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# Providing an approach to analyze the risk of central oxygen tanks in hospitals during the COVID-19 pandemic

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ABSTRACT

The central oxygen unit of hospitals is considered a high-risk unit, requiring high safety standards to maintain the integrity of the system during the COVID-19 pandemic. The linear reasoning assumption of conventional risk analysis methods cannot adequately describe these modern systems, which are characterized by tight connections and complex interactions between technical, human, and organizational aspects. Therefore, this study presents a new and comprehensive approach to oxygen tanks in hospitals during the COVID-19 pandemic. In this study, trapezoidal fuzzy numbers were used to calculate failure rates. After determining the probability of basic events (BEs), intermediate events (IE), and top event (TE) with fuzzy logic and transferring it into Bayesian Network (BN), deductive and inductive reasoning, and sensitivity analysis were performed using RoV in GeNIe software. The results of the case study showed that the IE of "Human Error" had the highest probability of fuzzy fault tree (FFT) and the probability of oxygen leakage was lower using FBN than FFT. According to the results, BE16 (failure to use standard and updated instructions) and BE12 (defects in the inspection and testing program of tank devices) had the highest posterior probability, while based on the FFT results, BE4 (defects in the external coating system of the tank) and, BE3 (Corrosive environment (acidity state)) had the least probability. According to the sensitivity analysis, basic events 10, 11, and 16 were the most important in the oxygen leakage event with a very small difference, which was almost in line with the results of posterior FBN ($FBN_{PO}$). Updating the existing guidelines, fixing defects in the inspection of all types of tank gauges, and testing related equipment can greatly help the reliability of these tanks. Root cause analysis of these events provides opportunities for prevention and emergency response in critical situations, such as the COVID-19 pandemic.

## 1. Introduction

Oxygen is used in various industrial applications, such as welding, cutting, soldering, and other metal fabrication activities, and medical and health applications [1]. The medical use and benefits of using oxygen are countless; however, it requires safe handling by

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qualified and trained staff, so that the lives of people, including the health status of the patient, are not endangered [1]. Oxygen is used as one of the most important ways of treatment, and the provision of oxygen in medical centers, especially hospitals, is considered one of the vital issues. Lack of oxygen can have severe consequences for patients, including irreversible brain damage and death [2].

Oxygen gas is compressed and filled in a high-pressure cylinder to make it easy to transport [1]. The behavior of oxygen is different from other inert gases and compressed air. An oxidizer is required as one of the elements of the fire triangle to create a fire [3]. If the environment is enriched with oxygen (23–24%), we will face very dangerous conditions in terms of fire and explosion risk, which is mainly caused by oxygen leakage. The causes of accidents caused by oxygen leakage mainly include corrosion of the cylinder outlet, defects in the regulator, the opening of the oxygen valve, wear and tear of the cylinder, and reduction of the thickness [4–6]. Materials that do not burn in the air, including fire retardants, may burn violently in oxygen-enriched air or pure oxygen [6]. A higher concentration of oxygen in the environment causes the fire to spread faster, increase the flame temperature, and decreases the minimum temperature or ignition energy to produce combustion [3,7–9].

Death from an oxygen cylinder is rare but dangerous. The European Commission's Joint Research Centre (JRC) reported that oxygen-enriched environments have caused deadly fires in hospitals where Covid-19 patients are being treated [6].

Millo et al. reported the devastating and lethal effect of oxygen gas pressure. A 25-year-old truck driver was loading an oxygen cylinder into his truck with two other people at an oxygen cylinder manufacturing plant. The malfunction in the approaches caused an explosion, throwing the person 20 feet away, and resulting in his death [4]. Fire by spontaneous combustion of oxygen cylinders was also investigated by Coumans et al. The spontaneous combustion of an oxygen cylinder was the cause of a fire in an operating room and an emergency medical service. According to this study, not opening the pressure relief valve while the oxygen supply valve is open can prevent this type of fire. Reports have shown that the probability of such an event is 1 in a million [5].

Currently, the COVID-19 pandemic has created a huge demand for oxygen gas cylinders for medical use, both in hospitals and at-home patients [10]. On the other hand, in hospitals, oxygen production and distribution centers (central oxygen) are responsible for producing oxygen and transporting it to patients' rooms. Although the occurrence of events, such as oxygen leakage, explosion, and lack of proper oxygen supply to patients in treatment units seems to be very rare, if it occurs, it will be catastrophic [11].

Anesthesiology and critical care staff play an important role in understanding the hospital's oxygen system and related contingency plans for internal disaster management. Therefore, the staff must be fully prepared and trained to support emergency response in the event of a central oxygen pipeline failure [11]. According to the study by Wood et al., in 2021, since the outbreak of the COVID-19 pandemic in March 2020, oxygen-related hospital fire incidents in various countries around the world have killed more than 200 people, most of whom were patients who were hospitalized due to coronavirus infection [7].

One of the effective measures to prevent such fatal events in central oxygen centers in hospitals is quantitative and comprehensive risk assessment, based on which appropriate preventive and control strategies can be defined at different stages of a system life cycle [12]. There are various methods for risk analysis and assessment; most of them have two major problems, including uncertainty and static structure [13–15]. The uncertainties of the studies are mainly related to the lack of appropriate knowledge [16]. Unfortunately, the present process has significant uncertainty due to incomplete and ambiguous knowledge about events, which is required for the estimation of failure probabilities. This may increase due to the poor quality of process hazard analysis.

There are two types of problem knowledge: a. Objective knowledge based on the formulation of the engineering problem (eg, by mathematical modeling and simulation), and b. Knowledge extracted from experts is often incomplete, imprecise, fragmented, unreliable, ambiguous, and contradictory [16,17]. Fuzzy logic may be useful when the dominant uncertainties are due to a lack of knowledge [16].

