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Hierarchical Multi-Attribute Decision Models and Their Application in Health Care

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Abstract. Hierarchical decision models are developed through decomposition of complex decision problems into smaller and less complex subproblems. They are aimed at the classification or evaluation of options and can be used for analysis, simulation and explanation. This paper presents a set of methods for the construction and application of qualitative hierarchical decision models in health care. We present the results of four ongoing projects in oncology, radiology, community nursing and diabetic foot treatment.

1. Introduction

Hierarchical multi-attribute decision models are aimed at the classification and/or evaluation of objects defined in attribute-value space [1,2]. They are based on decomposition of a complex decision problem into smaller and less complex subproblems. Subproblems are represented by variables, which are organized into a hierarchy.

Hierarchical decision models are extensively applied in decision support [3]. There, the problem is to choose an option from a set of available options so as to best satisfy the goals of decision maker. A decision model is designed to evaluate the options, and can also be used for the analysis, simulation, and explanation of decisions. In practice, this approach is most often used for technical or economical decision making, such as project or investment evaluation, portfolio management, strategic planning, and personnel management. In Slovenia, we have contributed to these fields by developing an expert system shell for multi-attribute decision support DEX [4] and applying it in several tens of real-world decision problems [5,6].

Some recent developments of hierarchical decision models have made them very attractive also for medicine and health care. In particular, some new methods facilitate the design of qualitative (or symbolic) decision models. In contrast with traditional quantitative (numeric) models, the qualitative ones are better suited for dealing with "soft" decision problems, which are typical for medicine in health care: less structured and less formalized problems that involve a great deal of expert judgement.

In this paper we present an approach to the development and application of qualitative hierarchical decision models based on the DEX shell. Section 2 defines basic concepts of hierarchical decision models. In section 3, these are illustrated by a case study of breast cancer risk assessment. Section 4 presents three other ongoing Slovenian projects that involve hierarchical models. The paper is concluded by a summary and proposals for further work.

2. Hierarchical Decision Models

In general, a *hierarchical decision model* is composed of attributes X_i and utility functions F_i (Figure 1). *Attributes* (sometimes also referred to as *performance variables* or parameters) are variables that represent decision subproblems. They are organized hierarchically so that the attributes that occur on higher levels of the hierarchy depend on lower-level attributes.

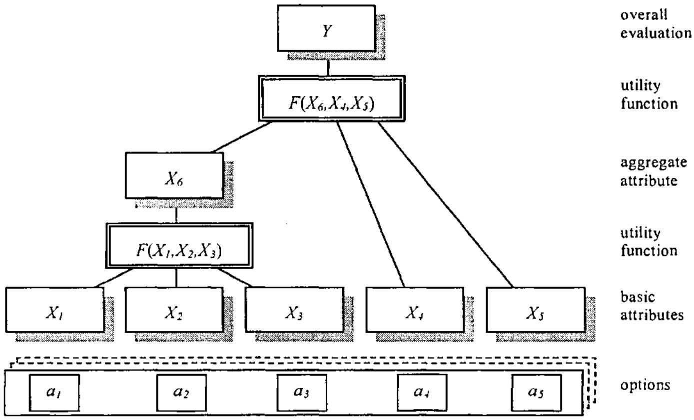

Figure 1: Components of a hierarchical decision model

In general, a hierarchy can be represented by a directed acyclic graph, but in practice it is usually simplified to a tree. According to their position in the hierarchy, we distinguish between *basic* attributes (leaves or terminal nodes) and *aggregate* attributes (internal nodes, including the roots of the hierarchy). In Figure 1, there are five basic attributes labeled from X_1 to X_5, and two aggregate attributes, X_6 and Y. For each aggregate attribute there is defined a corresponding *utility function F* that determines the dependence of that attribute on its immediate descendants in the hierarchy.

Options are described by values a_i of basic attributes. The *evaluation* of options is performed from bottom to the top by gradually aggregating their values according to model structure and utility functions. The overall evaluation (also called *utility*) of an option is finally obtained as the value of root attribute (Y in Figure 1).

A majority of contemporary multi-attribute decision methods is aimed at the development of *quantitative* decision models, in which all the attributes are continuous, and utility functions are typically defined in terms of attributes' weights, such as a weighted average of the lower-level attributes. In this paper we focus on *qualitative* decision models that are utilized by the DEX system. These models consist of *discrete* attributes, whose values are words rather than numbers, and utility functions that are represented by *decision rules* (see section 3 for examples of these).

Decision models are primarily developed for *option evaluation*: each option, described by values of basic attributes, is evaluated according to the model. By this, an overall evaluation is obtained for each option. On this basis the options are compared and ranked, and the best one is finally chosen.

However, this basic principle is insufficient for most practical applications. Decision models can become very complex, so they have to be thoroughly verified to reduce the chance of error. There is a need for an analysis and explanation of both the decision process and evaluation results. In the following case study, we highlight DEX's analysis and explanation methods that are particularly interesting for applications in medicine and health care.

