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Risk analysis of operating room using the Bayesian Network Model

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Abstract
Patient's safety requires the establishment of a quality health care service, safe and effective. This work aims to propose an integrated approach to risk management for a hospital system. Operating room is a high risk area for adverse event. To improve patient's safety, we should develop methods where different aspects of risk are taken into consideration. This paper represents application of Bayesian networks for quantitative risk analysis in the operating room. Bayesian networks provide a framework for presenting causal relationships and enable probabilistic inference among a set of variables. The methodology is used to analyse the patient's safety risk.

Keywords: Risk Analysis, Operating room, Bayesian Network, Risk Assessment

Introduction

Medical error is a leading cause of death and injury. Between 210,000 and 440,000 patients each year who go to the hospital for care suffer from some type of preventable harm that contributes to their death [1]. High error rates with serious consequences are most likely to occur in operating room [2]. A strong patient's safety culture in the operating room is very important to improve quality and reduce risks of adverse event and medical errors.

The operating room is an area where a complex activity is exercised, that involves several actors from different domains. This complexity calls into question patient's safety. Careless and dangerous errors can be produced in surgery, like operating on the wrong patient or part of the body, or left objects inside the patient after surgery or other adverse event.

Risks in a surgery can come from patients themselves as well as hospital resources. Anaesthesia types and duration, state of surgical team (skills, stress, tiredness, disease, alcohol abuse…), the quality of medical equipments also can play roles in leading to potentially surgical failures.

In this paper, we are going to propose a methodology of risk analysis for the operating room, using Bayesian networks. Bayesian networks are a powerful approach for risk modelling and analysis. In contrast with other classical methods of dependability analysis such as Markov chains, fault trees and Petri nets, Bayesian networks provide a lot of benefits. Some of these benefits are the capability to model complex systems, to make predictions as well as diagnostics, to compute exactly the occurrence probability of an event, to update the calculations according to evidences, to represent multi-modal variables and to help modelling user-friendly by a graphical and compact approach [3].

The rest of this paper is organized as follows. **Section 2** develops the approach of risk analysis. **Section 3** introduces the bases of Bayesian networks and explains why they are suitable to model complex systems. **Section 4** illustrates the application of the approach to patient's safety risk analysis in the operating room. **Section 5** discusses some of the main results, while **section 6** summarizes the paper with some concluding remarks.

Methodology of risk analysis of the operating room

In the following, a methodology of risk analysis of the operating room using Bayesian networks is proposed. The methodology follows four steps (Fig 1) and it is part of Continuous Improvement Process (CIP).

The first step involves determining the aim of the risk assessment process, the description of the problem and the definition of the scope.

Example:
Risk of patient's safety in the operating room.

The second step is to identify potential risks that can affect the quality and the efficiency of the operating room process. In this step, we may encourage creativity and involvement of the operating room team. The next rules are very interesting to lead a workshop of risk identification:

- Everything that has happened in a hospital can occur again in the same hospital or another.
- What is conceived by the imagination can happen.

The third step is the risk modelling. It consists in the development of the Bayesian networks graph (definition and choice of the variables to represent the nodes, describe the states of each node, building the structure of Bayesian networks in terms of links between the predefined nodes) and establishment of the quantitative relation between nodes through conditional probability. In this step, we can use the

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hospital data source and the expert's judgment to feed the model.

The last step is the analysis of the results: The model should give the best understanding of the risk problem. It is useful to discuss the goodness or appropriateness of the model. It is important to validate and calibrate the model using all available source of information (expert judgement, observation, statistical data…). We should then, analyse and interpret the result of risk measures to support decision making for safety improvement.

Finally, continuous improvement efforts must incorporate a risk assessment process to ensure the effectiveness and the quality of the process. The model must be updated with the new risks and factors.

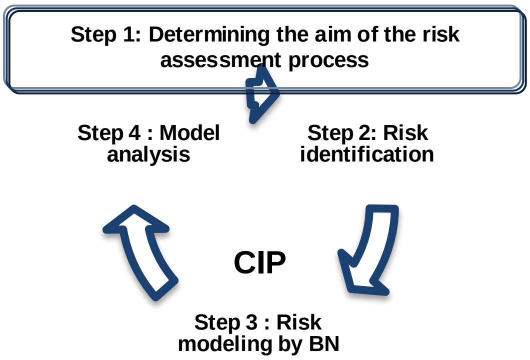


Fig.1. Methodology of risk analysis for operating room

Bayesian networks applications in risk analysis

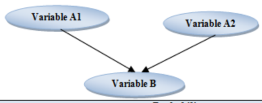
A. Definition

Bayesian networks were first introduced by Pearl in 1986 and are defined as: is a graphical model that permits a probabilistic relationship among a set of variables. One of the main advantages of Bayesian networks is their ability to model causal relationship among variables. This can be done from cause to effect and vice versa. Bayes rule can be expressed as follows:

$$P\left(\frac{A}{B}\right) = \frac{P\left(\frac{B}{A}\right) \times P(A)}{P(B)} \quad (1)$$

Networks are built on principles of adaptability and integrate uncertainties on the relationship between causes and effects (Figure2). Network model allows taking into account the dependency between the risk and the causes or the factors to compute the system's risk of failure.

