Applications of Qualitative Multi-Attribute Decision Models in Health Care

Marko Bohanec(1), **Blaž Zupan**(2,1), **Vladislav Rajkovic**(3,1)

(1) *Jožef Stefan Institute, Jamova 39, SI-1000 Ljubljana, Slovenia*

Tel.: +386 61 177 3309; Fax: +386 61 1251 038
E-mail: marko.bohanec@ijs.si

(2) *University of Ljubljana, Faculty of Computer and Information Sciences*

(3) *University of Maribor, Faculty of Organisational Sciences*

Keywords
Multi-attribute decision making, decision support, hierarchical models, qualitative models

Submitted to *International Journal of Medical Informatics*, December 1999.
Revised in April 2000.

Summary

Hierarchical decision models are a general decision support methodology aimed at the classification or evaluation of options that occur in decision-making processes. They are also important for the analysis, simulation and explanation of options. Decision models are typically developed through decomposition of complex decision problems into smaller and less complex subproblems; the result of such decomposition is a hierarchical structure that consists of attributes and utility functions. This article presents an approach to the development and application of qualitative hierarchical decision models that is based on DEX, an expert system shell for multi-attribute decision support. The distinguishing characteristics of DEX are the use of qualitative (symbolic) attributes, and "if-then" decision rules. Also, DEX provides a number of methods for the analysis of models and options, such as selective explanation and what-if analysis. We demonstrate the applicability and flexibility of the approach presenting four real-life applications of DEX in health care: assessment of breast cancer risk, assessment of basic living activities in community nursing, risk assessment in diabetic foot care, and technical analysis of radiogram errors. In particular, we highlight and justify the importance of knowledge presentation and option analysis methods for practical decision making. We further show that, using a recently developed data mining method called HINT, such hierarchical decision models can be discovered from retrospective patient data.

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. Variables are connected by utility functions that serve for the aggregation of partial subproblems into the overall evaluation or classification of objects.

The methodology of hierarchical decision models has been developed and extensively applied in relation to decision support [3]. There, the decision-makers are often faced with the problem of choice [4]: to choose an option from a set of available options so as to best satisfy the decision-maker's goals. In complex real-life decision processes, the problem of choice can be extremely difficult, mainly because of complex, interrelated or even conflicting objectives. To support the decision-maker, a decision model is designed to evaluate the options. Also, it can be used for the analysis, simulation, and explanation of decisions. In practice, this approach has been most often used for technical or economical decision problems, such as project or investment evaluation, portfolio management, strategic planning, and personnel management. We have contributed to these fields by developing an expert system shell for multi-attribute decision support DEX [5] and have applied it in several tens of real-world decision problems [6,7,8].

Some recent developments have made the hierarchical decision model approach very attractive also for problems in medicine and health care. In particular, some newly developed methods, including DEX, facilitate the design of qualitative (or symbolic) decision models. In contrast with traditional quantitative (numeric) models, the qualitative ones use symbolic variables. These seem to be better suited for dealing with "soft" decision problems, which are typical for medicine and health care: less structured and less formalized problems that involve a great deal of expert judgement as opposed to exact formal modeling and computation.

In this article we present the approach to the development and application of qualitative hierarchical decision models that is based on the DEX shell. Section 2 defines basic concepts of hierarchical decision models. In section 3, these are presented through a case study of breast cancer risk assessment. In particular, we illustrate various knowledge representation and option analysis methods, and emphasize their importance for practical decision making. To demonstrate the flexibility and applicability of the approach, section 4 presents three other applications of DEX in community nursing, diabetic foot treatment, and radiography. Three selected examples in Section 5 are used to illustrate a recently developed approach that uses retrospective patient's data to either automatically induce or support a development of DEX-based hierarchical decision models. A summary and proposals for further work conclude the article.

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>

In theory, a hierarchy is 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). Figure 1 shows an abstract model that consists of five basic attributes X_1 to X_5, and two aggregate attributes, X_6 and Y. For each aggregate attribute there is a corresponding *utility function* F that determines the dependency of that attribute with respect to its immediate descendants in the hierarchy.

Options are represented by values a_i of basic attributes. The *evaluation* of options is performed by an aggregation that is carried out from bottom to the top of hierarchy according to its structure and defined utility functions. The overall evaluation (also called *utility*) of an option is finally represented by the value of one or more root attributes (Y in Figure 1).

A majority of current multi-attribute decision methods is aimed at the development of *quantitative* decision models. In such models, all the attributes are continuous, and utility functions are typically defined in terms of attributes' weights, for example as a weighted average of lower-level attributes. In contrast, the system DEX, which is presented here, exclusively deals with *qualitative* decision models. These consist of *discrete* attributes, whose values are usually words rather than numbers. The corresponding utility functions are represented by *decision rules*. Examples of these components are presented in section 3.

Decision models are primarily developed for *option evaluation*: each option, described by values of basic attributes, is evaluated according to the model. This yields an overall evaluation for each option. On this basis, the options are compared and ranked, and the best one can be eventually identified and chosen by the decision-maker.

However, this basic principle of operation 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 the analysis and explanation methods of DEX that are particularly interesting for applications in medicine and health care.

3. Application in Oncology: Breast Cancer Risk Assessment

An early detection of breast cancer is of utmost importance for the patient [9]. 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 to a routine examination or, if necessary, mammography.

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 model's structure is shown in Figure 2. Cancer risk, which is assessed using a four-valued scale, is derived from features such as age, regularity of menstruation and fertility duration.

