

Development and application of a fuzzy occupational health risk assessment model in the healthcare industry

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ABSTRACT

Background: *Hazards of the workplace and their impacts on the healthcare industry affect the quality of patient care and safety and impose high costs on the healthcare industry. Occupational health in this industry requires proper identification of hazards and managing the related risks. In this study, the researchers attempted to develop an easy-to-use and high applicability occupational health risk assessment model with a fuzzy approach to evaluate risks more precisely.* **Methods:** *In this study, a fuzzy inference system (FIS) was designed and applied to develop a risk assessment model.* **Conclusions:** *This study showed that the developed model could be applied as a practical model for evaluating occupational health risks. The weight of each risk criterion was used to calculate the risk level by adopting a fuzzy approach. The risk assessment results construed using the fuzzy set theory provided a broad picture of risks and could work adequately in the presence of inaccurate and insufficient data to calculate the risk. This model calculates risk levels and provides us with the dispersion and distribution of the calculated value of the risk number.*

1. INTRODUCTION

Healthcare staff face many potential physical, chemical, and biological hazards [1]. Potential hazards of the workplace and their impacts on the healthcare industry affect the quality of patient care and safety and impose high costs on

healthcare organizations every year [2]. Therefore, a well-developed system is needed to organize and process the information to analyze and manage risks, monitor safety levels, and implement the required measures to prevent injuries and develop occupational diseases. The primary purpose of the risk management system is to monitor the safety level

at the site. The main aim of the monitoring system is to perform a complete analysis and evaluation and assess risks [3]. Risk management is one of the critical elements in any management system to keep risks at an acceptable level [4].

Risk management is the main factor in achieving safety and health in the workplace, and its effectiveness increases with accuracy assessment and robust analysis [5]. Risk management is usually divided into three categories: (i) risk identification and classification, (ii) risk analysis, and (iii) risk reduction [6]. Risk analysis is a potential hazard that involves determining an outcome and the probability of its occurrence regarding the presence or absence of control measures. Risk analysis results are the foundation for evaluating the risk level, reducing it, and determining its acceptability. A combination of outcome and probability determines the risk level. Risk analysis is the regular use of information to recognize causes and estimate risk levels. Risk assessment is one of the ways to provide the knowledge necessary for identifying failures in protective measures, mitigation barriers, and evaluating the effectiveness of risk control measures. As a critical risk assessment stage, the information used in risk analysis may include historical data, theoretical analyses, experts' opinions, and beneficiaries' attitudes [7]. In risk analysis, the conditions are complex, and there are uncertainties in decision-making [8]. According to Villemeu, uncertainties in safety analysis could be caused by three main factors:

1. Parameter-related uncertainties: For various reasons, the information in the system about data dependability is uncertain; a small sample causes a large confidence interval in data extrapolation from one installation to another, and so on;
2. Modelling-related uncertainties: This may be caused by a proximate dependability model. This is especially valid in modelling failures for a common reason, human errors or software bugs. Modelling can generally integrate all relevant variables with sufficient details without evaluating their relationships;
3. Uncertainties are related to the non-holistic nature of the analysis. The analyst cannot be

sure that his/her modelling considers all the essential factors, relevant figures, and critical interactions [9]. In this condition, the fuzzy theory can calculate the risk level more accurately and according to actual and uncertain conditions. Fuzzy logic is suitable for data causing ambiguity and uncertainty in risk assessment. It can overcome the shortcomings of traditional methods and their computational problems in risk assessment [8]. To deal with uncertainty because of inadequate expertise, knowledge, and/or time about a system, the FIS presents a great way to aggregate data for decision-makers to overcome ambiguity [10].

Debnath and Biswas [11] provided a fuzzy inference model to assess occupational risks in the construction industry. In their study, risk factors and control factors were used as the inputs of the fuzzy inference system. Gürcanlı and Müngen [12] also proposed a fuzzy inference model for risk assessment in the construction industry. Beriha and Patnaik [13] developed a risk assessment technique based on the Mamdani fuzzy inference model concerning medical costs, safety training, machine updates, and safety tools. Fuzzy inference based on fuzzy reasoning is more akin to human thoughts and natural language than to the existing reasoning systems and can be used to describe approximate and uncertain phenomena in the real world. The lack of a proper quantitative model and the simultaneous presence of objective and subjective data are the reasons for using the fuzzy logic and fuzzy inference system in risk assessment. Besides, fuzzy inference can be combined with expert knowledge and provide interpretable results [7, 14]. In this study, the researchers attempted to develop an easy-to-use and high applicability occupational health risk assessment model with a fuzzy approach to calculate risk levels more precisely.

2. LITERATURE REVIEW

In the late 19th century, Germany was the first country to develop the Occupational Exposure Limit (OEL) concept, and other countries followed. However, using OEL for health risk assessments has

some limitations. In addition, sampling and testing processes for hazardous substances are relatively specialized, complex, and costly and are not feasible for carrying out health risk assessments for businesses (especially small and medium-sized low-income industries) [15]. In the 1980s, the HSE Agency in the U.K. developed a qualitative tool called COSHH Essentials for assessing chemical risks [16]. In the early 1980s, industrialized countries and international organizations repeatedly issued guidelines and regulations for health risk assessment. In 1983, the U.S. National Research Council (NRC) defined a fundamental process for risk assessment that comprises four steps: hazard identification, dose-response assessments, exposure estimates, and risk characterization.

Occupational Health Risk Assessment (OHRA) is a tool for controlling health risks associated with potential health hazards. OHRA is a part of the comprehensive occupational disease prevention program and can be used to assess and control potential occupational hazards. Exposure risk is the possibility of a loss of economic capital or profits, physical harm or injuries, or delay due to uncertainty in the actions taken [8].