State of A1	Probability
S11	P(A1=S11)
S12	P(A1=S12)



State of A2	Probability
S21	P(A2=S21)
S22	P(A2=S22)

State of B	Probability			
Variable A1	S11		S12	
Variable A2	S21	S22	S21	S22
S1	P(B=S1/A1=S11, A2=S21)	P(B=S1/A1=S11, A2=S21)	P(B=S1/A1=S12, A2=S21)	P(B=S1/A1=S12, A2=S22)
S2	P(B=S2/A1=S11, A2=S21)	P(B=S2/A1=S11, A2=S21)	P(B=S2/A1=S12, A2=S21)	P(B=S2/A1=S12, A2=S22)

Fig.2. Bayesian network and conditional probability table

B. Bayesian Network and Risk Analysis

Risk analysis is a technique for identifying, characterizing, quantifying and evaluating critical event occurrence. The quantification of risk includes the estimation of the frequencies and the consequences of hazard occurrence. Since 2001, Bayesian networks have been used to analyze risky situations. Particularly, Bayesian networks represent a useful formalism in the risk analysis domain due to their ability to model probabilistic data with dependencies between events [3]. In [4], the authors propose a Bayesian network to quantitatively estimate the risk related to an industrial system operation, this model integrated qualitative information with quantitative knowledge. A methodology for application of Bayesian networks for risk analysis in electricity distribution system maintenance management is presented in [5]. Another application of Bayesian networks is proposed in [6], to quantify uncertainty in project cost and also provide an appropriate method for modelling complex relationships in a project, such as common causal factors, formal use of experts' judgments, and learning from data to update previous beliefs and probabilities. A model using Bayesian networks with causality constraints (BNCC) for risk analysis of software development projects is introduced in [7].

The benefits of using Bayesian network for risk analysis are:

- To be capable of modelling complex systems,
- To compute exactly the occurrence probability of an event,
- To update the calculations according to evidences,
- To represent multi-modal variables,
- To help modelling user-friendly by a graphical and compact approach,
- To quantify low probability events,
- To integrate different source of information such as statistical data, expert's judgment and observation.

Case study: patient safety risk analysis in the operating room

A. Determining the Aim of the Risk Assessment Process

The operative processes include the pre-operative, intra-operative and postoperative stages of a surgery. We are going to study the Operating Room Processes and in particular, the intra-operative stage. It starts when the patient enters the operating room and all members of the surgical team are expected to be in the operating room at this particular time. The process ends when the patient is able to leave the operating room. During this process, the patient is monitored, anesthetized, prepped and the operation is performed. Because of the lack of availability of actual data risk, we will forward a risk analysis based on different sources accidents described in the international literature. We will limit our study to events that cause a significant deviation of the operating room process compared to normal process and which have serious consequences for the patient (Re-intervention, hospitalization in intensive care, extension of the period of hospitalization, additional care, death...).

B. Development of the Bayesian Network Model

Figure 3 illustrates the Bayesian network model of patient's safety showing interrelationships of events that may lead to patient's injury. The model has 13 nodes with 1 utility node. The nodes are assessed using a literature source.

Surgery infection:

The incidence of surgical site infections (SSI) depends upon the patient risk-factors, surgical procedure and practices observed by the operating team.

Surgical foreign body:

Leaving things inside the patient's body, after surgery is an uncommon but a dangerous error. Sponges and scissors used during surgery have been left inside patients' bodies.

Operating on the wrong part of the body or wrong-site or wrong-patient or wrong-procedure surgeries:

The frequency of surgery admissions experiencing a wrong site or wrong side or wrong patient or wrong procedure or wrong implant is 0.028 a per 1000 admissions [8].

Medication error:

Wrong-dose, wrong-time, wrong-medication or transcription errors. "A medication error is any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient or consumer. Such events may be related to professional practice, health care products, procedures and systems including prescribing, order communication, product labelling, packaging and nomenclature; compounding; dispensing; distribution; administration; education; monitoring; use"[9]. In a review of medical records from hospitals in two American states there was a significantly higher incidence of preventable drug-related adverse events in patients aged >64 than in patients aged 16–64 years (5% compared with 3%) [10]. Errors are also significantly more likely in children;

Anaesthesia Equipment Failure:

Anaesthesia equipment problems may contribute to morbidity and mortality. The frequency of anaesthetic equipment problems is 0.05% during regional anaesthesia, and 0.23% during general anaesthesia [11].

