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A Fuzzy-based Multi-dimensional Risk Assessment Model for the Healthcare System

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Abstract

The adoption of multi-criteria risk assessment methods, such as probability and impact matrices, in the healthcare sector poses several risks, one of which is subjectivity and bias in decision making. To this end, the aim of this research is to develop a multi-criteria healthcare risk assessment model under fuzzy environment. To achieve this, a three-step research methodology was employed. The study identifies 29 risk factors, with insufficient team cooperation and communication, poor response to health pandemics, and misdiagnosis being the top three risks. The findings of this study might be of value to relevant medical personnel and organisations in effectively managing risks and developing appropriate risk interventions.

Keywords: healthcare, risk assessment, fuzzy set theory, China

1. Introduction

Hospitals provide healthcare services to patients with the primary goal of improving their quality of life during times of illness or unfavorable circumstances (Cure et al., 2014). While these services aim to alleviate or eliminate the undesirable conditions, there are potential risks associated with accepting healthcare interventions, which may increase the patient's vulnerability and lead to complications or even mortality (Rutherford, 2003).

Healthcare risks stemming from healthcare services have been reported on a global scale and have a significant impact on a substantial number of patients. Researchers in various countries have undertaken studies to assess the prevalence of healthcare risks, revealing concerning results. For instance, a study conducted in Australian hospitals revealed that healthcare risks constituted the major cause of 13.7% of permanent disabilities (Bevilacqua et al., 2018). Similarly, in Canadian hospitals, healthcare risks accounted for 20.8% of fatalities (Baker et al., 2004). In US hospitals, healthcare risks were identified as the primary factor behind 13% of cases being fatal or life-threatening, with an additional 11% having the potential for fatality (Rothschild et al., 2005). Lastly, in Swedish hospitals, adverse effects of healthcare risks were responsible for 55% of impairment or disability cases, with 9% being associated with fatalities (Soop et al., 2009).

These research findings underscore the significant healthcare risks faced by individuals in various countries. They highlight the urgent need for robust measures and improvements to ensure patient safety, minimize the occurrence of such risks, and enhance the overall quality of healthcare services. Given these findings, it is crucial for hospitals to develop a robust risk assessment method to appropriately manage healthcare-related risks. A better risk assessment method can not only prevent potential injury and death related to the patient but also help optimise healthcare resource allocation, improve treatment outcomes, and reduce healthcare costs. One of the most popular methods for risk assessment is the probability and impact matrices. However, the implementation of traditional risk matrices poses challenges due to the ambiguity in decision-making (Cox, 2008).

Numerous scholars have implemented multi-criteria risk analysis methods like risk matrices under uncertainty-reduction environments, such as fuzzy sets theory, to mitigate the limitations associated with risk matrices (see, e.g., Cagliano et al., 2011; Zaitseva and Levashenko, 2016; Zaitseva et al., 2020; Zaitseva et al., 2023 and others). To this end, the aim of this research is to present a multi-criteria fuzzy-based risk assessment model for analysing healthcare-related risks by surveying healthcare practitioners in China.

2. Methodology

A three-step research methodology was adopted in this research for data collection and analysis. The following sub-sections provide more details on the adopted research methodology.

Step One: Identifying the Risk Factors in the Chinese Healthcare System

Risk identification, based on the Project Management Institute (PMI), is the process of systematically identifying and documenting potential risks that may affect the successful completion of a project (PMI 2013). The healthcare system risks utilized in this research were obtained from the work of Zhang (2021), in which the author conducted a systematic literature review to identify the major risks confronting the healthcare system in China. The risks and their respective categories are presented in Table 1.

Table 1. Identified risk factors (Zhang, 2021)

