Patient Safety & Quality Improvement Journal
http://psj.mums.ac.ir
PSQI

Causal Inference and Analysis of Surgery Cancellation Risks

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ARTICLE INFO

Article type:
Original article

***Article History*:**
Received: 06-Mar-2019
Accepted:17-Feb-2020

Keywords:
Elective surgery cancellation, Fuzzy failure mode and effects analysis, Quality improvement. Operating room, Patient-facing risk assessment.

ABSTRACT

Introduction:
The provision of services in hospitals is the final level of the health care system chain, which usually provides the patients with advanced medical services, such as surgery. On the other hand, the cancellation of elective surgeries is one of the problems, which reduces the quality of service delivery and decreases hospital's efficiency and patients' satisfaction followed by increases in patients' costs. This study presented an approach based on a fuzzy inference system to better assess these hazards and eliminate the related risks and investigate effective factors in the cancellation of elective surgeries.

Materials and Methods:
The present study conducted a case study in Shahid Arefian Hospital Urmia, Iran, during 2016-2017. Principal factors of surgery cancellations were collected from surgery documents in the hospital. These factors were divided into five classes, including paraclinical, clinical, systematic, surgeon, and patient. The hazards identified in these classes caused surgery cancellation. They were identified using the contribution of an expert team, including operating room supervisors, female and male surgery hospitalization supervisors, as well as two physicians.

Results:
According to the results, the proposed approach was more appropriate for creating discrimination between surgery cancellation hazards, compared to the traditional risk priority number (RPN) method. Surgeon fatigue, high PPT and PT, and airway problems were the first to third important hazards with RPNs equal to 120, 105, and 96, respectively. On the other hand, according to obtained results, not having internal medicine specialist counseling, low thyroid stimulating hormone, and unavailability of beds at intensive care units were three important and priority potential hazards with FRPNs equal to 8, 8, and 6, respectively.

Conclusion:
The proposed approach can better map hospital experts' opinions to the fuzzy-based risk assessment system since it employs linguistic variables by hospitals' experts, compared to conventional approaches. Moreover, it can help the hospital managements apply hospital resources to maximise their impacts on improving hospital efficiency.

► Please cite this paper as:
Alizadeh A, Eshkevari M, Pashaei MR, Jahangoshai Rezaee M. Causal Inference and Analysis of Surgery Cancellation Risks. Journal of Patient Safety and Quality Improvement. 2020; 8(1):3-12. Doi: 10.22038/psj.2020.38946.1218

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Introduction

The need for a sustainable, efficient, and effective health care system has become a major concern for countries worldwide (1). In today's challenging and competitive environment, health systems, hospitals, and healthcare providers must focus on improving quality and efficiency to satisfy the increasing demand for high-quality and low-cost health care. Previous studies attempted to provide strategies and exerted efforts to improve the efficiency of healthcare systems (2). The operating room is a critical part of hospitals and is one of the costliest units in healthcare systems. However, this unit is also one of the largest contributors to the economic success of hospitals. Unsuitable scheduling of operating rooms and cancellation of surgeries are the two most important factors that cause unproductive operating rooms (3). Surgery cancellation bears many economic burdens on patients and hospitals. This practice wastes the time and resources of hospitals, which can result in non-productivity. Surgery cancellation also imposes substantial emotional pressure on patients and their families; moreover, it adds to their dissatisfaction (4).

The timing of surgery cancellation is a significant problem for healthcare organizations and may be divided into two main classes, namely elective surgeries and emergency surgeries. Elective surgery cancellations may be classified into preventable and unpreventable. Unpreventable surgery cancellation consists of cases that are beyond the control of staff members, such as patient illness and other health conditions. A significant number of cancellations can be prevented and some of the reasons for procedure cancellations consist of lack of preoperative instruments, nil per os (NPO)(Nothing by mouth) violations, changes in insurance coverage, legal issues, faults in the communication of surgery date and time, lack of necessary documents, and transportation issues (5).

