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Decision Making based on Quality-of-Information A Clinical Guideline for Chronic Obstructive Pulmonary Disease Scenario

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Abstract In this work we intend to advance towards a computational model to hold up a Group Decision Support System for VirtualECare, a system aimed at sustaining online healthcare services, where Extended Logic Programs (ELP) will be used for knowledge representation and reasoning. Under this scenario it is possible to evaluate the ELPs making in terms of the *Quality-of-Information* (*QoI*) that is assigned to them, along the several stages of the decision making process, which is given as a truth value in the interval 0…1, i.e., it is possible to provide a measure of the value of the *QoI* that supports the decision making process, an end in itself. It will be also considered the problem of *QoI* evaluation in a multi-criteria decision setting, being the criteria to be fulfilled that of a Clinical Guideline (CG) for Chronic Obstructive Pulmonary Disease.

Keywords: quality of information, clinical guidelines, artificial intelligence

1 Introduction

In general terms, Decision Theory (DT) is a means of analyzing which set of alternatives should be chosen when there is uncertainty about the results, in order to make an option. DT focuses its attention on identifying the “best” choice. The notion of “best” has different meanings, being the most common the one that maximizes the expected utility for the decision maker. On the other hand, Utility Theory (UT) attempts to infer subjective value (utility) from choices in three traditional ways, namely the descriptive, the normative and the prescriptive ones.

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The descriptive approach tries to describe people's utility functions. The normative approach attempts to use utility in a rational model for decision making. The third approach, the prescriptive one, tries to reduce the differences between the former two by considering the limitations people usually have with the normative one [1].

Indeed, any entity operating in a complex environment is naturally cautious about the state of the world. It does not have complete information about the state nor how it will evolve. Also, the purpose to maximize the expected utility for the decision maker is not always practical, once there are bounds on computational resources which prevent the search for the optimal solution. This situation call for decision models under bounded rationality, which aims to be rational in the sense of recommending the option with maximum expected utility, but which admit bounds on their resources, and so relax some premises of the optimal approach.

The Carnegie Decision Making Model (CMDM) also known as Cyert-March-Simon model [2] is an example of decision models that emphasizes bounded rationality. Decisions are made to *satisface* rather than to optimize the solution. In group decision making it will be accepted a solution perceived as satisfactory to all members, contrary to the rational approach, which assumes that every reasonably alternative is analyzed, a quick short-run solution is looked around and typically the first satisfactory one that emerges is adopted. In contexts of high uncertainty, when the information available is incomplete, and the outcome can be hazardous, the first solution that emerges cannot be adopted irrespective of the Quality-of-Information (QoI) available. We propose a method to evaluate the quality of information and a computational model that extends the CMDM, incorporating as threshold its QoI.

In this paper it is shown how this skeleton can be applied to problem solving on the health sector, where clinical guidelines set the criteria to be followed, and are given in terms of Extended Logic Programs (ELPs). We start by summarizing previous work on the evaluation of QoI, in section two. In section three we elaborate on a computational model for decision making that extends and subsumes CMDM. In section four we present some results of the combination of these methods and techniques with the Analytic Hierarchy Process (AHP) [3], used to support the decision process. Finally, in section five, we draw some conclusions.

2 Evaluation of the Quality of Information

Clinical guidelines (CG) have been developed for more than fifty years. More recently the emphasis has been centred on the development of evidence-based guidelines and their evaluation, and ease-of-use in daily practice. CG have drawn the attention of the Artificial Intelligence (AI) community, leading to the development of specific models, tools and languages to support their practical design and implementation, in what may be called Computer-interpretable Guidelines (CIG) [4] [5]. Guideline-based Decision Support Systems (GbDSS) are also emerging as a promising way to apply AI to healthcare practice [6] [7].

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One of the critical issues to implement computer-based CG is the depiction model. Several approaches using different description models are in use, namely Arden Syntax [8], Guideline Interchange Format (GLIF) [9], Asbru [10] and Pro*forma* [11], among others. Like the Proforma-based systems, we are particularly interested in approaches using logic programming and in combining general models of human decision-making with formal ones. On the other hand we draw on ELPs in order to handle positive and negative information in an explicit way, making possible the use of null values (Program 1). With this kind of construction it is possible to compute the QoI, with respect to an extension of a generic predicate P of an ELP, based on the cardinality of the exception set for that predicate. Combining the QoI for all predicate extensions, a global measure of the QoI in the decision process is made available at any time [12].

3 Decision Making

The background for decision making is set in terms of the VirtualECare project [13]; indeed, Group Decision Support Systems (GDSSs) in VirtualECare must address multi-criteria problems, layed down as incomplete ELPs.

The GDSS that supports VirtualECare is based on the limited or empiric rationality of Hebert Simon [14]. The propensity phase come about persistently, as a consequence of the natural interaction of GDSS with other components that make the VirtualECare framework. The identification of a problem triggers the formation of a decision group. The group assembling occurs in the pre-meeting phase, and a facilitator is entitled to choose the participants. The activities associated to the conception and choice occurred already at the meeting phase.

