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Human Reliability Analysis for Cardiopulmonary Resuscitation Process in Emergency Medicine Using a Modified Hybrid Method Based on the Markov Model and Fault Tree Analysis

*Shiva Rasouli[1], Katayoon Eshkofti[1], Seyed Mahmoud Hosseini[1], Elham Pishbin[2]

1. *Department of Industrial Engineering, Ferdowsi University of Mashhad, Mashhad, Iran.*
2. *MD, Emergency Department, Mashhad University of Medical Sciences, Mashhad, Iran.*

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ABSTRACT

Introduction:
In emergency departments (ED), human reliability assessment is essential for improving the quality of treatment and preventing medical accidents. A medical accident is expressed as an injury to a patient caused by the negligence of a doctor or nurse who is providing medical care. This study aimed to assess the human reliability in the cardiopulmonary resuscitation (CPR) process and recommend some comments to minimize human errors and improve patient safety.

Materials and Methods:
The main factors in the CPR process (such as rate and depth of chest compression and rate of ventilation) are identified based on the American heart association (AHA) roles. Data were recorded during three months in the evening shifts in the ED and CPR room of Imam Reza Hospital in Mashhad, Iran. In total, 42 samples were collected, and a modified hybrid approach according to the fault tree analysis and Markov method was proposed for the analysis of CPR team (including emergency medicine, medical interns, and nurses) reliability in the resuscitation process. Finally, the important basic events (errors) were selected using the Boruta algorithm by R software.

Results:
An FTA-Markov-based hybrid method is considered to compute the human reliability in the CPR process. The obtained results from human reliability analysis using the sensitivity analysis via Boruta algorithm and the proposed hybrid method show that an interrupt between chest compression process for rhythm control, the cycle of CPR, the depth of chest compression, and the discussion about reversible causes are the most effective factors in the human reliability of CPR process.

Conclusion:
The human reliability of the CPR process in the ED has been assessed using a hybrid method based on the FTA and Markov method for the first time. To improve the quality of treatment and prevent medical accidents during the CPR process, the main factors in the process are identified, and then, the proposed hybrid method is used to calculate human reliability.

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[1]****Corresponding Autor:***
Department of Industrial Engineering, Ferdowsi University of Mashhad, Mashhad, Iran.
E-mail: rasouli.shiva070@gmail.com

Introduction

Medical error is a preventable subject in healthcare delivery (1). Studies show that approximately every year, 44,000-98,000 Americans die in hospitals from medical errors (IOM, 1999) (2). Since IOM published this report, medical error and patient safety became a global challenge, and a lot of research has been conducted in this area (3-6). In this regard, Koricke and Teresa L. Scheid (2020) investigated the relationship between mandated reporting of errors and quality improvement in hospitals (7).

Wijaya et al. (2020) assessed the impact of shift schedule realignment on patient safety culture (8). Cohen et al. (2018) used Human Factors Analysis and Classification System (HFACS) for healthcare and identified its casual factors to classify and analyze surgical near-miss incidents reported. They brought up process improvements and better provided patient safety methods (9). In this situation, it seems that human reliability assessment has a strong influence on analyzing serious clinical incidents in healthcare and identifying the errors and faults in the medical process. One of the areas in healthcare that is exposed to a high probability of human error is the emergency department (ED) because of urgent and stressful conditions (10). Within the 50 hospitalized patients, one patient experiences an adverse event that is preventable, and above 3% of these events occur in EDs (11). Croskerry et al. (2001) described effective factors in medication errors in the ED (12). They conducted another research that described 15 adults and pediatric cases to indicate a variety of medical errors in ED (13). Kiymazand and Zoliha (2018) distinguished factors that have impacts on the orientation of nurses in the ED for making medical errors (14). Although there are various practices in the ED, Cardiopulmonary Resuscitation (CPR) plays a key role in saving lives from cardiac arrest, and the quality of different parts of this procedure is strongly dependent on the performance of the operator and CPR team. Therefore, identifying errors and weaknesses of the CPR team performance and correcting them can lead to improved quality and reliability of CPR. Flannery and Parli (2016) declared that the high levels of stress and tension in the resuscitation environment can lead to errors in prescribing, administering, preparing, dosing, and labeling medications (15). Similarly, Thiagarajan et al. (2007) determined human errors, such as poor communication, poor coordination, and suboptimal teamwork, which endanger children's safety with cardiac diseases that they should focus on them to improve safety (16). Human reliability analysis (HRA) techniques have been utilized over the last decades in various industries, such as nuclear power plants (17), shipping industries (18, 19), distribution power systems (20), and oil (21). Human error rates (HER) were estimated using fuzzy mathematical tools in underground coal mines (22). In another research, THERP [2], SPAR-H [3], and CREAM [4] were used to investigate human reliability analysis on Volkerak lock complex in Willemstad (23). In another study, Cai et al. (2018) reviewed the studies, which integrated Bayesian networks in the reliability evaluation (24).

