in this paper a decision aid approach. We aim to develop a new hybrid decision support tool which integrates multi-criteria decision aid and CBR. This work provides the theoretical basis of an approach that tends to solve a decision support problematic. It's based on a cooperative work between CBR reasoning and MCA, which is well suited for the medical context, and mainly focus on case retrieval. So, in future we would focus on two directions:

- Test our approach with other similarity measure well suited to medical features and compare results and choose a convenient similarity for our approach.
- Propose the concept of fuzzy descriptors in a medical situation because sometimes the physician is not sure 100% of his diagnosis. As a fuzzy set theory can be used in the similarity measure, we propose to use it for matching similarities in terms of degrees [0–1] between attribute values of previous cases and a new case. This will allow us to support the reasoning process by a fuzzy logic and a fuzzy similarity measure.
- On another side, we intend to more fully explore each type of contraceptive method and link each type, to a drug or a therapeutic plan to make a more strong decision aid than prescribing a usual and ordinary therapy. These drugs exist, e.g., for "Long-term contraception", there is Etonogestrel implant, marketed as Implanon NXT and Levonorgestrel IUD (hormonal IUD), known in Australia as Mirena [43]. There are also drugs for short-term contraception, such Injectable Contraceptive, or a large variety of pills such as Depot medroxyprogesterone acetate injection (for women under the age of 18 or over 45) or combined and Progestogen-only oral Contraceptive Pills [43]. So, our case-base will be improved by a brand-name drug instead of generic drug as proposed in the Contraceptive Method Choice case-base.

Acknowledgement

A preliminary version of this paper was presented at the SEAS 2013, the Second International Conference on Software Engineering and Applications, in Dubai, in November 2–3, 2013.

References

[1] I. Bichindaritz and C. Marling, "Case-based reasoning in the health sciences: foundations and research directions," in *Computational Intelligence in Healthcare 4: Advanced Methodologies*. Berlin, Germany: Springer, 2010, pp. 127-157.

[2] S. Montani, "Exploring new roles for case-based reasoning in heterogeneous AI systems for medical decision support," *Applied Intelligence*, vol. 28, no. 3, pp. 275-285, 2008.

[3] D. A. John and R. R. John, "A framework for medical diagnosis using hybrid reasoning," in *Proceedings of the International MultiConference of Engineers and Computer Scientists*, Hong Kong, 2010.

[4] I. Bichindaritz and S. Montani, "Introduction to the special issue on case-based reasoning in the health sciences," *Computational Intelligence*, vol. 25, no. 3, pp. 161-164, 2009.

[5] N. Armaghan and J. Renaud, "An application of multi-criteria decision aids models for case-based reasoning," *Information Sciences*, vol. 210, pp. 55-66, 2012.

