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Research Paper

Smartphone-based first responder alerting systems: proof of the advantages of applying Bayesian network approaches

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ABSTRACT:*The aim of this paper is to demonstrate the high advantages for the primary care of patients with out-of-hospital cardiac arrest (OHCA) by the additional use of smartphone-based first responder alerting systems (sbFRAS). For this purpose, typical processes in the alarming and initiation of the first aid chain in the actual emergency medical system (EMS) are compared with the systems expanded with sbFRAS. The comparison is based on a quantitative risk assessment using a Bayesian network approach (BN). It is shown that the sbFRAS represent an additional layer of protection and, with only a small additional effort in the control center, can not only improve the primary care, but also the overall physiological outcome of the patient. This work can be seen as a first attempt to estimate the degree of the prognostic advantage with BN for numerous but typical emergency locations and chains of events using uncertain data. For this purpose, available literature data from various studies and expert surveys were used to estimate an order of magnitude for the benefit of sbFRAS. However, the consideration of financial issues related to the introduction of these systems is not the subject of this work.*

KEYWORDS:*smartphone-based first-responder alerting,quantitative risk assessment,Bayesian networks*

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I. INTRODUCTION

In the event of an out-of-hospital cardiac arrest, the time factor plays an important role because with every minute without cardiopulmonary resuscitation (CPR) initiated, the patient's probability of survival drops by 10 percent[1–3]. Due to the low ischemic tolerance of the brain, irreversible brain damage and dieback of brain cells start as early as 3-5 minutes [3,4]. In Germany, the EMS is regulated by the individual federal states. Depending on state-specific legal requirements, it must not take more than 10, 12 or 15 minutes, from acceptance of the emergency call to the arrival of the first rescue team at the emergency location, which is known as the response time. This is a planning quantity which is not based on medical requirements [2]. However, it was found that it has a significant influence on the survival rate [5]. A time period of 5 minutes would be sensible in terms of emergency medicine, but cannot be achieved by just increasing the EMS due to financial reasons [1,2]. It can thus be seen that the response time is a compromise between emergency medical requirements and economic feasibility [3]. This raises the question of the possibility of bridging the period of time that elapses before the first rescue team arrives at the emergency location. Approximately half of the patients die from an OHCA due to a complete lack of resuscitation measures, which is partly due to the fact that the ambulance arrives too late. Even CPR by lay people could double or even quadruple the proportion of survivors [1], but this life-saving measure is not done in many cases. An attempt is being made to counteract this with first responder systems and telephone instructions for resuscitation measures (T-CPR). For a few years now, some municipalities have also been using so-called smartphone-based first responder alerting systems (sbFRAS). These are used to alert nearby qualified first aiders in addition to the EMS, who, due to their proximity to the emergency location, can arrive significantly before the emergency services[6,7].

Opinions about such systems currently differ and there are numerous concerns about the introduction of such systems. This paper aims to highlight the potential of sbFRAS for patients and society by investigating its advantages using a quantitative risk assessment. Here, the actual EMS is compared with an emergency service using sbFRAS additionally. For the representation of causal dependencies, for causal interference and for illustration, BN are used.

SbFRAS must not be seen as competition to the existing rescue system, since countermeasures against OHCA are a task for society as a whole [4], which requires new concepts and innovative solutions.

Figure 1illustrates the workflow of the investigation of the causal dependencies and the additional safety-related effect of these systems.

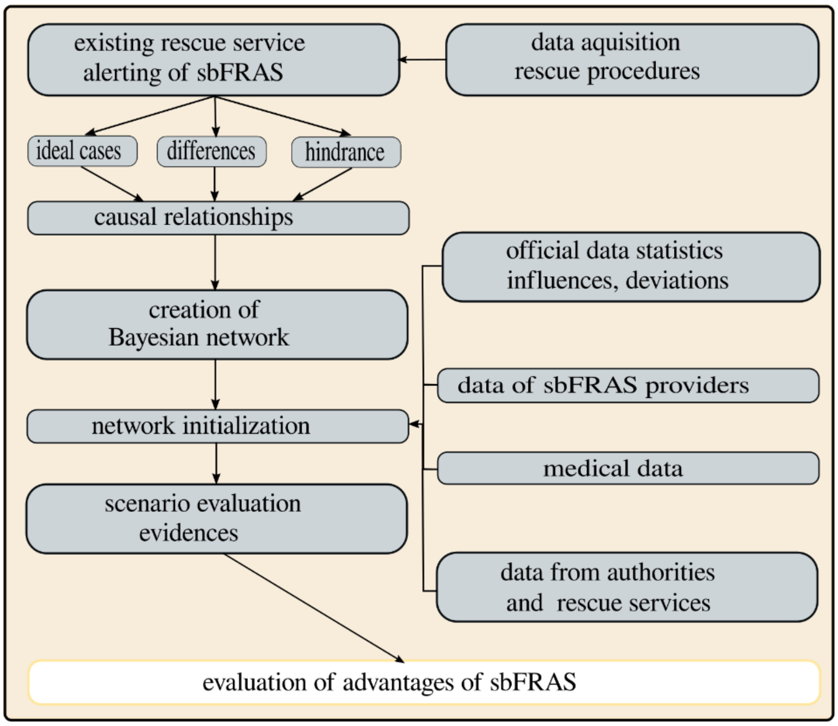

Figure 1: Illustration of the workflow for the investigation of causal dependencies and additional safety-related effect of sbFRAS and for the development of the Bayesian network. To estimate an order of magnitude for the benefit of these systems, data subject to high uncertainty must be processed.

The paper is organized as follows: Section IIexplains the basics of the EMS in Germany (in brief) and the supplementary systems for rescue services that have already been implemented. The operational sequences with and without sbFRAS as well as the impact on the survival rate are discussed. Section IIIdescribes the quantitative risk assessment based on BN approaches. The acquisition of the input data for the BN and the causal structure is discussed. The network after initialization is discussed in Section IV. Section V examines selected causal interferences (evidences). The advantages and influences that result from the addition of sbFRAS are discussed in detail. Section VI summarizes the paper.