Furthermore, the HRA has been performed in healthcare, and Sujan et al. (2018) carried out a study analyzing the challenges of medical HRA application (25). Foster et al. (2016) conducted a study to investigate the use of the OCHRA[5] method for analyzing the laparoscopic rectal surgery's technical performance and prospecting its validity and reliability (26). In another research, HEART[6] which is a modified version of HRA was applied to assess nursing tasks in a radiotherapy system (27). Hsieh et al. (2018) analyzed important human factors in ED. In their research, HFACS and MCDM[7] methods, such as AHP [8] and fuzzy TOPSIS [9] were employed to analyze the side effects in 35 ED in Taiwan and rate the importance of the error factors (28). Dhillon (2003) proposed

2 Technique for Human Error-Rate Prediction
3 Standardized Plant Analysis Risk-Human Reliability Analysis
4 Cognitive Reliability and Error Analysis Method
5 Objective Clinical Human Reliability Analysis
6 Human Error Assessment and Reduction Technique
7 Multiple Criteria Decision Making
8 Analytic Hierarchy Process
9 Technique for Order Preference by Similarity to Ideal Solution

nine methods and approaches for implementing human reliability assessment and error analysis in healthcare, which include FMEA[10], RCA[11], CAED[12], FTA[13], HAZOP[14], MMSA[15], ECRP[16], and probability tree method (29). The FTA can show the correlation between potentially serious faults and their causes in a complex system; therefore, it is considered an effective method in static analysis. In CPR, most factors, such as rates of chest compression and breath are associated with time, and therefore, it will be a difficult analysis in a traditional FTA. Accordingly, it is advised to employ a dynamic fault tree by considering the Markov model to assess the human reliability in the CPR. Markov models are generally accepted by academia and industry to address state transition problems. In some previously published works, their authors (Andeweg, Groenewoud, Wilt, Goor, and Bleichrodt, 2016) created a model based on Markov for the simulation of event flow in patients after non-surgically treated two-part acute colonic diverticulitis (30). Some researchers have deliberated on hybrid methods based on FTA and Markov and have utilized their hybrid models in reliability assessment of a power distribution systems customer (20) and reliability analysis in gastric esophageal surgery (31). Our intention in this study is the combination of dynamic analysis with the traditional static techniques to analyze the human reliability in the CPR process along with improving the Markov model's effectiveness. A modified hybrid method based on the dynamic FTA and Markov model is proposed for HRA in the CPR process in the ED. This study is organized as follows: Materials and Methods are introduced in section 2; section 3 is devoted to Results including computation of total reliability, Boruta algorithm, and sensitivity analysis, and then the Discussion section presents new findings. Finally, the Conclusions are presented.

Materials and Methods

Combination of the fault tree and Markov models

This study provided a risk assessment model via the fault tree dealing with static events. A fault tree consists of some basic parts, namely top event that demonstrates an undesirable accident, generally a system failure and basic event, which indicates the primary causes of an undesired event. It usually refers to failures of factors that are composed of human errors, systems, or environmental stresses. The basic event does not need to explain the cause of the error in more detail (Fig 1, each circle is a basic event).

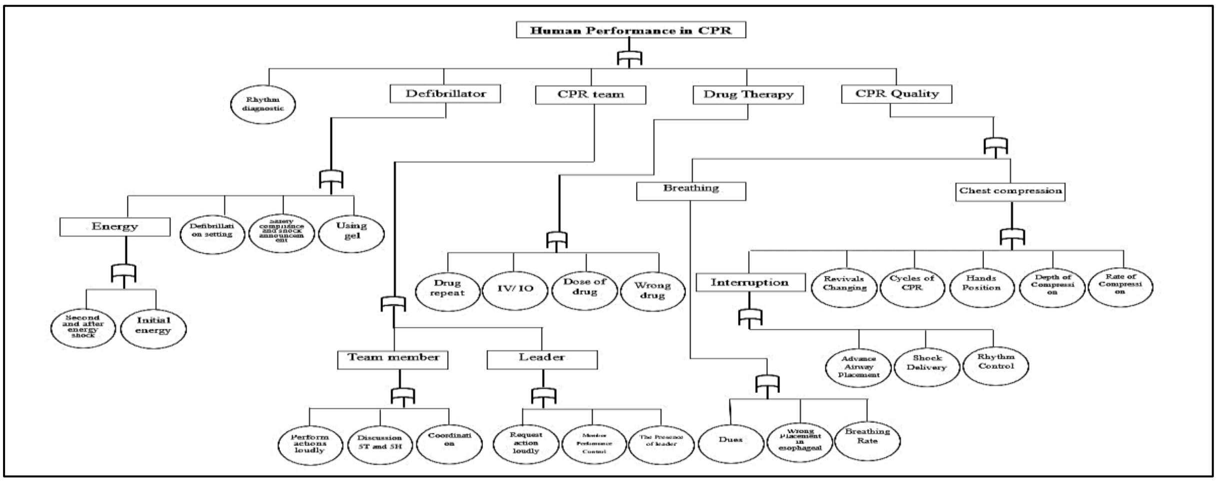

Fig 1: Fault tree of CPR process

[10] Failure Mode and Effects Analysis
[11] Root Cause Analysis
[12] Cause And Effect Diagram
[13] Fault Tree Analysis
[14] Hazard and Operability
[15] Man-Machine Systems Analysis
[16] Error-Cause Removal Program