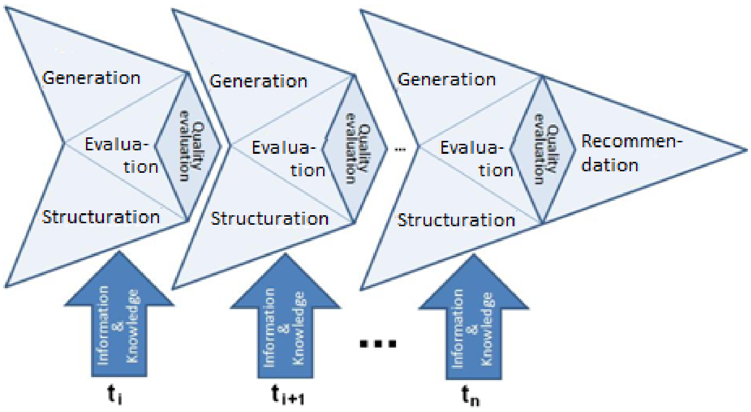

Fig. 1. Evaluation of the QoI along with the Decision Process

The process matures alongside a time line, centered on the description of the problem, until a suggested solution is reached; in the meantime it goes through consecutive stages (Fig. 1), namely that of options description (Generation), value judgments (Structuration), and operative rules (Evaluation), under a cycling mode.

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As a result, we finished with a meta model, with a neighborhood built around four layers, which can be instantiated with methods, tasks and tools – that is to say, instantiated with a specific model – and an area that borders all the previous ones, the Evaluation of the Quality of Information, as it is stated below :

Generation – it is a departure zone, of simultaneous exploration of potential alternative paths, information research, and problematic questions evaluation;

Structuration - it is a discussion zone, of understanding of other people's perspectives, of clarifying criteria, of revising the conjectures and restrictions, of creating a context that can be shared, that is of structuration of the decision process;

Evaluation – it is a convergence zone, of risk and consequence evaluation, hypothesis reduction, and voting; and

Recommendation – this is the end of the process, voting or final preference aggregation, following the selected decision method.

4 A Case Study

As an example we select a CG for the Chronic Obstructive Pulmonary Disease (COPD) from the National Guideline Clearinghouse (NGC) [15]. According to the World Health Organization (WHO), COPD is already responsible for 3 (three) million deaths a year, and will be the third world death cause by 2030. As demands for more patient care will continue to grow and the shortcomings of medical services are more and more recognized, systems like VirtualECare will be needed to help in the treatment and prevention of diseases like COPD, at the patient natural habitat.

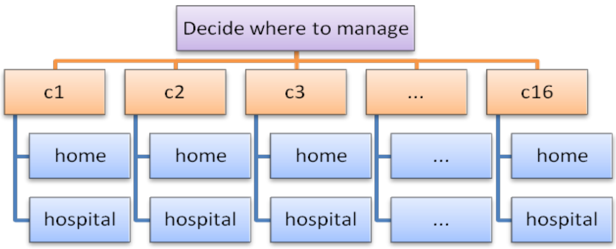

Fig. 2. Structure of the Problem (i.e. goals, criteria, and alternatives).

From the different algorithms that hold up COPD guidelines, we choose the one that supports the verdict where to treat COPD exacerbations - at the patient natural habitat or in the hospital – under the following scenario:

> *John is a patient that was brought to the hospital by neighbors, who he asked help, and to which now is diagnosed COPD. It was not still possible to contact the family. He is retired and lives at relatives' house, but there is not the certainty to be a structured family. Seemingly he has enough mobility to accomplish his tasks of personal hygiene, but the neighbors don't see him outdoors very often. He doesn't have recent clinical analyses.*

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In such a scenario, the COPD guideline suggests the evaluation of sixteen criteria (Table 1). The CG does not define a minimum set of criteria or possible combinations of criteria in order to make a final decision. We use the AHP method to structure the problem and compute a recommendation (Figure 2). We also presume that there is not complete information about all the sixteen criteria.

The weight of each criterion was evaluated using pairwise comparison, and is shown in Table 1.

Table 1. Exacerbations Treatment Criteria

	Criteria	Favours treatment at home	Favours treatment in hospital	Weight (wi)
c1	Able to cope at home	Yes	No	0,0101
c2	Breathlessness	Mild	Severe	0,0151
c3	General condition	Good	Poor/deteriorating	0,0075
c4	Level of activity	Good	Poor/confined to bed	0,0079
c5	Cyanosis	No	Yes	0,0228
c6	Worsening peripheral edema	No	Yes	0,0525
c7	Level of consciousness	Normal	Impaired	0,1463
c8	Already receiving LTOT	No	Yes	0,0129
c9	Social circumstances	Good	Living alone/not coping	0,0336
c10	Acute confusion	No	Yes	0,2022
c11	Rapid rate of onset	No	Yes	0,0595
c12	Significant comorbidity (particularly cardiac and insulin dependent diabetes)	No	Yes	0,0747
c13	Sao2 < 90%	No	Yes	0,0325
c14	Changes on the chest radiograph	No	Present	0,0480
c15	Arterial pH level	$\geq 7{,}35$	$< 7{,}35$	0,1412
c16	Arterial Pao2	$\geq 7\ KP_a$	$< 7\ KP_a$	0,1332
	Total			1.0000

As it may be observed, at a first glance, the information available leads to a knowledgeable representation as the one depicted by Program 1. With this (incomplete) data, the local values for each alternative, using Saaty scale [3], is the one given in Table 2.

