Issue
No 11

Hannover Re's Perspectives
Current Topics of
International Life Insurance

Ralf Lohse

Fuzzy Logic in Life Underwriting as illustrated by the cardiovascular risk assessment of Diabetes mellitus type II

Precision is not Truth

Henri Matisse, 1947

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Contents

1. Why Fuzzy Logic?

The expert seeking to evaluate a risk is confronted with a complex task. The available documentation indicates various influencing factors for the risk that is to be assessed. In the area of medical underwriting such factors are the anomalies of the applicant and the specific values attributable to these anomalies. The values describe the severity of the anomalies.

The dilemma posed by risk evaluation is that the values of the risk factors – i.e. the severity of the anomalies – cannot normally be described in simple "black and white" terms with "yes/no" or "present/not present" answers. Instead, the reality is one of grey shades and indeed, in theory, in medical underwriting – as in other areas of risk assessment – an anomaly can have an infinite number of values. Where multiple influencing factors are involved the situation becomes even more complex because the additional factors can also have a multitude of values. An expert seeking to comprehensively describe the evaluation of a certain risk with multiple influencing factors and several values would very quickly reach the limit of his capacity. This is evident from the following combinatorial example: a risk with three influencing factors, each of which has three values, has 27 possible states. If the number of factors and the number of values rise to five, the number of states increases to 3,125.

Expert knowledge is composed of the evaluations of the observed influencing factors and the rules for the combination of these evaluations. The expert formulates and describes his decision in a linguistic form in order to render it comprehensible to a layperson. Possibly, he will demonstrate only certain key values of the influencing factors.

If the aforementioned decision-making process is to be systematised, rendered transparent and perhaps reproduced in the form of electronic data processing, it must be mathematically formulated. Contrary to traditional logic with the values "true or false", Fuzzy Logic works with continuously logical grades between true and false.

The task now, therefore, is to transform the linguistic formulations made by the expert regarding the evaluation of values of the influencing factors and their combinations into Fuzzy Logic. Major advantages of Fuzzy Logic are, on the one hand, that the decisions of the expert are reproducible, and, on other hand, that the expert needs only evaluate essential states of the risk situation, leaving the Fuzzy Logic system to reach decisions for all possible values.

2. Historical development of Fuzzy Logic

Fuzzy Set Theory was developed in 1965 by Lotfi A. Zadeh, Professor of Electrical Engineering at the University of California, Berkeley, USA. The leap from mathematical formulation to product innovation and business success occurred in the 1980s in Japan with Fuzzy Control in the field of technical control systems. Fuzzy Control is one major practical sphere of application of Fuzzy Logic for the mathematical representation of systems behaviour. Fuzzy Control provides special variables and ways of combining these variables that make possible the mathematical rendering of expert statements regarding the structure and operations of systems. In the area of high-quality consumer goods, for example, Fuzzy technologies are used in washing machines, vacuum cleaners, cameras and videocassette recorders. In the industrial sector Fuzzy Control is particularly important in the control of manufacturing processes and transport systems. In the Japanese city of Sendai, for example, the underground railway is driven with the aid of Fuzzy Controllers. Trains accelerate and brake so smoothly that most passengers no longer need to "hold tight". The Fuzzy Logic system in this paper is built on the mathematical basis of Fuzzy Control.

Since the 1990s Fuzzy Logic has also been put to successful use in the area of financial decision systems. The American Express Company uses Fuzzy Logic when making credit decisions. In comparison with previously used systems, the duration of the decision process is shorter, the acceptance rate is higher and the loan loss ratio is lower.

The areas of application are so diverse and numerous because decision-making processes often follow similar lines. A multitude of input factors is first assessed, the evaluations are combined and an operable output factor is then determined.

3. Groups of diseases in life insurance medicine

In life insurance medicine the mortality of applicants within the period of insurance is assessed on the basis of present risk factors or diseases. An analysis of the cases at a major German insurance company revealed that more than 80% of medical anomalies are attributable to the following seven diseases.

Table 1: Disease/anomaly

Hypertension	18%
Lipometabolic disorders	15%
Alcohol-related disorders	13%
Overweight	12%
Diabetes mellitus	10%
Heart diseaes	10%
Asthma	6%
Other	16%

see also: P.-J., et al (1997), p. 82.

The group of cardiovascular diseases and their pre-stages (hypertension, lipometabolic disorders, overweight, diabetes mellitus) constitutes the principal disease group of medical anomalies with a share of 65%. A Fuzzy Logic system for the assessment of cardiovascular risks associated with type II diabetics is therefore of considerable significance for insurers' medical underwriting practice.

Cardiovascular mortality as a consequence of heart attack or stroke, for example, is assessed on the basis of heart diseases in the applicant's own medical history or family history as well as on the basis of anomalies in the established risk factors for cardiovascular disease, such as hypertension, lipometabolic disorders, overweight or diabetes mellitus.

