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A prognostic computer model to predict individual outcome in interventional cardiology

The INTERVENT Project

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It is not yet possible to predict an individual's outcome from percutaneous transluminal coronary angioplasty or alternative/adjunctive coronary interventional techniques. The purpose of the INTERVENT project is to redefine complications associated with coronary interventions, to set up a prognostic computer model to predict individual outcome and to compare the results to those of conventional statistical techniques.

2500 data items were analysed in 455 consecutive patients (mean age: 61·1 ± 8·3 years; range 33–84 years; 80·4% male, 16·7% unstable angina, 5·1%/10·1% acute/subacute myocardial infarction) undergoing coronary interventions at three university centres. In-lab/out-of-lab complication rates were 0·4%/0·9% (death), 1·8%/0·2% (abrupt vessel closure with myocardial infarction) and 5·5%/4·0% (haemodynamic complications).

Computer algorithms derived by applying techniques from artificial intelligence were able (1) to reduce the set of possible relevant risk factors from 2500 to about 40, (2) to predict individual risk with an accuracy of >95% and (3) to explain the structural relationship between outcome and risk factors. Patient data from two centres were used to construct and test the algorithm. Data from a third centre were used to evaluate the algorithm. The most important predictors were acute myocardial infarction, heart failure (NYHA class >II), unstable angina, complex lesions, high low density lipoprotein cholesterol and duration of coronary heart disease. Neither age nor gender impaired the percutaneous transluminal coronary angioplasty results in acute ischaemic syndromes; however, for stable angina, procedural risk increased with age. There was little risk from primary percutaneous transluminal coronary angioplasty in acute myocardial infarction in patients with NYHA heart failure classes I–II; however, the risk was high for patients in NYHA classes >II, either with or without additional thrombolysis. Alternative/adjunctive intervention techniques were no predictors for in-lab-, but were predictors for post-procedural complications.
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Key Words: Computer model, complications, coronary interventions, procedural outcome, PTCA, risk prediction.

Introduction

Percutaneous transluminal coronary angioplasty is regularly used to treat coronary artery stenoses. Despite extensive improvement in operator experience and balloon catheter technology, however, percutaneous transluminal coronary angioplasty still has its limitations. The primary success rate in non-occluded vessels is about 90%[1–7]. Peri- and post-procedural complications include acute coronary artery closure with evolving myocardial infarction, haemodynamic compromise, and death. Several retrospective and/or prospective univariate or multivariate analyses have revealed risk factors for the development of percutaneous transluminal coronary angioplasty-associated complications in patients with stable or unstable angina pectoris or acute myocardial infarction[2,6–26] (Table 1). However, the outcome of percutaneous transluminal coronary

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Table 1 Risk factors for PTCA- associated complications. Modified after[27]

Risk factors for death	Risk factors for acute vessel closure and myocardial infarction	Risk factors for haemodynamic compromise
Acute myocardial infarction[6]	Female sex[12]	Ejection fraction[14]
Early PTCA in AMI (day 0–1)[6]	High risk surgical status[13]	Lesion in 'last remaining artery'[14]
Age >63/65 years[6,12]	Unstable angina[10,15,18]	Angiographer's assessment[17]
Female sex[6,9,16]	Multivessel disease[8,15]	Myocardium at risk[17]
Prior CABG[12]	Number of stenoses >70%[21]	Multivessel disease[17]
Unstable angina[10]	ACC/AHA lesion type[11,20]	Pre-PTCA % stenosis[17]
Congestive heart failure[6,12]	Long stenosis[8]	Diffuse coronary artery disease[17]
Multivessel disease[9,12]	Bifurcation lesions[8]	
PTCA of proximal RCA[16]	Other stenosis in same vessel[8]	
Low ejection fraction[10]	Complex lesion morphology[15]	
Myocardium at jeopardy[9]	Pre-PTCA % stenosis[17,23]	
Abrupt vessel closure[16]	Angiographic signs of intimal rupture[18]	
	Thrombus-containing lesion[8,15,25]	
	Angulated stenosis[8,23]	
	Collaterals from target vessel[12]	
	Left coronary artery stenosis[23]	
	Increased platelet activity[22]	