The OHRA was implemented in China in the 1990s when the US EPA models were introduced in the nuclear industry. Since then, various Australian, Romanian, Singaporean, and ICMM models have been presented. The Australian, Romanian, and ICMM models are qualitative and have a broader scope. They are used to assess chemical, physical, and dust risks. The EPA model is quantitative and is used for chemical risk assessment [15]. AIHA developed the semi-quantitative HRR method in 2006. It uses the two following criteria: (i) Health Effect Rating and (ii) Exposure Rating. In this method, Exposure Rating estimates the exposure level associated with OEL [17]. The ART model assesses the risk of vapours, inhalable dust, and mist. This method cannot evaluate fumes, fibres, gases, and dust released during hot metal working [18]. Stoffenmanager is a free web-based instrument developed for small and medium-sized industries to assess, prioritize and control chemical hazards. This online tool offers a variety of options for health risk assessment, and the user can choose the control banding method or

quantitative risk assessment models [19]. A method was introduced by ANSI Z 590.3-2011: severity and probability of occurrence are combined in a matrix to calculate the risk number. It is not a proprietary method for health risk assessment, although it can be modified and used to assess chemical, physical, and biological hazards [20].

In their study, Samantra and Datta [21] introduced a framework for assessing occupational health risks using the fuzzy sets theory for coal mines. They used three criteria of exposure-outcome, exposure probability, and exposure time. The verbal variables scale was also used to determine the score of each criterion. Once the scale was determined, the three criteria were multiplied, and the risk number was calculated fuzzily and then de-fuzzied. The framework provided in the study by Samantra and Datta [21] was used to assess the risk of chemical, physical, biological, psychological, and ergonomic hazards in coal mines. Ilbahar, and Karaşan [22], using a Pythagorean fuzzy hierarchical analysis and fuzzy inference system, presented a framework for assessing safety and health risks in the construction industry. Their study used three measures of outcome risk, exposure probability, and occurrence frequency. The study focused mainly on the construction industry hazards and was explicitly designed to deal with them. In their study, Acuner and Cebi [23] used probability and severity measures to evaluate occupational accidents in combination with the fuzzy inference system.

Debnath, and Biswas [11] provided a fuzzy inference model to assess occupational risks in the construction industry. In their study, risk factors and control factors were used as the inputs of the fuzzy inference system. Gürcanlı and Müngen [12] proposed a Mamdani model for risk assessment of the construction industry workers. Beriha, and Patnaik [13] developed a risk assessment technique based on the Mamdani fuzzy inference model concerning medical costs, safety training, machine updates, and safety tools. Fuzzy inference based on fuzzy reasoning is more akin to human thoughts and natural language than to the existing reasoning systems and can be used to describe approximate and uncertain phenomena in the real world. The lack of a proper quantitative model and the simultaneous presence

of objective and subjective data are the reasons for using the fuzzy logic and fuzzy inference system in risk assessment. Besides, fuzzy inference can be combined with expert knowledge and provide interpretable results [7, 14]. Gul, Ak [24] recently used the fuzzy AHP and fuzzy VICOR method to introduce an approach for risk assessment in Turkish hospitals. In this approach, the FAHP was used to weigh five risk parameters. The parameters used were severity, probability of occurrence, undetectability, sensitivity to failure to maintain, and sensitivity to non-use of personal protective equipment (PPE). They also used the fuzzy VICOR method to prioritize hazards. Using only multi-criteria decision-making approaches to receive decision-maker feedback requires a significant volume of inputs. Available studies showed that the fuzzy inference system was not used in the health risk assessment of hospital units in the healthcare industry. In addition, none of the health risk assessment models examined is proprietary to the health care industry, and they all calculate the risk level using a dual-value logic and do not consider uncertainties caused by human thought ambiguities. However, fuzzy logic considers the subjectivity of human judgment and the uncertainty caused by human thought ambiguities. It models the reasoning and conclusion methods of the brain. The present study aimed to develop and apply a fuzzy model to calculate risk levels in the healthcare industry.

3. MATERIALS AND METHODS

The present applied study is quantitative research based on the data collection method. After the ethics committee had approved the study protocol, the study was conducted in three separate phases. In this study, we have developed a fuzzy risk assessment model based on a semi-quantitative method previously introduced to occupational health risk assessment in the healthcare industry [25]. In the first phase, the selected method for development has been introduced and explained. In the second phase, FIS has been used to simulate human reasoning and logic in uncertain conditions, which is impossible in most other methods. The FIS was designed using MATLAB software (version R2018b). Once the

FIS was designed, the results of identified hazards in a case study were used as input. Then the results of the risk level presented by the FIS and the semi-quantitative risk model were compared.

3.1. Phase I: A selected model for development

A previous study based on the needs of the health-care industry has presented a semi-quantitative risk assessment method. In this method, for a more accurate calculation of the risk level, the experts calculated the weight of each risk criteria using the fuzzy analytic hierarchy process (FAHP). Also, measured data and the standard exposure limit were used to determine the exposure rate, unlike some risk assessment methods in other industries. This semi-quantitative method has three risk criteria. These criteria include “probability of exposure (PoE), duration of exposure (DoE), and severity of consequence (SoC).” The Scoring system for these risk criteria is shown in Table 1-3. This semi-quantitative method calculated risk values recommended in Manuele’s book regarding the influence of each criterion [23]. The formula or method of calculating risk values in this method is as follows:

$$\text{Risk Number (RN)} = (W_{PoE} \times PoE) + (W_{DoE} \times DoE) \times (W_{SoC} \times SoC) \quad (1)$$

where:

$$\begin{aligned} W_{PoE} & (\text{the weight of exposure probability} = 0.391) \\ W_{DoE} & (\text{the weight of duration of exposure} = 0.170) \\ W_{SoE} & (\text{the weight of severity of the} \\ & \text{consequences} = 0.439) \end{aligned}$$

The method of calculating risk values proposed by the ANSI Z590.3 standard is multiplying the risk criterion by each other [26]. The formula regarding the weights of each criterion which was calculated in Chalak et al. study by FAHP presented as follows:

$$\text{Risk Number (RN)} = (W_{PoE} \times PoE) \times (W_{DoE} \times DoE) \times (W_{SoC} \times SoC) \quad (2)$$