3. Application in Oncology: Breast Cancer Risk Assessment

Breast cancer is a dangerous and unpredictable disease, where an early detection is of outmost importance [7]. To facilitate an early cancer detection, a screening procedure is often used where women of certain age or disease history in the family are invited for routine examination or mammography, if necessary.

In collaboration with the specialists from the Institute of Oncology in Ljubljana we developed a prototype model to assess the risk of breast cancer. The structure of the model is shown in Figure 2. Cancer risk, which is assessed using a four-valued scale, is derived by the model from features such as age, regularity of menstruation and fertility duration.

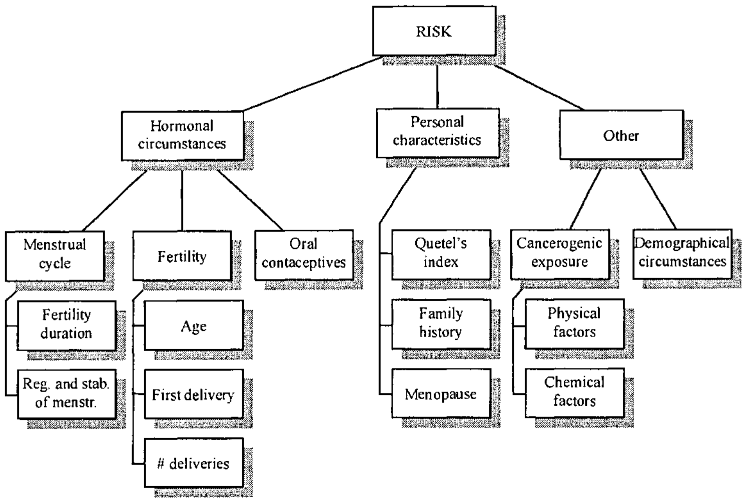

Figure 2: The structure of breast cancer risk assessment model

The risk of cancer is evaluated by decision rules defined by the experts. As an example, consider Table 1 that shows the rule that assesses the risk from the perspective of menstrual cycle and derives it from duration of fertility and regularity/stability of menstruation. Here, fertility duration can be either short (up to 30 years of menstrual period), average (30 to 40 years) and long (longer than 40 years), and menstruation either regular with a period of less than 28 days (R-28), regular with period longer than 29 days (R29+) or irregular (N).

This model was verified by the experts and tested on a small set of cases. A more exhaustive testing based on larger set of cases and comparison with independent examination of physicians is planned for the future.

Table 1: Decision rule to assess the risk specific to menstrual cycle

	Fertility duration	Reg. and stabil. of menstr.	Menstrual cycle
1	average	R-28	high risk
2	long	R-28	high risk
3	long	R29+	high risk
4	long	N	high risk
5	short	R-28	moderate risk
6	average	R29+	moderate risk
7	short	R29+	low risk
8	short	N	low risk
9	average	N	low risk

Knowledge representation and analysis of the model. The methods that support the analysis of model and provide different means for knowledge representation are primarily used to verify the model and detect potential errors. These methods either consider the model as a whole, or separately investigate a single utility function. A decision rule (such as the one in Table 1) may, for example, be interpreted as a training set given to some machine learning algorithm to devise a semantically equivalent representation. For example, consider Table 2 that was derived from Table 1 using the algorithm for induction of *complex rules* [8]. The resulting rule is more compact and in general easier to understand than its original.

Table 2: Complex rule as derived from Table 1

	Fertility duration	Reg. and stab. of menstr.	Menstrual cycle
1	≥ average	R-28	high risk
2	long	*	high risk
3	short	R-28	moderate risk
4	average	R29+	moderate risk
5	short	R29+, N	low risk
6	≤ average	N	low risk

Table 3: Attributes from breast cancer risk assessment model by their index of importance. Three different importance estimation methods were used. The indices of most important attributes are printed in bold

BREAST CANCER RISK	Regression	Informativity	Gini Index
Hormonal circumstances	**158**	**202**	**234**
Menstrual cycle	**125**	**123**	**130**
Fertility duration	**125**	**128**	**138**
Regularity and stability of menstruation	75	72	62
Fertility	111	99	130
Age	97	145	126
First delivery	**145**	**128**	**145**
# deliveries	58	27	29
Oral contraceptives	65	78	41
Personal characteristics	88	56	39
Quetel's index	29	5	11
Family history	**197**	**183**	**236**
Menopause	74	112	53
Other	55	42	27
Cancerogenic exposure	100	100	100
Physical factors	**160**	**166**	**179**
Chemical factors	40	34	21
Demographical circumstances	100	100	100

For a less detailed representation of utility functions we can use weights. These are derived by either a method based on regression [8], or by employing some measure to estimate the quality of attributes as used in machine learning [9]. For example, the rules in Table 1 determine the average weights of the attributes "Fertility duration" and "Regularity and stability of menstruation", which are, as computed by regression, 64% and 36%, respectively. That is, the first attribute is on average about twice as important as the second one.