AMI=acute myocardial infarction; CABG=coronary artery bypass grafting; RCA=right coronary artery; ACC/AHA=American College of Cardiology/American Heart Association.

angioplasty-associated complications is not predictable in the individual patient. The purpose of the INTERVENT project, a prospectively performed pilot evaluation was (1) to redefine the complications associated with coronary interventions, including alternative or adjunctive techniques to percutaneous transluminal coronary angioplasty, (2) to set up a prognostic computer model to predict the individual outcome after coronary interventions and (3) to compare the results with conventional statistical techniques. The computer model was based on a set of patient data items entered in a pilot phase at three university centres.

The algorithm was designed to provide a cardiologist, planning an interventional procedure for an individual patient, with a means of classifying peri- and post-procedural risk in relation to the intervention (percutaneous transluminal coronary angioplasty and/or adjunctive/alternative techniques, such as rotational atherectomy, stenting or laser angioplasty) as accurately as possible. The model should be easy to handle and provide ongoing 'self-learning' with regard to specific results and outcome characteristics for patients treated in cardiology centres performing invasive coronary interventions. Implementation of this computer model allows a cardiologist to classify a patient within 2 to 15 s, depending on the amount of data required by the program in order to reach a rapid conclusion.

Methods

Patient characteristics, data acquisition

The data of 455 consecutive patients (mean age 61·1 ± 8·3 years; range: 33–84 years; 80·4% male) (Table 2) were prospectively collected. All patients had undergone percutaneous transluminal coronary angioplasty and/or alternative/adjunctive interventional procedures (stenting with Palmaz–Schatz coronary stents, rotational atherectomy, excimer laser angioplasty) in the Departments of Cardiology of the University Hospitals of Cologne, Essen and Münster, Germany. The distribution of the various interventional techniques performed in the participating centres is summarized in Table 3. Patient data, consisting of 2500 items, were collected on computer-based case record forms. A summary of the most important clinical baseline characteristics and

Table 2 Patient age, gender distribution and unstable coronary syndromes as indication for intervention in the three different centres

	Total	Cologne	Essen	Münster
Patients (n)	455	118 (25·9%)	177 (38·9%)	160 (35·2%)
Mean age (all patients) (years)	61·1	60·2	61·8	61·0
Mean age (male/female patients) (years)	60·2/64·9	58·7/65·2	61·0/65·3	60·3/64·2
Male/female (%)	80·4/19·6	77·1/22·9	82·5/17·5	80·4/19·6
Acute myocardial infarction (%)	4·6	5·9	2·3	6·3
Unstable angina (%)	16·7	14·4	13·6	21·9

Table 3 Interventional procedures performed in all 455 patients at the three centres. Each procedure is counted separately if used in a particular stenosis either alone or as an adjunctive interventional technique (597 procedures in 455 patients)

Procedure	Total	Cologne	Essen	Münster
PTCA	473	123	186	164
Stent implantation	104	7	87	10
Rotational atherectomy	12	0	12	0
Directional coronary atherectomy	5	2	2	1
Laser angioplasty	3	0	3	0

angiographic findings in the patient group is given in Table 4. The pool of data items also contained comprehensive information on patient history, risk factor profile, pre-interventional clinical examinations, laboratory tests, X-ray, ECG, echocardiographic and angiographic findings as well as all procedural data characterizing the course and result of the coronary intervention performed. The last batch of data described the patients post-procedural in-hospital course and important in-lab/out-of-lab in-hospital complications (Table 5).