<Figure 2>

The risk of cancer is evaluated by decision rules, which were defined by the experts. As an example, consider Table 1 that shows the rule that determines the risk with respect to *menstrual cycle* and derives it from two input attributes: *fertility duration* and *regularity/stability of menstruation*. Here, the fertility duration can be either short (up to 30 years of menstrual period), average (30 to 40 years), or long (longer than 40 years). Menstruation cycle can be either regular with a period of less than 28 days (R-28), regular with period longer than 29 days (R29+) or irregular (N). For each combination of fertility duration and menstruation regularity/stability, the experts assessed the risk related to menstrual cycle and expressed it using a three-level scale: low, medium, and high. Each row in the table can thus be interpreted as an elementary *if-then* rule that assesses the risk for the corresponding values of the two input attributes. Also, each row represents a point in the space determined by all three attributes.

<Table 1>

The experts have defined similar tables for all the remaining aggregate attributes in the model. In total, there are seven tables, each one having from 9 to 48 rows (19.3 on average). When defining the tables, an important feature of DEX is to continuously supervise the process and warn the user whenever the newly defined row contradicts to already defined ones. In Table 1, for example, the risk is expected to increase with fertility duration, and this has been indeed ensured by DEX. All the tables and, consequently, the model itself are therefore guaranteed to be consistent and to represent a monotone function: with an increase of risk represented by some basic attribute, the overall risk assessed by the model will increase, too, or at least remain constant.

3.1 Knowledge representation and analysis of the model

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, but possibly more compact and comprehensible representation.

As an example, consider Table 2 that was derived from Table 1 using a machine learning algorithm for the induction of *aggregate rules* [10]. The idea is to merge several rows from the original table into a single row of the resulting table. This is facilitated by using *intervals* of attributes' values instead of single values in the conditional part of decision rule. The intervals are then represented by some meaningful symbols, such as in Table 2, where '*' represents any value from the whole interval, and '?' stands for "better or equal". Table 2 is by one third shorter than Table 1, and easier to read. For example, the rule 2 clearly states that the risk is high whenever the duration of fertility is long, regardless of the value of the second input attribute. To find out this from Table 1, one must have looked at three rules: 2, 3, and 4. With tables that are initially larger than Table 1 and have several tens of rows, this method works even better; it typically achieves a high reduction of size and considerably improves the comprehensibility of rules.

<Table 2>

For a less detailed representation of utility functions we can use *weights*: given a decision rule (such as in Table 1), we use some suitable method to estimate the average importance of each input attribute for determining the value of dependent variable. We then obtain weights by expressing these importances as percentages relative to each other attribute. This yields a very compact representation, which facilitates a quick overview and verification of a utility function.

Two methods are used to assess weights with DEX: one is based on regression [10], and the other on measuring attribute informativity as in machine learning methods [11]. With *regression*, the idea is to interpret a decision rule as a set of points in a multi-dimensional space and approximate it with a hyperplane in that space. Let $x_1, x_2, ..., x_n$ denote input attributes (such as “Fertility duration” and “Regularity and stability of menstruation” in Table 1) and y the dependent variable, which is required to be ordered (such as “Menstrual cycle”). For the purpose of this method, all qualitative values of attributes are represented by their ordinal numbers. Accordingly, we can interpret a decision rule (such as in Table 1) as a collection of points and approximate them by a hyperplane $y\ ?\ a_0\ ?\ a_1 x_1\ ?\ ...\ ?\ a_n x_n$. That is, we find the coefficients $a_0, a_1, ..., a_n$ so that the approximation is optimal in the least-squares sense. From now on, a_0 is usually omitted from the representation, and a_1 to a_n are transformed into weights by representing them as relative percentages:

$$w_i\ ?\ 100 a_i / \overset{n}{\underset{j?1}{?}} a_j\ ;\ i\ ?\ 1,2,...,n$$

For the two input attributes of Table 1, “Fertility duration” and “Regularity and stability of menstruation”, this method yields the weights 63% and 37%, respectively. That means that the first attribute is on average about twice as important as the second one. This might be an important information for the developer, for example to confirm that the decision rule has been defined as expected. Note, however, that in contrast with the aggregate rules presented above, this representation is only approximate and incomplete: from the weights themselves it is in general impossible to fully reconstruct the original decision rule.

As an alternative method, we can estimate the weights by means of *informativity* [11], a measure used in machine learning algorithms to identify the most relevant attributes [21]. This measure is based on the information-theoretic measure of entropy, $? ? p_i \log_2 p_i$, where p_i is the probability of the i-th event. For our case, this method yields weights that are very similar to the ones obtained by regression: 64% and 36%.

Representation with weights is particularly interesting when we consider a model as a whole. Even though the weights provide only a rough representation of utility functions and do not display any explicit relationships between attribute values and model outcomes, they allow a quick verification of the model, and are quite appreciated by decision-makers. Table 3 shows these weights for the breast cancer model, which were estimated by both methods: regression and informativity. To simplify the interpretation, the weights are shown as indices of importance, which are determined for each attribute separately as a ratio between the actual attribute weight and the weight that would be obtained if all the attributes in the model were equally important. The index of 100 therefore means that the underlying utility functions neither lower nor raise the importance of that attribute. Similarly, the index greater than 100 denotes an attribute whose importance is above the average. Table 3 shows relatively high indices for the attributes around “Hormonal circumstances”, highlighting their important contributions to the model’s outcomes. Other important attributes include the presence of disease in the family, exposure to physical cancerogenic factors, and age at first delivery.