II. SMARTPHONE-BASED FIRST-RESPONDER ALERTING SYSTEMS

2.1 Organization of the emergency services in Germany

In Germany, the EMS is organized by the federal states who usually delegate its implementation to the districts or self-governing cities. The rescue service laws of the federal states regulate the emergency rescue organization, qualified transportation of patients, and define the response time. The latter is the target value for the time from the emergency call to the arrival of the first rescue team at the emergency location.

Depending on the federal state, this time interval is 10, 12 or 15 minutes and is an important planning parameter for the deployment of the EMS [3,5]. If there is an emergency in which an emergency doctor is needed as well as the ambulance, the emergency doctor will drive separately from the ambulance with his own vehicle, the emergency medical vehicle (NEF). This is known as the rendezvous system and has the advantage that the emergency doctor is available again as soon as possible. As already mentioned in SectionI, there is a therapy-free time interval until the rescue team arrives. Its length has a significant influence on the survival of a patient in time-critical emergencies [5].

Various supplementary systems for emergency services have already been established to reduce this interval. In 2010, the T-CPR in which the emergency caller is instructed by the emergency medical dispatcher to carry out CPR in the event of an OHCA, was included in the European Resuscitation Council (ERC) guidelines

[8]. In addition, there are first responder systems in some federal states that can differ significantly in organization and structure. There are, among others, professional fire brigades who send emergency vehicles in parallel to the ambulance services [9] or relief organizations whose emergency personnel can be alerted to time-critical emergencies in their free time and who drive to the emergency location by private car or by an organizational vehicle [2,10]. Recently a few municipalities opted for sbFRAS where qualified first responders who are nearby can be called to the emergency location (see further below).

2.2 Existing supplementary systems for emergency services

Various supplementary systems have been developed in Germany to shorten the therapy-free interval. In a study from 1985 which was carried out in America it was found that instructions on the phone to carry out resuscitation measures significantly increased the number of preclinical resuscitations performed by lay people [11]. As written above, the T-CPR was included in the guidelines of the ERC in 2010. It represents the current state of the art, which is recommended by the ERC and which is to be implemented by the responsible agencies of the emergency services. Nevertheless, a survey during a conference of the German Medical Association in 2012 showed that only 63.6% of the control centers surveyed had implemented T-CPR as an integral part of their emergency call service at this time [12]. In some rescue service areas with professional fire brigades, specially equipped fire engines are alerted to life-threatening emergencies if they can reach the location faster than the ambulance [9]. These firefighters have training as paramedics and operational experience in the emergency services.

In rural areas, first responder units are set up by voluntary fire departments or organizations involved in emergency services or civil protection [10]. However, first responder units are not considered in this investigation, since they can be very different from each other and are not implemented in every district. Furthermore, there are no data available on the impact of the simultaneous use together with sbFRAS on the prognosis for the patient.

2.3 Functional principle of sbFRAS

The advantages of sbFRAS are apparent if qualified first aiders are in close proximity to the location of the emergency. Smartphone-alerted first responders (sbFR) must have a sufficient medical qualification. They have received medical training from work or voluntary work, such as doctors, rescue service associates, geriatric and nursing staff, firefighters, police officers and others. If the dispatcher is notified of a possible OHCA, a sbFR can be additionally sent to the emergency location.

The system locates available first responders in the vicinity and sends a call to one ore more (number adjustable) of the closest responders which have to confirm. After confirmation, they receive more detailed information about the emergency and can be navigated to the emergency location via the sbFRAS application on their smartphone. If a contacted first responder rejects the call, another one will be notified. When they arrive at the emergency location, the sbFR initiates all necessary measures, begins with life-saving immediate measures such as CPR and continues until the emergency services arrive. An alerted sbFR can also take an nearly located AED for rapid defibrillation [13]. After the patient has been handed over, they can further support the emergency services. For finishing and documentation, the smartphone-based first responder is usually asked to fill out a protocol log [4,6,14]. If the ambulance or the NEF arrives at the same time or even a little earlier, the first-responder who was alerted can take on important assistance tasks, including securing the emergency location in the event of an accident.

III. QUANTITATIVE RISK ASSESSMENT BASED ON BAYESIAN NETWORKS

3.1 General description of Bayesian networks

Bayesian networks (BN) are used for decision-making in case of uncertain knowledge in many areas in process- and system safety [15–18] and also in medicine [19,20]. The advantages of BN are their ability to process intrinsically uncertain data. Next, the network structure can be created intuitively from the knowledge of relevant causal chains. Even if there is an incomplete chain of events with data uncertainty, reasonable probability statements can already be made about the system under consideration. Despite the lack of knowledge, the BN at least allows the best possible conclusions to be drawn. If probabilities of variables are changing, the confidence in certain consequences can be examined with BN as well as integrating systemic changes in the network structure.

In medicine, BN are of particular interest for drawing optimal conclusions from a description given by a patient (symptoms) during anamnesis. Based on the degree of similarity, the doctor decides which real case of illness may be present and which can be excluded. However, many diseases show variability and heterogeneity, so the assignment of disease courses can be difficult. A medical system that supports doctors in dealing with complex decisions must be able to deal with these problems. Also, in such cases, uncertain input data have to be processed and used for optimal decision making [19,20]. Often, exact values for the probabilities are not mandatory since the estimation of an order of magnitude or to find out what is most likely can already be a decision-making aid. Nevertheless, it is clear that a model analysis can only be considered complete if uncertainties are taken into account. For the inclusion of expert estimates and tolerances to the input variables, approaches via Fuzzy Bayesian networks (FBN) [21–23] seem to be enforcing, next to general Bayesian reliability, evaluations using heterogeneous data sources [24]. This combination of methods seems to be able to deal with inherent uncertainties to the variables with manageable additional mathematical effort.

Here, the method described in [21] was used to weight the expert statements and to use them to determine defuzzyfied crisp numbers for the final network (see further below).

The structure, initialization and propagation of probabilities in BN up to questions of network optimization were mathematically examined and described in detail [15,25]. Therefore, a brief description of the method is sufficient here.