In this method, there are five risk levels, which include low ($RN < 2$), medium ($2 < RN < 3$), significantly ($3 < RN < 4$), high ($4 < RN < 5$), and very high

(RN \geq 5). After determining the score of risk criteria and using the formula for calculating the risk number (RN), the risk assessment results are interpreted with these levels. For more information on the method, see Chalak et al. [25]. The results of Chalak et al. study revealed that the technique mentioned above could be utilized as a proper tool for risk assessment compared to other methods. However, it also has some limitations [25]. In traditional risk assessment methods, uncertainties related to parameters and modelling or cases related to the non-comprehensive nature of the analysis can affect the results. In such cases, the level of risk may not be accurate and calculated under the actual conditions. The results of various studies on the development of traditional risk assessment methods have shown that fuzzy logic can provide more accurate results [7, 11, 12, 21, 22, 28]. Therefore, a FIS has been designed to improve and develop the risk assessment model in this study. In this study, in phase IV, the level of risk was calculated using the proposed fuzzy model and compared with the level of risk calculated using the semi-quantitative model in two modes of calculating method (Formula 1 and 2) also, in a brainstorming session, the expert team (N=6) has reviewed the output of the fuzzy model in terms of the rationality of presented risk levels. In this meeting, hospital workers' monitoring documents and complaints about facing the hazards were also considered.

3.2. Phase II: Design of Fuzzy Inference System (FIS)

3.2.1. An overview of the FIS

FIS is the commonly used application of fuzzy logic, which shows the uncertainty of knowledge or data by following part of human reasoning [29]. FIS has components that include the fuzzy set theory, fuzzy rules, and fuzzy logic, and it also contains a set of fuzzy membership functions as the input or output and a set of fuzzy rules as a rule engine. The system input contains some ambiguous and inaccurate rhetorical concepts for a particular event, and the output contains a fuzzy set or a precise set of specific features. The fuzzy input and output sets are the study's very

input and output variables. The input data of the FIS is converted to output data via rules. In an inference system, rules are obtained through the knowledge of the experts in the field under a certain framework [30]. In general, the following steps were used to design the inference system: (i) Defining linguistic variables for the criteria and levels of risk and creating fuzzy membership functions; (ii) Creating an if-then fuzzy rules database; (iii) Converting the input data to fuzzy values using fuzzy membership functions; (iv) Evaluating the rules in the fuzzy rules database and combining the results obtained from each rule; (v) Converting the output data into non-fuzzy values.

3.2.2. An overview of the Fuzzy membership functions

Unlike classical sets, fuzzy sets are expressed regarding the degree of elements belonging or membership of a particular set. In classical sets, each element's degree of belonging is 1, and that of the other elements is 0. In other words, the element in question is or is not a member of the A set. Fuzzy sets have no definite boundaries. Each fuzzy number is denoted by an interval of real numbers, each with a membership degree between 0 and 1. An \tilde{A} fuzzy subset of the x reference set can be defined by the membership function $\tilde{A}^{(x)}$ as follows:

$$\tilde{A} = \left\{ (x, \tilde{A}^{(x)}) \mid x \in X \right\} \quad (3)$$

In the \tilde{A} fuzzy subset, $x \in X$ indicates that the x element belongs to and is a member of the X reference set, and the membership equation $\left(\tilde{A}^{(x)} \right)$ shows the extent to which the element has the x properties of the \tilde{A} subset.

$$\tilde{A}^{(x)} : X \rightarrow [0,1] \quad (4)$$

The $\left(\tilde{A}^{(x)} \right)$ membership equation provides a limited description of the $\tilde{X} = \{x_1, x_2, x_3, \dots, x_n\}$ set.

3.3. Design of Fuzzy Inference System (FIS)

The Crisp input data was first transformed to fuzzy values using linguistic variables and membership functions in the fuzzification process to design

the system. Then the rules in the fuzzy logic system are considered as the inference processing core. The other part of the FIS is the fuzzy inference engine in which the fuzzy set of rules is deduced based on specific criteria and features and combines the results of the system decisions [11]. Finally, the fuzzy outputs become Crisp outputs in the de-fuzzification phase [31]. The corresponding model is shown in Figure 1.

The fuzzification stage input for determining the degree of membership in each input is the very general data obtained from the analysis of linguistic variables to describe the following criteria: exposure probability, exposure duration, and severity of potential hazards. A membership function is used to express linguistic terms. Different membership functions exist, including triangular, trapezoidal, Gaussian, linear, and nonlinear [7]. The present study determined linguistic variables and their membership functions for each criterion at the fuzzification stage according to the experts' opinions. Figures 2 and 3 illustrate the form of fuzzy sets and their membership functions.

The fuzzy inputs are evaluated using fuzzy logic operations to calculate the risk of each potential hazard. The calculated risk level is fuzzy and has to be de-fuzzified to quantify the risk level of potential hazards. The number of rules is determined by each system's membership functions and inputs. In the present study, considering the number of levels of the three risk criteria and multiplication of the number of their membership functions, 75 rules were required. The fuzzy rules were created based on the experiences of the research team. The research

team combined the risk criteria to formulate the rules and evaluate them for rationality. A formal request was made. The rules were sent to ten hospital health and safety experts with over ten years of experience to comment on them. Finally, after considering the experts' comments, the research team finalized the fuzzy rules. Figure 4 shows some of the rules defined for the final FIS.

After fuzzifying the inputs and building the rules database in the fuzzy logic system, the basic rules for controlling the output variable are presented and summarized using the "if-then" rules and judged. Each rule is assessed in a process called fuzzy inference. The fuzzy inference stage converts the rules into a mapping of the fuzzy set in the input and output spaces based on the principles of fuzzy logic. Two well-known fuzzy inference methods are Mamdani (min-max) and Takagi-Sugeno inference methods [7]. In the Mamdani system, the output is a fuzzy set that must be defuzzified, but the output is linear or constant in the Sugeno system. In the meantime, the Mamdani inference method increases the efficiency of the defuzzification process by reducing the computations and is used more widely in inferences. The overall result of any rule assessment is a fuzzy value. A function is made by the membership function of the output variables. Then, the fuzzy output value must be defuzzified and converted to a Crisp value [32]. In this study, the centroid defuzzification method was used [31]. The designed model aligns with the ANSI Z690 / ISO 31000 standard. Once the assessment model was designed, we used the results of a case study to verify it.