Therefore, in this study, fuzzy logic and Bayesian Networks (BNs) were used to reduce uncertainty. Fuzzy logic is used in conditions of ambiguity and uncertainty and multi-valued logic is used instead of two-valued. In other words, it can deal with uncertainties and inaccuracies where there are no clear boundaries [16]. Therefore, it is a suitable approach for risk management, which mostly deals with qualitative variables and uncertainty [18]. In addition, it is necessary to broaden the field of safety risk analysis not only by considering the accident precursors but also by changing the process parameters (such as temperature, pressure, flow, etc.). As a result, the probability of defects and accidents can be predicted and it can be constantly updated in a real-time process. Many techniques have been developed for accident scenario modeling and safety assessment, among which fault tree analysis (FTA), event tree analysis (ETA), and bow tie analysis (BTA) are very famous. FTA, ETA, and BTA standards are not suitable for analyzing large and complex systems, especially if the system includes additional components or exhibits dynamic behavior or time-varying parameters [19]. According to the studies, classical methods cannot accurately predict the occurrence of events [20–22]. In recent years, Bayesian analysis and especially BN have been widely used for safety assessment and management of chemical equipment. In the Bayesian method, the data of accident precursors are used in the form of a probability function through Bayes' theorem to update the analyst's previous belief about the probability of an accident or the probability of failure of safety barriers [23–25]. Due to the flexible graphic display and strong reasoning engine of the BN, it has been proven as a reliable method for evaluating the safety of a wide range of process equipment and factories [26]. BNs also have advantages over other models, including the ability to learn parameters or conditional probabilities, deductive and inductive reasoning, sensitivity analysis, and considering events with common failures [27].

With the advent of COVID-19, the healthcare systems have faced limitations and hospital liquid oxygen has been paid attention. Although the progress in the design and performance of the central oxygen by itself prevents system defects, due to the occurrence of accidents, it needs comprehensive risk assessment. According to studies, accidents caused by oxygen leakage have low repeatability but high intensity [2]. According to the available resources, most of the studies have focused on the oxygen transport pathways [2,11], and less attention has been paid to the tanks themselves, which are the main supplier of oxygen in hospitals. Therefore, in this study, a comprehensive approach was presented based on a fuzzy Bayesian network (FBN) for oxygen tanks in hospitals to reduce various uncertainties such as parameters and modeling. Thus, in this study, the importance of the aspects causing accidents in central oxygen tanks of hospitals was evaluated with this integrated approach and in a case study in ValiAsr Hospital, Birjand, Iran.

## 2. Method

Risk assessment was carried out in the central oxygen unit of the hospital after consulting with experts and reviewing the scientific literature to deeply analyze the causes and consequences of accidents and fully understand the functional conditions of the system.

The hazards of this unit were identified using the HAZOP method. Then, using FTA and FBN techniques, the probability of occurrence was calculated in the GeNIe software environment. Due to the lack of specific reference to estimate the probability rate of basic events, this step was done using experts' opinions and fuzzy logic. In the next step, the general nomogram of the study was drawn and the information was mapped in the BN. Fig. 1 shows the general flowchart of the study.

### 2.1. HAZOP

In this study, the HAZOP method, which is a reliable and widely used qualitative risk identification method in risk assessment [28], was used to identify and evaluate process and human risks as well as identify operational problems. This method was used for the first time in Imperial Chemical Industries (ICI) in 1963, to identify hazards and diagnose equipment errors that lead to accidents [29]. Therefore, in this study, deviations and possible consequences were identified using suitable guide words, and this information was used to develop FTA in the next step.

### 2.2. Fault tree analysis

The FTA graphically shows the failure propagation (progress) and the logical relationship that exists between the root causes and error paths [30]. In addition, FTA can provide a quantitative analysis using reliability theory, probability theory, and Boolean algebra [31]. FTA is a hierarchical diagram that deductively depicts all possible ways for system failure. This technique is based on the top event (TE), which represents the unwanted event, and then the tree graph is built using logic gates until it reaches the basic event (BE) [13]. Therefore, at this stage, the fault tree (FT) diagram was drawn.

### 2.3. Fuzzy logic

In this study, fuzzy logic and experts' opinions were used to determine failure probabilities due to the lack of probability for $BE_S$,