3.2 Mathematical basis of Bayesian networks

BN are graphical representations of causal relationships in the form of directed acyclic graphs. The graphs consist of nodes and arcs, where the nodes represent random variables in the mathematical sense and arcs the causal correlation. Acyclicity ensures that cause and consequence are clearly associated with each other. The BN represents the joint probability distribution of all random variables involved. If the BN is constructed with the random variables K_1, ..., K_n then one finds for the joint probability distribution [26]:

$$P(K_1, \ldots, K_n) = \prod_{i=1}^{n} P(K_i|parents(K_i)) \qquad (1)$$

These networks of causally connected events are used to calculate the total confidence in the states (hypotheses) of the random variables and to illustrate the strength of the causal correlation. On the other hand, with information about the state of a random variable (evidence), the state of the other variable can be updated by the process of probability propagation. This requires a priori probabilities for the root nodes, which are also considered to be statistically independent random variables and conditional probabilities for the inner nodes in the form of conditional probability matrices. However, the conditional probability matrices for an inner node are only conditionally dependent on the immediate parent nodes. The mathematical basis for this is the Bayesian theorem. With E being an event (evidence) and K_j being an hypothesis of a node K, one finds:

$$BEL(K_j) = P(K_j|E) = \frac{P(E|K_j) \cdot P(K_j)}{\sum_{j=1}^{m} P(E|K_j) \cdot P(K_j)} \qquad (2)$$

Here $P(K_j|E)$ measures the belief (BEL) in a hypothesis K_j , if event E was observed. Further one finds:

$$P(E) = \sum_{j=1}^{m} P(E|K_j) \cdot P(K_j) \qquad (3)$$

to be the total probability for the event E if K_j, $j = 1, \ldots, m$ is a complete set of disjunctive hypotheses.

Equation (2) allows two interpretations. Let S be the occurrence of a special event (e.g. the failure of an emergency vehicle) and E a consequence or detectable event (e.g. prognosis for the patient without sbFRAS). Thus, $P(E|S)$ describes the conditional probability for the prognosis for the patient without sbFRAS given the failure of an emergency vehicle. These are usually numerical values, which are to be entered into the network as a data basis (transfer matrix) or which are calculated by initializing the network. The conditional probability $P(S|E)$ would be the confidence in the failure of an emergency vehicle by manifesting an evidence E. This is calculated by updating the network via probability propagation.

3.3 Data basis for the Bayesian network

The BN is based on the variety of everyday operations of the emergency services and the sbFRAS. For the creation of the BN, all operations and events were omitted that are identical for the existing emergency services and for the sbFRAS.

This holds true in particular for the time before an emergency call is made as well as for the conversation with the dispatcher. Whatever has happened during this time can not be changed. Neither the EMS nor the sbFR have any influence on these factors. All other processes are integrated in the BN and provide an opportunity to compare the consequences for the emergency patient with and without sbFRAS. Statistical surveys on operational procedures were evaluated and used in the BN. Other important data sources were statistics on the degree of attainment of the response time of the emergency services in Saxony-Anhalt [27,28] as well as the annual reports of sbFRAS already used in Germany [29].

An important source of information was the recently published investigation of Stroop et al. [7]. The existing EMS and the rescue system expanded by sbFRAS had been compared by analyzing differences in the response time and improvements in the neurological outcome. For the cohort study, data from a German district Gütersloh (North-Rhine-Westphalia) had been selected in which sbFRAS have additionally been used for several years now.

Missing information and probabilities due to the lack of statistics were gained through discussion with experts. Here, numerous medical dispatchers, instructors of rescue services and experienced paramedics were consulted. In the event of deviations between the judgments of the experts, these judgments were weighted and averaged. The procedure for this is described further below.

Data on the accessibility of the emergency location and typical factors that influence the arrival conditions of the emergency services were affected. The expert opinions were always used when probabilities or conditional probabilities for the BN could not be estimated with the help of precise empirical literature data.

3.4 Inclusion of uncertainties using the Fuzzy Bayesian network approach

The data used in quantitative risk assessments are generally subject to uncertainty. Instead of using crisp probabilities without any tolerance specification, there are approaches in which Fuzzy theory and BN are combined. This can increase confidence in the conclusions.

There are two strategies for this coupling. At first, explicitly set intervals can be used for each probability or failure rate, for example cut sets like $(a_{min}, \hat{a}, a_{max})$[23]. As a result intervals for the target values are determined. In addition to the use of three parameters, there are also methods in which four parameters, so-called trapezoidal fuzzy functions (a_1, a_2, a_3, a_4), are used.

A disadvantage may be the fact that no large fluctuation ranges can be selected when specifying the intervals because otherwise the interval may be too broad for the target quantities. When evaluating experts, common relationships between linguistic terms and fuzzy sets are typically used [30]. Thus, the linguistic term *high* for a rate can mean *once in every 3-6 months* which can be translated to the trapezoidal set $(0.6, 0.8, 0.8, 1)$.

Another possibility is to use the defuzzyfication technique, which is used to calculate a representative mean from different sets [21,31].

When calculating these mean values, the interval data can be explicitly weighted. The mean value calculated in this way is afterwards processed like a crisp probability. The latter method was used here, too. If there were various non-identical expert assessments in the form of trapezoidal fuzzy sets for input data, the experts were weighted as described in [21].

If w_j is the weighting factor of expert j out of n experts, then the aggregated fuzzy value $\hat{a}_i$ is given by:

$$\hat{a}_i = \sum_{j=1}^{n} w_j a_{ij}. \qquad (4)$$

As a result, a weighted set $(\hat{a}_1, \hat{a}_2, \hat{a}_3, \hat{a}_4)$ follows. This set defines a so-called membership function:

$$\mu(x) = \begin{cases} 0, & x < a_1 \\ \frac{x-a_1}{a_2-a_1}, & a_1 \geq x \geq a_2 \\ 1, & a_2 \geq x \geq a_3 \\ \frac{a_4-x}{a_4-a_3}, & a_3 \geq x \geq a_4 \\ 0, & x > a_4 \end{cases} \qquad (5)$$

From this, the center of gravity was then calculated (defuzzyfication) and used for the BN:

$$\hat{a} = \frac{\int \mu(x)xdx}{\int \mu(x)dx} = \frac{(a_4 + a_3)^2 - a_4a_3 - (a_1 + a_2)^2 + a_1a_2}{3(a_4 + a_3 - a_2 - a_1)} \qquad (6)$$

Please see [21] for more details.