Risk management and assessment is a relatively new scientific field that has been widely used in a different scope of applications (6-9). Risk assessment provides decision support for choosing between alternatives, activities, and products, as well as for implementing risk reduction actions. Risk management is related to policy analysis and strategy selection. This field applies an influence of principles and plans of international organisations, governments, private sectors, and individuals to guide their decisions in gaining acceptable results and outcomes (10). Risk analysis is a decision-making framework that can be defined as a process that comprises problem definition and hazard identification, information gathering, and hazard evaluation. This framework can determine the risk class of hazards using the features.

Published literature provides various cases, which include successful and unsuccessful efforts and strategies to reduce surgery cancellation. These studies were conducted to identify avoidable and unavoidable factors (11). Laisi et al. studied surgery cancellation in a large community hospital to determine total cancellation and individual rates that corresponded to different surgical specialties (12). They analysed collected data through stochastic analysis tests. Moreover, Fong et al. reviewed published works and aimed to improve intraoperative efficiency and assessed their outcomes (2). Similarly, Luo et al. used machine learning methods, which included random forest, bagging, boosting, and Bayesian additive regression trees to predict surgery cancellation (13).

In a similar vein, Kaddoum et al. recorded the causes of surgery cancellation on the day of surgery in a tertiary teaching hospital. They emphasised the reasons that confirm 80% of avoidable surgical cancellations (14). Lee et al. implemented a nurse-patient preoperative call log to reduce the rate of cancellation in a pediatric ambulatory surgery centre (5).

Failure Mode and Effect Analysis (FMEA) is a popular method that has been extensively used for risk analysis (10,15). The FMEA has three assigned factors, namely the occurrence, detection, and severity of each hazard. Furthermore, it calculates a risk priority number (RPN) for the latter by multiplying their corresponding input factors. Real-world data contain uncertainties, which can be identified as the fuzzy set theory. With this background in mind, this study proposes a fuzzy FMEA model for analysing surgery cancellation risk with respect to the important role of surgery cancellation in healthcare organizations and the lack of studies in conducting risk analysis in this scope. In other words, this paper proposed an approach based on a fuzzy inference system to better assess these hazards and eliminate the related risks to investigate effective factors in the cancellation of elective surgeries.

The rest of this study is organised as follows. Section 2 describes the fuzzy logic and conducts surgery cancellation risk analysis of the traditional FMEA versus the fuzzy FMEA model. Section 3 presents the result of applying the methodology in a real case study. Section 4 contributes to the discussion and Section 6 provides conclusion.

Materials and Methods

This study was conducted in Shahid Arefian Hospital, Urmia, Iran, during 2016-2017. It should be noted that this hospital has the capacity for 137 active beds and four operating rooms, and includes four modes of hospitalisation, two parts of which are allocated to female and male hospital admission, and the other two are for female and male surgery.

The method of assigning values of detection, occurrence, and severity in the traditional FMEA method utilized in this study was based on experts' opinions. Moreover, the ability of the fuzzy inference method in translating quantitative values into computational expressions has been employed in this study.

Furthermore, experts' opinions are translated into a fuzzy inference system using a definition of fuzzy numbers and translating linguistic expressions such as low, medium, and high to fuzzy numbers. This goal prompted the collection of expert advice to form a fuzzy inference system (FIS) model, which is more reasonable than the traditional RPN method. The way to prioritize the surgery cancellation risks has been improved utilizing this approach.

Considering the nature of the case study as well as the improvement of the traditional method, it was not possible to compare the results with those of other studies.

The data were collected from surgery documents in the hospital. In addition, the observations and questionnaires/ interviews from doctors, nurses, and authorities related to the female and male surgery sectors of the hospital have been used to collect the necessary data. In total, 41 potential failure modes were identified after holding a brainstorming among the study team consisting of four sets of people. These individuals include operating room supervisors, female and male surgery hospitalisation supervisors, as well as two physicians.

Based on expert guidelines, identified hazards were classified into five classes, namely systemic, patient, paraclinical, clinical, and surgeon. The following section investigates the methods used in this study.

Fuzzy Inference System

The FIS is a robust method used for quantifying expert knowledge. This method is based on fuzzy set theory introduced by Zadeh (16).

In contrast to classical set theory, fuzzy set theory considers uncertainty by dedicating a membership function between (0 1) for each element belonging to the set. This method is based on if-then rules that have been defined and provided by experts to make up an inference engine employed to map out given inputs to outputs using fuzzy logic. Each rule consists of two main parts, namely antecedent and consequent to start with *if* and *then,* respectively.