<Table 3>

3.2 Evaluation and analysis of options

To illustrate the use of cancer risk model, consider a woman aged 42, who has two children, regular menstruation, and increased body weight (high Quetel's index). She does not use oral contraceptives and works in the environment that increases the risk of cancer by its physical and demographic characteristics. 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 influences to the risk. Such explanation is given in Table 5 and shows that the most important factors that contribute to the increased breast cancer risk are the age, increased body weight and environmental circumstances.

<Table 4>

<Table 5>

To handle missing and non-exact data, DEX incorporates mechanisms that are based on probabilistic or fuzzy distribution of attributes' values. For instance, assume that for the patient considered above we did not have data about chemical factors and oral contraceptives. For such case, the results of the evaluation are shown in the second column of Table 4. Note the use of asterisks for the missing data, which are interpreted as a uniform probabilistic distribution of the corresponding attributes' values. Even with two missing data items, the evaluation yields the same overall risk grade as originally, while the only difference is in the less exact assessment of hormonal circumstances, which is now expressed by a probability distribution. In Table 4, this distribution is denoted as "3/0.5, 2/0.5", which means that the probabilities of grades 2 and 3 are both equal to 0.5.

Another useful feature of DEX is a *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 in what would happen if the risks from physical factors and demographic circumstances were reduced. The third column in Table 4 shows that this leads to the reduction of breast cancer risk, which then evaluates to grade 2. Similarly, we can use the model and DEX to answer other relevant questions, for example, what would happen if the woman reduced her body weight, or what risk is she going to have when in menopause.

4. Other Applications

Currently, hierarchical decision models are in one way or another employed in several ongoing projects related to health care in Slovenia. The considered problems are quite different from each other, which, we believe, provides a strong evidence for the flexibility and applicability of the DEX approach. In this section, we outline some goals and achievements of three projects related to community nursing, diabetic foot care, and radiography.

4.1 Community nursing: Assessment of basic living activities

Community nursing is a special form of health care that assures an active health and social care of individuals, families and communities that are, due to their biological features or a disease, particularly exposed to harmful effects from the environment. The evaluation of patient's health condition is the basis for the determination of nursing problems and action planning. This provides nurses with feedback, which is not only essential for their activity, but also enhances their effectiveness and the quality of their work in general. The evaluation of the appropriateness of nursing activities is based on positive alternations of basic living activities. When monitoring the client's health conditions in living activities, we encounter the problem of aggregating the evaluated indicators into an overall evaluation of the client's or patient's health condition.

The process method in nursing [12] defines fourteen basic living activities, which need to be properly assessed and recorded at every visit of the nurse. The aim of this project was to develop qualitative models for the evaluation of all these activities and to embed them into an information system for community nursing [13]. Models for all fourteen living activities together with a model for comprehensive patient's living activity evaluation have been developed. As an example, the structure for the living activity "Physical Activity" is shown in Figure 3. All the attributes use five-grade Likert scales [14], and are in accordance with the International Classification for Nursing Practice [15].

<Figure 3>

4.2 Risk assessment for diabetic foot care

With a long-term goal to reduce the number of amputations in diabetic patients, a comprehensive diabetic foot care program was in 1995 launched in the diabetic clinic of General Hospital Novo Mesto, Slovenia [16]. The patients are screened for risk factors for developing foot pathology, which include: history of foot ulceration and amputation, symptoms of diabetic neuropathy, loss of protective sensitivity, angiopathy, and foot deformities. After screening, the patients are classified into four risk groups: (1) no pathology, (2) neuropathy, i.e., loss of protective sensation, (3) absent pedal pulses, and (4) highest risk due to a combination of basic findings or positive history for amputation/ulceration.

The motivation for employing DEX in this project was twofold. The first was to automate the assessment of patients' risk in an information system that is used in the diabetic clinic. The second, and more important one, was caused by the doctors' dissatisfaction with the classification into risk group 4; this group was found extremely heterogeneous and too large, containing about 50% of all patients. While it is easy to agree that all these patients are at high risk, this classification turns out to be quite useless for therapy planning, such as tailoring specific educational program, or policy for the prescription of shoes.

<Figure 4>

A model for the assessment of patient's risk status was developed (Figure 4). It consists of three main groups of attributes: *History* (data about previous ulcers and amputations), *present status* (data on symptoms, deformities and other changes), and the results of *tests* (loss of protective sensation, absence of pulse). Decision rules were carefully designed so as to provide a useful further decomposition of risk group 4.

The model was evaluated on data of 2925 diabetic patients. The risk group 4 was split into six subgroups with different risk levels (Figure 5). The largest subgroup is a combination of neuropathy and any deformity such as hallus valgus, fat pad atrophy, hammer toe, or Charcot foot. The next three groups represent the patients with ischemic foot in combination with deformity, neuropathy, or both. The last two groups are for patients who have already experienced ulcer or amputation, respectively. These subgroups are considerably more homogeneous than the original group 4, and are thus more appropriate for the planning of further diagnostic procedures and treatment. Actually, the largest subgroup "neuropathy and deformity" is still quite large and leads to problems with shoes prescription. This is why we additionally partitioned the patients on the basis of the extent of deformities. This was done by a slight modification of the model's decision rules, which resulted in an appropriate partition of patients into three new subgroups (Figure 6).

<Figure 5> and <Figure 6> (together if possible)

4.3 Radiography: Technical analysis of chest radiogram errors

The aim of this ongoing project is to model expert knowledge about the technical quality of chest radiograms. Numerous factors cause poor quality, which makes the diagnostics more difficult and requires repeated radiography, which, as a consequence, doubles both the costs and radiation doses received by patients.