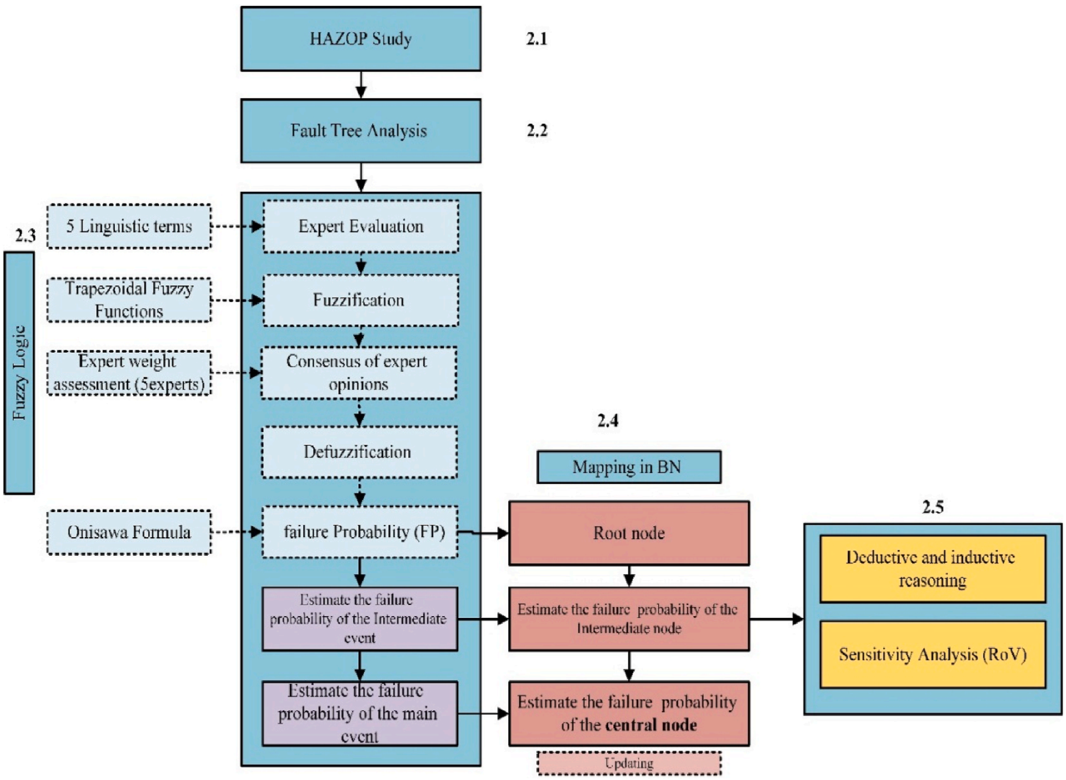


**Fig. 1.** Flowchart of the study.

and no generic or plant-specific data was used. There are various applications of fuzzy set theory to deal with uncertainties and ambiguities, including trapezoidal, triangular, Gaussian, and intuitionistic fuzzy numbers [32,33]. In this study, trapezoidal fuzzy numbers were used, which are explained in detail in the discussion section. In Table 1, experts' opinions regarding the probability of BEs were quantified. The experts' panel included a faculty member and inspector of oxygen tanks (E1), an industrial consultant expert (E2), a faculty member and safety science researcher (E3), an HSE inspector (E4), and a faculty member (E5). In this study, an expert is someone who has enough information about the system and is familiar with the structure of the FT. As mentioned, the experts of the present study were university faculty members, inspectors of oxygen tanks in hospitals, or HSE officials who were fully familiar with the structure of the tanks. The information of these people was obtained from the maintenance and repair unit of the hospital; they participated voluntarily and provided consent to participate. Following this, their opinions were obtained. Given that experts have different levels of expertise, background, and work experience and may show different perceptions about events, the weighted factor (WF) that can show the relative quality of different experts should be considered. The WF for each of the experts includes the sum of the Likert points obtained by each expert divided by the sum of the points obtained by all the experts. The scores of each expert were collected according to Table 2 [34].

After the group evaluation, it is necessary to gather the opinions of different experts about each item and finally provide a single number. Equation (1) was used for this purpose [35].

$$M_i = \sum_{i=1}^{m} W_j A_{ij}, j = 1, 2, \ldots, n \tag{1}$$

where $M_i$ is the "fuzzy error probability" representing the sum of the fuzzy values of event *i*. $A_{ij}$ is the linguistic variable assigned to the event *i* by expert *j*, m is the total number of events, n is the total number of experts, and $W_j$ is the weighting score of expert *J*. Table 2 and Equation (6) were used to perform the process of weighting the experts.

After fuzzification with Table 1, using Equations (2)–(5), fuzzy numbers were converted into probability. At first, fuzzification, the consensus of experts' opinions, defuzzification, and then the transformation of possibility into probability took place.

$$X^{*} = \frac{\int \mu_i(x) x dx}{\int \mu_i(x)} \tag{2}$$

$$\mu_{\sim A}(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1}, & a_1 \le x \le a_2 \\ 1, & a_2 \le x \le a_3 \\ \dfrac{a_4 - x}{a_4 - a_3} & a_3 \le x \le a_4 \\ 0, & x > a_4 \end{cases} \quad X^{*} = \frac{\int_{a_1}^{a_2} \frac{x-a}{a_2-a_1} x dx + \int_{a_2}^{a_3} x dx + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} x dx}{\int_{a_1}^{a_2} \frac{x-a_1}{a_2-a_1} dx + \int_{a_2}^{a_3} dx + \int_{a_3}^{a_4} \frac{a_4-x}{a_4-a_3} dx} \tag{3}$$

$$= \frac{1}{3} \times \frac{(a_4 + a_3)^2 - a_4 a_3 - (a_1 + a_2)^2 + a_1 a_2}{(a_4 + a_3 - a_1 - a_2)}$$

$$FP = \begin{cases} \dfrac{1}{10^K}, FPS \neq 0 \\ 0, FPS = 0 \end{cases} \tag{4}$$

$$K = \left[ \left( \frac{1 - FPS}{FPS} \right)^{1/3} \right] \times 2.301 \tag{5}$$

The calculation of the probabilities of IEs and the TE was also done using Equations (6)–(8) according to AND OR gates.

$$P_{OR} = 1 - \Pi_{i=1}^{n} (1 - P_i) \tag{6}$$

$$P_{AND} = \Pi_{i=1}^{n} P_i \tag{7}$$

$$P_{TE} = \Pi_{j \in M} \left(1 - \Pi_{BE_{i \in Qj}} (1 - P_i)\right) \tag{8}$$

**Table 1**
Fuzzy scales.

| Linguistic variable | Fuzzy numbers |
|---|---|
| Very low | 0, 0.1, 0.2 |
| Low | 0.1, 0.23, 0.25, 0.4 |
| Medium | 0.3, 0.5, 0.7 |
| High | 0.6, 0.75, 0.9 |
| Very high | 0.8, 0.9, 1.1 |

**Table 2**
Expert weighting criterion.

| Condition | Classification | Score |
|---|---|---|
| Organizational title | Professor, director, and senior engineer | 5 |
| | Supervisor, director, factory inspector | 4 |
| | Engineer, supervisor | 3 |
| | Foreman, technician | 2 |
| | Operator | 1 |
| Work experience (year) | >20 | 5 |
| | 15–20 | 4 |
| | 10–15 | 3 |
| | 5–10 | 2 |
| | <5 | 1 |
| Level of education (year) | PhD | 5 |
| | MSc | 4 |
| | BSc | 3 |
| | Diploma | 2 |
| | Less than a diploma | 1 |
| Age (year) | >50 | 4 |
| | 40–50 | 3 |
| | 30–40 | 2 |
| | <30 | 1 |

### 2.4. *Bayesian network*

At this stage, the data was entered into the BN in the GeNIe software environment. When event data and observations of equipment error are used to update failure probabilities in a real-time method, the special feature of BN is particularly important in probability updating [36]. New observations can be the probability of occurrence of BEs in predictive analysis or events in diagnostic analysis.