[6] M. Velasquez and P. T. Hester, "An analysis of multi-criteria decision making methods," *International Journal of Operations Research*, vol. 10, no. 2, pp. 56-66, 2013.
[7] B. Roy and D. Bouyssou, *Aide multicritère à la decision: méthodes et cas*. Paris, France: Economica, 1993.
[8] A. Aamodt and E. Plaza, "Case-based reasoning: foundational issues, methodological variations, and system approaches," *AI Communications*, vol. 7, no. 1, pp. 39-59, 1994.
[9] C. Marling, J. Shubrook, and F. Schwartz, "Toward case-based reasoning for diabetes management: a preliminary clinical study and decision support system prototype," *Computational Intelligence*, vol. 25, no. 3, pp. 165-179, 2009.
[10] M. K. Jha, D. Pakhira, and B. Chakraborty, "Diabetes detection and care applying CBR techniques," *International Journal of Soft Computing and Engineering (IJSCE)*, vol. 2, no. 6, pp. 132-137, 2013.
[11] X. Song, S. Petrovic, and S. Sundar, "A case-based reasoning approach to dose planning in radiotherapy," in *Proceedings of 7th International Conference on Case-Based Reasoning*, Belfast, UK, 2007, pp. 348-357.
[12] F. J. De Paz, S. Rodriguez, J. Bajo, and J. M. Corchado, "Case-based reasoning as a decision support system for cancer diagnosis: a case study," *International Journal of Hybrid Intelligent Systems*, vol. 6, no. 2, pp. 97-110, 2009.
[13] F. L. Schwartz, J. H. Shubrook, and C. R. Marling, "Use of case-based reasoning to enhance intensive management of patients on insulin pump therapy," *Journal of Diabetes Science and Technology*, vol. 2, no. 4, pp. 603-611, 2008.
[14] N. Belacel, "Multicriteria decision analysis methodology for medical diagnosis aid," 2003 [Online]. Available: http://nparc.cisti-icist.nrc-cnrc.gc.ca/npsi/ctrl?action=rtdoc&an=8914299&lang=en.
[15] M. Shanbezadeh, T. Soltani, and M. Ahmadi, "Developing a clinical decision support model to evaluate the quality of asthma control level," *Middle-East Journal of Scientific Research*, vol. 14, no. 3, pp. 387-393, 2013.
[16] G. Van Valkenhoef, T. Tervonen, J. Zhao, B. de Brock, H. L. Hillege, and D. Postmus, "Multicriteria benefit: risk assessment using network meta-analysis," *Journal of Clinical Epidemiology*, vol. 65. no. 4, pp. 394-403, 2012.
[17] A. Erjaee, M. Bagherpour, S. Razeghi, S. M. Dehghani, M. H. Imanieh, and M. Haghighat, "A multi-criteria decision making model for treatment of Helicobacter pylori infection in children," *Hong Kong Journal of Paediatrics*, vol. 17, no. 4, pp. 237-242, 2012.
[18] A. Bouhana, M. Abed, and H. Chabchoub, "An integrated case-based reasoning and AHP method for personalized itinerary search," in *Proceedings of 4th International Conference on Logistics*, Hammamet, Tunisia, 2011, pp. 460-467.
[19] K. A. Kumar, Y. Singh, and S. Sanyal, "Hybrid approach using case-based reasoning and rule-based reasoning for domain independent clinical decision support in ICU," *Expert Systems with Applications*, vol. 36, no. 1, pp. 65-71, 2009.
[20] S. Begum, M. U. Ahmed, P. Funk, N. Xiong, and M. Folke, "Case-based reasoning systems in the health sciences: a survey of recent trends and developments," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 41, no. 4, pp. 421-434, 2011.
[21] C. Marling, E. Rissland, and A. Aamodt, "Integrations with case-based reasoning," *The Knowledge Engineering Review*, vol. 20, no. 3, pp. 241-245, 2005.
[22] H. Li and J. Sun, "Hybridizing principles of the Electre method with case-based reasoning for data mining: Electre-CBR-I and Electre-CBR-II," *European Journal of Operational Research*, vol. 197, no. 1, pp. 214-224, 2009.
[23] G. F. Royes, "A hybrid fuzzy-multicriteria-CBR methodology for strategic planning support," in *Proceedings of IEEE Annual Meeting of the Fuzzy Information, 2004. Processing (NAFIPS '04)*, Banff, Canada, 2004, pp. 208-213.

[24] A. K. Araujo de Castro, P. R. Pinheiro, and M. C. D. Pinheiro, "Towards the neuropsychological diagnosis of Alzheimer's disease: a hybrid model in decision making," in *Proceedings of 2nd World Summit on the Knowledge Society (WSKS 2009)*, Chania, Greece, 2009, pp. 522-531.

[25] R. Schmidt, S. Montani, R. Bellazzi, L. Portinale, and L. Gierl, "Cased-based reasoning for medical knowledge-based systems," *International Journal of Medical Informatics*, vol. 64, no. 2-3, pp. 355-367, 2001.

[26] S. Begum, M. U. Ahmed, P. Funk, N. Xiong, and B. V. Scheele, "A case-based decision support system for individual stress diagnosis using fuzzy similarity matching," *Computational Intelligence*, vol. 25, no. 3, pp. 180-195, 2009.

[27] L. Verma, S. Srinivasan, and V. Sapra, "Integration of rule based and case based reasoning system to support decision making," in *Proceedings of International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)*, Ghaziabad, India, 2014, pp. 106-108.

[28] J. Agarwal and S. S. Bedi, "Implementation of hybrid image fusion technique for feature enhancement in medical diagnosis," *Human-centric Computing and Information Sciences*, vol. 5, article no. 3, 2015.

[29] K. M. Prabusankarlal, P. Thirumoorthy, and R. Manavalan, "Assessment of combined textural and morphological features for diagnosis of breast masses in ultrasound," *Human-centric Computing and Information Sciences*, vol. 5, article no. 12, 2015.

[30] V. Vijayarajan, M. Dinakaran, P. Tejaswin, Priyam, and M. Lohani, "A generic framework for ontology-based information retrieval and image retrieval in web data," *Human-centric Computing and Information Sciences*, vol. 6, article no. 18, 2016.

[31] F. M. Moghadam and M. R. Keyvanpour, "Comparative study of various Persian stemmers in the field of information retrieval," *Journal of Information Processing Systems*, vol. 11, no. 3, p. 450-464, 2015.

[32] R. Kumar, P. Chandra, and M. Hanmandlu, "A robust fingerprint matching system using orientation features," *Journal of Information Processing Systems*, vol. 12, no. 1, pp. 83-89, 2016.

[33] M. Szelag, S. Greco, and R. Slowinski, "Similarity-based classification with dominance-based decision rules," in *Proceedings of International Joint Conference on Rough Sets*, Santiago, Chile, 2016, pp. 355-364.