The antecedent itself consists of several parts, which are determined based on several system inputs and can be connected to others (AND, OR, XOR and NOT) using fuzzy operators as can be seen in the following:

- Rule *i*. Input 1=Very low, and Input 2=Low, and … and, Input n=Low, then, output=Low

In the fuzzification step, crisp inputs are converted into a fuzzy number. After rule base processing, fuzzy outputs are converted into crisp values based on the defuzzification step. The main steps of the fuzzy logic algorithm are expressed as follows:

- Define the linguistic variables and terms (initialisation)
- Construct the membership functions (initialisation)
- Construct the rule base (initialisation)
- Convert crisp input data to fuzzy values using the membership functions (fuzzification)
- Evaluate the rules in the rule base (inference)
- Combine the results of each rule (inference)
- Convert the output data into non-fuzzy values (defuzzification)

In the fuzzification step, the crisp input data system is converted into fuzzy variables using membership functions. Suitable membership functions are predefined by experts in types of triangular, trapezoidal, and Gaussian. In the inference step, two main phases, namely implication and aggregation are observed after applying fuzzy operators on antecedents as one phase. In the implication phase, AND operator is applied between the result of the last phase and the consequent. The result of the implication phase in all rules is aggregated in the aggregation phase and uses the OR operator. In the defuzzification step, the output of the aggregation phase is a fuzzy set. The procedure for converting the fuzzy output into crisp data is called defuzzification. Several methods can be used for defuzzification.

The Centre of Gravity may be the most popular method and can be calculated using Eq. (1):

$$COG = \frac{\int_a^b \mu_A(x)x}{\int_a^b \mu_A(x)}$$

Fuzzy Failure Mode and Effects Analysis

As a response to the drawbacks of traditional Failure Mode and Effects Analysis (FMEA), fuzzy FMEA was employed in various areas. This method considers uncertainty and vagueness using fuzzy logic and can consequently employ an expert's knowledge to prioritise potential hazards. In this method, certain membership functions are defined based on the expert's opinions of the RPN. Fuzzy rules are then contracted to prioritise hazards by mapping them from input space (S, D, and O) to RPN. Inputs and outputs are divided into different levels when assigning membership functions to inputs and outputs of the fuzzy FMEA model. These levels are demonstrated by linguistic statements (e.g., low, medium, and high). After a contraction of rules based on input levels using expert's opinions, the fuzzy FMEA model can prioritise hazards by assigning RPN to the latter. As a conventional approach, five levels are generally considered for inputs and outputs of FMEA, namely very low, low, medium, high, and very high (Table.1).

Table 1: Levels of O, D, S of Hazards

		Description		
Rating	**Label**	**Severity (S)**	**Occurrence (O)**	**Not detection (D)**
1,2	Very low	No injury or patient monitoring alone	Failure unlikely to occur	Failure mode almost will be detected certainly
3,4	Low	Temporary injury needing additional intervention or treatment	Relatively rare failure	Detect failure mode by proper chance
5,6	Medium	Temporary injury with a longer hospital stay or increased level of care	Occasional failure	Failure mode may be detected
7,8	High	Permanent effects on body functions	Recurrent or Repeated failure	Failure mode not likely to be detected
9,10	Very high	Death or permanent loss of major body functions	Failure is almost unavoidable	Failure mode not likely to be detected

Results

One of the main processes that can lead to improved patient and hospital costs is the reduced duration of hospital stays by decreasing the cancellation of surgeries. The result expects a reduction in the length of hospitalization, thereby leading to patient satisfaction. Therefore, hospital income increases owing to the increase in the number of hospitalised patients and the reduction of costs resulting from the elimination of deficiencies. Surgeries can be classified into elective and emergency. Considering an unexpected cancellation of surgeries, this study selected elective surgeries for consideration and employed a team of experts to identify the failure modes. The FIS was then constructed to prioritise identified failure modes. Furthermore, the RPN was calculated based on the knowledge of expert's fuzzy membership functions for input variables (S, O, and D).