In this regard, after calculating the probabilities of Bes, the probabilities of the IEs and TE were calculated and the initial probabilities were updated using a new set of evidence. To complete the tables of conditional probabilities in the present study, according to the AND OR gates, Equations (9) and (10) were used, respectively.

$$P(Y1 = 1|X1 = 0, X2 = 0) = 0$$

$$P(Y1 = 1|X1 = 1, X2 = 0) = 1$$

$$P(Y1 = 1|X1 = 0, X2 = 1) = 1$$

$$P(Y1 = 1|X1 = 1, X2 = 1) = 1 \tag{9}$$

$$P(Y2 = 1|X3 = 0, X4 = 0) = 0$$

$$P(Y2 = 1|X3 = 1, X4 = 0) = 0$$

$$P(Y2 = 1|X3 = 0, X4 = 1) = 0$$

$$P(Y2 = 1|X3 = 1, X4 = 1) = 1 \tag{10}$$

In which, X is the BE and Y is the IEs or TEs.

#### 2.4.1. *Sensitivity analysis and inductive and deductive reasoning*

In inductive reasoning, the probabilities of IEs and TE were calculated according to the type of gate from bottom to top (from BE to TE). The difference between BN and FT is considering probabilities using conditional rules in the BN. In the BN, the joint probability distribution of a set of variables X1 to Xn is performed using Equation (11).

$$P(U) = \prod_{i=1}^{n} P(X_i|Pa(X_i))(11) \tag{11}$$

In which, P (U) indicates the variables' joint probability distribution and Pa (Xi) represents the parent set of the variable Xi.

For predictive analysis, Equation (12) was used to calculate the probability of the central node T as P (accident/event). For diagnostic analysis, Equation (13) was utilized to calculate the probability of root nodes Xi in the form of P (event/accident) [37].

$$P(T=1) = \sum_{\lambda(T)} P(T=1|\lambda(T))P(\lambda(T)) = \sum_{\lambda(T)} P(\lambda(T), T=1) \tag{12}$$

$$P(X_i = 1 | T = 1) = \frac{P(T = 1 | X_i = 1)}{P(T = 1)} \tag{13}$$

To identify the most important RNs causing system failure, the RoV method was used (Equation (14)).

$$\mathrm{RoV}_{X_i} = \frac{\mathrm{FBN}_{\mathrm{PO}} - \mathrm{FBN}_{\mathrm{PR}}}{\mathrm{FBN}_{\mathrm{PR}}} \tag{14}$$

In which, $\mathrm{FBN}_{\mathrm{PO}}$ is the posterior probability and $\mathrm{FBN}_{\mathrm{PR}}$ is the prior probability of the RNs.

Therefore, in the present study, using causal reasoning, the managers were warned in time to take the necessary measures as soon as possible to eliminate the system defects.

## 3. Results

### 3.1. Oxygen tanks process

In this study, oxygen storage tanks were selected as the study node. Oxygen is separated from the air in the hospital central oxygen using special devices. Then, the high-purity oxygen (more than 95%) is transferred to the wards of the hospital through pipelines. The central oxygen unit consists of different parts, such as an air compressor, filter, oxygen generator tanks, oxygen storage tanks, and pressure and temperature gauge transmission lines, where the air is compressed by the compressor and passes through three different filters to remove moisture, particles, and oil. Then, high-purity oxygen is produced in oxygen-generating tanks containing zeolite and stored in oxygen storage tanks. Then it is transferred to the patient's room through copper pipes. The results of the HAZOP study are presented in Table 3.

After conducting various interviews with competent people, and examining deviations, processes, and HAZOP study by the research team and experts, the main scenario (oxygen leakage) was analyzed using FTA. The results showed that there are 17 BEs and 13 IEs for this scenario, which are shown in Figs. 2 and 3.

In this step, 5 experts were selected to answer the fuzzy questionnaire with different skills and sufficient knowledge of oxygen

**Table 3**
HAZOP study of oxygen storage tanks.

| Row | Guide word and parameter | Deviation | Cause | Consequence | Safety guard | Recommendations |
|---|---|---|---|---|---|---|
| 1 | More, Pressure | Obstruction of the outlet | Impact on the outlet pipe or obstruction by material particles caused by corrosion of pipes and tank | Tank explosion Lack of oxygen injection in the main line | Safety valve Pressure gauge on the tank Pressure gauge with the sensor on the device | Periodic visits Cleaning the path of pipes and valves by trained personnel |
| 2 | More, Pressure | Non-operation of the sensor for connecting and disconnecting | The sensor is removed from the circuit Disconnection of the sensor power wire | Tank explosion | Safety valve Pressure gauge on the tank | Installation of a pressure notification system inside the device |
| 3 | Less, Pressure | Closing the inlet valve | Negligence and ignorance of operators | Reducing the pressure inside the tank Increasing the possibility of burst pipes | Trained operator | Using an alarm system to simultaneously display the increase in pipe pressure and decrease in tank pressure<br>Preventing the closing of inlet and outlet valves by unqualified persons<br>Updating the operating instructions of the operators |
| 4 | Less, Pressure | Obstruction of the inlet in the oil filter | Clogging of filters by oil and water particles | Reducing the pressure inside the tank Increasing the possibility of burst pipes<br>No gas injection into the line | Periodic visits to filters | Installation of several parallel filters<br>Shorten the intervals of periodic visits<br>Installing some more powerful filters before entering the compressor |
| 5 | More, Pressure | Closing the outlet valve of the tank | Negligence and ignorance of operators<br>Human error | Explosion Failure to inject the required oxygen into the departments | Trained operator | Periodic training of operators<br>Daily and periodic inspections |
| 6 | As well as, reaction | Oil with the product | Inadequate filter performance | Tank explosion Reduction of O2 purity O2 and oil reaction | Purification inside the compressor Absorbent filters | Use of higher efficiency absorbers<br>Installation of several filters for better removal of oil and particles |