However, it should be noted that this procedure could not be used to cover all data uncertainties for the hypotheses fed into the BN. In particular, no uncertainties were known about the accessibility of the emergency location and typical factors that influence the travel conditions of the EMS and for the EMS extended by a sbFRAS. Therefore, the BN presented here must be seen as a first attempt to quantify the causal relationships.

3.5 General information about the Bayesian network

The developed BN after initialization is shown in Figure 8. It consists of 38 nodes, 61 arcs and has between two and six hypotheses per node. It was created using the GeNIe[32]software, which is free of charge for academic purposes. In terms of content, the network can be grouped into three parts: (i) the existing EMS consisting of ambulance and emergency doctor, (ii) the influence of an additional sbFR and (iii) a comparative part to highlight the advantages of an additional sbFRAS. For the illustration, the nodes were positioned accordingly and the subdivision was made clear.

A detailed description of all nodes in the BN must be omitted here because the network is too extensive. The aim is to specify basic ideas that were used in the creation of the network.

Important root nodes are the *composition of sbFR*, *weather conditions*, the *emergency location*, the *time of day* and possibly existing *major events*, but also events such as *violence* and *fire*, because the latter may complicate or even prevent intervention by sbFR.For example, a sbFR is usually not alerted in these cases. Furthermore, it depends on the *emergency location* whether an sbFR is alerted or not.

It is known that the majority of OHCA take place at home (e.g. in [7]≈ 76%). This was split up for the network. To reach the emergency location, a distinction is made between whether the home environment is in a town, a village or a city. This was done to be able to specify differences in arrival conditions and arrival times, both for the EMS and for the sbFRAS. At the node *emergency location* the hypotheses *town* (H_1), *village* (H_2), *country road* (H_3), *highway* (H_4) and *city* (H_5) are distinguished. Here, the a priori probabilities $(H_1, H_2, H_3, H_4, H_5) = (0.4,0.2,0.1,0.05,0.25)$ are used.

The data from the emergency services were taken into account in the input data or transfer matrices. The availability of the sbFR depends on this, in addition on the time of day. If the emergency site is on a highway, an sbFR will not be notified. On the other hand, the availability in a village or city was rated as higher. In this sense, the emergency location is of particular importance. The prior probabilities as well as the selection of the hypotheses *fire fighter* (H_1), *rescue service associates* (H_2), *others* (H_3) and *medical personel or doctors* (H_4) of the node *composition of sbFR* to $(H_1, H_2, H_3, H_4, H_5) = (0.15,0.60,0.05,0.20)$ are in good agreement with the average expert opinion and the data from[7].

Next, the causal chain for sbFRAS (Figure 8part A) will be described in more detail.If there is a *contraindication* due to *fire*, *violence* or *rescue*,the dispatcher will not alert a sbFR because other emergency services first have to rescue the patient or establish the necessary safety. Here, a total confidence of ≈4% for a contraindication was assumed.

The notification of an sbFR depends on the regulations for the dispatcher and on the emergency*situation*. At this node the hypotheses *contraindication*, *suspected OHCA* and *unclear* are distinguished.Typical alarming keywords leading to a *suspected OHCA* are lifeless person, cardiac arrest, unconsciousness and others. The dispatchers are also trained to specifically ask the caller to check the life functions in case of doubt in order to recognize an OHCA as such.However, there are still cases in which the situation remains unclear.Depending on the *situation* are the conditional probabilities of a *notificationsbFR* and subsequently the conditional probabilities of an*arrivalsbFR*.The hypotheses *before*, *expectation*,*after* and *none* were differentiated here.The expectation value here means an arrival of about five minutes after the emergency call.The other times are before and after five minutes, respectively. This value is somewhat more conservative than the median response time of 4 minutes given in[7]. This paper also stated that the availability of the sbFR was around 46% of the alerts.Alarm keywords were required for the alarming an sbFR.The transfer matrices were specified accordingly. This leads to a confidence of about 40% of all emergencies with actual OHCA in which the patients can expect a sbFR.

The latter node further depends on the node*availability of sbFR* which is itself causally dependent on the node *emergency location* and the node *time* (of day).Furthermore, the node *arrival sbFR* is a parent node of the node *arrival sbFR vs. existing system* (see Figure 8 part D) in which the arrival of the actual EMS is compared with the EMS plus sbFRAS.

Now the causal chain to the existing rescue service (Figure 8 part B) will be discussed.As stated above, the existing EMS was divided into ambulance and the emergency doctor arriving via NEF.If an emergency call is made, the NEF may not always be alerted in addition to the ambulance if there is a *misinformation dispatcher*. The latter is possible if the severity of the emergency is underestimated by the person making the emergency call or if the nature of the emergency was misjudged.Therefore, there is a connection with the node *emergency doctor alerted*.

Further, the network tacitly assumes that there is an emergency. Therefore, there is no node like "incoming emergency call" or something similar. Depending on the level of information, the ambulance and a NEF are alerted, which can be at different locations and therefore may have different travel conditions. It was also taken into account that there are situations that make it necessary to request an ambulance and NEF from the neighboring district. These in turn have their own arrival conditions. Therefore, the nodes *travel condition ambulance*, *travel condition ambulance neighbor district*, *travel condition emergency doctor* and *travel condition emergency doctor neighbor district* were specified. All of these nodes have a node that judges the arrival time as a child node and finally they lead to the node *arrival existing system*.As for the sbFRAS the hypotheses *before*, *expectation*, *after* and*none* were differentiated for the arrival time. The expectation value for the rescue system without sbFRAS is an arrival which takes place near the median response time of 8 minutes (experts). In [7]the median response time of the EMS was estimated to 7 minutes for the entire cohort[7]. Since this study appears to be very precise and favors the existing EMS, this value was taken.Note that the expectation for the arrival of a sbFR is still significantly lower than the expectation for the arrival of the EMS.The other times are *before* and *after*, respectively.

As already stated, the transfer matrices have a high importance for all conclusions drawn with the network. Due to the large number of transfer matrices, not all of them can be discussed in detail here.

As an example, the transfer matrix of the node *prognosis for patient with sbFRAS* (node P with hypotheses *good outcome* (P_1), *medium outcome*(P_2), *unfavorable outcome*(P_3),*death*(P_4)) is given and discussed.

