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A Fuzzy FMEA Approach to Prioritizing Surgical Cancellation Factors

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Abstract

Background and Objectives: Surgical cancelation is a significant source of time and resource waste, patient safety risk, and stress for patients and their families. In this study, a risk management-based approach is developed to prioritize factors contributing to surgical cancellation.

Methods: Factors leading to surgical cancellation were comprehensively classified based on literature review. A Fuzzy Failure Mode and Effect Analysis were developed for identifying the relative importance of the potential surgical cancellation factors. Validity of the results was examined by obtaining experts' opinions.

Findings: Our analysis identified inadequacy of recovery beds, inadequacy of ICU beds, high-risk surgery, and high blood pressure and diabetes as the most important factors contributing to surgical cancelation.

Conclusions: According to our results, the Fuzzy Failure Mode and Effect Analysis can successfully rank the factors contributing to surgical cancellation. Our results encourage further use of the risk management theory and tools combined with fuzzy set theory to support and facilitate the clinical decision-making process.

Keywords: Risk Management, Failure Modes and Effect Analysis, Surgical Cancellation, Fuzzy Set theory

Background and Objectives

Surgical operation is a key healthcare service, accounting for 40% of hospital expenditures [1-3]. For every surgical operation to be carried out on schedule, various departments and resources must be coordinated and all prerequisites must be met. Lack of the requirements at the time of admission to the operating room, will lead to cancelation of the surgical operation [4]. Surgical cancelation is a significant source of time and resource waste, patient safety risk, and stress in patients and their families [5].

Several studies have been carried out aiming at identifying causes of surgical cancelation [6, 7]; however, there is a lack of a comprehensive classification of cancellation factors in the literature [8]. Previous research have identified factors such as in-efficient processes and system failure [9], failure of equipment [10], inefficient teamwork, and inappropriate relationships between the departments and staff involved [11], among the major factors leading to surgical cancelation. On the other hand, efficient addressing of surgical cancelation problem require the identification of virtually all contributing factors and prioritization of them based on their frequency of incidence as well as their degree of contribution to the cancellation of surgery.

Given that numerous inadequacies can lead to the surgical cancelation, efficient meeting of such prerequisites require development of computational tools and expert advising systems facilitating analysis and ranking of the factors involved.

The purpose of this study was to introduce and examine the performance of a risk management approach to prioritizing surgical cancelation factors. Common methods existing for risk assessment are classified to three categories including qualitative, semi-quantitative and quantitative methods [12]. Although qualitative methods have been extensively

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used in previous studies, they offer limited information about the risk factors in question [12]. In addition, while quantitative methods enable prioritizing risk factors with a high degree of accuracy, their use require large datasets which are not always available. To overcome the above-mentioned limitations, use of semi-quantitative methods such as Failure Mode and Effects Analysis (FMEA) is proposed [12]. FMEA allows incorporation of the opinions of individuals directly contributing to the surgical operation, which in turn can lead to a more accurate prediction of surgical cancellation factors.

Traditional FMEA

Use of FMEA dates back to 1950s when for the first time this method was applied in aviation industry in system security assessment and confidence analysis [13]. Afterwards, this technique has been used in identification, prevention, removal, and control of the potential failure modes [14]. Failure mode is defined as an event whose occurrence can negatively impact a system [15]. Currently, FMEA is used in automotive, aerospace and electronics industries for identifying, ranking, and preventing potential system failures [16]. Extensive use of FMEA and its success in predicting system failure in different contexts has attracted the attention of healthcare industry as well [13-16]. In the field of health care, FMEA is described as a framework for systems thinking in promoting safety of medical practices [17].

In traditional FMEA, an index called Risk Priority Number (RPN) is used for ranking failure modes by multiplying three parameters, including Occurrence probability (O), Detectability (D), and Severity (S) of potential failures [15]. Occurrence probability accounts for frequency of potential failure factors. Detectability represents the possibility of predicting a particular failure before its occurrence. And Severity reflects the intensity of failure effect on the system.