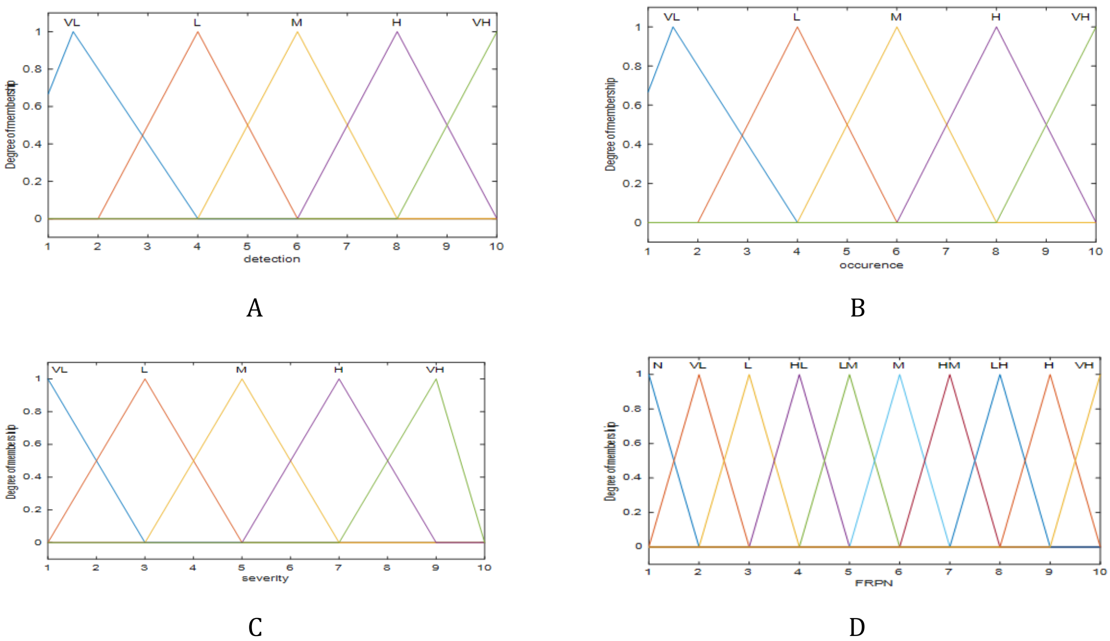

Figure 1: Membership Function of Input and Output Variables: a) Detection; b) Occurrence; c) Severity; d) FRPN

In total, five levels were considered for input variables (Figure 1). Given its importance, severity has different levels. Extra importance is assigned to S (Figure 1).
To attain improved distinction between RPNs, 10 levels were designed for RPN, namely N=None, VL=Very low, HL=High low, LM=Low medium, M=Medium, HM=High medium, LH=Low high, H=High, and VH=Very high.
In the context of research on medical care, the risk of accepting errors is lower than that in non-medical systems since the former directly affects human health. Medical systems differ from those in manufacturing industries as the severity factor of hazards is more important.
Consequently, the severity factor in this study was considered more important than the other factors. Based on the expert's knowledge (Table 2), a set of 125 rules were defined to define suitable rules and construct a knowledge base of FIS. The number of rules was then determined by multiplying the number of levels of inputs.
A few of these rules are expressed as follows:

- Rule 1. if Occurrence=VL and Severity=VL and not Detection=VL then
- RPN=N
- Rule 2. if Occurrence=VL and Severity=VL and not Detection=L then RPN=N
- Rule 3. if Occurrence=VL and Severity=VL and not Detection=M then RPN=VL

These defined rules suggest the difference in the sensitivity of output based on inputs. The sensitivity of output for non-detection in contrast to the occurrence is slightly higher (Figure 2a). Based on Figures 2b and 2c, the sensitivity of severity is higher than non-detection and occurrence (Figure 2a). As mentioned before, we attempted to consider the importance of severity in contrast to other inputs of fuzzy FMEA.