This paper describes a Fuzzy expert system with reference to the medical underwriting of the cardiovascular risk given the existence of non-insulin-dependent diabetes mellitus (diabetes mellitus type II). For reasons of simplification, the Fuzzy system will be presented for diabetes type II only, not for insulin-dependent diabetes mellitus (diabetes type I). Unlike hypertension or overweight, where risk assessment of the medical values is possible directly, the risk assessment of diabetes is a complex problem with a multitude of medical risk factors. Due to this complexity of this risk assessment, systematic evaluation of diabetes using a Fuzzy expert system is highly advantageous.

4. Basics of Fuzzy Logic

4.1 From the linguistic to the numerical level

Experts frequently verbalise medical knowledge in the form of linguistic statements.

- On the one hand, experts use terms to evaluate the influencing factors. For example, they refer to a blood sugar value below 70 mg/dl as "low", up to 110 mg/dl as "normal", up to 200 mg/dl as "elevated" and values beyond that as "high".
- On the other hand, experts describe the combination of evaluated factors in the form of linguistic rules.

Example of an expert rule:

If the blood sugar value is elevated and the HBA_{1c} value is normal, then the cardiovascular risk is normal.

Fuzzy Set Theory makes it possible to adequately transform linguistic evaluations of influencing factors – with their linguistic variables and combinations thereof – in the form of so-called rule sets into a numerical model.[1]

4.2 System structure (development phase)

4.2.1 Hierarchical structure of the model

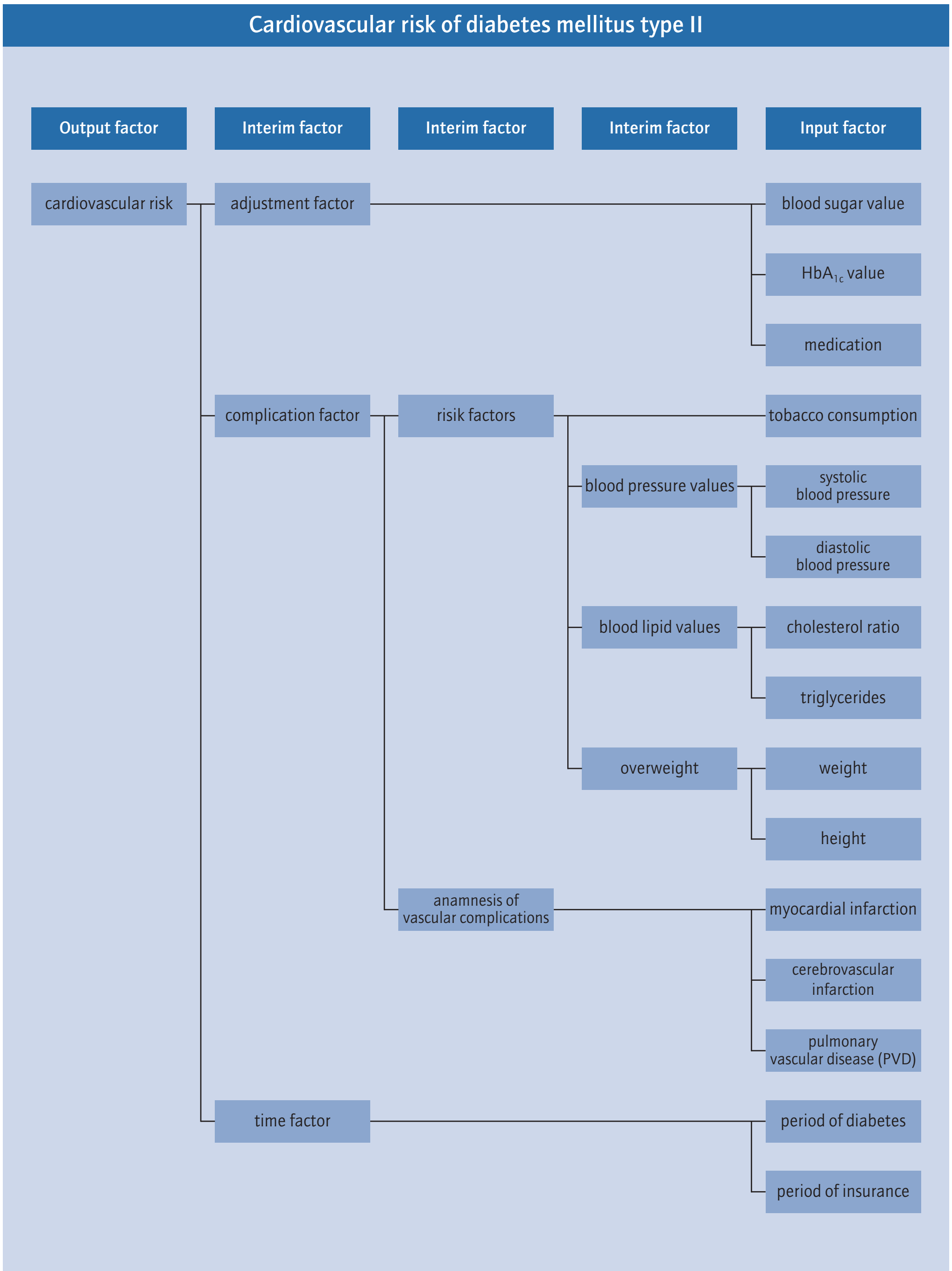
The risk factors are combined to produce the output factor of the risk assessment over several levels. The multi-level capability of the model structure has the advantage that for each combination on a certain level of the model only a limited number of factors have to be combined. The overall model can thus be divided into partial models. During system development the medical expert is able to construct these partial models independently and define the combination rules of the partial models on a higher level of the model.