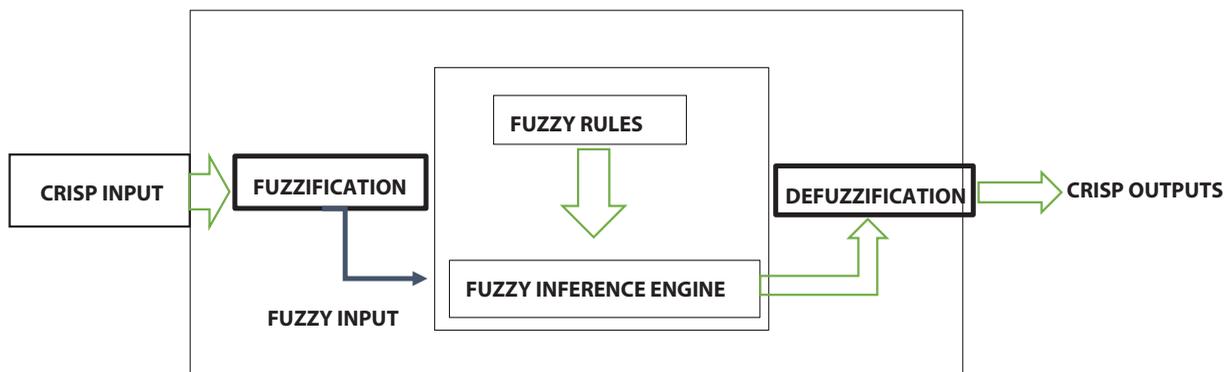


Figure 1. The model fuzzy logic.

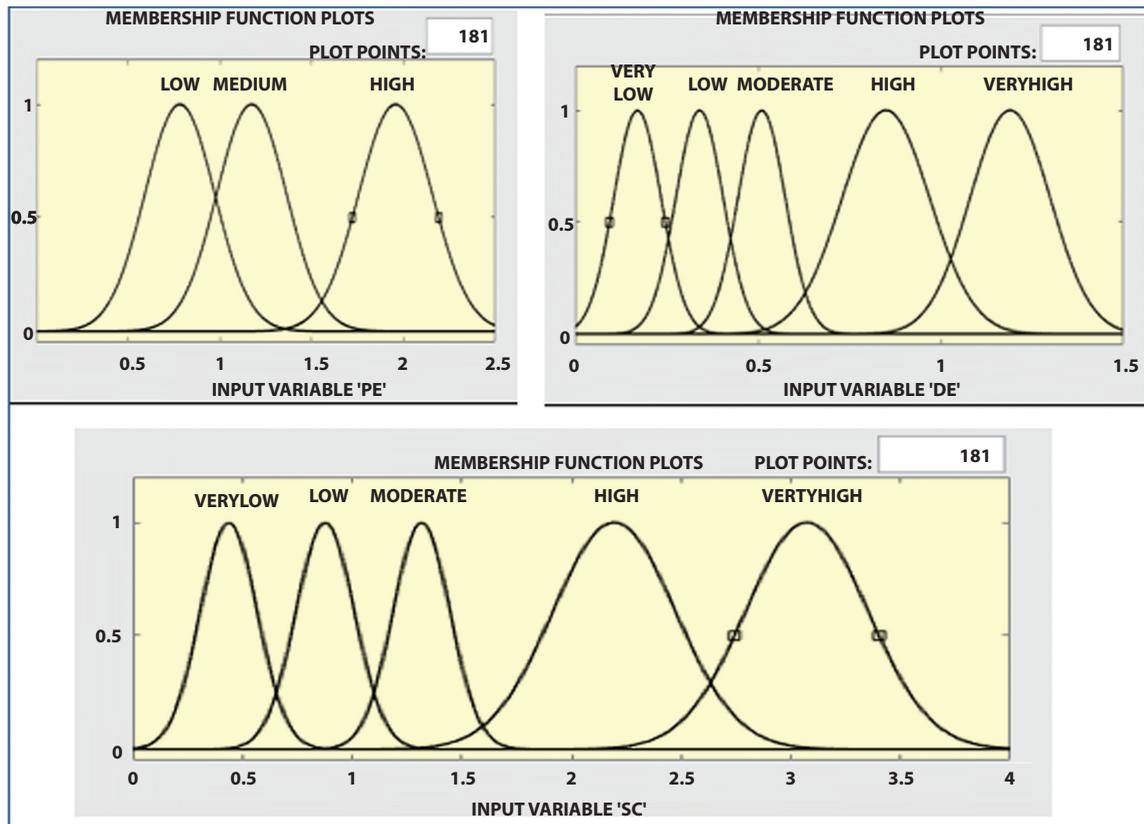


Figure 2. Gaussian membership function of the exposure probability criterion, the exposure duration criterion and outcome severity measure criterion.