A good outcome here means that the patient can be discharged from the hospital with minimal restrictions and can continue to live independently with a good prognosis. In medicine, theCerebral Performance Category (CPC) is often used to assess the outcome after e.g. an OHCA. A good outcomehere can be understood as CPC 1 score.Medium outcome means discharge with noticeable restrictions and shortened life expectancy (CPC 2), and unfavorable outcome means discharge or transfer of the patient with the need for permanent medical care (CPC 3 and 4). These three hypotheses can be summarized in the hospital discharge rate.

The selected node has the parent nodes*prognosis for patient without sbFRAS* (node $\bar{P}$ with hypotheses *good outcome* ($\bar{P}_1$), *medium outcome* ($\bar{P}_2$),*unfavorable outcome* ($\bar{P}_3$) and*death* ($\bar{P}_4$)), the node*arrival of sbFRAS* (denoted as node A) with hypotheses (*before* (A_1), *expectation* (A_2), *after* (A_3) and*none* (A_4))and the node *qualification of sbFR* (denoted as node Q) with hypotheses (*high* (Q_1),*medium* (Q_2) and *sufficient* (Q_3)).In total, 192 conditional probabilities have to be specified. Some of these are trivial and others depend on the current data situation. Here a subset will be selected and discussed:

$$\begin{pmatrix} P(P_1|\bar{P}_1Q_1A_1) & P(P_1|\bar{P}_1Q_3A_4) \\ P(P_2|\bar{P}_1Q_1A_1) & P(P_2|\bar{P}_1Q_3A_4) \\ P(P_3|\bar{P}_1Q_1A_1) & P(P_3|\bar{P}_1Q_3A_4) \\ P(P_4|\bar{P}_1Q_1A_1) & P(P_4|\bar{P}_1Q_3A_4) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix} \quad (7)$$

These selected conditional probabilities are trivial. Because the good outcome is already given by the existing EMS, the hypotheses of the other nodes do not change anything.In this sense, the worst possible outcome is always given by the outcome of the actual EMS.

The situation is completely different if a highly qualified sbFR (Q_1) arrives before (A_1) or within expectation (A_2), whereas if the actual EMS were to exist alone, the patient would be dead ($\bar{P}_4$):

$$\begin{pmatrix} P(P_1|\bar{P}_4Q_1A_1) & P(P_1|\bar{P}_4Q_1A_2) \\ P(P_2|\bar{P}_4Q_1A_1) & P(P_2|\bar{P}_4Q_1A_2) \\ P(P_3|\bar{P}_4Q_1A_1) & P(P_3|\bar{P}_4Q_1A_2) \\ P(P_4|\bar{P}_4Q_1A_1) & P(P_4|\bar{P}_4Q_1A_2) \end{pmatrix} = \begin{pmatrix} 0.03 & 0.02 \\ 0.09 & 0.09 \\ 0.07 & 0.07 \\ 0.80 & 0.82 \end{pmatrix} \quad (8)$$

These values had been specified mainly using results from[5]. The survival rate was specified which is to be expected if initial CPR is carried out by lay people.A distinction was made after time intervals until the arrival of the EMS.If the arrival takes place up to 2 minutes, about 22% survive, if it is up to 5 minutes, about 20% survive and 16% in the event of arrival by the 8th minute.These assumptions have been adopted approximately. Next, the distribution among the neurological outcomes was set according to the observations presented in[7], where more than 50%of the survivors have a CPC score of 1 or 2.All other conditional probabilities were specified in the same way.

Nevertheless, it should be noted that the specified conditional probabilities are estimates and were set after the literature study and expert survey.Small modifications of these numbers result in small changes of the confidences for the hypotheses.Therefore, the conclusions drawn by the use of the network are retained even if the parameters vary.However, the accuracy of the stored data could be further increased if there were more empirical data from districts which use sbFRAS.

IV. INITIALIZATION OF THE BAYESIAN NETWORK

The BN after initialization is shown in Figure 8. The strength of the arrows illustrates the degree of causal correlation between the nodes. A thin arrow indicates a weak correlation, while a thick arrow indicates a strong causal influence.As before with the data basis, not all nodes can be discussed in detail here. Therefore, two parts of the BN were selected.First some nodes from subnet A (sbFRAS) after initialization are going to be discussed. Figure 2illustrates this part of the BN.

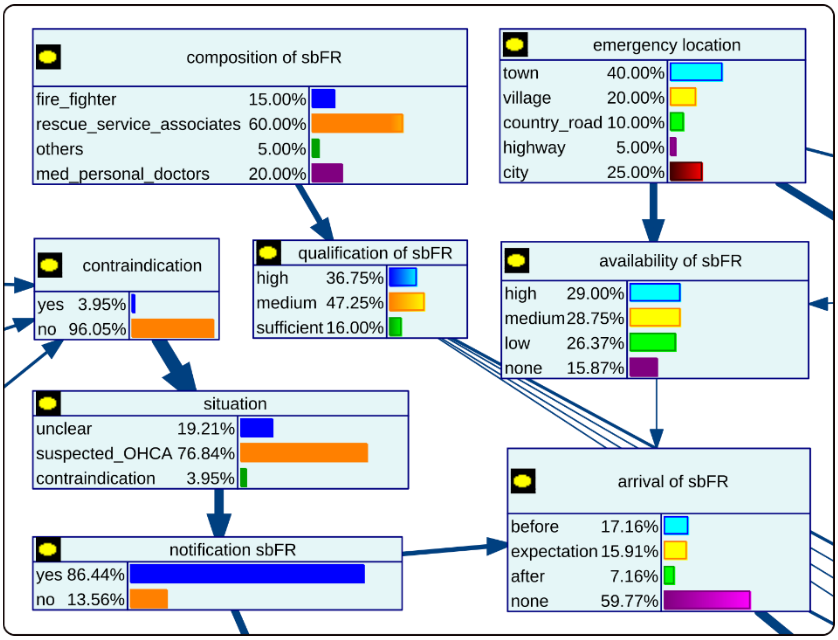

Figure 2: Illustration of selected nodes of the Bayesian network after initialization.Here, nodes which are important for the notification and the prognostic arrival of a sbFR had been selected.