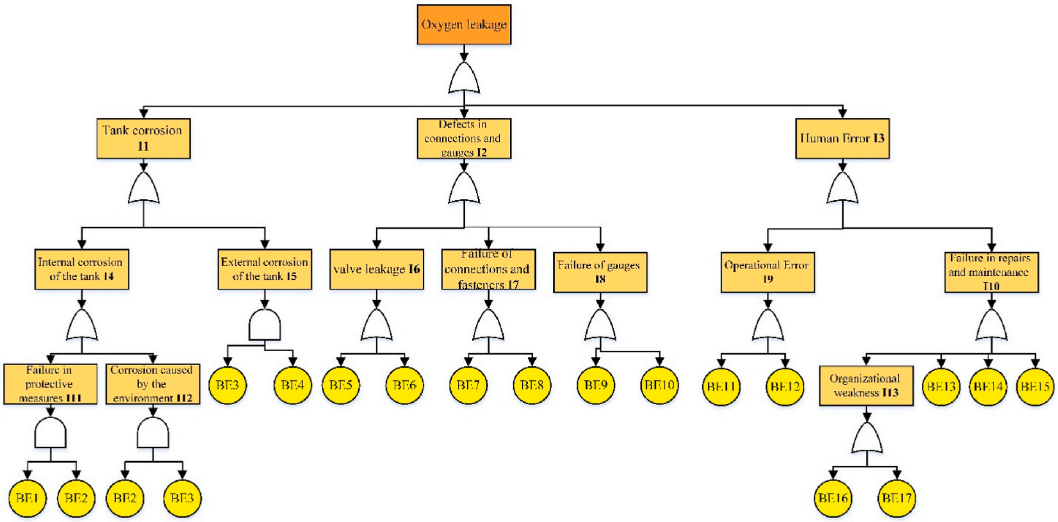


**Fig. 2.** FTA of oxygen leakage.

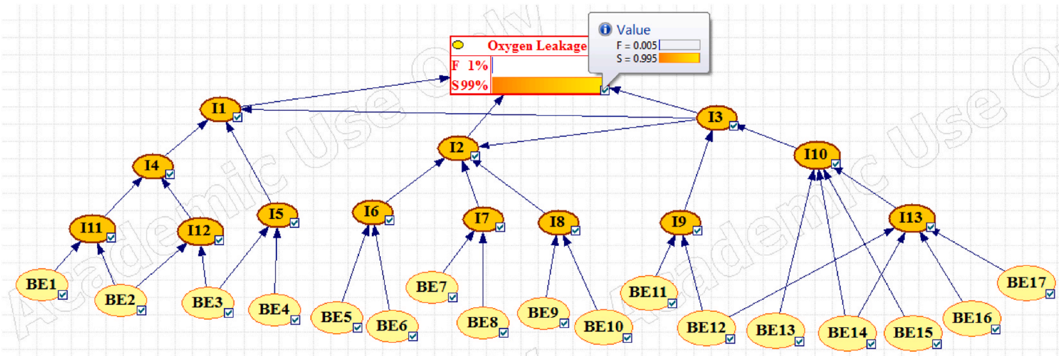


**Fig. 3.** Updating the failure probabilities of the BEs, IEs, and TE (oxygen leakage).

tanks. Table 4 reveals the experts' weighting. Expert 1 (0.237288) and Expert 5 (0.169492) had the highest and lowest WF, respectively.

Then, according to the method in fuzzy logic, using trapezoidal fuzzy numbers and 5 linguistic terms, the probabilities of the BEs were obtained as shown in columns 3 and 6 of Table 5. According to fuzzy fault tree (FFT) results, event 3 had the highest probability (90.2E-5). Then, according to the type of input gate, the probabilities of IEs were calculated, which is shown in column 6 of Table 5. The IE of "Human Error", which consists of multiple IEs and BEs, had the highest FFT probability (3.54E-03). The probability of oxygen leakage was also equal to 5.38E-03.

In the next step, the events were entered into the GeNIe software and analyzed in the causal BN (Fig. 3). The probabilities of the BEs, obtained from the FFT in the previous step, were defined in the BN to perform subsequent calculations. Then, according to the type of input gate, the table of conditional probabilities was defined according to Equations (11) and (12). Then the update with BN was done and the prior probability ($FBN_{PR}$) was obtained, the results of which can be seen in columns 2 and 5 of Table 6. I2, I1, and I3 had the highest probabilities after updating, respectively. The probability of the final event was also 0.0053797972 using FBN. Columns 3 and 6 of Table 6 also show posterior probabilities using FBN. If the final event happens 100%, the probabilities of other events may change.

**Table 4**
Experts weighting.

| Experts | Job | Age | Work experience | Education level | WF |
|---|---|---|---|---|---|
| E 1 | Faculty member and inspector of oxygen tanks | 44 | 17 | Ph.D. | 0.237288 |
| E 2 | Industrial consultant expert | 37 | 12 | Ph.D. | 0.203390 |
| E 3 | Faculty member and safety science researcher | 35 | 12 | Ph.D. | 0.203390 |
| E 4 | HSE inspector | 35 | 12 | MSc | 0.186441 |
| E 5 | Faculty member | 32 | 4 | MSc | 0.169492 |