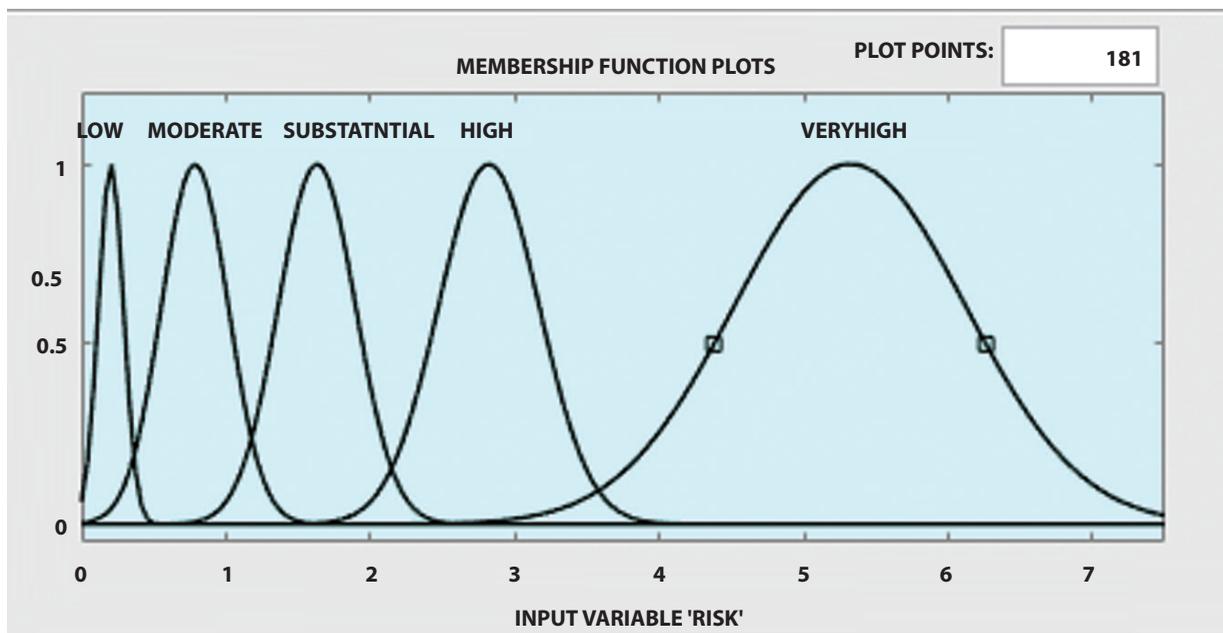


Figure 3. Output Gaussian membership function (risk level).

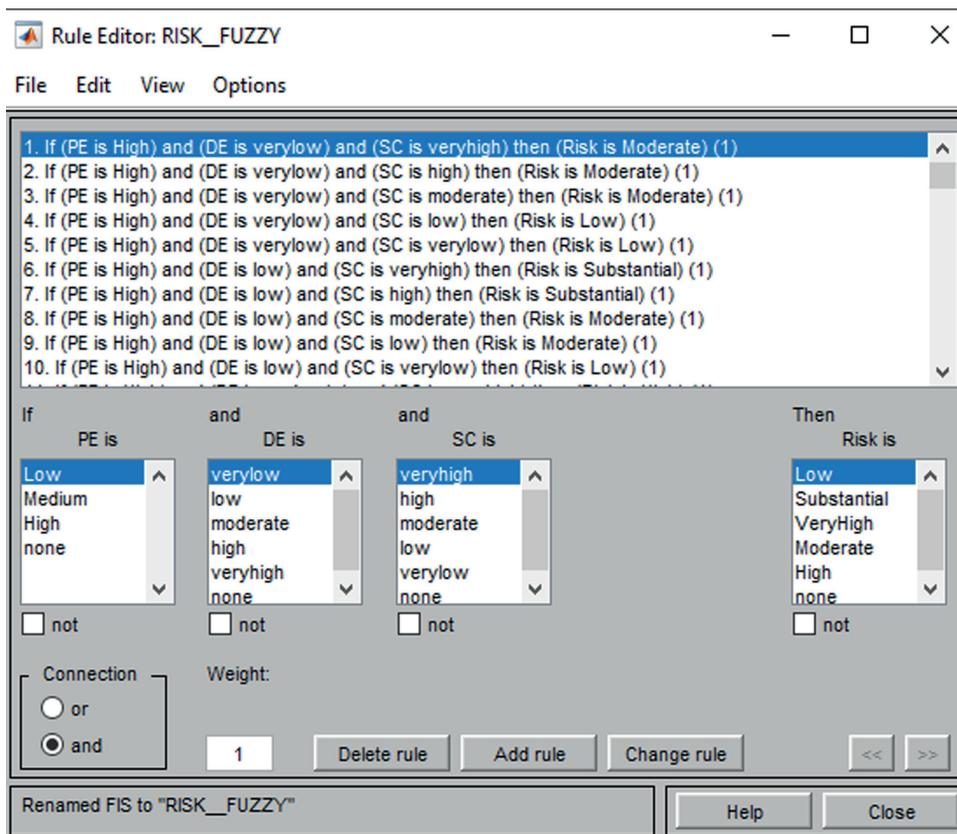


Figure 4. Defined rules for the final fuzzy inference system.

4. RESULTS

4.1 Phase III: Perform a risk assessment and their results

To validate the proposed model, we used the results of a case study that was performed in 2020 at a 700-bed hospital with 45 wards [25]. The results of hazard identification have been used to determine the risk levels for each hazard by FIS. The assessment team consisted of 6 experts who used tables 1 to 3 to score each risk criterion using the verbal variables scale. Then, the scores of all the risk criteria were entered into the FIS designed in MATLAB software, and the risk number and risk level of each hazard (N=43) were determined in 6 hospital units (Table 4).

The results showed that in the fuzzy model, 72.9% of the calculated risk levels are different from the semi-quantitative model, and in 72.9% of the cases,

the risk levels are lower than in the semi-quantitative model. In the fuzzy model, 29.9% of the calculated risk levels are similar to the semi-quantitative model. In the fuzzy model, 69.7% of the risk levels determined are different from the risk levels calculated using the ANSI Z590.3 proposed method, and at 30.2% of the calculated risk levels using the fuzzy model, the risk levels are similar to those calculated by the ANSI Z590.3.

Reviewing the expert team's risk levels in a brainstorming session and comparing the output results show that the proposed model works as a practical instrument for evaluating occupational health risks. Using the fuzzy model provides more logical outputs of risk. In the present study, the risks of six parts of the hospital, including laundry, lab sections, clinical wards, emergency departments, ICUs wards, operating rooms, and isolation rooms, were recognized and evaluated using the method introduced earlier. Tables 4 indicate the calculated risks as well

Table 1. Risk rating for Possibility of Exposure Criteria (PoE).