According to FMEA, a value within {0,1,…,10} is assigned to each of the three input parameters. The higher the value assigned to a particular parameter is, the more undesirable the effects of that parameter on the system will be [15]. After calculating RPN for a particular failure mode, factors with the highest RPN can be focused on and addressed [15].

Despite the wide application of FMEA in identifying failure modes, it has some drawbacks [18]. The main drawbacks of traditional FMEA include:

- While different combinations of O, S and D can lead to an identical RPN value, failure modes with the same RPN may correspond to different risk factors [15].
- In traditional FMEA, O, S and D are assumed to be of the same significance. However, in reality

the degree of their importance may vary [15].

- While RPN is simply calculated by multiplying the three input factors, the possible indirect relationships between these factors are not taken to account [18].
- The three parameters used in FMEA calculation do not cover the entire range of the causative factors leading to a failure mode, including mistakes, contradictions, uncertainties, and ambiguities [18].

Fuzzy FMEA

Considering the above-mentioned limitations of traditional FMEA, this method has undergone extensive modifications [16]. A particular approach to FMEA improvement is to combine FMEA with fuzzy set theory [16]. Specifically, the hybrid fuzzy FMEA method can be useful in cases where there is a lack of adequate datasets, data collection is difficult, or data are represented in linguistic terms and subjective values [19].

In addition, a hybrid Fuzzy FMEA method provides the following advantages [18]:

- In fuzzy FMEA, a combination of input factors is considered. Therefore, a failure mode has a high RPN if the combination of O, S and D parameters gives a high RPN value.
- In Fuzzy FMEA, contrary to traditional FMEA, the non-linear interactions of O, S and D are accounted for.
- Fuzzy FMEA allows using linguistic values, which in turn enables incorporation of experts' opinions in the model, thereby increasing the performance of failure mode detection.
- Fuzzy FMEA is more flexible as compared with traditional FMEA in terms of weighting input variables.

Methods

Setting

Dr. Shariati Hospital, a general health facility was selected as the target setting for data collection. This hospital has 857 fixed beds, 15 operating rooms, two recovery rooms, and two sterilization rooms. This hospital provides a variety of different healthcare services, including general surgery, orthopedics, neurology, urology, thorax, cardiac, gynecology and oral and maxillofacial surgeries.

Figure 1 displays the main steps of the proposed method for identifying and ranking surgical cancelation factors.

Identifying and classifying surgical cancelation factors

Surgical cancellation data were collected by reviewing patient records documented during 2011-2012. In consultation with operating room experts including surgeons, these data were used to develop a three-level taxonomy of surgical cancellation factors (Figure 2). At the first level

Table 1   Linguistic variable definition used in Fuzzy FMEA

Linguistic variables	Symbol	Rank	Fuzzy Number	O	Not-D	S	RPN
Very Low	VL	1,2	(0 0 2)	0%-5%	Detectable	no severity	No risk
Low	L	3,4	(1 3 5)	5%-10%	Detectable with high probability	Low severity	Low risk
Medium	M	5,6,7	(3 5 7)	10%-15%	Detectable with 50%-50% probability	Medium severity	Medium risk
High	H	8,9	(5 7 9)	15%-20%	Detectable with low probability	High severity	High risk
Very High	VH	10	(8 10 10)	20%=>	Not detectable	Very high severity	Very high risk

the surgical cancellation factors are represented in three abstract themes, including managerial, technical, and human resources factors. These factors are then classified into more detailed items at the second levels. Ultimately, the taxonomy introduces 36 detailed surgical cancellation factors at the third level. These factors are analyzed for identifying their relative importance using fuzzy FMEA method.

Development of a hybrid fuzzy FMEA model

The fuzzy FMEA framework for identifying the relative importance of surgical cancellation factors was implemented according to the following steps:

1- Defining the membership functions and linguistic variables
2- Defining fuzzy rule base
3- Defining the fuzzy inference engine
4- Defining fuzzifier and defuzzyfier algorithms.

The Fuzzy Toolbox of Matlab 2012a was used for analysis. Figure 3 illustrates the developed framework.