Table 2: Procedure for Constructing Rules

Occurrence = Very low						
		S				
S		Very low	Low	Medium	High	Very high
D	Very low	None	Very low	Very low	Low High	low
	Low	None	Low	Low	High low	Low medium
	Medium	Very low	Low	Low	Low medium	Medium
	High	Low	High low	High low	Medium	High medium
	Very high	Low	Low medium	High low	High medium	High
Occurrence = Low						
		S				
S		Very low	Low	Medium	High	Very high
D	Very low	None	Very low	High low	Low medium	Low medium
	Low	None	Low	Low medium	Medium	Low medium
	Medium	Very low	High low	Medium	High medium	Medium
	High	Low	Low medium	High medium	Low high	High
	Very	Low High	Low medium	Low high	High	high
Occurrence = Medium						
		S				
S		Very low	Low	Medium	High	Very high
D	Very low	Low	Very low	Low medium	Low	Low high
	Low	Very low	High low	Medium	High low	Medium
	Medium	Low	Low medium	High medium	Low medium	High medium
	High	High low	Medium	Low high	High medium	Low high
	Very high	Low medium	High medium	High	Low high	High
Occurrence = High						
		S				
S		Very low	Low	Medium	High	Very high
D	Very low	None	Very low	Low	Low medium	Medium
	Low	Very low	Low	High low	Medium	High medium
	Medium	Low	High low	Low medium	High medium	Low high
	High	Low	Low medium	Medium	Low high	High
	Very high	High low	Medium	High medium	High	Very high
Occurrence = Very high						
		S				
S		Very low	Low	Medium	High	Very high
D	Very low	Very low	Low	High low	Low medium	High medium
	Low	Very low	High low	High low	Medium	Low high
	Medium	Low	High low	Low medium	High medium	High
	High	Low	Low medium	Medium	Low high	Very high
	Very high	High low	Medium	High medium	High	Very high

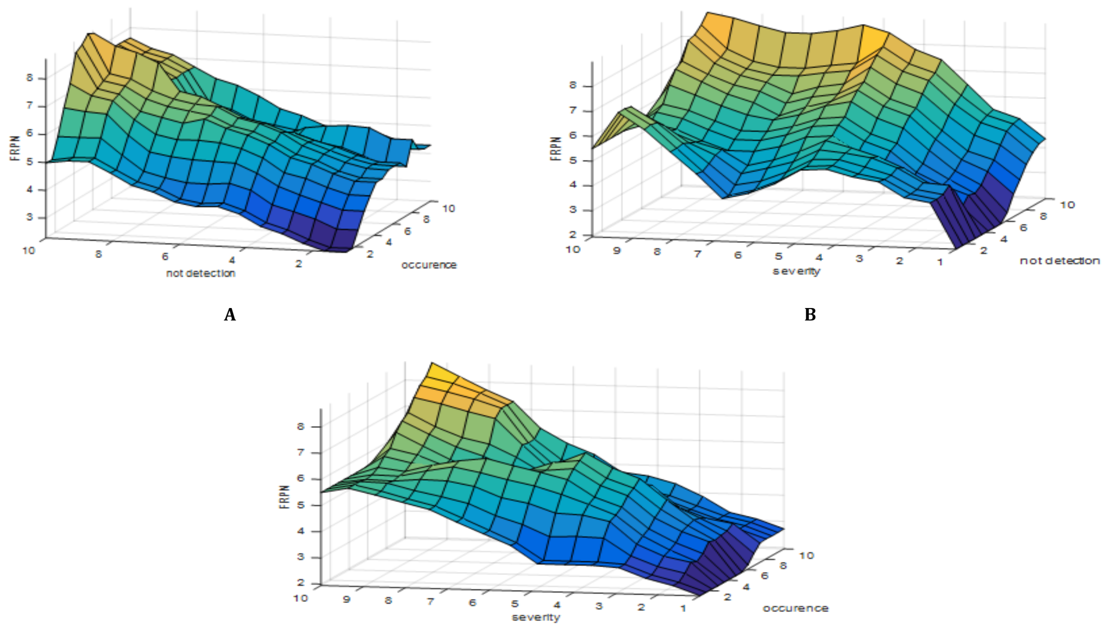

Figure 2: Surface Views of the Relationship between Fuzzy Inference System Outputs and Inputs

Figure 3 shows the cause and effect chart of hazards, which was identified in this study.