**Table 5**
Probability of BEs, IEs, and oxygen leakage events in FFT.

| Events | Descriptions | Probability | Events | Descriptions | Probability |
|---|---|---|---|---|---|
| BE 1 | Defects in the tank coating | 81.2E-5 | BE 16 | Failure to use standard and updated instructions | 76.2E-5 |
| BE 2 | Defect in the tank dryer | 76.2E-5 | BE 17 | Weak education system | 32.2E-5 |
| BE 3 | Corrosive environment (acidity state) | 90.2E-5 | I 1 | Tank corrosion | 1.88E-06 |
| BE 4 | Defects in the external coating system of the tank (paint, etc.) | 63.3E-5 | I 2 | Defects in connections and gauges | 1.84E-03 |
| BE 5 | Defects in inlet and outlet valves (V1) | 48.2E-5 | I 3 | Human Error | 3.54E-03 |
| BE 6 | Defects in inlet and outlet valves (V2) | 48.2E-5 | I 4 | Internal corrosion of the tank | 1.31E-06 |
| BE 7 | Defects in connecting tank fasteners (F1) | 6.2E-5 | I 5 | External corrosion of the tank | 5.71E-07 |
| BE 8 | Defects in connecting tank fasteners (F2) | 6.2E-5 | I 6 | Valve leakage | 9.64E-04 |
| BE 9 | Defect in the tank reliability gauge | 14.3E-5 | I 7 | Failure of connections and fasteners | 1.24E-04 |
| BE 10 | Defect in the tank pressure gauge | 61.3E-5 | I 8 | Failure of gauges | 7.56E-04 |
| BE 11 | Defects in tank equipment repairs | 63.2E-5 | I 9 | Operational error | 1.35E-03 |
| BE 12 | Defects in the inspection and testing program of tank devices | 72.2E-5 | I 10 | Failure in repairs and maintenance | 2.19E-03 |
| BE 13 | Inadequacy of people's skills | 37.3E-5 | I 11 | Failure in protective measures | 6.18744E-07 |
| BE 14 | Weakness in the installation of tank equipment | 41.3E-5 | I 12 | Corrosion caused by the environment | 6.87324E-07 |
| BE 15 | Weakness in purchasing tank equipment (low quality) | 32.3E-5 | I 13 | Organizational weakness | 1.08E-03 |
| TE | Oxygen leakage | 5.38E-03 | | | |

**Table 6**
Determining the probability of oxygen leakage events using FBN ($FBN_{PR}$ and $FBN_{PO}$).

| Events | Prior probability ($FBN_{PR}$) | Posterior probability ($FBN_{PO}$) | Events | Prior probability ($FBN_{PR}$) | Posterior probability ($FBN_{PO}$) |
|---|---|---|---|---|---|
| BE 1 | 81.2E-5 | 0.000926198 | BE16 | 76.2E-5 | 0.141641030 |
| BE 2 | 76.2E-5 | 0.001003099 | BE17 | 32.2E-5 | 0.059853557 |
| BE 3 | 90.2E-5 | 0.000902000 | I1 | 0.003543592 | 0.658685160 |
| BE 4 | 63.3E-5 | 0.000738413 | I2 | 0.005377931 | 0.999653160 |
| BE 5 | 48.2E-5 | 0.089594455 | I3 | 0.003541723 | 0.658337680 |
| BE 6 | 48.2E-5 | 0.089594455 | I4 | 1.30550E-06 | 0.000242668 |
| BE 7 | 6.2E-5 | 0.011524598 | I5 | 5.70966E-07 | 0.000106131 |
| BE 8 | 6.2E-5 | 0.011524598 | I6 | 0.000963767 | 0.179145730 |
| BE 9 | 14.3E-5 | 0.026580928 | I7 | 0.000123996 | 0.023048481 |
| BE 10 | 61.3E-5 | 0.113944820 | I8 | 0.000755912 | 0.140509450 |
| BE 11 | 63.2E-5 | 0.117476550 | I9 | 0.001353543 | 0.251597530 |
| BE 12 | 72.2E-5 | 0.134205800 | I10 | 0.002911563 | 0.541203170 |
| BE 13 | 37.3E-5 | 0.069333469 | I11 | 6.18744E-07 | 0.000115012 |
| BE 14 | 41.3E-5 | 0.076768693 | I12 | 6.87324E-07 | 0.000127760 |
| BE 15 | 32.3E-5 | 0.060039438 | IE13 | 0.002217226 | 0.412139460 |
| TE | 0.0053797972 | 1 | | | |

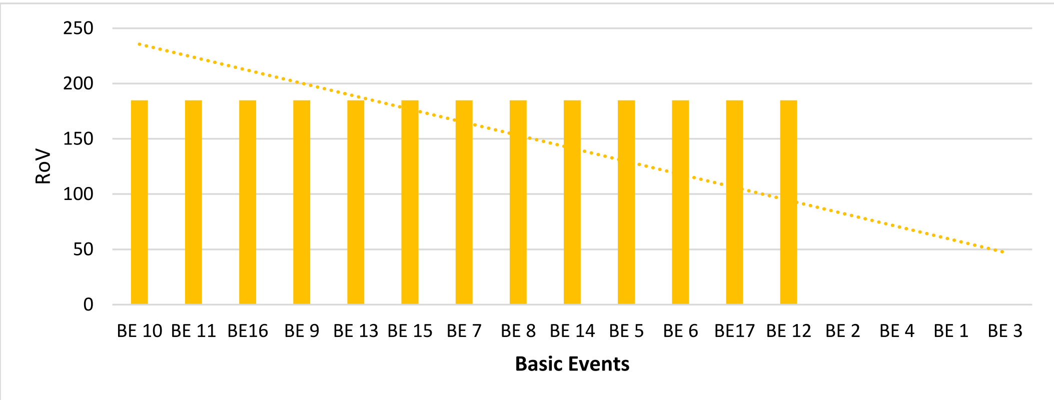


**Fig. 4.** RoV values for the most important BEs in oxygen leakage.

According to the results, BE16 (failure to use standard and updated instructions) and BE12 (defects in the inspection and testing program of tank devices) had the highest posterior probability, while contrary to the FFT results, BE4 (defects in the external coating system of the tank) (paint, etc.), and BE3 (corrosive environment (acidity state)) had the lowest probability.

In the last step, the sensitivity analysis was done with the RoV method, the results of which are shown in Fig. 4. According to Fig. 4, BEs 10, 11, and 16 were the most important in the oxygen leakage event with a very small difference, which was almost in line with the results of FBNPO. BE3 had also the least importance.

## 4. Discussion

### 4.1. Discussion, review, and comparison with the existing approaches of central oxygen risk assessment

In this study, a new approach using HAZOP, FTA, BN, and fuzzy logic techniques was used to reduce the existing uncertainties. Uncertainty refers to a situation in which the probability of events cannot be measured due to the lack of sufficient information in oxygen tanks. In the study of Markowski et al., various methods were also mentioned to reduce uncertainty, including expert methodology, sensitivity analysis, statistics, and fuzzy logic [38].