The following figure 1 shows the model structure of the risk assessment of cardiovascular diseases, such as myocardial infarction (heart attack), cerebrovascular infarction (stroke), aneurysm (pathological vasodilation) and pulmonary vascular disease (PVD), given the presence of diabetes mellitus. The output factor of the cardiovascular risk for diabetics is composed of the interim factors "adjustment factor, complication factor and time factor". The complication factor is subdivided into "risk factors and vascular complications". The lowest level of the model has 15 input factors.[2] There are no factors previous to the input factors on the lowest level, which are determined directly by the values of the applicant.

The output factor and the interim factors are calculated in each case from the evaluated factors of the previous model level. The input factors "blood sugar value, glycosylated haemoglobin A_{1c} value (HbA_{1c} value) and medication", for example, are determined by the applicant's information, and the "adjustment factor" – as an interim factor – is calculated on the basis of the model evaluation of these previous factors. Subsequently, on the next level of the model, the interim factors "adjustment factor, complication factor and time factor" are combined to produce the output factor "cardiovascular risk".

[1] Clear introductions to Fuzzy Logic are provided by Bothe, H.-H. (1993), pp. 41–51 and Horgby, P.-J. (1999), pp. 543–559.
[2] See also: Horgby, P.-J., et al. (1997), pp. 79–104.

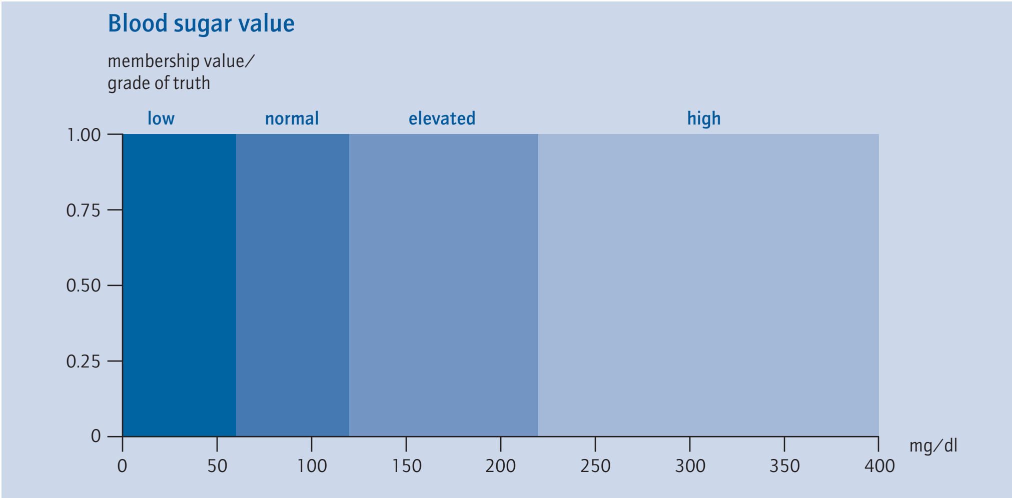
Figure 1: Model structure



4.2.2 Linguistic variable

In the classical form of medical rating the expert assigns his linguistic evaluations of the risk factors to certain values ranges. Blood sugar values, for example, can be assessed as low, normal, elevated or high. For certain intervals of blood sugar values these linguistic terms are numerically assigned the truth values of 1 for true or 0 for false. This situation is illustrated in figure 2.

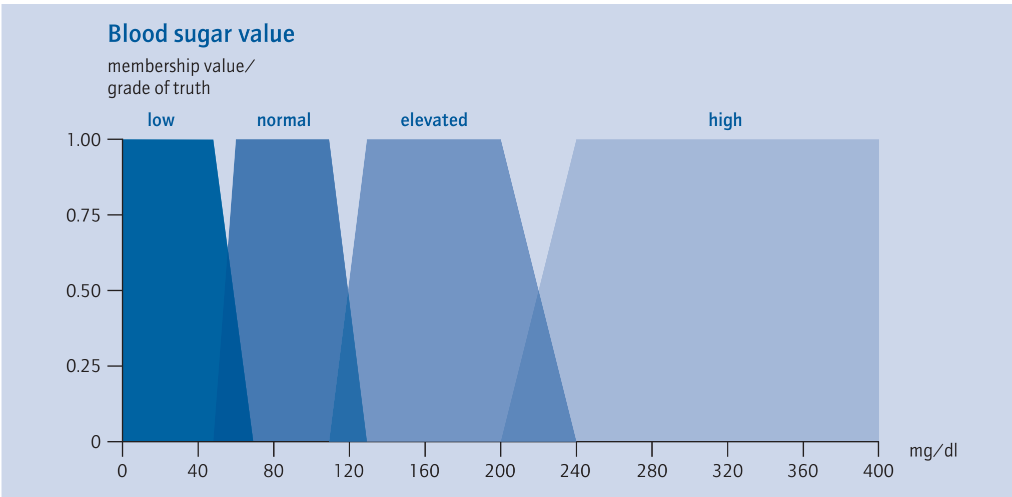
Figure 2: Variable in classical logic



This gives rise to the problem that in the marginal areas of the intervals small changes in the numerical values of risk factors can lead to inappropriately large changes in evaluations. For example, if the limit between normal and elevated blood sugar values is 120 mg/dl in the conventional classification model, a blood sugar value of 119 mg/dl will be assessed as normal and a blood sugar value of 121 mg/dl as elevated.