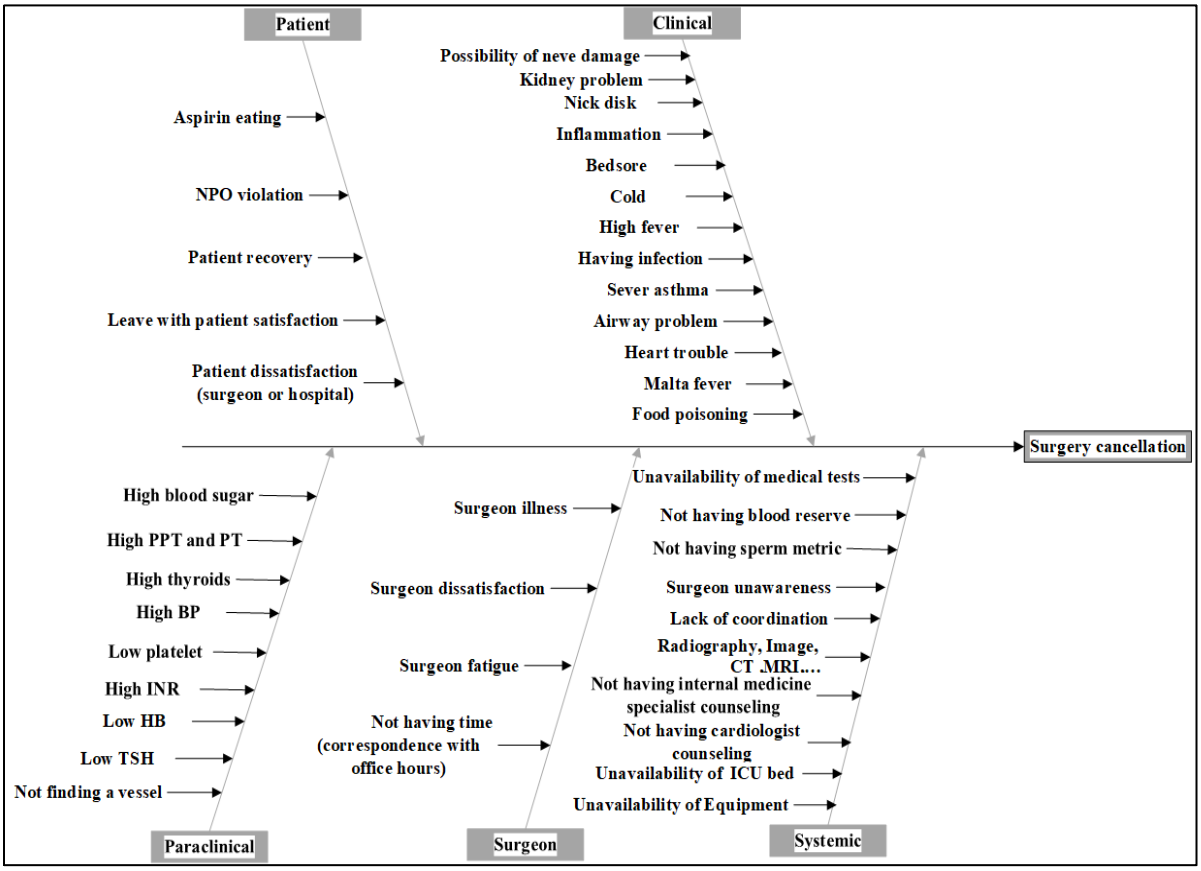

Figure 3: Cause and Effect Diagram of Hazards

After collecting potential hazards, experts were rated by dedicating S, O, and D to them and for each hazard. The final values of S, O, and D were calculated from the arithmetic mean of all experts' values. The RPNs were then calculated, and hazards were prioritised based on the corresponding RPNs. Table 3 tabulates the computation results for both traditional and fuzzy FMEA. The RPN of certain potential hazards is the same based on traditional FMEA (e.g., 2, 3, 29, and 30), whereas their values are different based on fuzzy FMEA (Table 3).

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The RPN of certain potential hazards is the same based on traditional FMEA (e.g., 2, 3, 29, and 30), whereas their values are different based on fuzzy FMEA (Table 3).

Surgeon fatigue is an important hazard based on traditional FMEA. High PPT and PT and airway problems are the second and the third important hazards, respectively.