The next one is an undeveloped event that represents a fault event that is not further developed since the information is not available, or which is of unimportant consequences (32). The probability of occurrence of the top event in the fault tree is the probability of system failure and the probability of human error in the CPR process. In CPR, risks arise in 5 steps, including CPR quality, drug therapy, CPR team, defibrillator, and rhythm diagnostic. For time-dependent events for CPR risks, a Markov state transition model is introduced to indicate the time-based failure probability. Markov is a strong technique that is commonly used in safety and reliability research, and it can likely handle more cases than other methods in these fields (29).

$\{X_n, n=1,2,...\}$ is assumed to be a random process that has a limited number of values. Nonnegative integers $\{0,1,2,...\}$ are assigned to these values. $X_n = i$ means state i at time n in the process. Assuming the process is in the state i, then P_{ij} is defined as a transition probability to the next state, j. In other words, we have:

$$P\{X_{n+1} = j | X_n = i, X_{n-1} = i_{n-1}, ..., X_1 = i_1, X_0 = i_0\} = P_{ij} \quad (1)$$

Consequently, the Markov chain is characterized by a probabilistic process comprised of states $i_0, i_1, ..., i_{n-1}, i, j$ in which $n \geq 0$. Eq. 1 implies that any future state X_{n+1} with conditional distribution is merely dependent upon the present state X_n rather than past ones, $X_0, X_1, ..., X_{n-1}$ (33).

Fig 2 displays a simple Markov model. Human performance can be expressed with a CPR including basic states, such as the proper operation of human before the placement of advance airway state, human error before the placement of advanced airway state, proper operation of human after the placement of advance airway state, and human error after the placement of advance airway state. When an advanced airway was inserted, the system's state transfer from state ‘0’ to state ‘1’.

Data gathering

A CPR is used as the object of the case study, and its fault tree (Fig 1) is developed based on the American Heart Association (AHA) targets (34). The failure probabilities were calculated according to the direct observation of the performance of the cardiac resuscitation team in the CPR room of the emergency unit in Imam Reza Hospital in Mashhad, Iran, in the afternoon shift, for three months.

In the CPR room under evaluation, all CPRs were executed by the emergency medicine team, interns, and nurses. In total, 42 CPRs were performed during this time. Indeed, a checklist was developed based on the AHA guidelines.

One of our team members, who was trained by watching educational movies of the CPR process and participating in training classes, recorded the data by being present next to the cardiac arrest victim and CPR team under the supervision of emergency medicine doctors. Nonetheless, sometimes, the data collector recognized the errors according to the leader's words during the CPR process.

In the chest compression section, the leader instructed the person conducting the chest compression to push hard, warning (showing) her/his error in performing the procedure. Additionally, sometimes, it was obvious that the compression depth was not adequate; therefore, it was recorded as an error.

Probability of occurrence of the basic and top event

The CPR fault tree is depicted in Fig 1. Basic events displayed in the fault tree are independent. This study identifies four human error states.

Human errors that are dependent on the advanced airway placement include CPR team performance before advanced airway placement, CPR team performance after advanced airway placement, occurrence of the error in CPR team performance before advanced airway placement, and occurrence of the error in CPR team performance after advanced airway placement.

Markov model of a CPR team error that is related to the airway placement is illustrated in Fig 2, and Table 1 shows the transition states and properties.

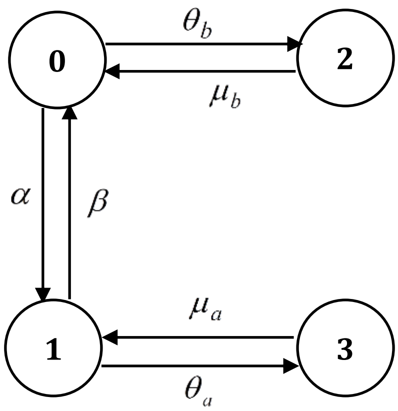

Fig 2: Markove model for a human error that related to airway placement

Table 1: States and properties for human error

States	Properties
0	CPR team performance before advanced airway placement
1	CPR team performance after advanced airway placement
2	The occurrence of the error in CPR team performance before advanced airway placement
3	The occurrence of the error in CPR team performance after advanced airway placement

In the Markov model, the transition rates between states can be described as below:
θ_b is a fixed rate of human error before the placement of advanced airway.
θ_a is a fixed rate of human error after the placement of advanced airway.
μ_b is a fixed rate of human error correction before the placement of advanced airway.
μ_a is a fixed rate of human error correction after the placement of advanced airway.
α is a fixed rate of changing process conditions before the placement of advanced airway up to finishing it.
β is a fixed rate of changing process conditions between after placement of advanced airway and before that.
$P_i(t)$ is the occurrence probability of state i that is time-dependent.