Within this project, we developed a model to assess the quality of chest radiograms. The model consists of 25 basic and 16 aggregate criteria that belong to two principal groups: (1) quality of equipment and (2) recording procedure. For each radiogram, the model aggregates the 25 basic evaluations into a judgement of whether it is necessary to repeat that radiogram or not. The reasons for and against such a decision are then assessed by means of selective explanation (see section 3.2).

In this way, the decision about the repetition of radiography is supported by a "second opinion" from the model. It has been shown in practice that such an evaluation often turns the radiography engineer away from unnecessary repeated radiography and at the same time points out possible flaws in the procedure or devices that need to be eliminated. As this is particularly important in education, where radiography engineers are trained for practical work, this model seems to have the greatest potential for radiography training and is currently being evaluated for this purpose.

5. Discovery of hierarchical decision models from data

Medicine is an environment rich both in knowledge and data. With proliferation of laboratory, clinical and hospital information systems, the data about patients are systematically collected and are available for subsequent analysis. On the other end, a variety of data mining and intelligent data analysis methods have recently been designed that allow the construction of highly predictive and interpretable models from retrospective patient's data [17,18].

The hierarchical decision models presented in this paper so far were developed "manually", i.e., through collaboration between the expert and decision analyst, who used DEX mainly as a computer-based editor and storage of models. Recently, however, a new data mining method that supports structure and utility function development from pre-classified data called HINT was developed [19,20]. Given a set of pre-classified data, e.g., retrospective patient's data with assigned outcomes, HINT can be viewed as a data mining method that induces a definition of the target concept (outcome) in terms of a hierarchy of intermediate attributes and their definitions. In this respect, HINT can be used to automatically construct hierarchical decision models from data. Furthermore, HINT can also incorporate existing domain knowledge in the form of a partially specified hierarchical decision model. For example, only the structure of model may be known and HINT may be requested to, using the available data, discover the underlying utility functions. Or alternatively, HINT may use the information about the structure with only some of the utility functions specified, thus using the data to induce the remaining utility functions.

Let us illustrate the utility of HINT on three examples. In the first example, the task was to reconstruct the breast cancer risk assessment model. The hierarchical model (as presented in Figure 2) was used to generate 20000 randomly selected examples. Each example included only the values of basic attributes and associated outcome (risk factor); the remaining aggregate attributes were excluded from the data. In our experiments, only a subset of these examples was used by HINT to induce the hierarchical model; the classification accuracy of the model was tested on the remaining examples. HINT was compared to C4.5 [21], a well-known classification tree induction program.

<Figure 7>

Learning curves for this experiment are shown in Figure 7. HINT was very successful in the reconstruction, as it managed to derive a complete model consistent with the original model using a rather small subset of examples (about 4000 examples were sufficient for the reconstruction). In this, it outscored C4.5, which performed worse in this domain. Similar successful uses of HINT in hierarchical model reconstruction are reported in [20].

For the second example, we summarize the results on hierarchical model construction from neurophysiological data originally reported in [22]. The task was to induce a model of the influence of six nerve fiber properties to the conduction of action potential. HINT induced the model from a set of 3000 examples. The structure of the model (Figure 8) was interpreted by the expert (J.A. Halter, Baylor College of Medicine, Houston, TX). He found that the discovered attributes (c_1, c_2 and c_3) constitute useful intermediate biophysical properties. The intermediate attribute c_1, for example, couples the axonal properties and the combined current source/sink capacity of the axon, which are the driving force for all propagated action potentials. Furthermore, the attribute c_2 appropriately couples the myelin sheath properties. The experiment confirmed that the interpretation of machine-induced hierarchical model need not be a difficult task, provided that a sufficient domain expertise is available.

<Figure 8>

Our third example is different from the previous two, since the hierarchical structure for the problem was already designed by the expert, and so were the functions for all but the topmost (target) attribute. The task was to construct a prognostic model for the long-term outcome after femoral neck fracture treatment with implantation of hip endoprosthesis [23]. Initial experiments with a naïve Bayesian machine learning algorithm to build a prognostic model using the data records of 112 patients (patients admitted and operated at Department of Traumatology of University Clinical Center in Ljubljana from January 1988 to December 1996) that included 28 features and an outcome yielded marginally significant models of relatively poor performance. Instead of initial 28 features, HINT employed a given hierarchical decision model to build the missing topmost utility function. These included only six intermediate attributes, and were used to construct a naïve Bayesian-based model. The final prognostic model thus combined a hand-crafted DEX-like hierarchical model to derive six abstract attributes, plus a naïve Bayesian model that mapped these six attributes to an outcome. Experimental results [23] indicate that such a schema can yield a significantly better performance than when traditional modeling based on only original attributes is used, thus stressing the potential value of domain knowledge when expressed through hierarchical decision models.

6. 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, such as DEX, allow the structuring of domain knowledge and are capable of dealing with qualitative variables and utility functions. They also provide means for model and data analysis, evaluation in the presence of missing or inaccurate values, and explanation of evaluation. All these features provide a foundation for a systematic, transparent, and justified decision-making, which is especially important for “soft” decision problems that often occur in medicine and health care. We believe that the number and diversity of real-world applications presented in this article confirm the applicability, maturity, and flexibility of the approach.