In contrast to traditional FMEA and based on fuzzy FMEA, the absence of internal medicine specialist counselling, low TSH and unavailability of ICU beds are considered important potential hazards. In terms of prioritisation based on fuzzy FMEA, the RPNs that are greater than the arithmetic mean ($mean = 4.608$) are the 1^{st}, 3^{rd}, 4^{th}, 11^{th}, 15^{th}, and 16^{th} hazards, which belong to the class of systemic hazards.

The 6^{th}, 7^{th}, 9^{th}, 12^{th}, 13^{th}, and 16^{th} hazards are clinical hazards. Moreover, the 2^{nd},5^{th}, 10^{th} ,and 17^{th} belong to the class of the paraclinical class. Eventually, the 8^{th} hazard is related to surgeon class.

Table 3: Classical and Fuzzy *FMEA Risk Analysis for Surgery Cancellation

Hazard class	Hazards	D	O	S	RPN	Prioritization	FRPN	Prioritization
Systemic	Unavailability of medical tests	2	5	6	60	14	4.001	31
	Not having blood reserve	3	4	6	72	10	5.064	11
	Not having sperm metric	4	3	6	72	9	4.604	17
	Surgeon unawareness	3	3	5	45	24	3.587	35
	Lack of coordination	3	2	5	30	37	2.549	39
	Radiography, Image, CT, MRI, and so on	2	3	4	24	34	4.805	16
	Not having an internal medicine specialist counseling	2	4	3	24	33	8.000	1
	Not having cardiologist counseling	2	4	4	32	29	5.999	6
	Unavailability of ICU bed	2	4	4	32	30	6.000	3
	Unavailability of equipment	2	3	4	24	35	4.805	15
Patient	Aspirin eating	3	3	7	63	13	4.586	20
	NPO violation	3	3	7	63	12	4.586	19
	Patient recovery	2	2	2	8	40	1.858	40
	Leaving with patient satisfaction	1	2	2	4	41	1.587	41
	Patient dissatisfaction (surgeon or hospital)	2	4	4	32	28	6.000	4
Preclinical	High blood sugar	2	3	6	36	27	3.605	34
	High PPT and PT	3	5	7	105	2	4.555	21
	High thyroids	3	4	5	60	15	4.549	22
	High BP	2	5	7	70	11	4.002	30
	Low platelet	3	3	5	45	22	3.587	36
	High INR	3	3	5	45	23	3.587	37
	Low HB	4	2	7	56	17	4.000	33
	Low TSH	2	4	3	24	36	8.000	2
	Not finding a vessel	2	3	3	18	39	5.239	10
Surgeon	Surgeon illness	2	7	6	84	5	4.002	29
	Surgeon dissatisfaction	2	4	6	48	20	4.501	23
	Surgeon fatigue	3	5	8	120	1	5.359	9
	Not having time (correspondence with office hours)	2	3	5	30	32	3.081	38
Clinical	Possibility of nerve damage	4	3	6	72	10	4.603	18
	Kidney problem	3	4	6	72	7	5.064	12
	Nick disk	2	4	5	40	26	4.000	32
	Inflammation	3	5	5	75	6	4.064	28
	Bedsore	2	4	6	48	19	4.501	25
	Cold	3	3	6	54	18	4.130	26
	High fever	2	3	7	42	25	4.081	27
	Having infection	2	4	7	56	16	5.000	13
	Severe asthma	2	5	8	80	50	5.533	7
	Airway problem	4	4	6	96	3	5.500	8
	Heart trouble	2	4	6	48	21	4.501	24
	Malta fever	2	4	4	32	31	6.000	5
	Food poisoning	2	3	4	24	38	4.805	14

*FMEA: Failure Mode and Effects Analysis

Surgeon fatigue is an important hazard based on traditional FMEA. High PPT and PT and airway problems are the second and the third important hazards, respectively. In contrast to traditional FMEA and based on fuzzy FMEA, the absence of internal medicine specialist counselling, low TSH and unavailability of ICU beds are considered important potential hazards. In terms of prioritisation based on fuzzy FMEA, the RPNs that are greater than the arithmetic mean ($mean = 4.608$) are the 1st, 3rd, 4th, 11th, 15th, and 16th hazards, which belong to the class of systemic hazards. The 6th, 7th, 9th, 12th, 13th, and 16th hazards are clinical hazards. Moreover, the 2nd,5th, 10th ,and 17th belong to the class of the paraclinical class. Eventually, the 8th hazard is related to surgeon class.