The transition ratio between different states is calculated as follow:

$$\textit{Transition rate} = \frac{e}{T} \quad (2)$$

Where e is defined as the number of errors, and T is the duration of sampling which in this case it took 6.5 hours per day within 90 days. Therefore, the amount of T is calculated as below:

$$T = 90 * 6.5 * 60 = 35100 \text{ min} \quad (3)$$

In the Markov model, the state transition matrix is:

$$A = \begin{bmatrix} -(\alpha+\theta_b) & \alpha & \theta_b & 0 \\ \beta & -(\beta+\theta_a) & 0 & \theta_a \\ \mu_b & 0 & -\mu_b & 0 \\ 0 & \mu_a & 0 & -\mu_a \end{bmatrix} \quad (4)$$

In the case of a Markov process, there is a $P = [P_0, P_1, \ldots, P_n]$, that can meet the equation of $PA = \frac{dP(t)}{dt}$, and then the following expressions can be obtained:

$$\frac{d}{dt}\left[P_0(t)\ \ P_1(t)\ \ P_2(t)\ \ P_3(t)\right] = \left[P_0(t)\ \ P_1(t)\ \ P_2(t)\ \ P_3(t)\right]\begin{bmatrix} -(\alpha+\theta_b) & \alpha & \theta_b & 0 \\ \beta & -(\beta+\theta_a) & 0 & \theta_a \\ \mu_b & 0 & -\mu_b & 0 \\ 0 & \mu_a & 0 & -\mu_a \end{bmatrix} \quad (5)$$

$$-(\alpha+\theta_b)P_0(t) + \beta P_1(t) + \mu_b P_2(t) = \frac{dP_0(t)}{dt} \quad (6)$$

$$\alpha P_0(t) - (\beta+\theta_a)P_1(t) + \mu_a P_3(t) = \frac{dP_1(t)}{dt} \quad (7)$$

$$\theta_b P_0(t) - \mu_b P_2(t) = \frac{dP_2(t)}{dt} \quad (8)$$

$$\theta_a P_1(t) - \mu_a P_3(t) = \frac{dP_3(t)}{dt} \quad (9)$$

Taking Laplace transform on both sides of equations (6) to (9)

$$\mathcal{L}\{-(\alpha+\theta_b)P_0(t) + \beta P_1(t) + \mu_b P_2(t)\} = \mathcal{L}\left\{\frac{dP_0(t)}{dt}\right\} \quad (10)$$

$$\mathcal{L}\{\alpha P_0(t) - (\beta+\theta_a)P_1(t) + \mu_a P_3(t)\} = \mathcal{L}\left\{\frac{dP_1(t)}{dt}\right\} \quad (11)$$

$$\mathcal{L}\{\theta_b P_0(t)-\mu_b P_2(t)\}=\mathcal{L}\left\{\frac{dP_2(t)}{dt}\right\} \quad (12)$$

$$\mathcal{L}\{\theta_a P_1(t)-\mu_a P_3(t)\}=\mathcal{L}\left\{\frac{dP_3(t)}{dt}\right\} \quad (13)$$

Since $\mathcal{L}\left\{\frac{dP_i(t)}{dt}\right\}=s\overline{P}_i(s)-P_i(0)$ and $\mathcal{L}\{cP_i(t)\}=c\overline{P}_i(s)$; $c=cte$ we can write down the equations (10) to (13) in the form below:

$$-(\alpha+\theta_b)\overline{P}_0(s)+\beta\overline{P}_1(s)+\mu_b\overline{P}_2(s)=s\overline{P}_0(s)-P_0(0) \quad (14)$$

$$\alpha\overline{P}_0(s)-(\beta+\theta_a)\overline{P}_1(s)+\mu_a\overline{P}_3(s)=s\overline{P}_1(s)-P_1(0) \quad (15)$$

$$\theta_b\overline{P}_0(s)-\mu_b\overline{P}_2(s)=s\overline{P}_2(s)-P_2(0) \quad (16)$$

$$\theta_a\overline{P}_1(s)-\mu_a\overline{P}_3(s)=s\overline{P}_3(s)-P_3(0) \quad (17)$$

In the initial condition at time 0, the distribution of the system states are as $P_1(0)=P_2(0)=P_3(0)=0$ and $P_0(0)=1$; accordingly, it is easy to observe that:

$$-(\alpha+\theta_b)\overline{P}_0(s)+\beta\overline{P}_1(s)+\mu_b\overline{P}_2(s)=s\overline{P}_0(s)-1 \quad (18)$$

$$\alpha\overline{P}_0(s)-(\beta+\theta_a)\overline{P}_1(s)+\mu_a\overline{P}_3(s)=s\overline{P}_1(s) \quad (19)$$

$$\theta_b\overline{P}_0(s)-\mu_b\overline{P}_2(s)=s\overline{P}_2(s) \quad (20)$$

$$\theta_a\overline{P}_1(s)-\mu_a\overline{P}_3(s)=s\overline{P}_3(s) \quad (21)$$