Possible weaknesses of the method are twofold. Practical experience indicates that, in comparison with traditional quantitative modeling techniques, the development of qualitative models may take more time, and may require more effort and skills from both the decision maker and decision analyst. This is because qualitative models in general need a more detailed and more refined hierarchy of attributes than their qualitative counterparts, and also require a detailed elaboration of decision rules. Another potential problem of DEX is that it currently supports only qualitative attributes and utility functions, but provides no facilities for dealing with quantitative ones. As this seems highly desirable for many practical problems, our further work will be particularly focused on an integration of qualitative and quantitative modeling techniques.

Until recently, most of the employed hierarchical decision models were developed manually. With an increased use of laboratory, clinical and hospital information systems, large volumes of retrospective patient data has become available from which prognostic and diagnostic models can be induced using machine learning and data mining techniques. Within this framework, we presented the utility of HINT, which is a data mining method that supports structure and utility function development from pre-classified patient’s data. We show that HINT can be used to discover hierarchical decision models and may perform well both in terms of classification accuracy and discovery of meaningful concept hierarchies. We strongly believe, though, that the most promising feature of HINT is to build decision models in interaction with the expert: expert may express partial knowledge about the structure, or about the utility functions, and the rest of the model is induced from the data by HINT. In such an approach, both the information from retrospective data and existing medical knowledge are combined to construct potentially useful and highly predictive medical decision models.

Acknowledgement

The authors wish to thank the oncologists Prof. Dr. Maja Primic-Žakelj, M.D., and Prof. Dr. Jurij Lindtner, M.D., senior nurse Dr. Olga Šušteršic, trauma surgeon Dragica Smrke, M.D., diabetologist Milivoj Piletic, M.D., and radiography engineer Majda Budna, B.Sc., for their initiative and collaboration in developing the hierarchical decision models presented in this article.

References

[1] Chankong, V., Haimes, Y.Y.: *Multiobjective decision making*. North-Holland, 1983.

[2] Vincke, P.: *Multicriteria decision-aid*. John Wiley & Sons, 1992.

[3] Nagel, S. (ed.): *Computer-aided decision analysis: Theory and application*. Quorum Books, 1993.

[4] A.H. Simon: *The new science of management decision*. Prentice-Hall, 1977.

[5] Bohanec, M., Rajkovic, V.: DEX: An expert system shell for decision support. *Sistemica* 1, 145–157, 1990.

[6] Urbancic, T., Kononenko, I., Križman, V. (1991): *Review of applications by Ljubljana Artificial Intelligence Laboratories*. Institut Jožef Stefan, Report DP-6218, 1991.

[7] Bohanec, M., Rajkovic, V.: Multi-attribute decision modeling: Industrial applications of DEX. *Informatica* 23, 487–491, 1999.

[8] Bohanec, M., Cestnik, B., Rajkovic, V.: Evaluation models for housing loan allocation in the context of floats. In: *Context sensitive decision support systems* (eds. Berkeley, D., Widmeyer, G.R., Brezillon, P., Rajkovic, V.), Chapman & Hall, 174–189, 1998.

[9] Primic-Žakelj, M., Evstifeeva, T., Ravnihar, B., Boyle, P.: Breast-cancer risk and oral contraceptive use in Slovenian women aged 25 to 54. *Int. J. Cancer* 62, 414–420, 1995.

[10] Rajkovic, V., Bohanec, M.: Decision support by knowledge explanation. *Environments for supporting decision processes* (eds. Sol, H.G., Vecsenyi, J.), North-Holland, 47–57, 1991.

[11] Mingers, J.: An empirical comparison of selection measures for decision-tree induction. *Machine Learning* 3, 319–342, 1989.

[12] Henderson, V.: *Basic principles of nursing care*. IOS Press, 1997.

[13] Leskovar, R., Šušteršic, O., Rajkovic, V., Bitenc, I., Zelic, I.: The development and testing of information system for community nursing. *Medical Informatics Europe 99* (eds.: P. Kokol et al.), IOS Press, 930–934, 1999.

[14] Šušteršic, O., Rajkovic, V., Kljajic, M.: An evaluation of community nursing process in the frame of the International Classification for Nursing Practice. *2nd European Telenurse Conference*, Sesimbra, 1998.

[15] Mortensen, R.A. (ed.): *The International Classification for Nursing Practice ICNP with TELENURSE introduction*. Alpha version. Copenhagen: P.J. Schmidt, Vojens, Denmark, 1996.

[16] Plaper, G., Piletic, M., Bohanec, M., Rajkovic, V., Urh, B.: Hierarchical multi-attribute models for decision support in the management of diabetic foot

syndrome. *Medical Informatics Europe 99* (eds. P. Kokol, et al.), IOS Press, 970–972, 1999.

[17] Lavrac, N., Keravnou, E., Zupan, B. (eds.): *Intelligent data analysis in medicine and pharmacology*. Kluwer, 1997.

[18] Lucas, P.J.F., Abu-Hanna, A.: Prognostic methods in medicine (editorial). *Artificial Intelligence in Medicine* 15(2), 105–119, 1999.

[19] Zupan, B., Bohanec, M., Demšar, J., Bratko, I.: Feature transformation by function decomposition. *IEEE Intelligent Systems* 13(2), 38–43, 1998.

[20] Zupan, B., Bohanec, M., Demšar, J., Bratko, I.: Learning by discovering concept hierarchies. *Artificial Intelligence* 109(1-2), 211–242, 1999.

[21] Quinlan, R.: *C4.5: Programs for machine learning*, Morgan Kaufmann Publishers, 1993.

