# Personalized arterovenous fistula management through utility maximization with Influence Diagram

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**Abstract**

In this paper we propose an early stage decision support system for personalized arteriovenous fistula (AVF) management. The goal of the model is to identify an optimal strategy to recognize the onset of a stenosis and intervene to prevent the failure of the AVF. We used an Influence Diagram (ID) that combines a risk model, clinical tests, angioplasty and searches a series of policies that optimizes the cost of treatment.

**Keywords**

Chronic Kidney Disease, Arteriovenous Fistula, Influence Diagram.

## 1. Introduction

Chronic Kidney Disease (CKD) is a common pathology and the number of cases is increasing all over the world. CKD includes a variety of conditions characterized by a degrading of the main kidneys functions: blood filtering, body hydration homeostasis, hormones production, etc. Over a certain level of disease severity, the patient needs a Renal Replacement Therapy (RRT) or an organ transplantation. Hemodialysis is the most common RRT and it consists of an extracorporeal blood filtration realized by a machine. The blood of the patient is withdrawn (and returned) through the Vascular Access (VA). There are different types of VA, AVF is considered one of the most effective.

In this paper we present a preliminary version of an ID for personalized AVF management in CKD patients. One of the main risks of failure for an AVF is the formation of a stenosis. The main goal of our model is to find a personalized sequence of actions to monitor the health status of the AVF and promptly intervene in case of stenosis.

The rest of the paper is organized as follows. In Section 2 we describe what is an AVF and what is an ID. In Section 3 we propose an ID for personalized AVF management built in collaboration with domain experts. We then summarize our conclusions and discuss future extensions of the model in Section 4.



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# 2. Background

## 2.1. Arteriovenous Fistula

Accordingly to [1] an AVF is a vascular access commonly used during the hemodialysis. An AVF is created through surgery connecting a vein and an artery. The creation of a well-functioning AVF is a delicate task and require several weeks to be ready for use.

One of the complications related to AVF is the stenosis. A stenosis is a reduction of the vascular lumen that determines a decrease of the blood flow and increases the chances of AVF failure. Early detection of a stenosis facilitates correction through angioplasty which increases the survival rate of the AVF. In order to identify a stenosis several methods have been developed [2]. In this paper we will consider: Physical Examination (PE), Access blood flow (Qa) and Angiography. We also use a risk model [3] developed by Fresenius Medical Care based on XGBoost that exploits data recorded in routine clinical practice such as: biochemical parameters, vital signs, dialysis treatment parameters, AVF-related parameters. The goal of this model is to evaluate the risk of failure within three months.

## 2.2. Bayesian Networks and Influence Diagrams

Bayesian Networks (BNs) are probabilistic network models [4] capable of representing probabilistic knowledge. A BN is composed of a qualitative element and a quantitative one. The qualitative element is a Directed Acyclic Graph (DAG) encoding a set of conditional dependences and independences among a set of random variables. The quantitative element describes the relationships among random variables with probability theory [5]. Formally a BN is defined as follows: $\mathcal{BN} = (\mathcal{X}, \mathcal{G}, \mathcal{P})$. Where $\mathcal{X}$ is the set of random variables, $\mathcal{G} = (V, E)$ is a DAG representing conditional independences among variables in $\mathcal{X}$ and $\mathcal{P}$ is a set of conditional probability distributions.

The construction of a BN requires to learn both the qualitative component $\mathcal{G}$ and the quantitative component $\mathcal{P}$. The learning phase can be carried out using data, expert knowledge or a mixed strategy. The latter approach can be effectively applied in healthcare where the domain expert knowledge can be integrated with data [6].

BNs can be used as the basis for performing inference and analysis of the domain. Decision options and utilities associated with these option can be integrated into a BN: the resulting model is ID. ID is an effective model for representation and analysis of decision-making under uncertainty. Similarly to Bayesian networks an ID is formally described as follows: $\mathcal{ID} = (\mathcal{X}, \mathcal{G}, \mathcal{P}, \mathcal{U})$. Where $\mathcal{X}$ is the set of random variables and decision variables, $\mathcal{G}$ is a DAG, $\mathcal{P}$ is a set of conditional probability distributions and $\mathcal{U}$ is a set of utility functions. The DAG $\mathcal{G} = (V, E)$, contains nodes $V$ representing random variables, decision variables and utility functions.