The nodes *fire*,*violence* and*rescue* leading to the node*contraindication* are not shown.For this node BEL(yes) ≈ 0.04 was set in accordance with the experts estimate of the contraindications.The node *situation* specifies the emergency situation as the dispatcher interprets it from the information given by the caller.It was assumed that ≈ 80% of all cases of OHCA which are transmitted to the dispatcher are noticed as such.In its basic setting, the network indicates that notification occurs in ≈ 71% of all cases.The BEL at the nodes*emergency location*, *availability* and *composition of sbFR* have been discussed before and show the current assessment of the experts or literature data in this regard. For the subnet A of the BN, the nodes*qualification of sbFR* and *arrival sbFR* are important because they have a significant impact on other parts of the network.It was assumed that not all sbFR have high qualifications, but at least a sufficient one.For a high qualification the proportion of sbFR was estimated that regularly performs CPR and is thus specially trained in it.The confidence in the arrival of a sbFR was set to ≈ 40% (see discussion further above).

Next, the confidences in the hypotheses of the nodes *arrival of sbFR* (subnet part A),*arrival ambulance*, *arrival emergency doctor* and *arrival EMS* (subnet part B),*arrival sbFR vs. EMS* (subnet part D), as well as the hypotheses of the nodes *prognosis of patient with sbFR* and*prognosis patient without sbFR* (subnet part C) are going to be discussed. The selected nodes were rearranged to present them together in Figure 3.First it can be seen at node *arrival EMS* that in 85% of all cases the ambulance or an NEF arrives at the emergency location within the response time. The assessment of the arrival situation of the EMS is in good agreement with the present observations and expert estimates. If the actual EMS is compared with the EMS expanded by sbFR (node *arrival sbFR vs. EMS*) one finds that the patient does not have any benefit from the sbFR in the majority of cases. This is because no sbFR is alerted in certain cases or no suitable sbFR accepts the request, even if available. However, if a sbFR accepts the request, the data from[7] shows that the sbFR arrives before the EMS in 90% of all cases. This can be found if the proportion of the hypothesis*no sbFR* is excluded accordingly. The survival rate (hospital discharge rate, node *prognosis patient without sbFR*) of an OHCA for the actual EMS is in the range of (8-10)%[7]. This is reproduced by the BN after initialization. A sbFR is an additional layer of protection. In the event that they accept the request for help, the expected response time is less than the one of the actual EMS. This has a positive influence on the hospital discharge rate. The network predicts an improvement of around 5% at node *prognosis of patient with sbFR.* However, the distribution of the hospital discharge rate among the underlying hypotheses may be plausible but contains high uncertainty.

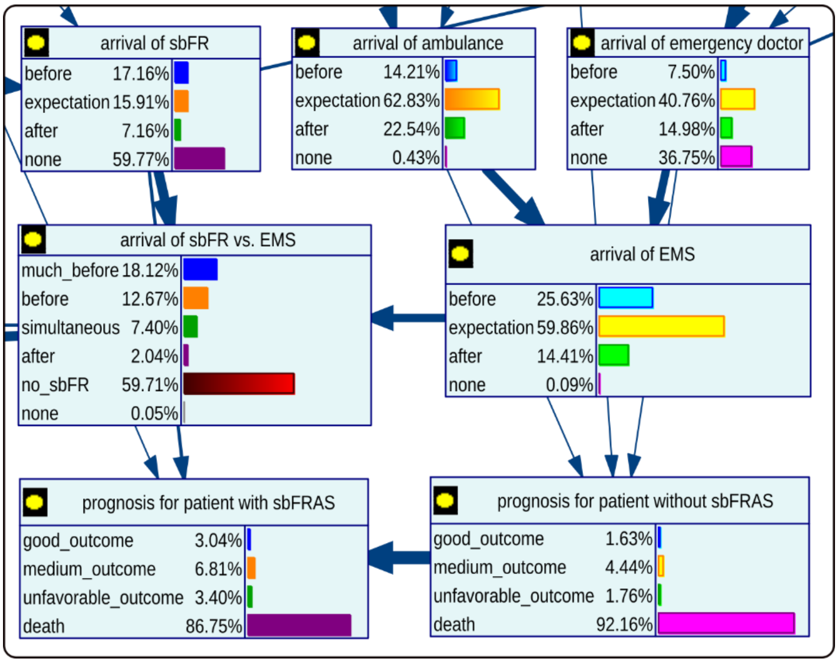

Figure 3: Illustration of selected nodes of the Bayesian network after initialization. Here, the arrival situation and the prognosis for the patient had been selected.

V. DISCUSSION OF CAUSAL INTERFERENCES

An advantage of using the BN is the ability to change initial circumstances to predict the consequences. Compared to pure data studies, forecasts can be made to predict which influences different alarm conditions, travel conditions, arrival situations or others may have on the final nodes.In this section, some evidence will be considered. Evidence here means that the conditional probability of a selected hypothesis is set to 1 ≙100%.For reasons of space, selected nodes showing the arrival situation and prognosis are shown after the update only.

5.1 No EMS available in the district

At first it is assumed that neither the ambulance nor an NEF is available for the district in question. Only EMS from the neighboring district and the sbFR (which is alerted) remain for the rescue.After setting these three pieces of evidences, the network was updated and is shown in Figure 4.

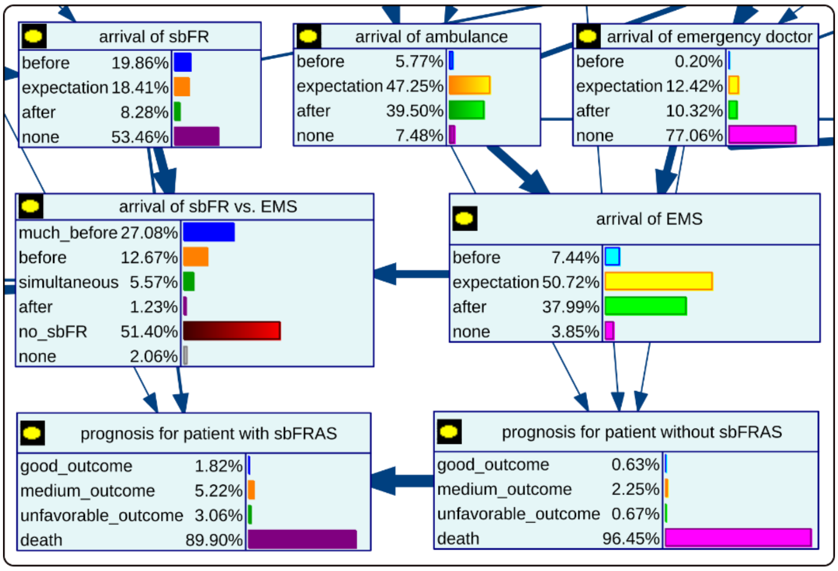

Figure 4: Illustration of selected nodes of the Bayesian network after the evidence: *travel condition ambulance: none*, *travel condition emergency doctor: none* but with a *notification sbFR: yes*.