[22] Zupan, B., Halter, J.A., Bohanec, M.: Concept Discovery by Decision Table Decomposition and its Application in Neurophysiology. In: *Intelligent data analysis in medicine and pharmacology* (Lavrac, N., Keravnou, E., Zupan, B., eds.), Kluwer, 261–277, 1997.

[23] Zupan, B., Demšar, J., Smrke, D., Božikov, K., Stankovski, V., Bratko, I., Beck, J. R.: Predicting patient's long term clinical status after hip arthroplasty using hierarchical decision modeling and data mining (submitted).

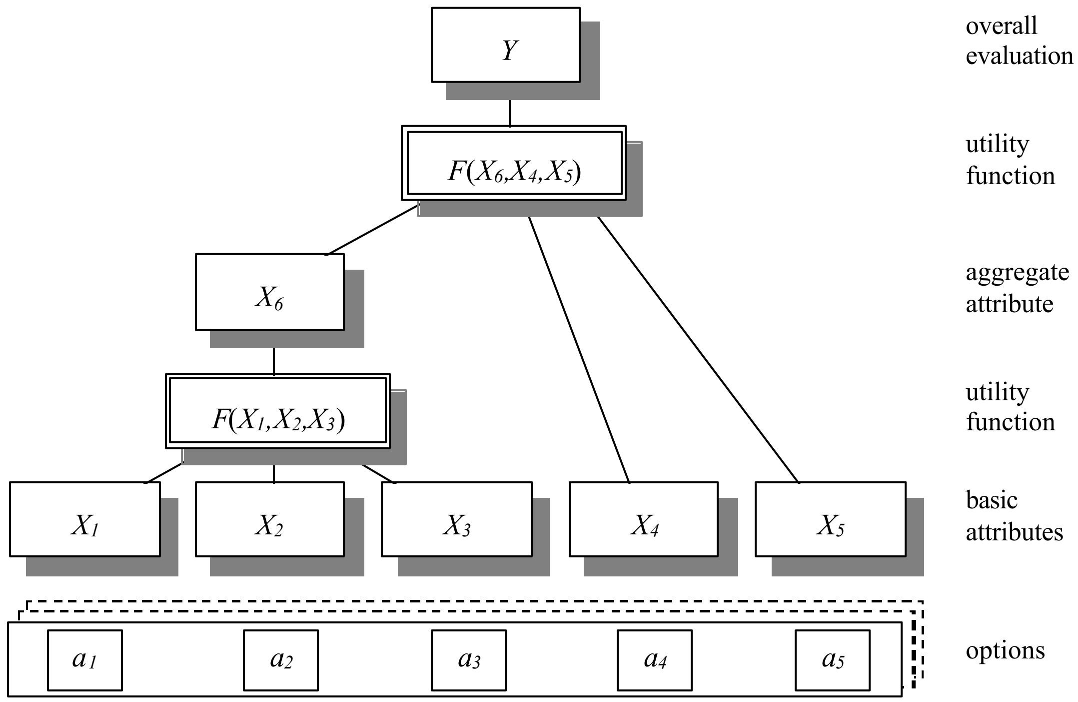