[34] H. Malekpoor, N. Mishra, S. Sumalya, and S. Kumari, "An efficient approach to radiotherapy dose planning problem: a TOPSIS case-based reasoning approach," *International Journal of Systems Science: Operations & Logistics*, vol. 4, no. 1, pp. 4-12, 2016.

[35] A. Bouhana, A. Zidi, A. Fekih, H. Chabchoub, and M. Abed, "An ontology-based CBR approach for personalized itinerary search systems for sustainable urban freight transport," *Expert Systems with Applications*, vol. 42, no. 7, pp. 3724-3741, 2015.

[36] J. Qi, J. Hu, and Y. Peng, "Hybrid weighted mean for CBR adaptation in mechanical design by exploring effective, correlative and adaptative values," *Computers in Industry*, vol. 75, pp. 58-66, 2016.

[37] B. Noori, "Developing a CBR system for marketing mix planning and weighting method selection using fuzzy AHP," *Applied Artificial Intelligence*, vol. 29, no. 1, pp. 1-32, 2015.

[38] H. Wang, B. Sun, and X. Shen, "Hybrid similarity measure for retrieval in case-based reasoning systems and its applications for computer numerical control turret design," *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 2016. https://doi.org/10.1177/0954405416654432.

[39] J. Uddin, R. Islam, and J. M. Kim, "Texture feature extraction techniques for fault diagnosis of induction motors," *Journal of Convergence*, vol. 5, no. 2, pp. 15-20, 2014.

[40] T. Pelaccia, J. Tardif, E. Triby, C. Ammirati, C. Betrand, and B. Charlin, "Comment les médecins raisonnent-ils pour poser des diagnostics et prendre des décisions thérapeutiques? Les enjeux en médecine d'urgence," *Annales Françaises de Médecine D'urgence*, vol. 1, no. 1, pp. 77-84, 2011.

[41] J. P. Kassirer, "Teaching clinical reasoning: case-based and coached," *Academic Medicine*, vol. 85, no. 7, pp. 1118-1124, 2010.
[42] World Health Organization: Sexual and Reproductive Health [Online]. Available: http://www.who.int/topics/family_planning/en/.
[43] World Health Organization: Family Planning/Contraception [Online]. Available: http://www.who.int/mediacentre/factsheets/fs351/en/.
[44] B. Roy, "The outranking approach and the foundations of ELECTRE methods." *Theory and Decision*, vol. 31, no. 1, pp. 49-73, 1991.
[45] S. B. Mena, "Introduction aux méthodes multicritères d'aide à la décision," *Biotechnologie, Agronomie, Société et Environnement*, vol. 4, no. 2, pp. 83-93, 2000.
[46] J. A. Recio-Garcia, B. Diaz-Agudo, and P. Gonzalez Calero, *jCOLIBRI2 Tutorial*. Madrid, Spain: Universidad Complutense de Madrid, 2008.
[47] J. A. Fortney, "The importance of family planning in reducing maternal mortality," *Studies in Family Planning*, vol. 18, no. 2, pp. 109-114, 1987.
[48] L. R. Beach, B. D. Townes, F. L. Campbell, and G. W. Keating, "Developing and testing a decision aid for birth planning decisions," *Organizational Behavior and Human Performance*, vol. 15, no. 1, pp. 99-116, 1976.
[49] E. B. Schwarz, S. M. Parisi, S. M. Handler, G. Koren, E. D. Cohen, G. J. Shevchik, and G. S. Fischer, "Clinical decision support to promote safe prescribing to women of reproductive age: a cluster-randomized trial," *Journal of General Internal Medicine*, vol. 27, no. 7, pp. 831-838, 2012.
[50] V. Setty-Venugopal and U. D. Upadhyay, *Birth Spacing: Three to Five Saves Lives*. Baltimore, MD: Population Reports, 2002.
[51] M. L. Kavanaugh and R. M. Anderson, *Contraception and Beyond: The Health Benefits of Services Provided at Family Planning Centers*. New York, NY: Guttmacher Institute, 2013.
[52] UCI Machine Learning Repository, "Contraceptive Method Choice Data Set," 1999 [Online]. Available: https://archive.ics.uci.edu/ml/datasets/Contraceptive+Method+Choice.

Mansoul Abdelhak https://orcid.org/0000-0002-0715-7604

He is a computer science teacher in the Department of Computer Science at the University of Skikda. He is currently a PhD candidate in the Computer Science Department at the University of Oran 1 Ahmed Ben Bella. His research interests include knowledge management, knowledge discovery, modelling, information retrieval and decision aid.

Atmani Baghdad

He is a Professor of Computing Science at the University of Oran 1 Ahmed Ben Bella. His field of interests are data mining and machine learning tools. His research is based on knowledge representation, knowledge-based systems and CBR, data and information integration and modelling, data mining algorithms, expert systems and decision support systems. His research is guided and evaluated through various applications in the field of control systems, scheduling, production, maintenance, information retrieval, simulation, data integration and spatial data mining.