Defining membership function and linguistic variables

To develop the fuzzy FMEA framework, first, linguistic variables and fuzzy membership functions were defined. O, S and D were defined as the independent input parameters, and RPN was defined as the output of the fuzzy membership function. Table 1 shows the linguistic variables and fuzzy numbers assigned to them. Assignment of the fuzzy selection of linguistic variables and assigning their values was carried out based on previous studies [12,15] as well as consultation with experts. After defining the linguistic variables, fuzzy triangular membership functions were defined (Figure 4 and Figure 5)

Defining fuzzy rule base

The logical rules were extracted from literature [18] and
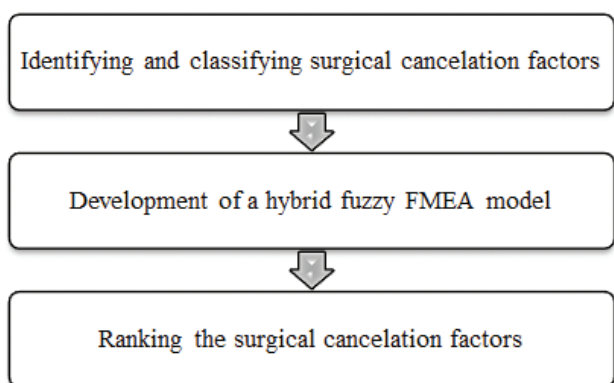
Figure 1   Study steps

through consulting with operating room experts. There were three input variables each of which assignable to five linguistic variables. Therefore, 125 fuzzy rules were extracted. The entire set of extracted rules is given in Additional File 1.

Choosing the appropriate fuzzy inference engine

In this study, Mamdani inference engine was used for its high accuracy as reported in previous studies [12, 14, 16, 18].

Choosing appropriate fuzzifier and defuzzifier methods

The central gravity method was used for defuzzification regarding its popularity [12, 14, 18, 25].

Distribution of Surgical Cancellation Rate over the Overall Cancelation Factors

Statistical analysis of surgical cancelation data at the first level of our taxonomy of the surgical cancellation risk factors identified managerial factors as having the major contribution (Figure 6).

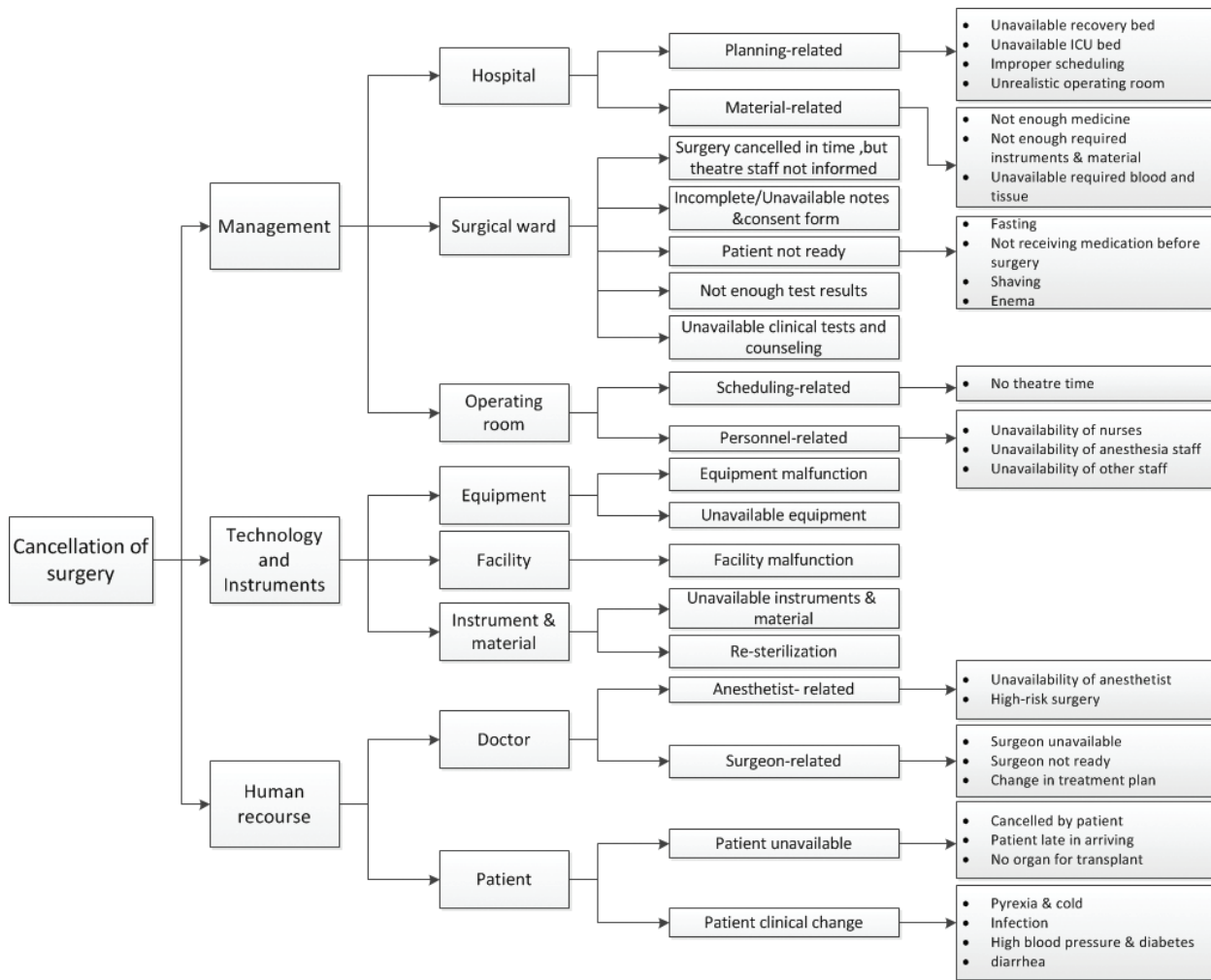Fuzzy PRN (FRPN) was calculated using Fuzzy Toolbox