Different approaches have been used in studies, some of which are mentioned. In the study of Léa A. Deleris (2006) in California, which was conducted on hospital oxygen supply devices, FMEA and PRA static risk assessment methods were used for benefit-cost analysis. The analysis focused on the oxygen pump system and examined the cases leading to failure, including external events (earthquakes and storms) and internal events (fire, power outage, construction accidents, and human error) [2]. In 2014, Mostert and Coetzee conducted a case study in South Africa related to the failure of central oxygen pipelines. The accident in this study was caused by an undetected oxygen leakage and at the same time welding by one of the technical staff without knowing about the leakage, which caused an explosion in the main valve and a complete cut off of oxygen. This study examined the effect of lack of oxygen supply in endangering the patients' lives. This study recommended some cases, including daily checking of pressure failure alarms before starting treatment, routine evaluation of gas supply devices, and communication between clinical and technical departments [11]. They reported that to ensure the patient's safety, in case of central oxygen pipeline failure, a systematic approach is required to prevent and manage such an event [11]. Therefore, most studies have focused on the ways of oxygen transfer and less attention has been paid to the tanks themselves, which are the main supplier of oxygen to hospitals. Most of these studies have not tried to reduce the uncertainty of the existing studies and have had a static risk assessment structure.

In 2020, Feiz Arefi et al. conducted a study to identify and analyze the event scenarios in the central oxygen unit of a hospital in Hamadan (Iran). In this study, the FTA method was used to identify risks, and the semi-quantitative LOPA method was used for risk assessment. The results showed that an independent protection layer (IPL) can significantly reduce the risk. The most important cause of oxygen leakage in the patient's room was due to taking off the mask from the patient's face or using a mask that does not fit the patient's face [39]. In the study by Shaban et al. (2022), the STPA technique was proposed to analyze the risks related to the oxygen supply system, which helps to identify occupational and process safety risks [40]. Therefore, different studies have many strengths and weaknesses. In general, the oxygen supply system includes complex interactions between humans and equipment, and traditional risk analysis methods do not consider the complex interactions of the system. Failure to pay attention to the static structures of risk assessment and uncertainty in most of these studies [2,11,39], caused this study to use BN and fuzzy logic to cover these weaknesses.

The use of BN provides a comprehensive and dynamic qualitative and quantitative graphical modeling of the event scenario process. The deductive reasoning of these networks can reduce uncertainty and update the probability of root events and final consequences, and if it is used along with consequence modeling, it will lead to a dynamic, accurate, and practical quantitative risk assessment in process units [41]. The BN uses Bayes' theorem to update the BE's probability of occurrence according to the new evidence, such as the statistics of the occurrence of events, information related to the real-time monitoring of processes, and pseudo-incidents to calculate the updated probabilities [42,43]. The integration of the BN with many quantitative and qualitative risk assessment methods, such as FTA helped to increase the accuracy of the study and reduced uncertainty [44,45]. The BN can perform four types of reasoning, including prediction, diagnosis, causal relations, and hybrid reasoning [46].

In this study, qualitative data and fuzzy logic were used to quantitatively evaluate risk components, such as the leaking possibility of central oxygen tanks. Given that there is no defect rate for many types of equipment or there are many differences due to various cultural, social, and economic reasons (for example, in the case of human and managing errors: cultural and social differences and in the case of technical errors: the type of equipment and its different characteristics), in risk assessment studies, there are uncertainties and in this study, like many similar studies [47,48], fuzzy logic was used to reduce uncertainty. Fuzzy theory is a suitable tool for conditions with ambiguity and uncertainty that can convert qualitative expressions into numerical probabilities [49]. In developing countries, it is not possible to calculate the probability due to the lack of a suitable database and the lack of a defect rate system in this field, so fuzzy logic can reduce these uncertainties [50–52]. The results of the present study also showed that when dealing with vague and approximate data, the use of fuzzy logic may provide accurate results.

In this study, the experts' selection, to calculate probabilities using fuzzy logic, was performed based on the studies of Cooke et al. [53], Lavasani [54], and Yazdi et al. [34]. People's specialized knowledge is influenced by individual views and goals [55]. There are several applications of fuzzy set theory to reduce uncertainty and inaccuracy in experts' judgment, including the use of triangular, intuitionistic, trapezoidal, and Gaussian fuzzy numbers [56–58]. Trapezoidal and triangular fuzzy numbers linearly describe the fuzzy membership function. Moreover, the Gaussian function describes the fuzzy membership in a non-linear and more flexible way, but this method is more complicated than linear methods. This complexity may cause more inaccuracy [56]. Choosing a specific type of membership function depends on the nature of the problem [59]. Therefore, in this study, trapezoidal fuzzy numbers were used, since under some weak assumptions, they can easily solve the problem. In various studies, triangular and trapezoidal fuzzy numbers have been used due to their flexibility and simplicity [60–62].

### 4.2. Discussion and analysis of the case study results

The results of the case study showed that the IE of “Human Error” had the highest probability of FFT and the probability of oxygen leakage using FBN was lower than FFT, and the difference was not significant. According to the results, it can be concluded that FBN will not necessarily increase the possibilities, but it depends on different conditions.

#### 4.2.1. Comparison of FFT, FBN, and RoV results

According to the results, BE16 (failure to use standard and updated instructions) and BE12 (defects in the inspection and testing program of tank devices) had the highest posterior probability, while contrary to the FFT results, BE4 (defects in the external coating system of the tank) (paint, etc.), and BE3 (corrosive environment (acidity state)) had the least probability.

According to the sensitivity analysis with the RoV method, BEs 10, 11, and 16 were the most important in the oxygen leakage event with a very small difference, which was almost in line with the results of $FBN_{PO}$. BE3 had also the least importance. In this study, FFT and FBN had different results in the diagnosis of the most critical BEs and FPs. Conditional probability tables (CPTs) and common cause failures were the main causes of this difference. An example of events with common causes is BE 12 of common causes I9 and I13 considering causal relationships. It should be noted that according to Fig. 4, the impact of 13 basic events was almost equal to the main event, and Bayesian critical events including BE 16 and BE 12 are also among them.