Classification	Verbal scale	Raw rating	Risk rating with criteria weight (PoE × 0.391)
Exposure rate < 50% of standard limit	L ¹	2	0.782
50% < Exposure rate < 100% of standard limit	M ²	3	1.173
Exposure rate > standard limit	H ³	5	1.955

¹L= Low, ²M= Medium, ³H= High.

Table 2. Risk rating table for Duration of Exposure Criteria (DoE).

Classification	Verbal scale	Raw rating	Risk rating with criteria weight (DE × 0.170)
One per year	VL ¹	1	0.170
Numerous times per year	L ²	2	0.34
Several times in a month at short periods	M ³	3	0.51
2 < DoE < 8	H ⁴	4.5	0.85
8 hours < DoE	VH ⁵	6.7	1.19

²L= Low, ³M= Medium, ⁴H= High, ¹VL= Very Low, ⁵VH= Very High.

Table 3. Risk rating table for Severity of Consequences Criteria (SoC).

Classification	Verbal scale	Raw rating	Risk rating with criteria weight (SC × 0.439)
Exposure at this level isn't harmful to humans	VL ⁴	1	0.439
Outcomes reversible and not endangering human life	L ¹	2	0.878
Effects on quality of life and life expectancy	M ²	3	1.317
Health consequences causing mild limitation or disability	H ³	4,5	2.195
Effects diminishing the quality of life or life expectancy	VH ⁵	6,7	3.073

¹L= Low, ²M= Medium, ³H= High, ⁴VL= Very Low, ⁵VH= Very High.

Table 4. The risk number and risk level of each hazard.

Wards	Hazards	Risks criteria			Semi-quantitative risk model		Fuzzy model		ANSI Z590.3	
		PoE	DoE	SoC	RN	RL	RN	RL	RN	RL
Emergency department	Bloodborne pathogens	1.95	1.19	2.19	6.90	VH	5.31	H	5.10	H
	The bodily fluids	1.95	1.19	2.19	6.90	VH	5.31	H	5.10	H
	Airborne pathogen (Bacillus s)	1.95	1.19	1.31	4.14	H	2.89	S	3.06	S ¹
	Airborne pathogen (Staphylococcus)	1.95	1.19	1.31	4.14	H	2.89	S	3.06	S
	Airborne pathogen (Mold)	1.95	1.19	1.31	4.14	H	2.89	S	3.06	S

(Continued)

Wards	Hazards	Risks criteria			Semi-quantitative risk model		Fuzzy model		ANSI Z590.3	
		PoE	DoE	SoC	RN	RL	RN	RL	RN	RL
Operating room	Isoflurane (anesthetic gas)	1.17	0.51	1.31	2.21	M	0.87	L	0.78	L
	1,3-butadiene	1.95	0.51	3.07	7.57	VH	2.97	S	3.06	S
	Benzene	1.95	0.51	3.07	7.57	VH	2.97	S	3.06	S
	Furfural	1.95	0.51	2.19	5.41	VH	2.97	S	2.18	M
	Bloodborne pathogens	1.95	0.51	2.19	5.41	VH	2.97	S	2.18	M
	Bodily fluids	1.95	0.51	2.19	5.41	VH	2.97	S	2.18	M
	Airborne pathogen (Bacillus sp)	1.95	0.51	1.31	3.24	S	1.11	M	1.31	L
	Airborne pathogen (Staphylococcus)	1.95	0.51	1.31	3.24	S	1.11	M	1.31	L
	Airborne pathogen (Mold)	1.95	0.51	1.31	3.24	S	1.11	M	1.31	L
Isolation room	Bloodborne pathogens	1.95	0.85	2.19	6.15	VH	5.31	H	3.64	S
	Bodily fluids	1.95	0.85	2.19	6.15	VH	5.31	H	3.64	S
	Airborne pathogen (Bacillus sp)	1.95	0.85	1.31	3.69	S	2.89	S	2.18	M
	Airborne pathogen (Staphylococcus)	1.95	0.85	1.31	3.69	S	2.89	S	2.18	M
	Airborne pathogen (Mold)	1.955	0.85	1.31	3.69	S	2.89	S	2.18	M
Clinical Services	blood borne pathogens	1.955	0.85	2.19	6.15	VH	5.31	H	3.64	S
	Airborne pathogen (Bacillus sp)	1.955	0.85	1.31	3.69	S	2.89	S	2.18	M
	Airborne pathogen (Staphylococcus)	1.955	0.85	1.31	3.69	S	2.89	S	2.18	M
	Airborne pathogen (Mold)	1.955	0.85	1.31	3.69	S	2.89	S	2.18	M
Lab	X-ray	1.955	0.85	2.19	6.15	S	5.31	H	3.64	S
	Formaldehyde	1.955	0.85	2.19	6.15	S	5.31	H	3.64	S
	Toluene	1.173	0.85	2.19	4.44	H	2.74	S	2.18	M
	Xylene	0.782	0.85	2.19	3.58	S	2.02	M	1.45	L
	Bloodborne pathogens	1.955	0.85	2.19	6.15	VH	5.31	H	3.64	S
	Airborne pathogen (Bacillus sp)	1.955	0.85	1.31	3.69	S	2.89	S	2.18	M
	Airborne pathogen (Staphylococcus)	1.955	0.85	1.31	3.69	S	2.89	S	2.18	M
	Airborne pathogen (Mold)	1.955	0.85	1.31	3.69	S	2.89	S	2.18	M
	Bleach or sodium hypochlorite	1.955	0.85	2.19	6.15	VH	5.31	H	3.64	S
	Methanol	0.782	0.85	1.31	2.14	M	0.99	M	0.87	L
Ethanol	0.782	0.85	1.31	2.14	M	0.99	M	0.87	L	