Data analysis

Death, acute vessel closure resulting in myocardial infarction and haemodynamic compromise were defined as adverse event end-points. To investigate whether an outcome risk classification, using the categories 'low risk' (=probability of experiencing at least one end-point ≤10%), 'moderate risk' (=probability of experiencing at least one end-point: 75–90%) or 'high risk' (=probability of experiencing at least one end-point: 90–95%), for adverse events could be obtained pre-procedurally, the 2500 data items from the 455 patients were analysed by machine learning[28], a method derived from techniques used in artificial intelligence[29]. The computer model was based on the set of patient data items entered in the pilot phase at the three university centres. The patient data from two centres were used as a training module in order to construct and test the algorithm. Data from the third centre were used to evaluate the algorithm prospectively. This procedure was done in a cyclic manner by interchanging the centres showing no measurable differences in results.

Machine learning is a means both of engineering rule-based systems (expert systems) from sample cases volunteered interactively, as well as a method of data analysis whereby rule-structured classifiers for predicting the classes of newly sampled cases are obtained from a training set of pre-classified cases. In the

Table 4 Clinical baseline data and angiographic stenosis characteristics of the total patient group (n=455)

Angina pectoris class (CCS)	I 14·0%	II 22·5%	III 30·7%	IV 25·0%
Heart failure class (NHYA)	I 16·0%	II 27·6%	III 19·5%	IV 8·0%
Number of vessels/ stenoses treated	single vessel, single stenosis 84·0%	single vessel, multiple stenoses 8·8%	multivessel, multiple stenoses 7·2%	
Stenosis length	<1 cm 35·4%	1–2 cm 46·6%	>2 cm 18·0%	
Stenosis eccentricity	eccentric 71·2%	concentric 28·8%		
Vessel bending	<45° 50·3%	45°–90° 35·2%	>90° 14·5%	
Vessel contour	smooth 35·0%	irregular 65·0%		
Vessel tortuosity (proximal segment)	minimal 46·8%	moderate 41·7%	severe 11·5%	
Stenosis calcification	none 41·8%	low 37·3%	moderate 20·9%	
% stenosis (pre PTCA)	<70% 12·1%	70%–79% 43·5%	80%–89% 0%	90%–99% 44·4%

Table 5 Major complication end-points in the catheterization laboratory and during the post-procedural in-hospital stay (number of patients)

	In lab	Post-procedural (in-hospital)
Death	2 (0·4%)	4 (0·9%)
Acute vessel closure/		
Myocardial infarction	8 (1·8%)	1 (0·2%)
Haemodynamic compromise	25 (5·5%)	18 (4·0%)

INTERVENT project, the machine learning technique was used to facilitate a classification learning process to analyse the data for the three risk classes mentioned above.

Classification learning is characterized by data-description language, language for expressing the classifier (rules, formulae, decision trees etc.) and the learning algorithm (inductive inference) itself (specific-to-general, general-to-specific). For any given purpose, the main issues of the would-be-classifier are accuracy, speed and comprehensibility. Accuracy means that the rule is reliable, which is usually represented by the proportion of correct classifications. With regard to this aspect, two kinds of limitation may afflict the machine learning process. On the one hand, there are machine learning problems when the set of given attributes is not sufficient to classify without error or, on the other, when the set of given attributes or samples is underspecified or inherently noisy. The speed of the classifier is also of major importance. A classifier that, for example, is 90% accurate may be preferred to one that is 95% accurate if the first is 100 times faster. In the clinical setting, sometimes prognostic classification with regard to adverse events must be obtained immediately in a session in advance. This means that the number of parameters to be entered and the calculation time have to be well balanced in order to achieve a sufficiently high accuracy (which will increase concomitantly with the number of parameters entered) without increasing data acquisition and calculation time above clinically acceptable time frames. In the present model, the accuracy goal was defined as >95%. Comprehensibility means that if a physician is to apply the classification procedure, the procedure must be easy to understand in order to avoid mistakes in data interpretation and decision-making.