It would therefore be more sensible if the linguistic terms "low" and "normal", "normal" and "elevated" and "elevated" and "high" did not transition directly into one another. The expert can determine which ranges of blood sugar values should be assessed exclusively as low, normal, elevated or high. These ranges are assigned the (numerical) truth grade of 1. Between these unambiguous terms – for example, between "low" and "normal" – there is a gradual transition. While the grades of truth for the term "low" decrease from 1 to 0, the grades of truth for the term "normal" increase from 0 to 1. This form of representation – applied to blood sugar values – is shown in figure 3.

Figure 3: Linguistic Fuzzy variable: Blood sugar value



In this sense Fuzzy Logic extends the value range of the grades of truth. Logical statements can thus be gradually (partially) true or false. The variable becomes a Fuzzy variable. With Fuzzy variables, small changes in the numerical values of risk factors produce commensurately small changes in the evaluations.

Figure 4 specifies the logical statements for the term "normal blood sugar value", which is illustrated graphically in figure 3. The statements "true and false" then correspond to the grades of truth 0 or 1.

Figure 4: Statements about "normal" blood sugar values

Value		Statement	Grade of truth
up to	50 mg/dl	false	0
from	70 to 110 mg/dl	true	1
from	130 mg/dl	false	0

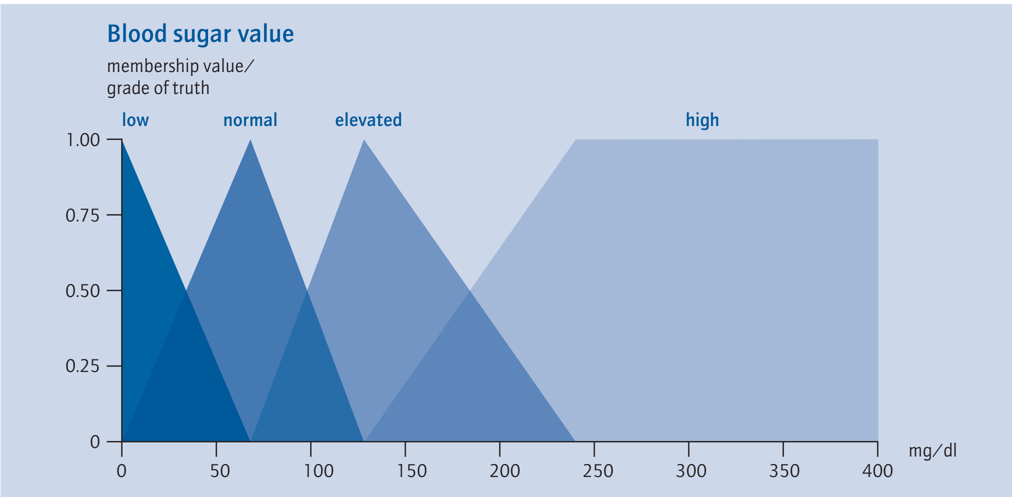
For blood sugar values from 50 mg/dl to 70 mg/dl (from 110 mg/dl to 130 mg/dl) the grade of truth increases (decreases) from 0 to 1 (from 1 to 0). The expert assesses all values from 70 mg/dl to 110 mg/dl as "normal" blood sugar values and the grade of truth is 1.

When defining the membership functions (of the grade of truth) the expert should bear in mind the plausibility rule that for all numerical values of the linguistic variables the sum of the membership values with respect to the linguistic terms amounts to 1. Otherwise the numerical values would have undefined portions of grades of truth with respect to the terms. For example, if a blood sugar value of 120 mg/dl has a grade of truth of 0.50 with respect to "normal" and 0.25 with respect to "elevated" blood sugar, the remaining grade of truth relative to 1 in the amount of 0.25 would not be defined.

This plausibility rule is geometrically fulfilled if – as shown in figure 3 – the increasing and decreasing straight lines for the grades of truth between two adjacent terms are symmetrical.

There are situations where the expert assigns the terms low, normal, elevated and high to only a single blood sugar value each. These values are given the grade of truth 1 and between them there are transitions between 0 and 1 and vice versa as explained above. This situation for the linguistic variable "blood sugar value" is illustrated in figure 5.

Figure 5: Fuzzy variable with single values of total membership



The smaller the intervals of numerical values with total membership with respect to one of the terms, the larger the intervals of gradual membership and hence the better the application of the idea of Fuzzy Logic, namely that a numerical value of a variable is assigned gradually to multiple evaluations.