Wards	Hazards	Risks criteria			Semi-quantitative risk model		Fuzzy model		ANSI Z590.3	
		PoE	DoE	SoC	RN	RL	RN	RL	RN	RL
Laundry	Bloodborne pathogens	1.955	1.19	2.19	6.90	VH	5.31	H	5.10	VH
	Bodily fluids	1.955	1.19	2.19	6.90	VH	5.31	H	5.10	VH
	Airborne pathogen (Bacillus sp)	1.955	1.19	1.31	4.14	H	2.89	S	3.06	S
	Airborne pathogen (Staphylococcus)	1.955	1.19	1.31	4.14	H	2.89	S	3.06	S
	Airborne pathogen (Mold)	1.955	1.19	1.31	4.14	H	2.89	S	3.06	S
	Noise	1.173	1.19	1.31	3.11	S	1.64	M	1.83	L
	Excessive heat	1.173	1.19	0.87	2.07	M	0.79	L	1.22	L
	Poor Lighting	0.782	1.19	0.87	1.73	L	0.79	L	0.81	L
	Bleach or sodium hypochlorite	1.955	1.19	2.19	6.90	VH	5.31	H	5.10	VH

¹S= *substantial*.

as the risk levels. Based on the results of the fuzzy model in the emergency department and isolated rooms, the risk of biological hazards was highest. The risk of biological and chemical hazards from surgical smoke was high and had a substantial level in the operating room. Physical hazards (X-rays) and biological hazards had the highest level in clinical wards, and in laboratory wards, biological and chemical hazards had the highest priority. In the laundry sector, the risk level of chemical hazards had the highest priority. Figure 5 shows the major risks in various hospital sections.

5. DISCUSSION

This study developed a fuzzy model to calculate different risk levels in every hospital unit. Using linguistic expressions and experts' opinions in a FIS improves the model's efficiency. The present study results show that using the fuzzy model provides more logical outputs of risk levels. Traditional models calculate the risk levels using a dual-value logic and do not consider uncertainties caused by human thought ambiguities. However, fuzzy logic considers the subjectivity of human judgment and

the uncertainty caused by human thought ambiguities. It models the reasoning and synthesis methods of the brain. In the study by Petrović et al., a risk assessment model for mining equipment failure using the fuzzy logic approach and FIS was proposed, and the results of the case study showed that the risk analysis results based on the fuzzy model and the experts' judgments and use of this approach made the assessment model more efficient compared to traditional methods [7], which is consistent with the results of the present study. However, to determine the exposure probability in this study, the measurement data were used to focus less on the subjective nature of the experts' judgment and to calculate the risk levels more accurately. Regarding their different types of activity, health care industries are highly sensitive. Biological risks could affect staff and also harm the patients. Thus, the levels of each risk must be calculated more precisely, and engineering and management control measures need to be taken more seriously. Using direct measurements, the data presents further reliable data on the probability of exposure to a harmful agent, and the data is no longer subjective. Therefore, the levels of each risk will be determined more precisely [25].

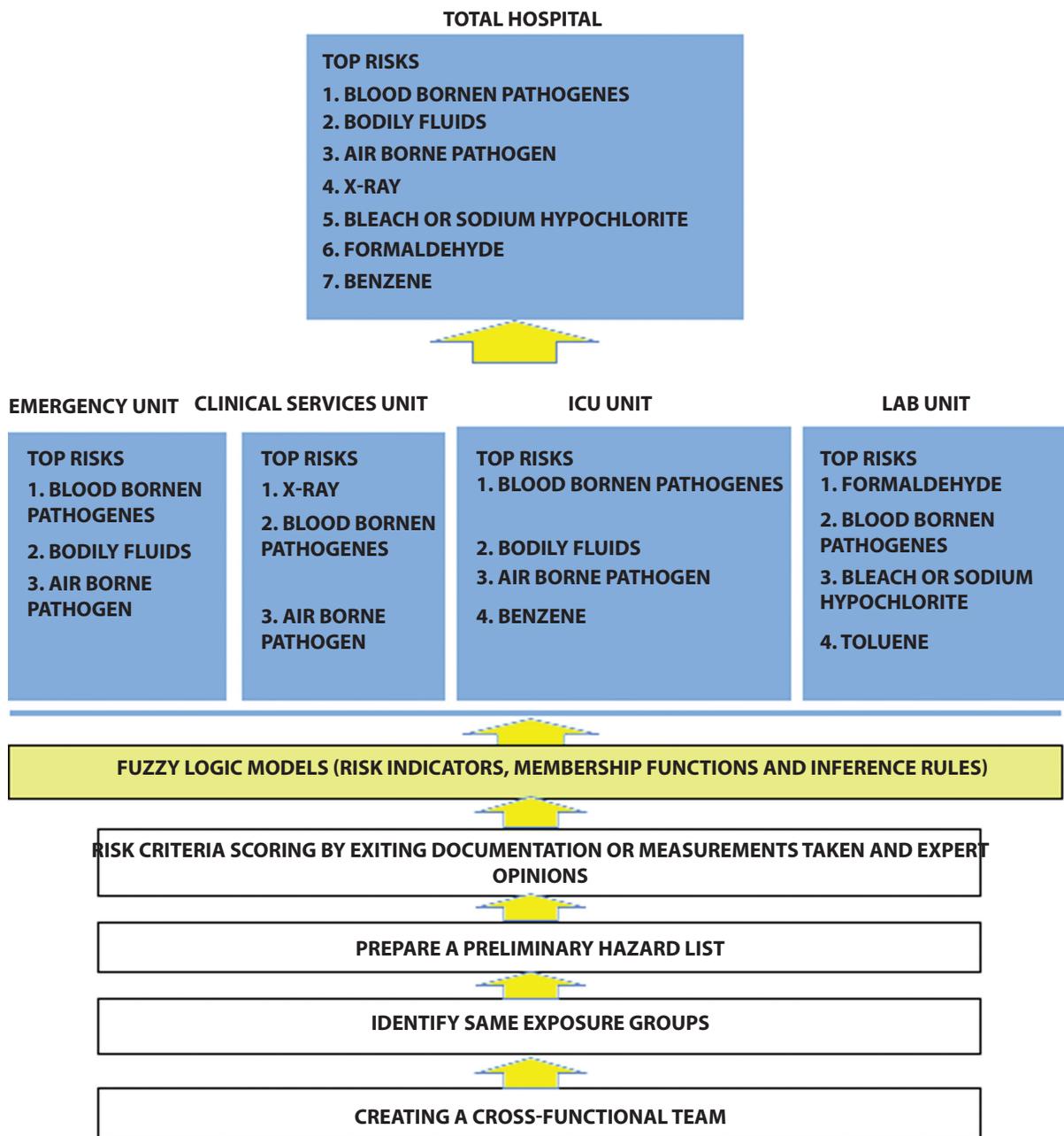


Figure 5. Important risks in different parts of the hospital.