Discussion

In systematic hazards, "not having blood reserve" and "not having sperm metric" are the most important hazards based on traditional FMEA. However, in fuzzy FMEA, this ranking has been changed so that "not having an internal medicine specialist counseling" is the most important hazard in this class.

In patient class, "Aspirin eating" and "NPO violation" have been determined as the most important hazards in traditional FMEA, whereas in the proposed method, "Patient dissatisfaction (surgeon or hospital)" has been identified as a significant hazard. Additionally, "High PPT and PT" and "not finding a vessel" have a high RPN and FRPN in paraclinical class, respectively. In surgeon class, "Surgeon fatigue" obtains the same rank in traditional FMEA and fuzzy FMEA. Finally, "Airway problem" and "Malta fever" are identified as the most important hazards in the "Clinical" class based on assessing with traditional FMEA and fuzzy FMEA, respectively. In general, according to Table 2, the significant change in determining the most important class of hazards is observed. As assessed by the traditional method, the "Surgeon" class has a high average RPN, whereas the "Systemic" class obtains the high average FRPN according to the proposed method. Nonetheless, both methods have identified "Patient" class as the less important hazards based on average RPN and FRPN, respectively.

According to the results, fuzzy FMEA proposes more distinctive results, compared to traditional FMEA, and the traditional FMEA hazards have achieved the same RPN with different S, O, and D numbers. On the other hand, fuzzy FMEA has dedicated different risk values for different hazards concerning their S, O, and D numbers. Accordingly, fuzzy FMEA's results are more reliable. Based on the results, not having internal medicine specialist counseling and low thyroid-stimulating hormone (TSH) which have achieved an FRPN of 8, are more important, compared to other hazards.

On the contrary, leaving with patient satisfaction with FRPN of 1.578 and patient recovery with FRPN of 1.858 have been recognized as less important hazards. The remaining hazards have received an FRPN of between 3.081 and 6. Regarding hazard classes, systemic hazards with an average FRPN of 6.95 have been detected as a more important class of hazards, whereas, the patient class with an average FRPN of 5.27 has been recognized as a less important class. Moreover, clinical, paraclinical, and surgeon factors received the second, third, and fourth-degree of importance, respectively. From the observations above, it can be concluded that a most important class of hazards is systemic which can be addressed by taking appropriate schemes and planning in line with the forecast.

This study was intended exclusively for the elective general surgeries. Specialist surgeries and emergency surgeries can also be considered for more investigation. Moreover, hazards are considered separately; however, there are in fact causal relationships among hazards. Therefore, cognitive maps may be useful in this regard to eliminate this limitation.

Conclusion

This study presented an approach based on FIS integrating with FMEA to prioritise and assess the failures caused by the cancellation of surgeries. This approach is closer to reality because of the used linguistic variables instead of numerical variables, compared to the conventional approaches. In the actual case studies, especially in health care studies, the knowledge of hospital experts is far from the knowledge of an analyst. To address this limitation, linguistic variables may remove such problems. For an accurate and improved understanding of hazards, the effective factors were divided into five classes, and related hazards were then identified in each class. These classes include clinical, paraclinical, systematic, surgeon, and patient factors. According to the proposed approach, the absence of an internal medicine specialist counselling, low TSH, and unavailability of ICU beds were three important and priority potential hazards. These factors, especially internal medicine specialist counselling, are extremely important according to surgery documents and experts' opinions. These results can help the hospital managements apply hospital resources to maximise their impacts on improving hospital efficiency, especially operating room efficiency. The utilization of other methods for prioritising, data mining, and analysing the results of the proposed approach are few suggestions for future endeavours.

Acknowledgment

The authors would like to thank the doctors, operating room nurses, and staff in Shahid Arefian Hospital, Urmia, Iran, for their cooperation in providing the data, documents, and professional views and opinions in this study.

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