4.2.3 Rule set

The evaluated risk factors are combined on the basis of linguistically formulated expert rules. If the medical expert defines rules for the combinations of the evaluations of the blood sugar value and HbA1c value, for example, he has to establish rules for all combinations of the terms of evaluation of the variables. If the blood sugar value and the HbA1c value have 4 terms of evaluation "low, normal, elevated and high", the rule set of the combinations consists of 16 single rules.

The hierarchical model structure with the combination of a limited number of risk factors per model level has two advantages. On the one hand, the number of rules of a rule set is limited, meaning that the expert is able to verify the consistency of the rule decisions among one another. If, for example, 4 influencing factors in the model each needed to be combined with 4 terms of evaluation, 256 rules would be required. Yet the medical expert is hardly able to simultaneously verify the consistency of several hundred rules. On the other hand, the individual rules are less complex when a limited number of risk factors are combined. The more variables are combined per rule, the more difficult the assessment for the expert, who has to consider simultaneously the interactive influences of all variables.

The expert rules consist of condition parts on the input side and a conclusion part on the output side. The expert assigns a linguistic conclusion of the rule to the condition parts of the rule. In combining the blood sugar value and HbA_{1c} value, for example, the expert generally has to assess the risk of a normal HbA_{1c} value and a high blood sugar value. The expert assesses this combination of condition parts of the rule as a bad adjustment factor on the conclusion side of the rule.

The rule can be expressed formally as follows:

	Parts of the rule
If the HbA_{1c} value is **normal**	Condition part 1
and the blood sugar value is **high**,	Condition part 2
then the adjustment factor is **bad**.	Conclusion part

Figure 6 below shows the rule set for all combinations of the evaluations of the blood sugar value and the HBA1c value. The specimen rule from the last paragraph is highlighted in dark blue.

Figure 6: Rule set

Condition part 1	Condition part 2	Conclusion part
HbA$_{1c}$ value	Blood sugar value	Adjustment factor
Term	**Term**	**Term**
low	low	good
low	normal	good
low	elevated	normal
low	high	normal
normal	low	normal
normal	normal	normal
normal	elevated	normal
normal	high	bad
elevated	low	bad
elevated	normal	bad
elevated	elevated	bad
elevated	high	very bad
high	low	bad
high	normal	bad
high	elevated	very bad
high	high	very bad

Since the numerical values of the variables in the Fuzzy system can be allocated to multiple terms of evaluation (see figure 3), when combining the evaluations in a rule set it is also possible for multiple rules to have positive membership values and hence be incorporated into the calculations.

In a conventional classification model the numerical values of a risk factor will be assigned only to one term of the risk factor. Consequently, only a single rule of a rule set is relevant to the combination of the evaluations. The problem of potentially large changes in evaluations as a consequence of a small change in the numerical value of a risk factor persists on the level of combinations. In a classification model a minimal change in the value of a single risk factor can cause the total risk to be assigned to another evaluation class.

4.3 System process (application phase)

4.3.1 Introduction

The essential modules of the Fuzzy system are the linguistic variable with the assignment of the numerical level of the risk factors to the linguistic evaluation level of the expert as well as the rule set of the combination of the evaluated risk factors. In this section the method of calculation in the Fuzzy system will be demonstrated using a concrete specimen case. The specimen case is the assessment of the adjustment factor for the diabetes risk on the basis of a blood sugar value of 110 mg/dl and a HBA_{1c} value of 6.4%.

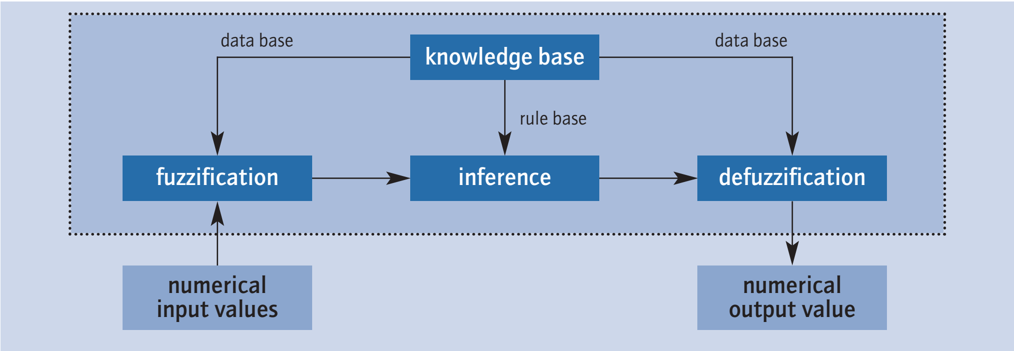
The method of calculation consists of the three main components

- fuzzification,
- inference and
- defuzzification.

The first step in the calculation is fuzzification, where the numerical input values are evaluated. The evaluation is performed by assigning the numerical values to the linguistic terms of the variable (for example, low, normal, high). The second step is inference, where the evaluated input values are combined in rule sets. Where the Fuzzy system has a hierarchical model structure, combination can be performed multiple times. The third step of the calculation is defuzzification, where a numerically operable output value is derived from the evaluation on the highest level of the model structure. In our specimen case, the output factor is the adjustment factor with the unit of the percentage increase in the risk of cardiovascular disease.