# 3. Model

Recognizing a stenosis as early as possible, increases the probability of an effective intervention in order to reestablish the patency and prolong the AVF life. For this reason, different diagnostic

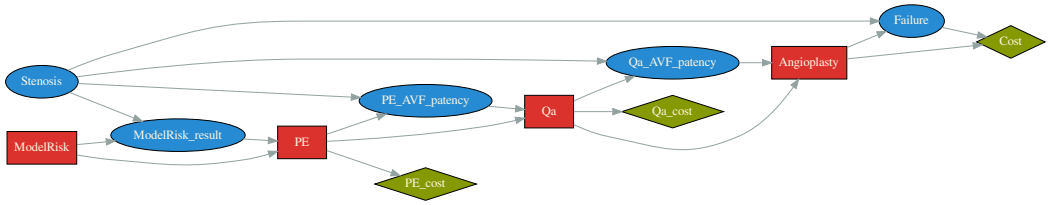


**Figure 1:** AVF model - Red squares are decision variables. Blue ellipses are random variables. Green diamonds are utility functions.

techniques have been developed, including PE, Qa, angiography and risk models. Our goal is to develop an ID and combine all the detection techniques in one tool capable of defining a set of optimal policies for the stenosis identification.

### 3.1. Structure identification

The structure identification of an ID is a critical task. In fact, if the structure doesn't represent the underling process, the model is not able to find an effective policy. For this reason we decided to involve into the structure identification process a domain expert. We introduced some simplifications to maintain the model governable and interpretable: **1.** The model imposes an order in the decision-making sequence, **2.** The model uses only a subset of the possible tests for stenosis identification. **3.** The model is based only on the current state of the patient. We depicted the resulting model in Figure 1 using the three types of nodes made available from the ID model: **Decision variables**: *ModelRisk*, *PE*, *Qa*, *Angioplasty*. **Random variables**: *Stenosis*: binary variable representing the presence or absence of the stenosis. *ModelRisk_result*: variable representing the result of the model if we decided to use the ModelRisk. Otherwise, it is set to none. *PE_AVF_patency*: variable representing the result of the PE if it has been performed. Otherwise, it is set to none. *Qa_AVF_patency*: variable representing the result of the Qa if it has been performed. Otherwise, it is set to none. *Failure*: binary variable representing the failure of the AVF. **Cost Function**: *PE_cost*: costs related to the physical examination. *Qa_cost*: costs related to the Qa test. *Cost*: combined costs of angiography, angioplasty, failure of the AVF.

The predictive variables used for the ModelRisk could influence our a priori knowledge on the effectiveness of Qa and PE tests. However, we preferred to exclude these variables from the decision model as we have no data to estimate their influence on the probability distribution of the tests. For this reason we decided not to insert the predictive variables of the ModelRisk in our influence diagram.

### 3.2. Parameters learning

For the parameters learning task we combined expert knowledge and medical literature ([3], [7], [8]). The sensitivity and specificity of the risk model, PE and Qa have been used to fill the conditional probability distribution of ModelRisk_result, PE_AVF_patency and Qa_AVF_patency respectively (Table 1).

| | *ModelRisk_result* | | | | *PE_AVF_patency* | | *Qa_AVF_patency* | |
|---|---|---|---|---|---|---|---|---|
| Stenosis | *Low* | *Middle* | *High* | *VeryHigh* | *Yes* | *No* | *Yes* | *No* |
| *Yes* | 0.11 | 0.32 | 0.53 | 0.04 | 0.75 | 0.25 | 0.88 | 0.12 |
| *No* | 0.47 | 0.39 | 0.13 | 0.01 | 0.20 | 0.80 | 0.19 | 0.81 |

**Table 1**
Probability distribution of ModelRisk_result, PE_AVF_patency, Qa_AVF_patency given Stenosis

| *Stenosis* | |
|---|---|
| *Yes* | *No* |
| 0.07 | 0.93 |

| | | *Failure* | |
|---|---|---|---|
| *Angioplasty* | Stenosis | *Yes* | *No* |
| Yes | *Yes* | 0.05 | 0.95 |
| | *No* | 0.1 | 0.9 |
| No | *Yes* | 0.8 | 0.2 |
| | *No* | 0.0001 | 0.9999 |

**Table 2**
Probability distribution of Failure given Stenosis and Angioplasty

| *PE_cost* | |
|---|---|
| *Yes* | *No* |
| -10 | 0 |

| *Failure* | *Angioplasty* | *Cost* |
|---|---|---|
| *Yes* | Yes | -564 |
| | No | -1933 |
| *No* | Yes | -343 |
| | No | 0 |

| *Qa_cost* | |
|---|---|
| *Yes* | *No* |
| -25 | 0 |

**Table 3**
Utility functions of Physical Examination, Qa test, Angioplasty and AVF failure

The probability distribution of the Stenosis node and the Failure node (Table 2) have been retrieved from the literature .