To solve equations (18) to (21), the Laplace transforms of $P_i(t), i=0,1,2,3$ are defined by:

$$\overline{P}_0(s)=\frac{(\mu_b+s)(\beta\mu_a+s\beta+s\mu_a+s\theta_a+s^2)}{s(s^2\alpha+s^2\beta+s^2\mu_b+s^2\theta_a+s^2\theta_b+s^3+s\alpha\mu_b+s\beta\mu_b+\alpha\mu_b\theta_a-\beta\mu_a\theta_b+s\alpha\theta_a+s\beta\theta_b+s\mu_b\theta_a+s\theta_a\theta_b)} \quad (22)$$

$$\overline{P}_1(s)=\frac{\alpha(\mu_b+s)(\mu_a+s)}{s(s^2\alpha+s^2\beta+s^2\mu_b+s^2\theta_a+s^2\theta_b+s^3+s\alpha\mu_b+s\beta\mu_b+\alpha\mu_b\theta_a-\beta\mu_a\theta_b+s\alpha\theta_a+s\beta\theta_b+s\mu_b\theta_a+s\theta_a\theta_b)} \quad (23)$$

$$\overline{P}_2(s)=\frac{\theta_a(\beta\mu_a+s\beta+s\mu_a+s\theta_a+s^2)}{s(s^2\alpha+s^2\beta+s^2\mu_b+s^2\theta_a+s^2\theta_b+s^3+s\alpha\mu_b+s\beta\mu_b+\alpha\mu_b\theta_a-\beta\mu_a\theta_b+s\alpha\theta_a+s\beta\theta_b+s\mu_b\theta_a+s\theta_a\theta_b)} \quad (24)$$

$$\overline{P}_3(s)=\frac{\alpha\theta_a(\mu_b+s)}{s(s^2\alpha+s^2\beta+s^2\mu_b+s^2\theta_a+s^2\theta_b+s^3+s\alpha\mu_b+s\beta\mu_b+\alpha\mu_b\theta_a-\beta\mu_a\theta_b+s\alpha\theta_a+s\beta\theta_b+s\mu_b\theta_a+s\theta_a\theta_b)} \quad (25)$$

In our study, the human error correction rate is not considered; therefore, $\mu_a=\mu_b=\beta=0$. For a Markov model, there is a $P=[P_0,P_1,\ldots,P_n]$, that can meet the equation of $PA=\frac{dP(t)}{dt}$, and then the following relationships can be obtained:

$$-(\alpha+\theta_b)P_0(t)=\frac{dP_0(t)}{dt} \quad (26)$$

$$\alpha P_0(t)-\theta_a P_1(t)=\frac{dP_1(t)}{dt} \quad (27)$$

$$\theta_b P_0(t)=\frac{dP_2(t)}{dt} \quad (28)$$

$$\theta_a P_1(t)=\frac{dP_3(t)}{dt} \quad (29)$$

Then, the probability in the states and can be calculated as following equations, (30) and (31). In fact, P_2+P_3 is the stable failure probability of human error that corresponds to the basic event occurrence probability.

$$P_2(t)=\frac{\theta_b}{(\alpha+\theta_b)}-\frac{\theta_b e^{-t(\alpha+\theta_b)}}{(\alpha+\theta_b)} \quad (30)$$

$$P_3(t)=\frac{\alpha}{(\alpha+\theta_b)}-\frac{\alpha e^{-t(\theta_a)}}{(\alpha+\theta_b+\theta_a)}+\frac{\alpha\theta_a e^{-t(\alpha+\theta_b)}}{(\alpha+\theta_b)(\alpha+\theta_b-\theta_a)} \quad (31)$$

Some human errors are dependent on true (right, appropriate) or false (wrong, inappropriate) performance of the CPR team to carry out a particular action in each cycle (every 2 minutes is a cycle) or in CPR.

In this study, two states of human error are identified for the aforementioned type of human error, namely proper performance of the CPR team in each cycle or CPR process and inappropriate performance of the CPR team in each cycle or CPR process. Markov model of a CPR team error that is not related to the airway placement is illustrated in Fig. 3, and Table 2 summarizes the transition states and properties.

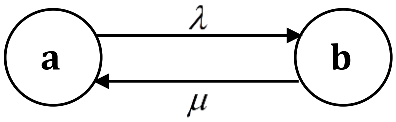

Fig 3: Markov model for a human error that dependent on true or false performance of CPR team to carry out a particular action in each cycle

λ is a fixed rate of human error.
μ is a fixed rate of human error correction.