The knowledge base of the expert for the development of the Fuzzy system is divided into the data base and the rule base. The data base comprises the expert knowledge for the definition of membership functions of linguistic variables. The input factors and the output factor are the linguistic variables of the model. The rule base contains the expert knowledge for the evaluation of the combination rules. The knowledge base of the Fuzzy Logic system is constituted on the basis of published analyses of epidemiological or clinical studies and the expert's medical experience.

Figure 7: Method of calculation



4.3.2 Fuzzification

The first step in the calculation method of the Fuzzy system is to determine the membership values of the numerical input values with respect to the linguistic terms of the risk factors. The following figures 8 and 9 show the membership functions and map in graphical form the determination of the membership values of the numerical input values with respect to the evaluation terms of the expert. The HbA_{1c}-value of 6.4% has a membership of 0.25 with respect to the term "normal HbA_{1c} value" and 0.75 with respect to the term "elevated HBA_{1c} value". The blood sugar value of 110 mg/dl has a membership of 0.75 with respect to the term "normal blood sugar value" and 0.25 with respect to the term "elevated blood sugar value".

Figure 8:
Step 1 of the calculation: Fuzzification (variable 1)

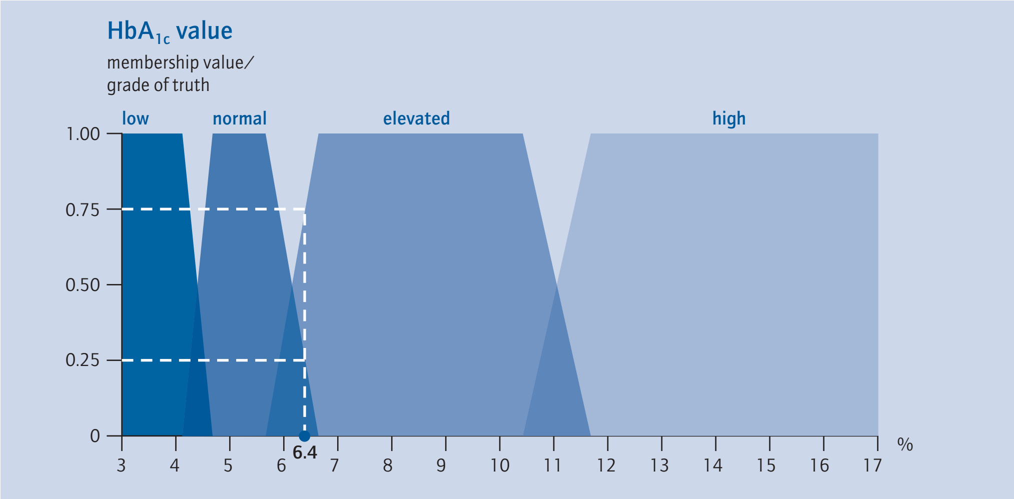
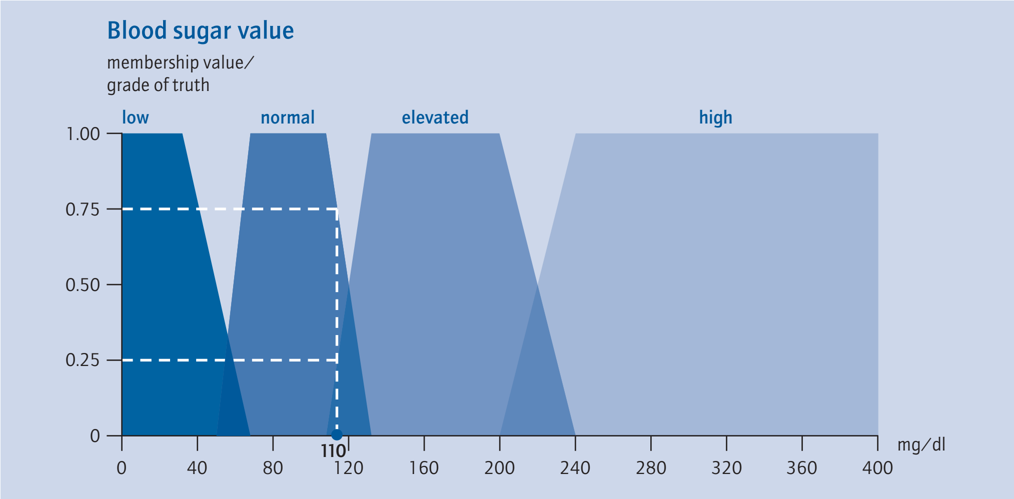


Figure 9:
Step 1 of the calculation: Fuzzification (variable 2)



4.3.3 Inference

The next step of the calculation in the Fuzzy system is to combine the evaluations of the input factors. The terms of the risk factors with positive grades of truth are combined using the expert rules. Figure 10 contains the rule set of all combinations of terms of the risk factors, i.e. the totality of all rules. In the conclusion parts of the rules the expert assesses all combinations of the condition parts of the rules.