Mathematical background

The construction of a classification procedure (=pattern recognition, discrimination or supervised learning) is based on a given sample of input–output pairs of an unknown class-membership function (e.g. the unknown relationship between observed attributes or features such as age, sex, stenosis morphology etc. and the grade of risk for adverse events during interventional procedures). A conjectured reconstruction of a function must be in a form of rule-based expressions (if-then-(else)-rule sets), which describes the unknown class membership. This type of data-derived classification serves two purposes: (1) to predict the response variable (here: risk of death, acute myocardial infarction, or haemodynamic complications) corresponding to future measurement vectors (age, sex, stenosis morphology, procedure performed etc.) as accurately as possible and (2) to understand the structural relationship between the response and the measured variables. For this purpose, three main historical strands of technique are evaluable: statistical (linear, logistic or quadratic discriminants), machine learning (NewID, AC2, Cal5, CN2, C4.5, ITrule, CART) and neural networks (multi-layer perception — backprop or cascade — Kohonen self organizing nets etc.). In this project we restricted ourselves to machine learning techniques. Machine learning is generally taken as encompassing automatic procedures based on logical or binary operations that learn a task from a series of examples. It aims to generate classifying expressions simple enough to be easily understood by humans ('mental fit classifier').

Computer system requirements

The computer hardware components necessary to operate the INTERVENT program consist of an 80486 or pentium-based IBM-compatible computer with at least 8 megabytes of memory. If Win 95® (Microsoft® Corporation) is used, at least 16 megabytes of memory are recommended. The hard disk should have ≥20 megabytes of free space. Additionally, a monitor and a Super-VGA graphic card (800 × 600), a mouse and a printer supported by Windows® (Microsoft® Corporation) are required. The INTERVENT software can be installed in connection with Windows 95® or Windows NT® (all: Microsoft® Corporation). It is a 32-bit application.

Results

Based on the data pool generated by entering 2500 items from the 455 patients of the pilot phase, the computer system was able to propose decision rules ('decision trees') for characterizing patients at high, moderate or low risk when undergoing coronary interventions by applying an inductive acquisition method based on the probabilistic inference technique. It could detect the inherent probabilistic patterns in the data in the form of explicit prediction rules with the associated probabilistic weight of evidence. In the patient group evaluated, high and low risk patients could be classified by only 40 parameters with a precision of >95%. These include the presence of antithrombotic therapy, coronary artery disease, angina class, stenosis morphology, hyperlipoproteinaemia, concomitant medication and other parameters. Based on these results, in the clinical setting, new cases can be classified quickly and accurately the day before the coronary intervention — or even at the cath-lab prior to the procedure — by entering into the computer software individual data for the previously identified 40 key items.

Figure 1 gives a typical example of a decision tree generated by computer as a result of the preceding data input. The proposed decision tree generated in this example classified the underlying patients' data set with an accuracy of 97%. It has to be mentioned that the composition of a certain decision tree may vary according to pre-selection and number of parameters available in the individual context. From the exemplary decision tree created (Fig. 1), it follows evidently that the most important prognostic factor for adverse events is acute myocardial infarction. The second most important factors are NYHA heart failure class and the factor unstable angina, respectively. The next branches of the decision tree are characterized by stenosis morphology and AHA/ACC stenosis classification[11] data. Following the branches of the decision tree, female sex, for example, is an additional risk factor only for the subpopulation of patients without acute myocardial infarction and without unstable angina, but with moderate or severe stenosis calcification and age $\geq$60 years, under the subconditions mentioned in the side-branch of the decision tree. When following the decision tree, again one should keep in mind that there are various more or less equivalent sets of prognostic factors, all of which can characterize the adverse events with similar precision in a different decision tree. Another equivalent set of prognostic factors determining the risk of adverse events with the same accuracy comprehends, for example, the factors acute myocardial infarction, NYHA heart failure class, unstable angina, number of stenoses present, activated partial thromboplastin time, vessel contour, vessel bending, AHA/ACC stenosis class, stenosis morphology, stenosis length, stenosis calcification, stenosis (%) pre-intervention, age, sex, low density lipoprotein cholesterol and duration of coronary heart disease history.