The study by Samantha et al. also considered the standard exposure limit to measure the probability of exposure [21]. However, it should be noted that experts' opinions are also recommended to be used in addition to the information obtained from measurements data, because while evaluating the bio-aerosols risk, although their indoor air concentration

is measured, they are highly variable in indoor air. Therefore, bioaerosols concentration is continually shifting [25].

In this study, we selected a semi-quantitative method that considered the relative significance of risk criteria [25]. Samantha et al. study, unlike the present study, did not consider risk criteria weight,

and the weight of each risk criteria had been considered the same [21]. The present study considered the essential criteria in risk level measurement and used linguistic expressions and experts' opinions in a FIS in order to not only fix the shortcomings of traditional models but also provide a fuzzy model with good usability and ease of use. Ilbahar et al. used Pythagorean fuzzy analytic hierarchy and FIS to provide a framework for assessing safety and health risks in the construction industry. In their study, the probability and intensity parameters were also obtained through the FAHP, and the experts also determined the frequency parameter. Then, the information about the parameters was used as the input to the FIS [22]. Using the FAHP method will make the assessment process time-consuming and tedious if the number of parameters is high, and the ease of use will be consequently reduced [33]. For instance, if we have 35 hazards, each expert may need to make 595 pairwise comparisons in the AHP method about the probability criterion and 595 pairwise comparisons about the severity criterion. The present study used a FIS to calculate the risk level. The inference system processes the risk criteria after entering the FIS, which quickly calculates risk levels in a short time.

In the study of Çalıř Boyacı and Selim (2021), a two-step approach was used to assess the risks of OHS. In this approach, the Fine-Kinney method and the set of multi-criteria fuzzy language terms (HFLTS) were used. In the Fine-Kinney method, the risk number is obtained by multiplying the 3 parameters of probability, frequency, and intensity, and the weight and importance of each parameter are not considered. The risk number is considered from this proposed method for OHS hazards applied in the operating room of a public hospital in Turkey. This study, like the present study, considers the weight of risk criteria and presents the HFLTS method as a solution for calculating risk when experts have doubts about several linguistic expressions. In the present study, to calculate the risk levels more accurately for the exposure probability parameter, the measured data were used so that the assessment by experts is not purely subjective. Also, FIS with specialized knowledge was used to provide more interpretable and accurate results.

Samantha et al., like this study had used three criteria, including exposure outcome, exposure probability, and exposure duration, to assess the risks and applied the verbal variables scale to determine the score of each criterion. However, like in traditional methods, in Samantha et al. study, three risk criteria were multiplied, and the risk number was fuzzily calculated and then defuzzied [21]. The ANSI Z590.3 standard has also proposed that in cases where three criteria are used, the risk value can be determined by multiplying the risk criteria. But when the results are obtained by multiplying the three risks criteria, severity reduces in the calculated risk value, and the risks determine less accurately [26]; also when there are three risk criteria in the equation, each criterion weighs the same (33%) of the final risk score [34]. Unlike the study by Samantha et al., the present study used the FIS to calculate the risk level in order to improve the efficiency of the method.

Moreover, the framework proposed by Samantha et al. was used to evaluate the risk levels of chemical agents, biological, physical, psychological, and ergonomic hazards in coal mining [21]. In the present study, the range of chemical, physical, and biological hazards was also considered, which is in line with Samantha et al. However, they examined psychological and ergonomic hazards and involved them in the scope of their study. In contrast, the present research did not consider these hazards because the consequences of psychological risks are so different. There is a broad and different range of individual talents in physiological responses to stress situations and workloads. People's reactions to low or high levels of exposure to these hazards significantly vary. One may experience greater psychological responses and effects at a lower level of exposure. The proposed model did not consider psychological and ergonomic hazards.

The research results showed that the risk of injury from blood and airborne pathogens was highly prioritized. The injuries caused by sharp-pointed objects contaminated with blood pathogens are one of the ways of transmitting pathogens such as HIV and type B and type C hepatitis. Various studies have investigated the risk of injuries from sharp-pointed objects and contact with pathogens of good origin. A study conducted in a hospital in Zahedan indicated

that this risk was highly prioritized, with 69.9% of the people being injured during their working time [35]. The results of another study conducted by Nasiri et al. in Mazandaran province showed that 76% of teaching and non-teaching hospital staff experienced at least one injury with sharp objects during their employment periods, and the risk of injuries by blood pathogens was reported to be high [36]. This is in line with the results of the present study.

The proposed model did not consider psychological and ergonomic hazards and should utilize other appropriate techniques. It has also recommended using the measurements data to determine the level of exposure probability properly. The measurement process is costly for some organizations in a middle-income country. Furthermore, because the healthcare industry is more sensitive than other industries, managing hazards and associated risks must be regularly implemented to lead tolerable risk levels.

6. CONCLUSIONS

In this case study, different risks in various sections were identified and analyzed with a systematic approach. The assessment outcomes achieved by the fuzzy set theory produced a wide picture of risks as an essential factor affecting the risk management system and the performance of the health and safety management system.

It could work properly in the presence of inaccurate and insufficient data to calculate the risk level. This model calculated the levels of each risk and gave us the distribution of calculated risk numbers. It indicates that the risk levels could be parts of various classes with suitable membership functions, showing the risk trend. This is also proved in the Dejan et al. study [7]. Effective management of potential hazards in different hospital sections can lead to better control of the risks and ultimately increase the hospital workers' safety as well as patients' and improve the healthcare quality.

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