Figure 10:
Step 2 of the calculation: Inference

Rule set

condition part 1		condition part 2		conclusion part	
HbA_{1c} value		blood sugar value		adjustment factor	
term	**msv**	**term**	**msv**	**term**	**msv**
low		low		good	
low		normal		good	
low		elevated		normal	
low		high		normal	
normal		low		normal	
normal	0.25	normal	0.75	normal	0.25
normal	0.25	elevated	0.25	normal	0.25
normal		high		bad	
elevated		low		bad	
elevated	0.75	normal	0.75	bad	0.75
elevated	0.75	elevated	0.25	bad	0.25
elevated		high		very bad	
high		low		bad	
high		normal		bad	
high		elevated		very bad	
high		high		very bad	

minimum msv of terms of condition parts

maximum msv of terms of conclusion parts

membership values (msv) of the terms of the output factor

adjustment factor	
term	**msv**
good	0.00
normal	0.25
bad	0.75
very bad	0.00

The numerical values of the input factors have positive grades of truth with respect to the terms "normal and elevated". The rule set of this step of the calculation in the specimen case includes four rules (highlighted in colour in figure 10) which contain combinations of these terms in the condition parts of the rules. These four rules are relevant to the combination of the evaluations of the risk factors.

The combination is often performed using the minimum-maximum method. The first step of this method is to calculate for each rule the membership value of the conclusion part as a minimum membership value (msv) of the condition parts. The minimum operator for combining the condition parts of a rule is appropriate in order that the membership value of the conclusion part equals the lowest membership of the condition parts. By analogy, a chain is only as strong as its weakest link. The membership values of the condition parts of the rule "if the HbA_{1c} value is elevated and the blood sugar value is elevated, then the adjustment factor is bad" are

0.25 and 0.75. The membership value of the conclusion part of this rule is the minimum of 0.25.

The second step of the minimum-maximum method is to calculate the maximum value of the conclusion parts given several rules with equal terms and positive membership values of the conclusion parts. The maximum operator is appropriate for combining several rules with equal conclusion terms in order that in each case the rule with the highest membership value is used in the model calculation. By analogy, the strongest rule prevails in the competition of rules. In the rule set, two rules with the conclusion term "bad adjustment factor" have positive membership values of 0.25 and 0.75. The membership level of the conclusion part corresponds to the maximum of these values of 0.75.

Overall, the combination of the numerical input values produces a membership value of 0.25 with respect to a normal adjustment factor and a membership value of 0.75 with respect to a bad adjustment factor.

4.3.4 Defuzzification

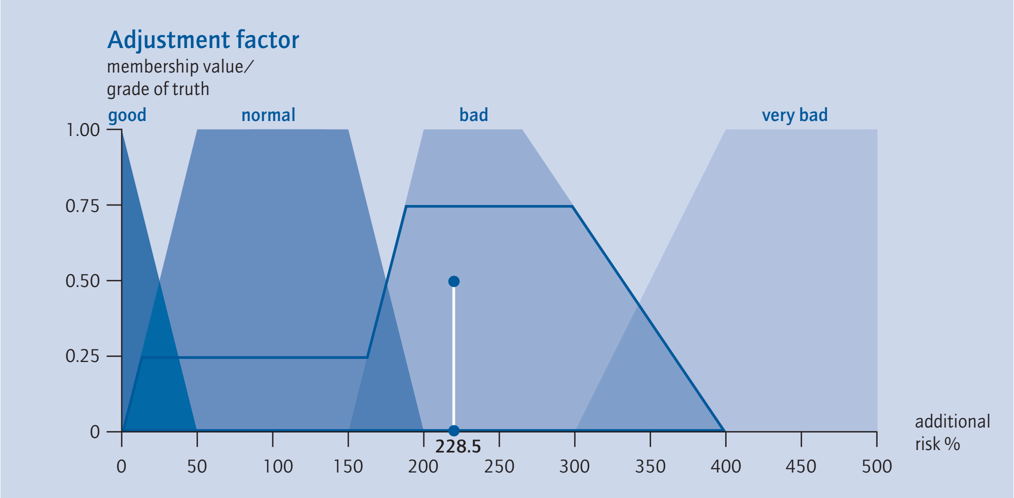
The fuzzification of the input factors and the combination of the evaluated variables result in an evaluation of the output factor of the Fuzzy system. Several or all linguistic terms of the output factor can have positive membership values. The highest membership value with respect to each of the terms is determined for the numerical values of the output factor. The graph for these maximum membership values represents the Fuzzy output set.

The medical risk assessment requires a numerically exact value. The third calculation step of the defuzzification in the Fuzzy system is therefore the translation of the Fuzzy output set to a single numerical output value.

The most frequently applied method of calculation in defuzzification is the "centre of area" method, where the balance point of the area below the graph is computed as the representative value for the total area. The exact numerical output value is the abscissa value of this balance point.

Figure 11 shows the Fuzzy output set of the adjustment factor, the centre of area of the area below the graph and the numerical output value of 228.5%.

Figure 11:
Step 3 of the calculation: Defuzzification



5. Reasons for using Fuzzy Logic in medical underwriting

The essential advantage of Fuzzy Logic lies in the mathematical formulation of expert knowledge. The linguistic statements of an expert can be transferred to a numerical model and mapped in a computer-aided application system.