The practicability and relevance of this quick process of patient–risk classification by using computer-generated decision trees can be easily demonstrated by the example of three imaginary patients (patients A, B, C) using the algorithm of the decision tree imaged in Fig. 1: Patient A is male, 62 years old. At the start time of the percutaneous transluminal coronary angioplasty procedure, he is in the state of unstable angina pectoris. In the given situation, his procedure-related risk of experiencing abrupt vessel closure resulting in myocardial infarction, haemodynamic compromise or death can be classified with an accuracy of 97% by using additional information about the number of stenoses present/ vessels stenosed, stenosis classification (AHA/ACC), stenosis morphology, accessibility of the stenosed segment and NYHA heart failure class. Patient B is also male, 59 years old, but is in the situation of acute myocardial infarction. He can be classified with the same accuracy, as at high risk of experiencing at least one of the three end-points, if he is in NYHA heart failure classes III–IV, and as at low risk if he is in classes I–II regardless of other conditioning factors. Patient C is of the same age and gender, but in stable angina pectoris. Under these circumstances, he will be classified as low risk if there is no stenosis calcification. If there is moderate stenosis calcification, then age, gender, angina class (CCS) and presence or absence of subacute myocardial infarction influence the classification. With moderate to severe vessel calcification, the low density lipoprotein cholesterol serum level, stenosis length and duration of coronary artery disease ('known since') have to be entered to complete the classification process.

From the structural relationship obtained by the computerized data analyses, we can conclude a whole set of statements, some of which are presented in the following. The most important prognostic factors for the three major adverse events selected (abrupt vessel closure resulting in myocardial infarction, death or haemodynamic compromise) related to coronary interventions are: acute myocardial infarction or unstable angina pectoris as an indication for the need for intervention, heart failure (NYHA class >II), number of stenoses present (multiple, multivessel as compared to single stenosis), stenosis morphology (high rated in the modified AHA/ACC classification, stenosis length >2 cm, calcification, difficult access to proximal segment), patient age (>60 years for women and >75 years for men) and gender, low-density lipoprotein cholesterol serum level (in connection with moderate to severe stenosis calcification) and the duration of history of coronary heart disease (known for how long?). Age or gender do not diminish the results of percutaneous transluminal coronary angioplasty in selected patients with acute myocardial infarction or unstable angina. On the other hand, age carries an adverse effect in patients with neither acute myocardial infarction nor unstable angina. If, in addition, this subgroup has a moderate calcification of the coronary stenosis treated, then female gender is an additional risk predictor. Primary percutaneous transluminal coronary angioplasty in acute myocardial infarction is beneficial in patients in NYHA heart failure classes I–II. Patients with acute myocardial infarction in NYHA heart failure classes III–IV, however, have a very poor risk–benefit ratio associated with percutaneous transluminal coronary angioplasty, either as an adjuvant to thrombolytic therapy or instead of thrombolysis. Alternative interventional techniques, such as excimer laser angioplasty, high speed or directional rotational atherectomy and stenting (Palmaz–Schatz) are not predictors of procedural complications. Single predictors such as acute myocardial infarction or unstable angina pectoris cannot completely describe the individual outcome.

The computer model chosen is able to classify an underlying patient's data set with an accuracy of more than 95% and up to 97% according to low, moderate or high (post)procedural risk. Based on the data items of the pilot phase, the system can be operated by entering 40 parameters obtained routinely in clinical patient