Representation with weights is particularly interesting when we consider a model as a whole. Although it provides only a rough representation of utility functions, it may allow a quick verification of the model. Table 3 shows such weights for the breast cancer risk model. To ease the interpretation, the weights are represented as indices of importance, which are defined as a ratio between the actual attribute weight and the weight that would be obtained assuming all the attributes in the model were equally important. The index of 100 denotes that utility functions neither lower nor raise the importance of the attribute. Table 3 shows that the group of attributes "Hormonal circumstances" most influences the outcome of the model. Other important attributes include the presence of disease in the family, exposure to physical cancerogenic factors, and age at first delivery.

Evaluation and analysis of options. To demonstrate the utilization of the model, consider a woman aged 42, having two children, regular menstruation, and increased body weight (high Quetel's index). She does not use oral contraceptives and works in the environment that by its physical and demographical characteristics increases the risk of cancer. There was no cancer disease in her mother or sister. The results of risk assessment are given in the first column of Table 4. She obtained grade 3: an increased but not critical breast cancer risk. An explanation for such a risk can be found by the inspection of intermediate results in Table 4. Alternatively, a method of *selective explanation* can be used, which finds the subtrees of attributes that indicate particularly positive or negative influence to the risk. Such explanation is given in Table 5 and shows that the most important factors that contributed to the increased breast cancer risk are the age, increased body weight and environmental circumstances.

Table 4: Examples of evaluation and analysis of breast cancer risk

	Basic evaluation	**Missing data**	**What-if analysis**
BREAST CANCER RISK	**3**	**3**	**2**
Hormonal circumstances	2	3/0,5,2/0,5	2
Menstrual cycle	moderate risk	moderate risk	moderate risk
Fertility duration	average	average	average
Regularity and stability of menstruation	R29+	R29+	R29+
Fertility	moderate risk	moderate risk	moderate risk
Age	over 40	over 40	over 40
First delivery	29 or younger	29 or younger	29 or younger
# deliveries	up to 4	up to 4	up to 4
Oral contraceptives	no	*	no
Personal characteristics	1	1	1
Quetel's index	29+	29+	29+
Family history	no	no	no
Menopause	no	no	no
Other	high risk	high risk	moderate risk
Cancerogenic exposure	high risk	high risk	moderate risk
Physical factors	higher	higher	*lower*
Chemical factors	no	*	no
Demographical circumstances	high risk	high risk	*moderate risk*

Table 5: Selective explanation of evaluation

Reasons FOR higher risk		**Reasons AGAINST higher risk**	
Age	over 40	Personal characteristics	1
Quetel's index	29+	Family history	no
Other	high risk	Menopause	no
Cancerogenic exposure	high risk	First delivery	29 or younger
Physical factors	higher	Oral contraceptives	no
Demographical circumstances	high risk	Chemical factors	no

DEX incorporates mechanisms to handle missing and non-exact data. For example, assume that for the case considered we do not have data on chemical factors and oral contraceptives. For such case, the results of the evaluation are shown in the second column of Table 4. The final risk grade is the same as originally, while the only difference is in the less exact assessment of hormonal circumstances which is now expressed with probability distribution.

Another useful feature of DEX is "what-if" analysis. Here, we are interested in the effects of changing one or more attribute values. In the case examined so far, we may be interested what would happen if the risk from physical factors and demographical circumstances were reduced. The third column in Table 4 shows that this leads to the reduction of breast cancer risk, as it evaluates to grade 2. Similarly, we can use our model and DEX to answer, for example, what would happen if the woman would reduce her body weight, or what risk is she going to have while in menopause.

4. Other Applications

In Slovenia, there are three other ongoing projects that in one way or another employ hierarchical decision models:

1. *Radiology: Technical analysis of errors for lung roentgenogram*: For the purposes of education and systematizing the knowledge and for purposes, a model to assess the

quality of lung roentgenogram was developed. It includes 25 basic criteria that belong to two principal groups: the quality of equipment and recording procedure.

2. *Community nursing: Assessment of basic life activities*: In nursing, there are 14 basic life activities, which need to be properly assessed and recorded at every visit of the nurse. The aim is to develop models for all these activities; several prototype ones have already been developed, such as the one for patient's secretion [10] and physical activity [11].
3. *Risk assessment for diabetic foot syndrome*: With a long-term goal to reduce the number of amputations in diabetic patients, we recently launched the development of a model for assessing risk factors for developing foot pathology.

5. Conclusion

Hierarchical decision models are increasingly used within health care. For practical applications, it is particularly important that these models and supporting decision making tools allow the structuring of domain knowledge, can utilize qualitative variables and utility functions, and provide means for model and data analysis, evaluation in the presence of missing or inaccurate values, and explanation of evaluation.

The cases presented in this paper are based on a manual development of models. Recently, a new data mining method that supports structure and utility function development from pre-classified data called HINT was developed [12]. There is a growing number of such data bases and repositories within health care and medicine, and therefore an increased potential for these to enable an easier and better synthesis of decision models.

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