Fuzzy Logic can improve the underwriting decision process in several areas. A Fuzzy system assesses the risk within a structured process. A model comprised of risk factors and their combinations is developed for the assessment of the total risk. The structure of the model for the assessment of blood pressure, for example, is composed of the lower blood pressure value and the upper blood pressure value as well as their combination to produce the output factor "blood pressure". The expert evaluates the risk factors and their combination rules. In the blood pressure example the expert evaluates the single blood pressure values and the rules for the combination of the single assessments.

Objective computer-aided risk assessment is independent of the subjective influences of personal underwriting. The system decisions are traceable for verification purposes and reproducible for the subsequent comparison of estimated and observed results as actual risk experiences become known. The decision process of the Fuzzy system can be adapted to the underwriting philosophy of the individual company. Thus, in the blood pressure example, the evaluations can be defined more restrictively with an eye to risk policy or more liberally with an eye to marketing policy.

The structured system development, in which the medical expert defines the structure, evaluates the risk factors and specifies the rules for combining them, safeguards the quality of the system. The expert is not required to model every conceivable decision. The system development, with its graphical and tabular support, concentrates on modelling the critical values of the risk factors and the essential combination rules. System development too can thus be carried out efficiently with an eye to cost and quality considerations. This advantage of defining the expert's essential system components becomes all the more pronounced, the greater the number of risk factors and the number of combination levels. In assessing the upper and lower blood pressure value, for example, the expert does not need to evaluate all defined values, but must merely specify the value ranges where the blood pressure is categorised as "normal, elevated and high". With respect to the combination of the assessments of the upper and lower blood pressure values, it is not necessary to evaluate all combinations of numerical values, but only the combinations of the linguistic terms "normal, elevated and high". In the field of medical underwriting, with a multitude of risk factors, numerical scales and combination levels, an assessment system can thus be constructed with considerably greater efficiency by applying Fuzzy Logic – or indeed it may not otherwise be possible.

6. Further insurance-related areas of application for Fuzzy Logic

Further areas of insurance medicine where Fuzzy Logic can be applied are the risk assessment of cardiovascular diseases (in non-diabetics) and asthma disorders. The model of risk factors for the medical risk assessment of cardiovascular diseases has already been established. The risk of cardiovascular disease is assessed on the basis of blood pressure values, various metabolic factors as well as tobacco and alcohol consumption. Fuzzy Logic lends itself particularly well to the structured combination of a multitude of risk factors associated with a medical disease.

The relevant risk factors for the risk assessment of asthma are the frequency of asthma attacks, the pulmonary values, the types and number of medications as well as the frequency of asthma-related hospitalisations.

Further potential insurance-related applications of Fuzzy Logic[3] come to mind in connection with the development of the general contractual relationship between insured and insurer. In chronological order, Fuzzy Logic can be used in assessing the chances of successfully concluding a contract, the risk of cancellation and the risk of insurance fraud in the event of a claim.

An insurance company's field service is faced with the question of how likely it is that contracts in other lines of business will be concluded with existing insureds. Company factors (state of the market, position of the company), product factors (product quality, price) and personal factors (biometric/socio-economic factors) are the risk factors of a Fuzzy system in this context. With the aid of a Fuzzy system the field service can perform a portfolio selection in order to identify insureds with whom additional contracts can be successfully concluded with a certain degree of probability.

The preventive avoidance of cancellation is a key problem facing insurance companies. A conversation with the client held prior to the latter's decision to cancel a contract increases the likelihood of contract continuity. The risk factors associated with the risk of cancellation are client factors (economic situation, need for insurance), company factors (shortcomings when the contract was concluded or during claim settlement, poaching by banks/other insurers) and contract factors (duration of the contractual relationship). With the aid of a Fuzzy system it is possible to identify clients who may potentially cancel and take timely measures to safeguard the portfolio.

A further insurance-related area of application for Fuzzy Logic is in assessing the risk of insurance fraud in the event of a claim. Insurance fraud may rest in the merits of the claim or in the amount of the claim. Insurance companies already investigate claims for fraud by computer assisted programmes. The risk factors for insurance fraud are inconsistent statements by the insured (witnesses, loss assessors, state of the damaged object), invoices (authenticity, correctness), personal factors (socio-economic/behavioural), contract conditions (policy period to date, legitimacy of exclusion clauses) and claims data (amount of reported claim, claims that were not settled in the past). The Fuzzy system is able to estimate the probability of insurance fraud for most simpler claims. The claims adjuster can use the fraud assessments as an indicator and is able to concentrate on the more complex cases with closer fraud investigation.

The areas of application described above clearly show that in many areas of insurance – from underwriting and the assessment of the cancellation risk to the investigation of fraud in the event of a claim – Fuzzy Logic can provide users with a computer-assisted decision basis.

[3] Published examples of the insurance applications of Fuzzy Logic can be found in Lemaire (1990), pp. 33–56, Cummins and Derrig (1993), pp. 429–465, Ostaszweski (1993), Derrig and Ostaszewski (1995), pp. 447–482, Young (1996), pp. 461–484 and Horgby (1998), pp. 63–82.

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Published in November 2004