- acute myocardial infarction = yes:
  - heart failure—NYHA = 0: low risk
  - heart failure—NYHA = 1: low risk
  - heart failure—NYHA = 2: low risk
  - heart failure—NYHA = 3: high risk
  - heart failure—NYHA = 4: high risk
- acute myocardial infarction = no:
  - unstable angina = yes:
    - stenosis = multiple: good risk
    - stenosis = multivessel: high risk
    - stenosis = single:
      - stenosis classification—AHA/ACC = A: low risk
      - stenosis classification—AHA/ACC = B_1: low risk
      - stenosis classification—AHA/ACC = C_2: high risk
      - stenosis classification—AHA/ACC = B_2 or C_1:
        - proximal segment = good access: low risk
        - proximal segment = severe tortuosity: high risk
        - proximal segment = moderate tortuosity:
          - heart failure—NYHA = 0: low risk
          - heart failure—NYHA = 1: low risk
          - heart failure—NYHA = 2 or 3 or 4:
            - stenosis morphology = eccentric: high risk
            - stenosis morphology = concentric: low risk
  - unstable angina = no:
    - calcification = none: low risk
    - calcification = moderate:
      - age ≤ 75:
        - sex = m: low risk
        - sex = f:
          - age ≤ 60: low risk
          - age > 60:
            - angina pectoris—CCS = 0: low risk
            - angina pectoris—CCS = 1 or 2:
              - subacute myocardial infarction = yes: high risk
              - subacute myocardial infarction = no: low risk
            - angina pectoris—CCS = 3 or 4:
              - stenosis = multiple: high risk
              - stenosis = multivessel: high risk
              - stenosis = single: good risk
      - age > 75:
        - proximal segment = good access: low risk
        - : proximal segment = moderate tortuosity: good risk
        - : proximal segment = severe tortuosity: high risk
    - calcification = moderate-to-severe:
      - LDL < = 213: low risk
      - LDL > 213:
        - stenosis length = 1–2 cm: low risk
        - stenosis length = < 1 cm: low risk
        - stenosis length = > 2 cm:
          - CHD known since < = 1: low risk
          - CHD known since > 1: high risk

Figure 1 **Computer-generated 'decision tree' which is able to classify patients undergoing PTCA and/or adjunctive alternative procedures into 'high', 'moderate' or 'low' risk of experiencing (one of) the adverse endpoints (death, acute vessel occlusion with consecutive myocardial infarction or haemodynamic compromise). Accuracy of prediction: 97%.**

evaluation to achieve this accuracy. The data input time for a new patient does not exceed 3–5 min. The use of the computer software developed to generate the decision trees was judged as adequate and comfortable for the clinical situation by all clinical investigators participating in the project.

Discussion

The aim of the INTERVENT project was to develop a risk classification system able to determine the individual risk of a particular patient. The system was based on a patient undergoing coronary intervention and took into account their individual history and clinical conditions and their likelihood of experiencing the adverse end-points death, myocardial infarction subsequent to acute vessel closure or haemodynamic compromise, respectively. The topic of risk prediction has been addressed in a variety of previous studies[2,6–26] that characterized demographic, clinical or angiographic risk factors (Table 1) as predictive for major complications during or after percutaneous transluminal coronary angioplasty or adjunctive/alternative interventional procedures. The risk conditions identified as decisive in the decision trees generated in the INTERVENT project (Fig. 1) are in concordance with parameters identified in previous studies. Acute myocardial infarction[6], unstable angina[10,15,18], heart failure[6,12], multivessel disease[9], ACC/AHA lesion type[11,20] or complex lesions[15], age[6,12], female sex[6,9,12,16], vessel tortuosity[8,23] and stenosis length[11,20] have all been identified as risk factors in large studies and very often in multicentre trials. In the INTERVENT project these parameters were already identified as decisive, based on the datapool of only 455 patients. The INTERVENT program also revealed the structural interactions of risk factors for coronary interventions, which have been documented by previous large data collections, such as the 'California statewide experience' in 1989[6] based on a population of 24 883 patients. The authors reported that multiple regression showed only female sex to be a predictor of mortality in the absence of acute myocardial infarction. The same conclusion can be derived from the INTERVENT decision tree in Fig. 1. DeFeyter and colleagues[15] found an additive effect of multivessel disease, unstable angina and complex lesion morphology as risk factors for acute vessel occlusion during percutaneous transluminal coronary angioplasty. In complete concordance, when following the INTERVENT decision tree at the branch with positive unstable angina, the next sub-branches leading to high risk for adverse end-points are characterized by multivessel disease and high ACC/AHA stenosis class. For patients with unstable angina and single vessel disease, the 'Guidelines for PTCA of the ACC/AHA Task Force'[11] attribute those patients to indication class III (=conditions for which there is general agreement that coronary angioplasty is not ordinarily indicated) who have type C lesions. A similar result is obtained when following the INTERVENT decision tree. There is, however, a risk differentiation between C_1-lesions (high risk only with severe vessel tortuosity or moderate tortuosity, heart failure and stenosis eccentricity) and C_2 lesions (in this patient subgroup: high risk in any case).