Table 2: States and properties of human error dependent on cycle or CPR process

States	properties
a	Proper performance of the CPR team in each cycle or CPR process.
b	False performance of the CPR team in each cycle or CPR process.

Similarly, the calculation process of the hazard probabilities for medical errors that are dependent on the placement of advanced airway, are considered as follows utilizing Laplace inversion:

$$P_0(t)=\frac{\mu}{(\lambda+\mu)}+\frac{\lambda}{e^{t(\lambda+\mu)}(\lambda+\mu)} \quad (32)$$

$$P_1(t)=\frac{\lambda}{(\lambda+\mu)}-\frac{\lambda}{e^{t(\lambda+\mu)}(\lambda+\mu)} \quad (33)$$

Laplace transform is applied as an alternate method to find time-dependent probabilities. Same as the calculation method for medical error dependent on the placement of advanced airway, medical error correction is not considered; therefore, $\mu=0$, and a basic event's failure probability (in P_b') can be represented by a function of λ:

$$P_b(t)=1-e^{-\lambda t} \quad (34)$$

In our case study, all gates in FTA are OR gates; as a result, the occurrence probability of the system is calculated as follow:

$$P_{total}(t)=1-\prod_{i=1}^{n}(1-F_i(t)) \quad (35)$$

Where F_i (t) is the failure rate of a subsystem event in time t, and n is the number of subsystems.

Results

Initially, the calculations for the error probability of the CPR are conducted, then Boruta algorithm and sensitivity analysis will be discussed as follows:

Total error probability in the CPR

In the fault tree (Fig 1), 27 basic events can contribute to the top event occurrence. As mentioned before, basic events are grouped as human errors that are dependent on the type of breathing include two events (Table 3), five of basic events are assigned to human errors that are dependent on cycle (Table 4), and eventually 20 of them are human errors that are dependent on CPR process (Table 5).

The correct form of performing each event by rescuers is also mentioned in the tables. Moreover, the transition rates in each state were calculated with equation (2).

Following that, according to the Markov model, for each basic event, the occurrence probabilities were worked out. Actually, for errors with four states, it was figured based on the sum of equations (30) and (31), and for errors with two states, it is calculated based on equation (34). Finally, the total failure probability of the system is calculated based on equation (35). This study selected important errors with Boruta Algorithm and examined the total reliability increasing by considering important errors. The next section is dedicated to the description of the Boruta Algorithm and its outputs.

Table 3: Events from human errors that dependent on the type of breathing and their occurrence probabilities

Row	Event/Cause	Rescuers Should	P(10^{-3})
B_1	Rate of Compression (without advanced airway)	Compressions and ventilations at a ratio of 30:2	0.291
B_2	Rate of Compression (with advanced airway)	Continuous compressions at a rate of 100-120/min	1.420
B_3	Breathing Rate (without advanced airway)	Give 2 breaths after 30 compression	0.330
B_4	Breathing Rate (with advanced airway)	Give 1 breath every 6 seconds (10 breaths/min)	0.760

Table 4: Events from human errors that dependent on cycle and their occurrence probabilities

Row	Event/Cause	Rescuers Should	P(10^{-3})
B_5	Depth of Compression	Push hard at least 2 inches (5 cm)	1.420
B_6	Hands placement	2 hands on the lower half of the breastbone (sternum)	0.620
B_7	Cycles of CPR	Be approximately 2 minutes	1.600
B_8	Rescuers switching	Switch rescuers (chest compressors) every 2 minutes	0.910
B_9	rhythm/ pulse Control	Interrupt compressions for less than 10 seconds	1.860

Table 5: Events from human errors that dependent on CPR and their occurrence probabilities

Row	Event/ Cause	Rescuers Should	P(10^{-3})
B_{10}	Rhythm diagnostic	Cardiac arrest can be caused by 4 rhythms: VF, VT, Asystole, and PEA	0.031
B_{11}	Wrong placement an advanced airway in esophageal	placement of a flexible plastic tube into the trachea	0.000
B_{12}	Dues	Wrong placement of advanced airway may injure the ribs	0.000
B_{13}	Wrong drug		0.125
B_{14}	Dose of drug	Epinephrine: 1mg, and Amiodarone: first dose 300 mg and second dose 150 mg	0.000
B_{15}	IV/ IO	Correct put IV/IO to infusion done correctly	0.000
B_{16}	Drug repeat	Epinephrine every 3-5 minutes and Amiodarone every 10 minutes	0.093
B_{17}	The presence of a leader	The presence of a person as a leader	0.530
B_{18}	Member performance control	The leader must control the Member's performance	0.960
B_{19}	Request action loud	The leader should say loudly an action from members	0.620
B_{20}	Coordination	The task of members should be known before starting to maintain coordination between them	0.870
B_{21}	Discussion 5T and 5H	Leader and members during action should talk about reversible causes	1.150
B_{22}	Perform actions loudly sound		1.120
B_{23}	Using gel	Using special gel before a shock delivery	0.000
B_{24}	Safety compliance and the shock announcement	The person who wants delivered shock should say loudly to all of the members go away from	0.093
B_{25}	Defibrillation settings	Set on Asynchronize mode	0.000
B_{26}	Initial energy	200 j	0.093
B_{27}	Second and after energy shock	270 j	0.093
B_{28}	Advance airway placement	Interrupt compressions for less than 10 seconds	0.499
B_{29}	Shock delivery	Interrupt compressions for less than 10 seconds	0.370