Figure 1: Components of a hierarchical decision model

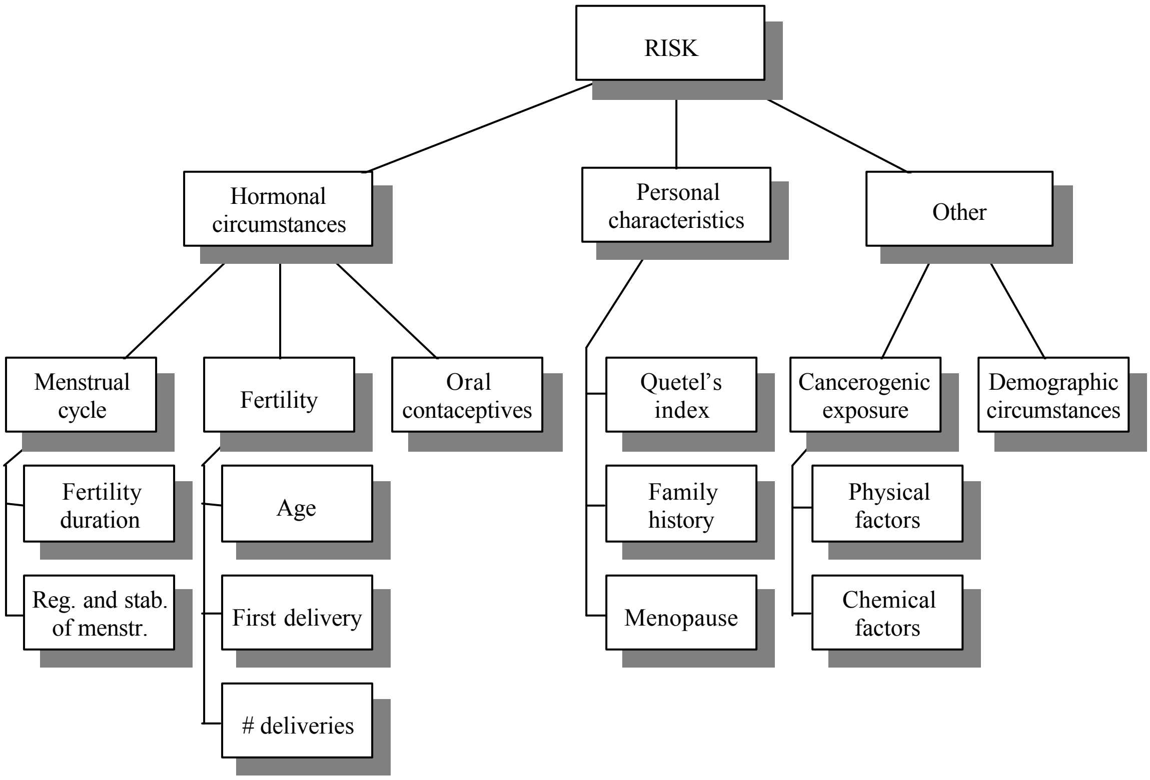

Figure 2: The structure of breast cancer risk assessment model

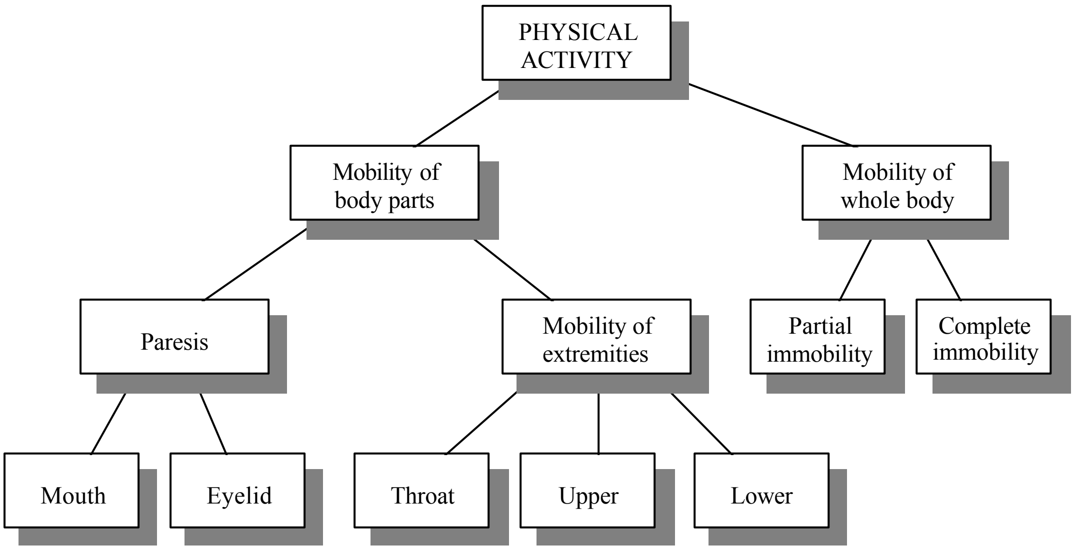

Figure 3: The structure of Community Nursing model for assessing Physical Activity

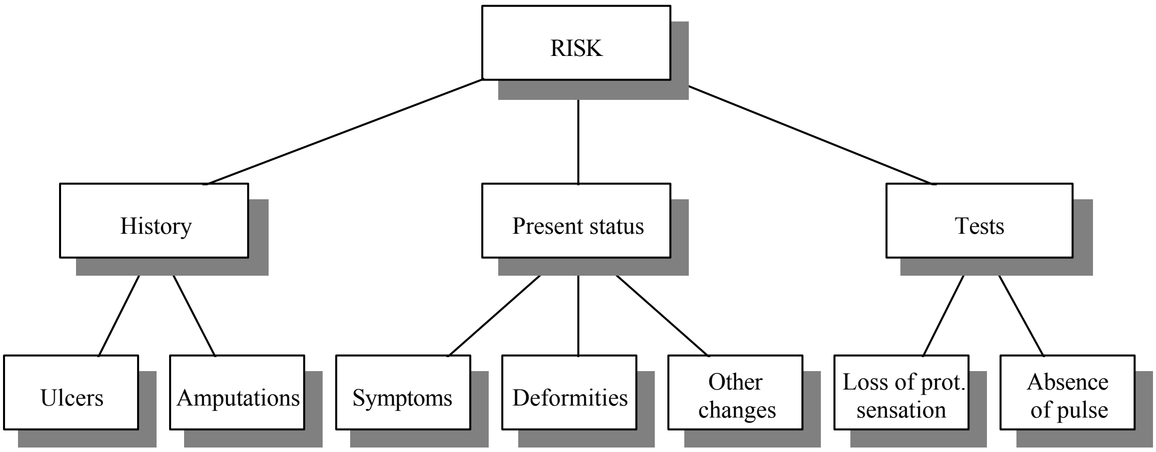

Figure 4: The structure of model for risk assessment in diabetic foot care

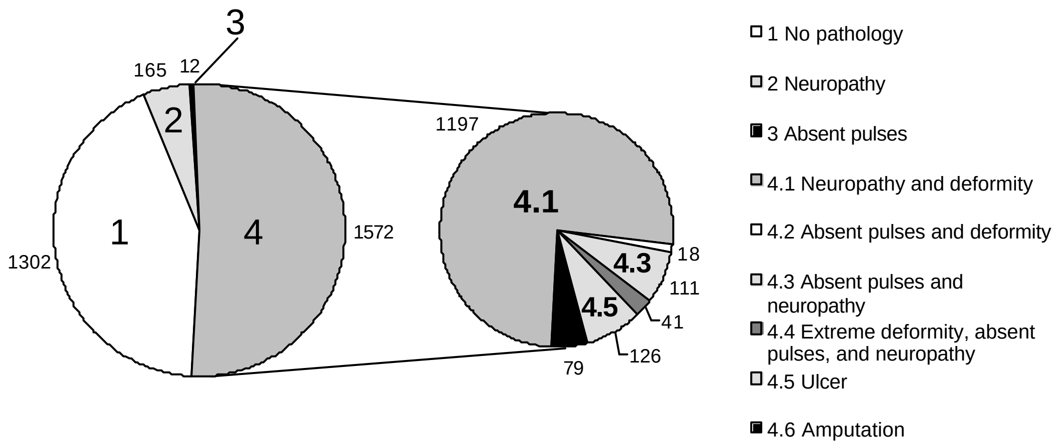

Figure 5: Partition of diabetic patients into risk groups (left) and subgroups of group 4 (right)