$\neg$ *ableToCopeAtHome(E, V)* $\leftarrow$ *not ableToCopeAtHome(E, V),*
not exception(ableToCopeAtHome(E, V))
exception(ableToCopeAtHome(E, V)) $\leftarrow$ *ableToCopeAtHome(E,* $\perp$*)*
ableToCopeAtHome (john, $\perp$*)*
exception(dyspnoea(john, moderate))

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exception(dyspnoea(john, bad))
generalCondition(john, bad)
exception(levelOfActivity(john, sedentary))
exception(levelOfActivity(john, moderate))
cyanosis(john, yes)
arterial_pH_level(john, ⊥)
arterial_PaO2(john, ⊥))

Program 1. Initial state of Knowledge (excerpt), where the symbol ⊥ stands for a null value of the type unknown.

Table 2. Local values of the alternatives for each criterion

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10	c11	c12	c13	c14	c15	c16
home	0	0	.1	0	.1	.9	.9	.9	0	.9	0	.9	0	0	0	0
hospital	0	0	.9	0	.9	.1	.1	.1	0	.1	0	.1	0	0	0	0

Now we can compute the global weighing of each alternative using the values from Table 3 and the weights from Table 1, which leads us to: patient natural habitat = 0,44; hospital = 0,07. This means that the information available favours the treatment at the patient natural habitat (home). Let us analyze the QoI that supports this recommendation. Table 3 shows the scoring values for each predicate`s extension, according to the available information.

Table 3. Some QoI values for the Predicate Extensions in Program 1 (partial table)

$V_{\text{ableToCopeAtHome}}(john) = 0$	$V_{socialCircumstances}(john) = 0$
$V_{\text{dyspnoea}}(john) = .5$	$V_{acuteConfusion}(john) = 1$
$V_{doLTOT}(john) = 1$	$V_{arterial\_PaO2}(john) = 0$

Now we can compute the global QoI (also graphically depicted in Figure 3 in terms of the dashed area), using the expression (1):

$$V_{COPD}(john) = \sum_{j=1}^{16} w_j * V_j(john) = 0.5304 \quad (1)$$

As it can be seen the QoI is very low. A minimum threshold of 0.8 was defined, so no decision is made in the meantime. We need more information in order to reduce uncertainty. The patient family is contacted and some clinical exams and analysis are made, so that in a second moment we have more information. Program 2 shows the corresponding changes at the knowledge representation level.

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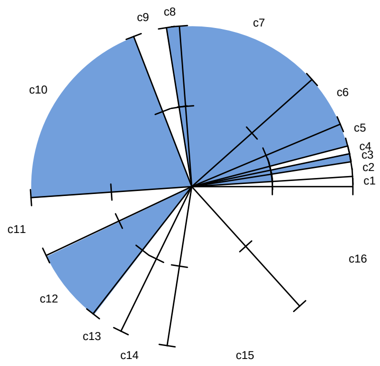

Fig. 3. QoI for Program 1

ableToCopeAtHome (john, no)
dyspnoea(john, severe)
levelOfActivity(john, sedentary)
socialCircumstances(john, no)
rapidRateOfOnset(john, yes)
lowSaO2(john, no))
arterial_pH_level(john, 7.32)
arterial_PaO2(john, 6.8))

Program 2. New knowledge (excerpt)

Computing again the values for the two recommendations, new values are obtained: patient natural habitat = 0.39; hospital = 0.55. As we can see, the recommendation has changed! Let's compute the value of the QoI now, to validate the premises for a decision. The value is now 0.95, fairly above the 0.8 threshold. So the system may deliver a recommendation for the decision.

5 Conclusions

In this paper we present an example of the evaluation of QoI to a multi-criteria decision process. A CG for COPD was used to define the criteria and conditions for the decision in a simulated clinical scenario. An ELP was used for the knowledge representation and reasoning and to support the QoI evaluation. AHP method was used to compute the preferences for each alternative.

In the beginning, the system was able to issue a recommendation but with a very low value for QoI, indeed bellow the predefined threshold. This value of QoI discouraged any immediate action based on the recommendation. In a posterior moment, a second iteration, after improving the available information, leads to a much better QoI, suggesting that the recommendation can be accepted and the corresponding actions executed. We emphasize that, from the first to the second iteration, the recommendation changed and lead, in the end, to an opposite alternative.

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The combination of techniques and methods from different areas, namely AI and DT, can support decision making in a very effective way.

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