Boruta Algorithm

The selection of important features that play pivotal roles in predictive modeling is a major step in a comprehensive analysis. Many methods are aiming at dimensionality reduction. However, the utilization of an appropriate algorithm will lead to more realistic models with better results. As the number of features in the aforementioned case study is considerable, it is recommended to conduct a feature selection method to check whether any dimension reduction is possible or not. This procedure helps to less computational efforts while the efficiency will be maintained at a satisfactory level. Boruta is a wrapper algorithm that is an improved version of the random forest method.

In this research, the Boruta algorithm has been implemented via R software. The plot in Fig 4 identifies important features (confirmed variables) with green boxes.

Red and yellow boxes are rejected and tentative variables, respectively. As it is obvious from the following plot, 17 variables have been identified as important ones.

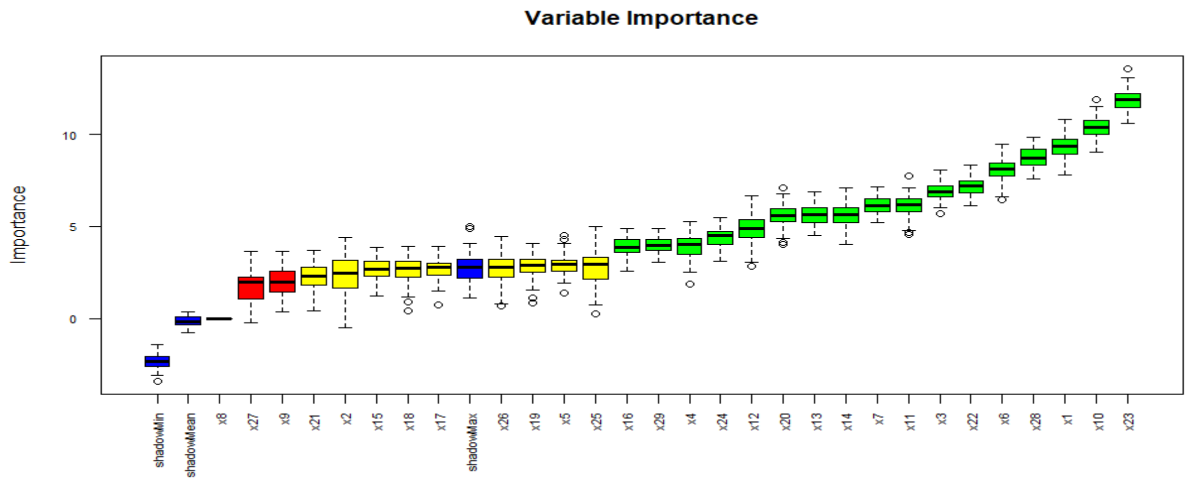

Fig 4: Important Variables

The output of the algorithm in R software is provided below:

Boruta performed 99 iterations in 3.066057 secs.

Tentatives roughfixed over the last 99 iterations.

19 attributes confirmed important: x1, x10, x11, x12, x13 and 14 more;

10 attributes confirmed unimportant: x27, x8, x9;

9 tentative attributes left: x15, x17, x18, x19, x2 and 5 more;

To decide whether tentative variables can be confirmed or not, comparisons between the median Z-score of the variables with the median Z-score of the best shadow variables should be made. The output of thiscomparison by R software is shown in Fig 5 which determines 19 variables as important ones which are listed in Table 6. This means that two tentative variables have been added to the group of important variables.

Boruta performed 99 iterations in 3.066057 secs.
Tentatives roughfixed over the last 99 iterations.
19 attributes confirmed important: x1, x10, x11, x12, x13 and 14 more;
10 attributes confirmed unimportant: x27, x8, x9;
9 tentative attributes left: x15, x17, x18, x19, x2 and 5 more;

The modified plot of key variables is illustrated in the following figure (Fig 5):