First a deterioration of the arrival situation of the existing EMS can be seen. The confidence that the EMS of the neighboring district will arrive within the response time drops to around 58%.Without sbFRAS, the patient's probability of survival would decrease compared to the initial situation to ≈ 4%.

As a result of the notification of the sbFR, the probability of arrival increases to 47%.The advantage of adding a sbFRAS can be seen at the node *prognosis of patient with sbFR* because the probability of survival of ≈10% is significantly better.Assuming that the sbFR arrives in any case (*arrival of sbFR: none*=0%), the survival rate continues to increase to the value of ≈ 18%.This also represents the best case scenario for the advantage of the additional system with the given evidence.The nodes after the network update are shown in Figure 5.

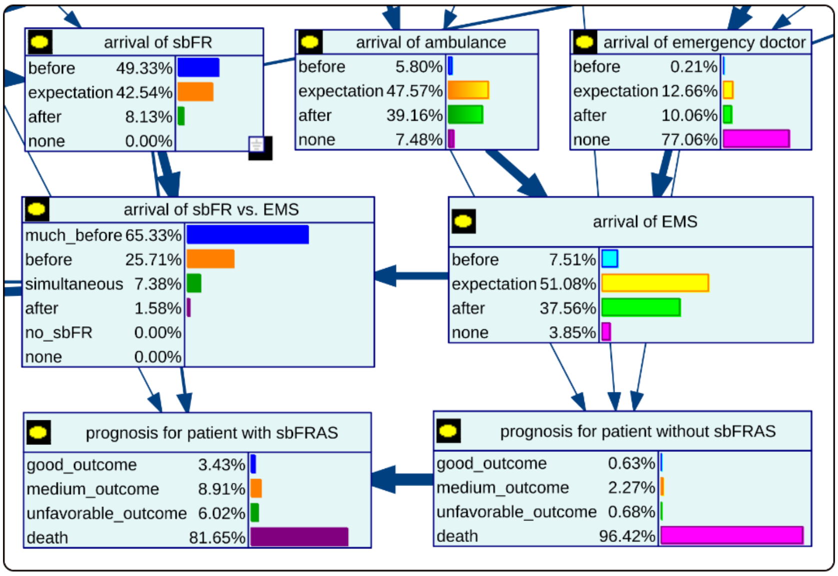

Figure 5: Illustration of selected nodes of the Bayesian network after the evidence: *travel condition ambulance: none*, *travel condition emergency doctor: none* but with a *notification sbFR: yes* and*arrival of sbFR: none=0%*.

5.2 Comparison of low and high availability of sbFR

Now the situations of low and high availability of the sbFR are going to be compared. Figure 6 first shows the case of low availability (*availability of sbFR: low* =100%).

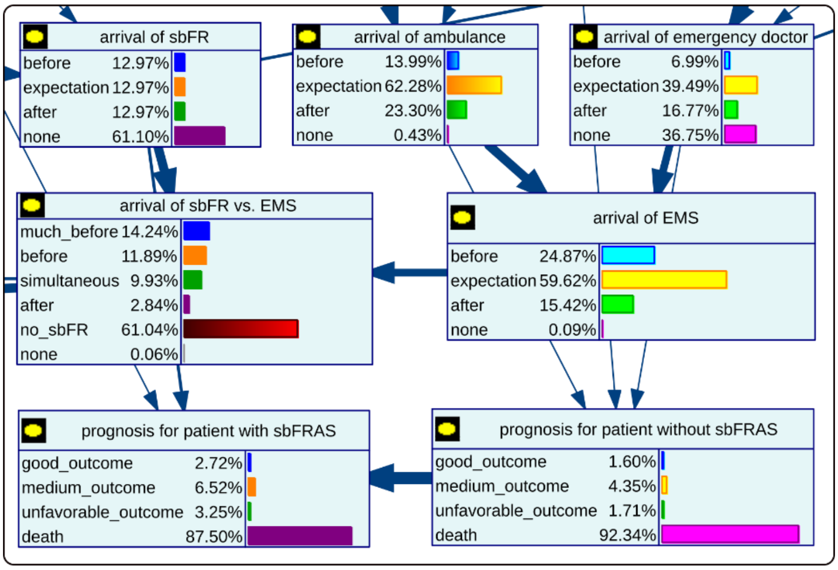

Figure 6: Illustration of selected nodes of the Bayesian network after the evidence: *availability of sbFR: low=100%.*

The basic settings in the network lead to the confidence of about 39% for an arrival of a sbFR at the emergency location.It turns out that there is a noticeable benefit for the patient, even with low availability of the sbFR. This is due to the fact that it is often vital for a patient that the necessary CPR is carried out in the first place. Therefore, the remaining availability is immediately reflected as an advantage.In Figure 7the case of the high availability (*availability of sbFR: high* =100%) of sbFR is shown.