Operation error:

An error may occur in surgery due to different adverse events**.**

Patient injury:

An error may or may not cause an adverse event. Adverse events are injuries that cause harm to the patient (death, life-threatening illness, disability at the time of discharge, prolongation of the hospital stay, etc.)

In the following, some risk factors are given:

Patient risk:

We consider two states for patient's risk: high and normal. The risk in surgery can come from patients themselves.

Age:

For the age factor, we assume that the patient may be child, elderly or adult. The age can increase the patient's risk, the risk of fall and the risk of medication error. These risks are much higher for elderly and child than adult.

Anaesthesia type:

We consider two categories of anaesthesia: regional and general. We assumed that 'Failure in anaesthesia equipment' depends on anaesthesia type as explained in [11].

Table 1 to 5 shows conditional probabilities of states of different nodes. The marginal probabilities of some adverse events are shown in table 6. Each risk of adverse event is considered with two states (True if the risk exists and false if the risk does not exist). To aggregate the impact of injuries into a single risk measure, we use utility node 'Patient Death'. So the task is to find the conditional probabilities tables by using only the correlations and the marginal frequencies.

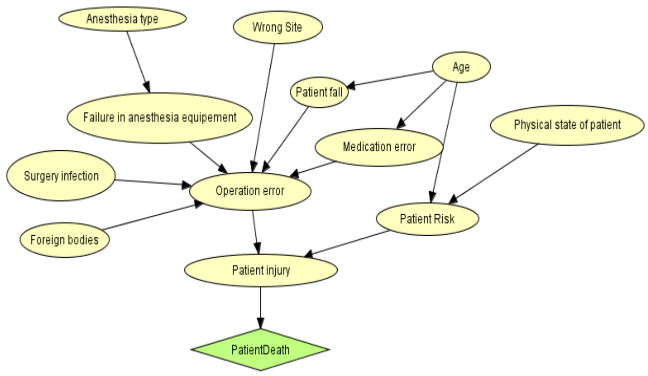


Fig.3. Bayesian network for patient safety model for the Operating room

TABLE.1. Conditional probability for patient injury

Operation Error	**TRUE**		**FALSE**		
Patient Risk	**High**	**Normal**	**High**		**Normal**
No	0.01	0.01	0.99		1
Small	0.18	0.81	0.009		0
Severe	0.81	0.18	0.001		0

TABLE.2. Conditional probability for patient fall

Age	**Adult**	**Elderly**	**Child**
TRUE	1.16E-5	1.16E-4	1.16E-4
FALSE	0.9999884	0.999884	0.999884

TABLE.3. Conditional probability for medication error

Age	**Adult**	**Elderly**	**Child**
TRUE	0.03	0.05	0.06
FALSE	0.97	0.95	0.94

TABLE.4. Conditional probability for patient risk

Physical state	Weak				Normal	
Age	**Adult**	**Elderly**	**Child**	**Adult**	**Elderly**	**Child**
High	0.6	0.8	0.9	0	0	0
Normal	0.4	0.2	0.1	1	1	1

TABLE.5. Conditional probability for failure in anaesthesia equipment

Anaesthesia type	Regional	General
TRUE	5 10^{-5}	2.3 10^{-3}
FALSE	1- (5 10^{-5})	0.9977

TABLE.6. Probability of some adverse events

Risk	Probabilities
Surgery infection	2.5 10^{-2}
Wrong site	2.6 10^{-5}
Foreign bodies	10^{-3}

TABLE.7. Probability of some factors

Factor	State	Occurrence
Anaesthesia type	Regional	0.5
	General	0.5
Physical state	Weak	0.1
	Normal	0.9
Age	Adult	0.5
	Elderly	0.2
	Child	0.3

C. Analysis of the Result

After the structure of the Bayesian network is completed and probabilities are determined, the inference can be performed to estimate the probability of patient's safety risk. The dependency and correlation among risks and factors are captured in nodes 'Operation error' and 'Patient injury'.

Hence, the task is to find the probabilities of patient's death after surgery by using only the correlations and the probabilities of adverse events and the frequency of influencing factors. The probability of the death of patient is 6.37 10-3. If the state of one or more variable is known, the model can be updated and the probability of patient injury and operation error will change. This should result in decision of not to operate the patient or postpone the surgery. For instance, the risk is much higher when the patient has a weak physical state, it is 0.02 instead of 5.03 10-3 for the risk of death if the patient has a normal physical state. Knowing the age of patient, we can estimate the risk of death, it is 4.98 10-3 for adult, 7.08 10-3 for elderly patient and 8.2 10-3 for child (Table 8). It should be noted that the model and data used in this paper have limitations. The model should be enhanced by taking into account different causes of adverse events. Data should be prevented from an adverse event database reporting system and from expert's judgement.