Risk categories	**Risk factors**
Patient-sourced risk	F1. Inadequate patient education
	F2. Workplace violence
	F3. Language barriers
Staff-sourced risks	F4. Delay diagnosis
	F5. Medication errors
	F6. Misuse of medical resources
	F7. Misdiagnosis
	F8. Readmission and prolonged hospital
Equipment-related risks	F9. Poor designed equipment
	F10. Poor equipment maintenance procedures
Communication risks	F11. Insufficient team cooperation and communication
	F12. Poor nurse-physician communication
Task-related risks	F13. Poor response to health pandemics
	F14. Poor management of telemedicine
	F15. Poor in identifying complicated disease
Organisational risks	F16. Poor shift schedule management
	F17. Poor management mechanisms (such as bureaucratic)
	F18. Inappropriate autonomy
	F19. Insufficient healthcare staff training
	F20. Poor staffs' mental health management
	F21. Poor hospital related infections management
	F22. Poor surgical procedure training
Organizational risks	F23. Poor prescription management system
	F24. Insufficient number of registered nurses
	F25. Poor referral system
	F26. Poor medication management system
External risks	F27. Poor healthcare cyber-physical system
	F28. Aging population problem
	F29. Malware/ ransomware attack

Step Two: Developing a Risk Assessment Model for Healthcare Risks

As previously stated, the risk matrix is a widely 3 tilized risk assessment tool. However, its effectiveness can be limited due to several factors. Firstly, the risk matrix relies on subjective assessments of the likelihood and severity of risks, which can vary depending on the individual or the organization conducting the assessment. This subjectivity can lead to inconsistent results and hinder the ability to compare and prioritize risks accurately (Al-Mhdawi et al., 2023a; Al-Mhdawi, 2022; Singhal and Banati, 2013).

In order to enhance effectiveness and optimize the probability and impact matrices, the authors incorporated a new dimension derived from the DREAD model. The DREAD model is extensively employed in addressing computer security risks and encompasses five dimensions: damage potential, reproducibility, exploitability, affected users, and discoverability (Singhal and Banati, 2013). Within this study, particular emphasis was placed on the discoverability dimension, as it enables medical professionals to estimate the ease of identifying specific risk factors within a hospital setting. By incorporating this new dimension, medical professionals gain additional insights to complement the probability and impact dimensions when assessing healthcare risk factors. Consequently, the risk weight (RW) was calculated by multiplying the probability (P) of risk occurrence by the impact (I) on the project's objectives and the discoverability (D) of the risk, as demonstrated in Equation (1).

$$RW=P*I*D \tag{1}$$

Fuzzy sets theory

In this study, fuzzy set theory was 3tilized to control the inconsistency of expert subjective judgment concerning the ranking of healthcare risk factors, as recommended by several scholars (see e.g., Cagliano et al., 2011; Khasha et al., 2013; Chanamool and Naenna, 2016; Al-Mhdawi, 2020; Al-Mhdawi et al., 2022a; Al-Mhdawi et al., 2022b and others). The following process was 3tilized to develop the model:

a. Fuzzification

Fuzzification is a fundamental process in fuzzy set theory that involves transforming crisp or deterministic data into fuzzy or uncertain data. In other words, fuzzification is the process of mapping precise numerical values or discrete states onto fuzzy values, which are represented by membership functions.

The current study utilised the triangular membership function for this purpose. This method is commonly used to represent fuzzy sets due to its simplicity and effectiveness (Al-Mhdawi, 2022). The triangular membership function is characterised by three parameters: the left, center, and right values, which determine the location of the function's peak and the width of the function. Triangular membership functions have proven to be particularly useful in capturing subjective and imprecise information, and they offer the advantage of allowing for easy definition of the input range and straightforward arithmetic calculations (Sadollah, 2018; Al-Mhdawi et al., 2023).

The inputs to the model, namely P, I, and D, as well as the output variable, Fuzzy Risk Weight (F-RW), in this research were defined using a five-point Likert scale. This scale represented the levels of very low (VL), low (L), moderate (M), high (H), and very high (VH), as depicted in Figure 1.

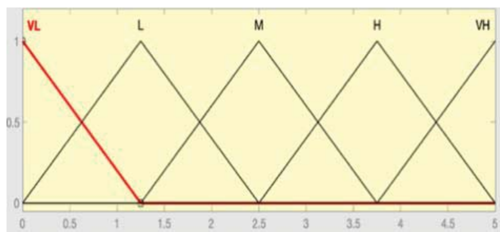

Figure 1. Membership function for P, I, D, and F-RW

b. Fuzzy interference

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. In this study, the Mamdani fuzzy inference system (MFIS) was used to assess the output variable. The MFIS is one of the most widely used fuzzy inference systems. It uses if-then rules that relate the input variables to the output variables (Kumru and Kumru, 2013). The MFIS also has an intuitive nature that makes it easy for experts to interpret and use, and it is particularly suitable for subjective inputs that are difficult to quantify (Al-Mhdawi et al., 2023). In this research, a total of 125 if-then rules were employed, and examples of these rules are presented in Figure 2.