In conclusion, the INTERVENT program is able to offer decision algorithms that can predict high, moderate or low risk with an accuracy of 97%. This is sufficient to serve as a basis for clinical decision-making. The algorithm, despite its high accuracy, is based on a relatively small data input. The system is able to learn actively from previous data input and to consider comprehensively experiences in all preceding cases of the total patient group. This new approach, using techniques derived from artificial intelligence for risk factor classification in interventional cardiology, as far as the authors' are aware, has never been used before. As planned, this type of data-derived classification is able to predict individual risk on the basis of a set of parameters and to understand the structural relationship between the response and the measured variables. Decision trees are applicable to each patient and congruent with the result–experience in all preceding cases in the total group of 455 patients. A novel result–experience in a particular patient will immediately be integrated into the system. If a single result differs from the existing decision tree, the decision tree will immediately be modified integrating the 'new' information so that it is available for application in the next patient. Thus, prediction accuracy should be increased.

The advantage of the machine learning technique is its ability to analyse high numbers of parameters and experiences simultaneously and multidimensionally within a relatively short time frame, which cannot be provided by a single operator. When creating a decision tree, the computer system does not refer to established knowledge and decision structures, such as literature data etc. It creates a new independent decision algorithm based on the single experiences gained by the data input of preceding patients. With this technique, a bias produced by selective or non-objective result interpretation, that may mislead an operator, can be avoided. Nevertheless, the system takes account of the specific theory-to-outcome relationship in a given cardiological centre, as the results obtained in the individual cases are the basis for generation and modification of new decision trees. This process can also encompass the results of a particular intervention technique used by an individual operator, in comparison to other intervention techniques used by other operators at the same centre under comparable preconditions.

The INTERVENT hardware and software components can easily be integrated into the computer facilities of a modern interventional cardiological catheterization laboratory. With regard to future computer networks being established in an increasing number of hospitals, data input facilities could be provided not only at the catheterization laboratory but also at other places in the cardiology department (ECG or echocardiography lab, outpatient area, cardiac care unit etc.). They can also be established in other departments of the same hospital (radiology department, outpatient area, central laboratory etc.) or even at other hospitals. Thus, all relevant data could be entered into the system immediately after being generated or reported.

The INTERVENT program may be used for risk classification in the routine process of clinical decision-making in the catheterization conference the day before the intervention, or even immediately before or during the session in an interventional cardiological centre. Predicting high, moderate or low risk in a given patient allows the selection in advance of high-volume operators for presumably risky cases. It also enables the need for different surgical stand-by categories to be calculated in hospitals with non-permanent cardiothoracic surgical back-up, or to plan haemodynamic support procedures in high-risk percutaneous transluminal coronary angioplasty.

Future versions of the program may be used not only for prospective risk prediction but also as a learning program for interventional cardiologists at the beginning of their training. For this purpose, the program may be complemented by graphically augmented schemes, tables and figures appropriately visualizing, different interventional options in a given situation, or outcome statistics derived from previous interventions of a similar type. Quality assurance programs and statistics could be integrated, as well as other organizational program components, such as storage management or accountancy. Each operator could obtain an individual statistic summary of his or her procedural results, complications or material use per defined intervention.

With regard to research topics, the system is open to address an almost unlimited number of important problems in clinical interventional cardiology. This could be the prediction of restenosis after coronary interventions, the risk of reocclusion after stenting, thrombolysis in acute myocardial infarction, or the value of alternative techniques in certain coronary lesion types. These topics may be subject to consecutive study designs.

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