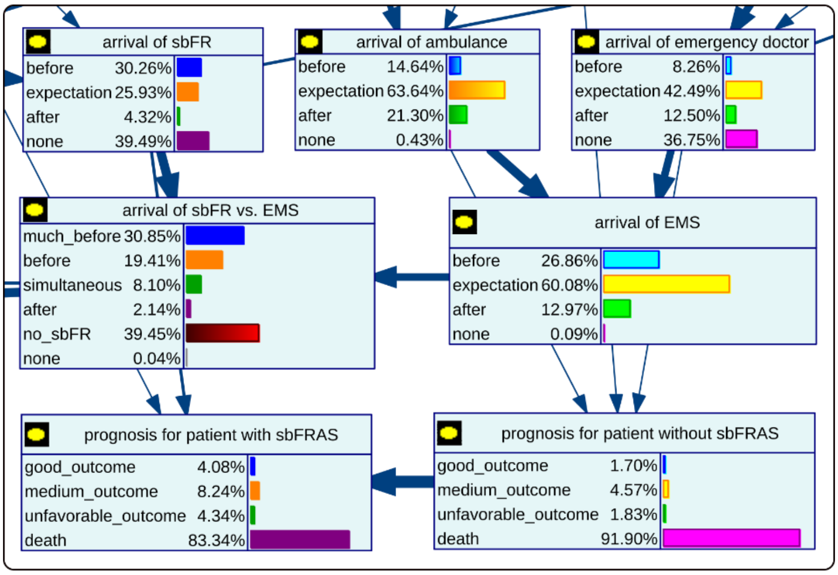

Figure 7: Illustration of selected nodes of the Bayesian network after the evidence: *availability of sbFR: high=100%.*

This is a desirable optimal situation with an arrival probability of the sbFR of 0.6 which also shows the benefits of the additional sbFRAS in case there are enough motivated sbFR.The analysis of the network also shows that the use of sbFRAS does not cause any disadvantage. For example, there is no situation in which an sbFR would hinder the actual EMS causing a deterioration in the outcome for the patient.The reason for this is that the additional sbFR does not require any resources from the existing EMS.

VI. SUMMARY

In this paper, it has been demonstrated that sbFRAS represent a very useful additional safety level to improve the outcome of patients with suspected OHCA. With only a little extra workload for the dispatchers, they represent an extension of the actual EMS without competing with it. This paper can be seen as an attempt to quantify the benefit for the patient suffering from an OHCA. For various implementation strategies, patient situations and chains of events, the Bayesian network approach can be used to estimate a situation-dependent benefit effect. It can be concluded that there is always a high level of confidence in a measurable advantage from this system in rural to urban areas. This is mainly due to the fact that there is almost always a minimum number of first aiders available who are required for this. In contrast, for areas that are difficult to access or for places that are not within walking distance (country roads, highways), the expected value for the benefit decreases. The potential of sbFRAS for improving the hospital discharge rate and the long-term prognosis for the patient is impressive, as well as the significant reduction in the number of fatal outcomes in particular. In this work the total costs associated with the introduction of these systems were not considered. Nevertheless, it turns out that the strategic introduction to reduce the response time can be very useful in many municipalities.

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APPENDIX A. BAYESIAN NETWORK ILLUSTRATIONS

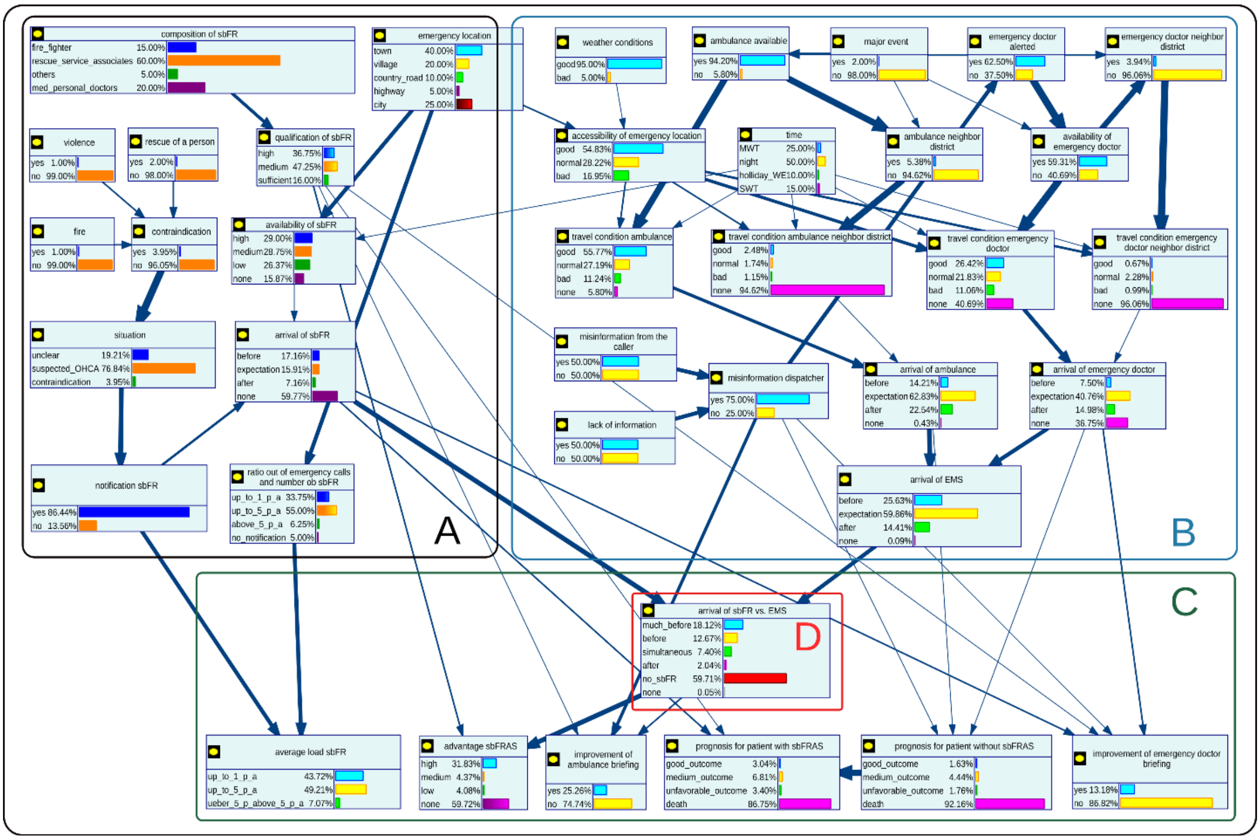

Figure 8: Illustration of the Bayesian network for the confidence in the prognostic advantage of sbFRAS for numerous but typical accident locations and chains of events. The BN is subdivided into four parts. A: subnet for the sbFRAS, B: subnet for the actual rescue system, C: subnet for system comparison and D: main decision node.