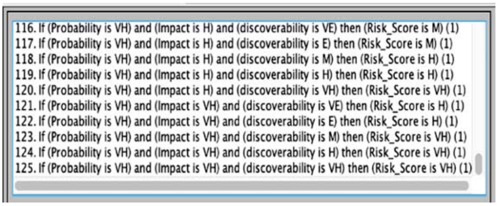

Figure 2. Examples of the 4tilized If- then rules

c. Defuzzification

Defuzzification is the process of converting the fuzzy output of a fuzzy inference system back into a crisp or numerical value that can be used as a decision or an action. In this study, the centroid of area method was employed for this purpose. The centroid of area method is a widely used method of defuzzification that reflects the viewpoint of the experts. It calculates the center of mass of the fuzzy set by taking the weighted average of the fuzzy values or membership grades. The result is a crisp value that represents the center of the fuzzy set and can be used for further analysis or decision-making (Kayacan and Khanesar, 2016).

To this end, the authors used MATLAB (V. 2015b), for developing the risk assessment model.

Step Three: Administering Questionnaire Surveys to Healthcare Professionals in China

Following the model's development, a total of 100 questionnaire surveys were distributed to healthcare professionals in China to quantitatively assess the significance of the identified risk factors across three distinct dimensions of analysis (i.e., P, I, and D). Out of the 100 surveys disseminated, 65 were returned. However, it is important to note that two of these responses were considered incomplete, resulting in a final count of 63 surveys that were included in the subsequent analysis. The demographic profile of the respondents is presented in Table 2, which reveals that a significant proportion (61.9%) of the respondents had over 16 years of experience in the healthcare sector. Additionally, the respondents encompassed various healthcare roles, including risk managers (12.7%), physicians (33.33%), nurses (30.16%), hospital managers (19.05%), and other healthcare practitioners (4.76%). Furthermore, the majority of respondents held a Master of Science (MSc) degree, accounting for 58.73% of the total, while 15.87% possessed a Ph.D. degree. Hence, the profile of the respondents highlights the extensive diversity in terms of experience, healthcare roles, and educational qualifications within the cohort.

Table 2. Profiles of survey respondents

Respondent's profile	Category	Distribution (%)
Range of experience (years)	1-5	4.76%
	6-15	33.33%
	16-25	34.92%
	>25	26.98%
Healthcare role	Risk manager	12.7%
	Physician	33.33%
	Nurse	30.16%
	Hospital manager	19.05%
	Other	4.76%
Educational background	BSc	25.4%
	MSc	58.73%
	PhD	15.87%

Survey validity and reliability

Before proceeding with an in-depth analysis of the gathered data, it is crucial to ensure the accuracy and validity of the survey data and scales. To accomplish this, the authors calculated Cronbach's alpha values for the levels of probability, impact, and discoverability. The results of this analysis revealed alpha values of 0.98 for the probability level, 0.99 for the impact level, and 0.98 for the discoverability level. These findings indicate that the distribution of the survey was both valid and reliable, as it surpassed the threshold of 0.70 (Al-Mhdawi et al. 2023b)

3. Result and Discussion

F-RW for each healthcare risk factor was determined by calculating the mean values of all the responses obtained from the survey and processing them under fuzzy environment. Table 3 depicts the outcomes of the analysis, wherein the Relative Weights (RWs) and corresponding ranks assigned to each risk factor in the Chinese healthcare system are presented.