In the study by Lin and Hussain (2018), which was conducted on the gas oxygen supply system, hitting the tanker body and the fasteners inside the pipes were mentioned as the main causes of oxygen leakage [63]. According to the results, it can be said that due to the different capabilities of the BN, such as the dynamic nature and conditional dependencies between events with common causes, and deductive and inductive reasoning [64,65], the FBN results were more realistic than the FFT results.

#### 4.2.2. Human error

The IE 3 or “Human Error” is very important in the occurrence of the main event and according to the results of BN, and also directly affected the probability of occurrence of I1, I2, and oxygen leakage. This is one of the good features of BN. The use of updated instructions, proper planning in tank testing and inspection, and repairs and maintenance are among the things that can significantly reduce the amount of human error. According to the results of Figs. 3 and 5, if the most critical events related to human error are removed (related to the above solutions (BE 16, 12, and 11)), the failure rate of the main event and human error event will be significantly reduced.

The drawing of arcs in BN was almost based on the SHIPP approach [66]. In the SHIPP method, a sequential modeling approach and organizational barriers and human factors were used in addition to process factors [66].

Using causal reasoning, safety managers are warned in time to take necessary measures as soon as possible to eliminate the defects of oxygen tanks. Therefore, this study recommends that hospitals recognize their risks as part of their responsibility and pay attention to chemical risk management and oxygen tanks. Therefore, the investigation of these dangerous events to extract causes and learned lessons should be used to highlight opportunities for prevention as well as emergency response so that in critical situations, such as the COVID-19 pandemic, the situation can be controlled more safely. The proper location of oxygen tanks in hospitals is also an extremely important issue. Location is one of the principles of safe design and it is necessary to pay special attention to minimize the domino consequences caused by explosion and fire as much as possible. Failure to pay attention to natural disasters, such as floods,

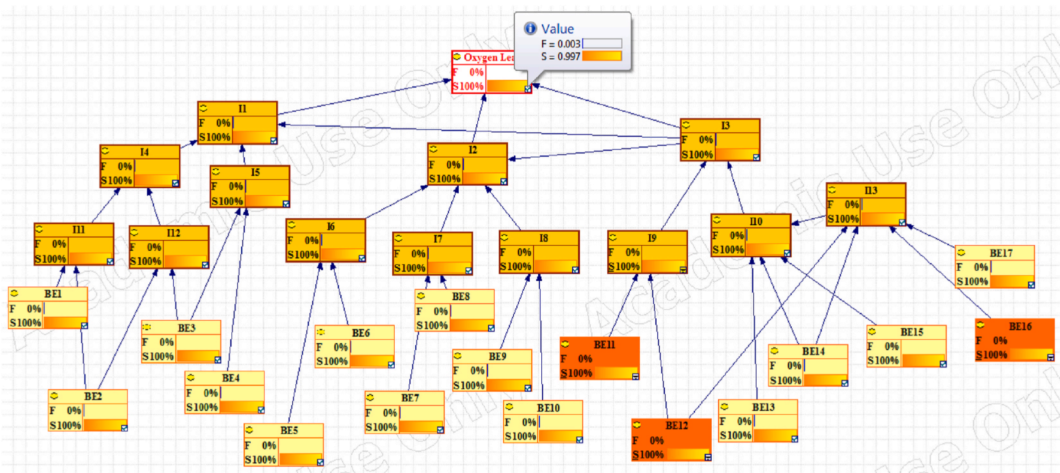


**Fig. 5.** The impact of the most critical events (BE16, 12, & 11) related to human error (I3) on the top event.

earthquakes, lightning, etc. was one of the limitations of the present study, which is recommended to be further discussed in future studies. Also, the lack of a tangible and quantitative criterion to evaluate the reduction of uncertainty was one of the other limitations of the present study, but according to the characteristics and nature of the appropriate approaches used in this study, it can be concluded that the uncertainty has been reduced. In this study, the existing condition of tanks to prevent oxygen leakage was investigated. If the purpose of the study is the design of tanks, land use planning (LUP), and investigation of domino effects, more attention should be paid to the position of oxygen tanks in the hospital. Evaluating the domino effects of possible explosion or fire is also one of the important topics in the continuation of this research.

## 5. Conclusion

In this study, a comprehensive approach was presented based on BN and fuzzy logic to reduce uncertainty to some extent in the risk assessment of hospital oxygen tanks during the COVID-19 pandemic due to the nature of the study approaches. Considering the dynamic nature of variables affecting the risk of accidents and the static nature of FT, the BN made the model more realistic due to its dynamic nature and considering the conditional dependence between events with common causes and deductive and inductive reasoning, and the uncertainty was reduced. Also, in this study, human factors were investigated in addition to technical failures. The results showed that “Human Error” had the highest probability of FFT among IEs, and the probability of oxygen leakage using FBN was lower than FFT, and the difference was not significant. Critical events identified in FFT were completely different from FBN and RoV results. In this model, BN can reduce uncertainty and investigate complex causal relationships and successive dependent failures, and its combination with fuzzy logic led to more reliable results. “Failure to use standard and updated instructions” and “defects in the inspection and testing program of tank devices” had the most FBNPO, which was almost in line with the RoV results. This study recommends that hospital managers recognize the risks of oxygen tanks and pay attention to the risk management of oxygen tanks. Updating the existing guidelines in this field, fixing defects in the inspection of all types of tank gauges, and testing related equipment can greatly help increase the reliability of these tanks. The results showed that if the most critical events related to human error are removed, the failure rate of the main event and human error will be significantly reduced. Therefore, due to the spread of diseases, such as the COVID-19 pandemic, conducting such studies increases the safety of the staff and helps save the lives of patients. Also, finding the root causes of these events provides opportunities for prevention and emergency response in critical situations, such as the COVID-19 pandemic.

## Author contribution statement

Fereydoon Laal: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Analyzed and interpreted the data; Wrote the paper.

Saber Moradi Hanifi, Rohollah Fallah Madvari: Analyzed and interpreted the data; Wrote the paper.

Amir Hossein Khoshakhlagh: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Maryam Feiz Arefi: Conceived and designed the experiments; Wrote the paper.

## Data availability statement

No data was used for the research described in the article.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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