TABLE.8. Probability of the death of patient

Risk	Probabilities
Death of patient	6.37 10-3
Death of weak physical state patient	0.02
Death of normal physical state patient	5.03 10-3
Death of child patient	8.2 10-3
Death of adult patient	4.98 10-3
Death of elderly patient	7.08 10-3

Several actions can be done to reduce risk and improve the safety of the patient in operating room. For instance, we can reduce the risk of retained foreign body during operation by using an appropriate sponge counts and obtaining x-rays if needed to check for any retained foreign body. If we reduce this risk by 95%, the risk of the death of patient become 6.28 10-3. Furthermore if we reduce the risk of surgery infection by 80%, the risk of the death of patient pass to 4.5 10-3 instead of 6.28 10^{-3}. By acting only on 'retained foreign body' and 'surgery infection' adverse events, the risk can be reduced by 30%.

Discussion

The aim of this paper has been to illustrate a methodology of risk analysis in operating room using Bayesian networks. Bayesian networks offer the flexible combination of multiple sources of information such as expert's knowledge, historical data, observation or a mixture of these information sources. This methodology gives a clear picture of the risk problem in operating room. It helps to perform a root cause analysis and to make the focus on the most important causes. It provides quantitative risk assessment and support the decision making. The risk measurement should insist that the person in charge makes changes in processes to mitigate risks. Repeated measurement of risk might determine if these changes have reduced the risk. That helps to take the best decision to reduce risks and improve safety and quality.

The model presented is not exhaustive and the quantitative data used must be updated according to expert's opinion to better estimate the risk of patient safety in operating room. The quality of the results of the model depends on the quality of the input data. The case studied in this paper shows that even for simple model, there is a need of significant amounts of input data. Due to the lack of data about adverse event and the fact that the adverse event reporting system doesn't exist, the input data of risk modelling will be provided by expert's opinion. The quality of such data must be discussed. We must help experts to provide reliable quantitative data. That can be done by the fuzzy set theory. Fuzzy Bayesian Networks (FBN) are used in [12] to safety risk analysis under uncertainty in tunnel construction.

In addition, when the size of the graph is important, the model becomes incomprehensive. We can resolve that, by using Object-Oriented Bayesian Network (OOBN). OOBN is a type of Bayesian network, comprising both instance nodes and usual nodes. An instance node is a sub-network, representing another Bayesian network. Using OOBNs, a large complex Bayesian network can be constructed as a hierarchy of sub-networks with desired levels of abstract on [13]. Therefore, model construction is facilitated and communication between the model's sub-networks is more effectively performed. OOBN has a better model readability which facilitates the extending and improvement of the model.

Remedy actions are always conducted by doctors and nurses upon hazardous occurrences. Timely rescue can largely reduce the practical risks of patient's injury. By contrast, delayed remedies are of less use. It is therefore necessary to take into account the time. Consideration and incorporation of time-dependent in the risk assessment to represent equipment failure or human reliability is very important. This can be done through Dynamic Bayesian Network (DBN) models. DBN is an extension of Bayesian network; it is used to describe how variables influence each other over time based on the model derived from past data. A DBN can be thought as a Markov chain model with many states or a discrete time approximation of a differential equation with time steps. A Dynamic Bayesian Network methodology has been developed to model domino effects in [14]. Another application of DBN is presented in [15] to evaluate stochastic deterioration models.

The Bayesian network presented in this paper is a model for assessing risk of patient's safety in operating room. The model aims to capture and measure risk in the background knowledge (namely common causes and observed adverse event). Including the expert's judgment in the risk model is essential for providing a reliable risk picture supporting the decision making. The use of adverse event database reporting system may be very useful for getting statistics and determine the probabilities of occurrence of the adverse events.

Conclusion

Safety is very essential in healthcare system. Thus, we should make more effort to prevent potential hazards for becoming accidents and protect the patient. Bayesian methods are used to model and to provide quantitative risk assessment in the operating room.

Bayesian networks allow to:

- Model the risk among various factors and events using the causal relationships and conditional dependency among them.
- Perform complex "what-if?" analysis, from causes to effects and reverse.
- Incorporate expert's judgment.
- Learn from data so that the predictions become more relevant and accurate.

The application of this approach has been explained by the use of a simple model. The aim of this paper is to demonstrate how Bayesian networks can be employed to capture complex issues such as patient's safety risk analysis and to increase the understanding of risk problem. However, it is hard to find statistical data for risk and factors of risk in hospitals. Therefore, the input data for model will be based in expert's judgement or the mixture of other available sources of information such as statistical data and observation and expert's judgement.

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