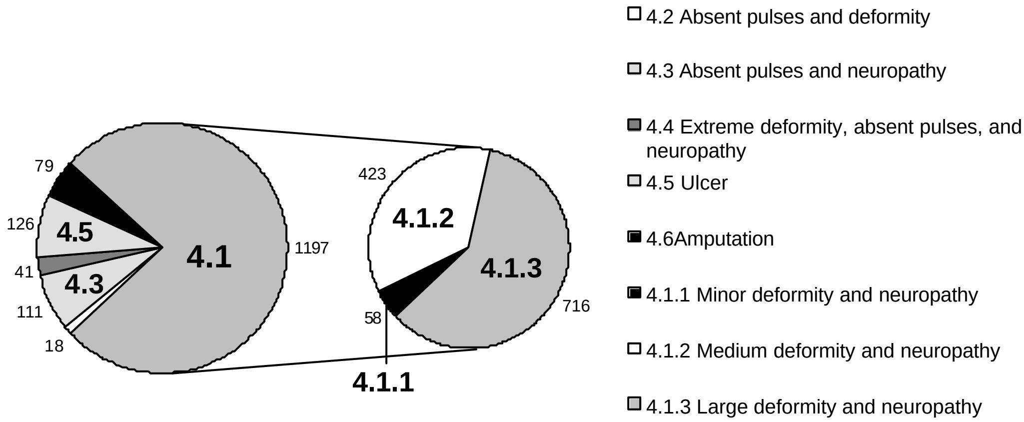

Figure 6: Additional partition of subgroup 4.1 based on the extent of deformities

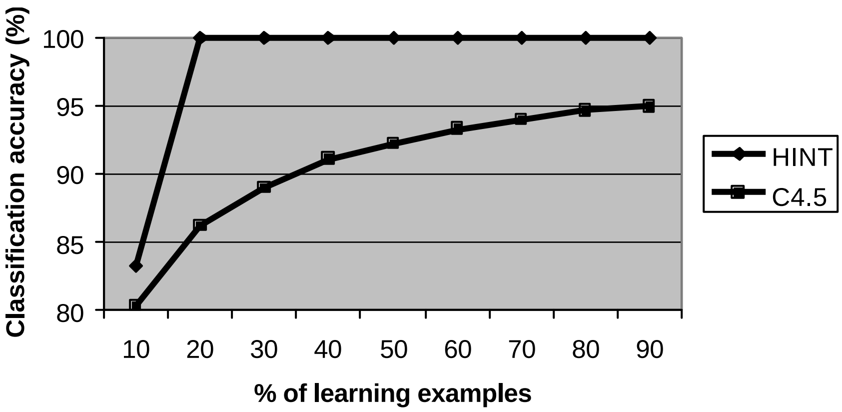

Figure 7: Learning curves for C4.5 and HINT on breast cancer risk data

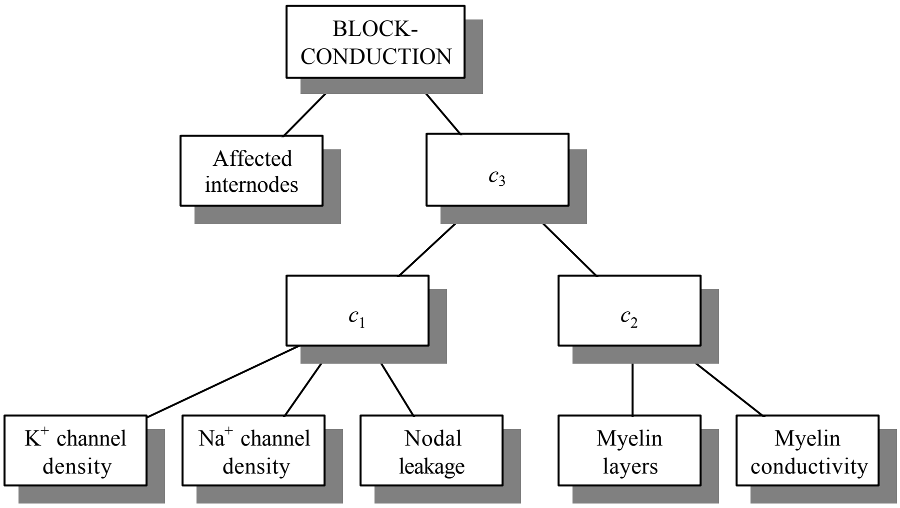

Figure 8: Attribute structure as discovered from neurophysiological data on nerve-fiber conductivity

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

	Fertility duration	Reg. /stab. of menstruation	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

Table 2: Aggregate rule as derived from Table 1

	Fertility duration	Reg. /stab. of menstruation	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 model by their index of importance, estimated by regression and informativity. The indices of most important attributes are printed in bold.

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

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/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
Demographic circumstances	high risk	high risk	*moderate risk*

Table 5: Selective explanation of evaluation

Reasons FOR high risk		Reasons AGAINST high 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
Demographic circumstances	high risk	Chemical factors	no