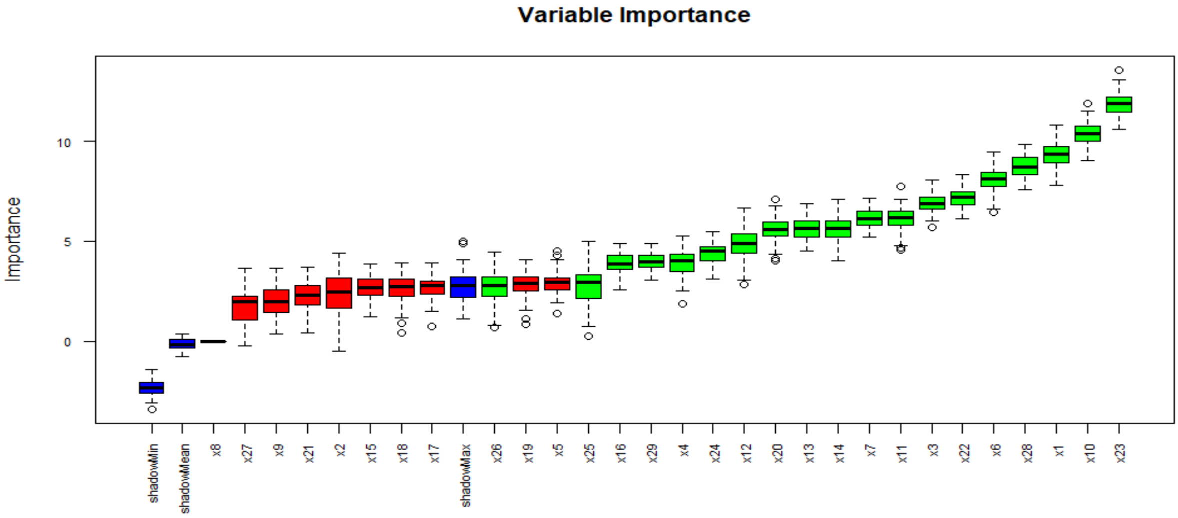

Fig 5: Modified plot of important variables

Sensitivity analysis

In this study, Brutal Algorithm identified important variables. Total human reliability analysis in the CPR process including all the failure causes are calculated for 42 samples. Subsequently, important variables were obtained from Boruta Algorithm, and the total HRA of the CPR process was calculated again. The impact of considering important variables on total human reliability in the CPR process can be found in Fig 6. As it is obvious, total human reliability increases by about 2%-7%.

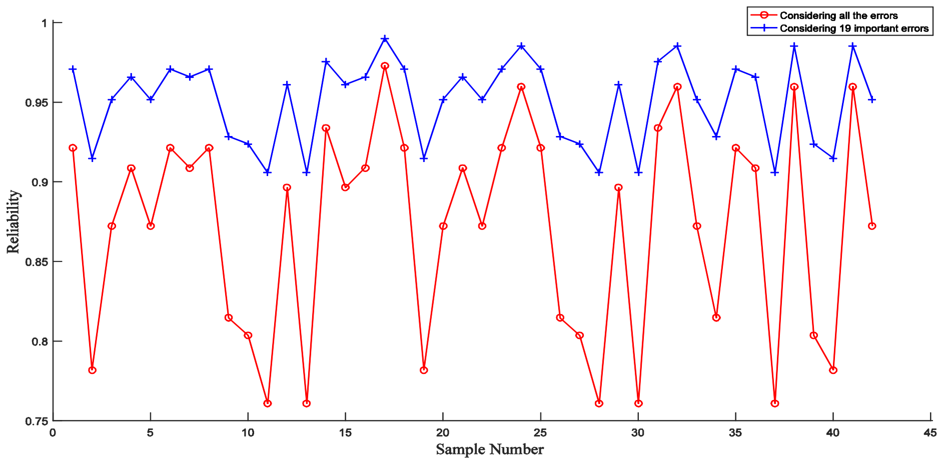

Fig. 6: Changes in total reliability by considering important variables

Discussion

It should be emphasized that human errors in the aforementioned case study are all dependent upon time.

Furthermore, underlying assumptions in the Markov model, such as the exponential nature of transitions and their constant rates may be undergone some alterations in real world situations. In this case, regarding the pivotal roles of important variables in increasing total human reliability of the CPR process, we recommended some comments to improve the performance of the CPR team:

1. The person who does the chest compression should count all the

compressions loudly, and other members should not interrupt him/her until the required rate of chest compression finish. This will help them to be accurate in that stressful situation.

2. Regarding the depth of chest compression, they can use some tools that are designed for improving the CPR process quality. These tools encompass sensors that measure the depth of chest compression (e.g., gloves equipped with sensors).

3. To reduce the time of interruption for the placement of the advanced airway, it is recommended that people with higher relevant skills and experiences do that.

4. Each work shift should have a CPR team with specific duties assigned to each member; therefore, when they face a patient with cardiac arrest, they will be able to start the process as soon as possible.

5. The presence of a member who checks the times with a chronometer, and in addition to controlling (monitoring) the injection of drugs, s/he announces the times loudly in a situation where injection (this action) should be repeated.

Conclusions

The CPR risk analysis is computed based on a fault tree built with AHA guidelines. To model time-dependent events, Markov models are combined with the tree. Human errors probability rates in basic events are calculated from Markov's state solution methods. Following that, the occurrence probability of the top event is obtained. Furthermore, in this article, some important variables, which have significant impacts on CPR quality are identified via Boruta Algorithm. Finally, some suggestions were made for improving the CPR team's performance.

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