The costs of the tests and the angioplasty can vary a lot among the different clinics. We decided to use plausible values suggested by a domain expert (Table 3). However, these values intended to be used only for the evaluation of the model.

### 3.3. Policies

The main goal of our model is to generate a set of policies to improve diagnostic effectiveness through the minimization of the overall cost function. It should be noted that the cost function can incorporate some measures about patient health outcomes and quality of life index.

We used the pyAgrum tool [9] to evaluate the ID and discover the best policies (Table 4). The outcome of our analysis has highlighted some interesting results. The *ModelRisk* result has a strong impact on the other decisions. If the patient has a *ModelRisk_result* equal to Low no further tests will be performed. As the risk level rises the model is more inclined to suggest angioplasty even if *PE* and *Qa* get discordant results.

### 3.4. Sensitivity analysis

The elicitation of utilities and probabilities is a delicate task. During the development of our ID we have encountered particular difficulties in specifying the costs of the treatments. Since the

| *ModelRisk* | *ModelRisk_result* | *PE* | *PE_AVF_patency* | *Qa* | *Qa_AVF_patency* | *Angioplasty* |
|---|---|---|---|---|---|---|
| Yes | Low | No | ND | No | ND | No |
| Yes | Middle | Yes | Yes | Yes | Yes | Yes |
| Yes | Middle | Yes | Yes | Yes | No | No |
| Yes | Middle | Yes | No | No | ND | No |
| Yes | High | Yes | Yes | No | ND | Yes |
| Yes | High | Yes | No | No | ND | No |
| Yes | VeryHigh | Yes | Yes | No | ND | Yes |
| Yes | VeryHigh | Yes | No | Yes | Yes | Yes |
| Yes | VeryHigh | Yes | No | Yes | No | No |

**Table 4**
Set of optimal policies identified by the ID.

| *Parameter* | *Min* | *Current* | *Max* |
|---|---|---|---|
| $PE\_cost \vert PE = Yes$ | -26 | -10 | 0 |
| $Qa\_cost \vert Qa = Yes$ | -49 | -25 | 0 |
| $Cost \vert Angioplasty = Yes, Failure = Yes$ | -3623 | -564 | 860 |
| $Cost \vert Angioplasty = No, Failure = Yes$ | -3845 | -1903 | -1384 |
| $Cost \vert Angioplasty = Yes, Failure = No$ | -588 | -343 | -192 |

**Table 5**
Sensitivity analysis results

cost of a treatment and its availability can widely change among different clinics we decided to conduct a one-way sensitivity analysis [10]. This study allow us to define an interval in which the cost of a single treatment can change without changing the set of optimal policies.

The results reported in Table 5 show that the intervals in which the parameters can vary without affecting the optimal policies are quite large. Furthermore, the current values of the *Qa_cost*, *PE_cost* and *Cost* are centered with respect to these intervals.

## 4. Discussion

In this exploratory paper we introduced an ID for the early detection of stenosis in patients with an AVF. The decision support system combines a Model Risk with two clinical tests (PE and Qa) to quantify the risk of stenosis and evaluate the possibility of proceeding with angioplasty. The model is in an early stage, and it has many simplifications. First the strong order among the decision variables is not realistic especially for PE and Qa. Furthermore, the model doesn't take into account any measure specifically designed to evaluate the health and the quality of life of the patient or the long therm effects of the angioplasty; we simply minimize the cost of the decision sequence. Despite this the model seems to suggest a reasonable policy. In the future we would like to address these limits and expand the model by introducing new tests. After a comparison with domain experts we realized that another simplification of the model is the possibility of carrying out each test only once. In clinical practice tests are often repeated before submitting the patient to angioplasty.

In conclusion, we are aware of the large limitations of such a simple model. However, we are convinced that this paper can be a starting point for the development of a collaboration with doctors and nurses that could make the model a valid tool for personalized AVF management.

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