Table 3. Calculated risk weights and their rank

Risk factors	P (Mean value)	I (Mean value)	D (Mean value)	F-RW	Rank
F1	1.89	2.00	1.83	2.55	29
F2	2.41	2.22	2.19	2.97	8
F3	1.98	2.11	1.89	2.67	28
F4	2.11	2.25	2.10	2.95	10
F5	2.24	2.17	2.02	2.81	18

Table 3. *Continued.*

Risk factors	P (Mean value)	I (Mean value)	D (Mean value)	F-RW	Rank
F6	2.13	2.06	2.16	2.8	20
F7	2.37	2.27	2.27	3.09	3
F8	2.00	2.16	2.05	2.79	22
F9	1.97	2.30	1.97	2.92	14
F10	2.03	2.16	2.14	2.81	18
F11	2.25	2.40	2.16	3.19	1
F12	2.00	2.06	2.02	2.7	26
F13	2.27	2.32	2.25	3.15	2
F14	2.56	2.11	2.24	2.94	13
F15	2.06	2.13	2.32	2.8	20
F16	2.24	2.30	2.02	2.95	10
F17	2.44	2.37	2.05	3.07	4
F18	2.21	2.14	2.08	2.82	17
F19	2.14	2.17	2.22	2.89	15
F20	2.25	2.24	2.14	2.96	9
F21	2.13	2.16	2.21	2.87	16
F22	2.00	2.11	2.35	2.74	24
F23	1.95	2.38	2.25	3.01	7
F24	2.10	2.06	1.97	2.68	27
F25	2.46	2.29	2.16	3.04	6
F26	2.03	2.29	2.33	2.95	10
F27	1.94	2.17	2.25	2.76	23
F28	2.06	2.24	1,81	2.74	24
F29	2.14	2.32	2.25	3.06	5

Based on Table 3, the highly ranked critical risk factor was F11: insufficient team cooperation and communication, with an F-RW value of 3.19. F11 refers to a situation where there is a lack of effective collaboration and communication among healthcare team members. This means that the individuals responsible for providing healthcare services, such as doctors, nurses, and other healthcare professionals, are not effectively working together or communicating with each other. This finding is consistent with previous research that has elucidated the deleterious effects of inadequate communication among healthcare team members on timely hospital discharge, thereby increasing the risk of patient readmissions (Opper et al., 2019). Likewise, in high-risk settings such as operating rooms, errors resulting in patient harm or fatalities have been attributed to deficient communication among team members (Green et al., 2017). Numerous studies have also established a correlation between poor teamwork and communication with adverse events, heightened patient morbidity, and mortality (Koshy et al., 2011; Rabol et al., 2011).

The second highest critical risk factor identified was F13: poor response to health pandemics, with an F-RW value of 3.15. F13 pertains to a situation where the healthcare system exhibits suboptimal or inadequate responsiveness to health pandemics. This indicates that the healthcare system may encounter challenges in effectively detecting, containing, and responding to outbreaks or epidemics of infectious diseases, such as the recent global outbreak of Covid-19.

The third highest critical risk factor based on our analysis was F7: misdiagnosis, with an F-RW value of 3.09. F7 refers to a situation where there is a significant risk of incorrect or inaccurate diagnoses in the healthcare system. Misdiagnosis can occur due to various factors, such as inadequate medical knowledge or expertise, errors in medical tests or interpretation of results, biases in clinical judgment, or communication breakdowns between healthcare professionals and patients. It can have severe consequences for patient outcomes, including compromised health, prolonged illness, or even mortality in some cases (Balogh et al., 2015).

4. Concluding Remarks

In this research, the authors modified the traditional risk matrix method by adding a new dimension to the risk analysis. The resulting three-dimensional risk analysis model, comprising probability, impact, and discoverability, was employed to analyse the key risks facing the healthcare system in China. By multiplying the scores of all three criteria, distinct levels of risk were generated. However, acknowledging the potential presence of subjective bias in risk scoring, the proposed risk assessment model was implemented within a fuzzy environment to account for such subjective-related uncertainties.

The study findings revealed that the top three significant risk factors were insufficient team cooperation and communication, poor response to health pandemics, and misdiagnosis. The outputs of this research hold great promise in benefiting the broader healthcare community by providing valuable insights into the key risk factors and enabling the development of effective risk mitigation strategies tailored to the specific needs of the Chinese healthcare system.

This research is limited to a set of 29 identified risk factors. New risks could be added, particularly in relation to the post-COVID-19 pandemic. Moreover, the current research solely focuses on three dimensions of risk analysis: probability, impact, and discoverability. To achieve a more comprehensive understanding of the level of risk associated with healthcare, it would be beneficial to incorporate additional dimensions such as vulnerability, resilience, and adaptability. By expanding the model to encompass these aspects, a more holistic assessment of healthcare risks can be obtained.

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