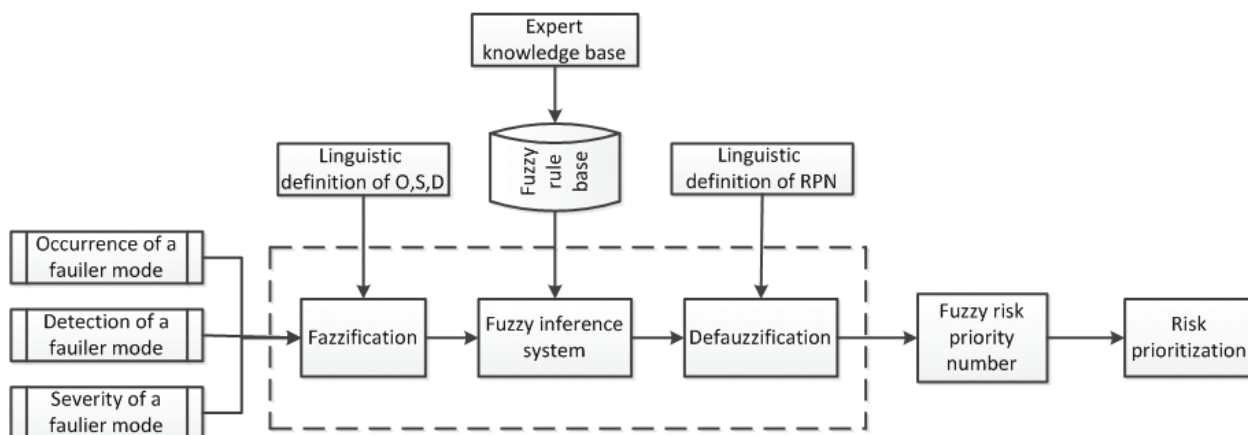**Figure 2**   Taxonomy of the surgical cancellation factors

Figure 3   The fuzzy FMEA framework for prioritizing surgical cancellation factors

of Matlab 2012 (Table 2). The parameter O was calculated using data presented in Table 1.

The value of parameter D was suggested by head nurse of the operating room, according to the linguistic variables presented in Table 1. Parameter S was defined according to the result of interviews with 30 personnel of operating rooms including the physicians, anesthesia staff, and nurses.
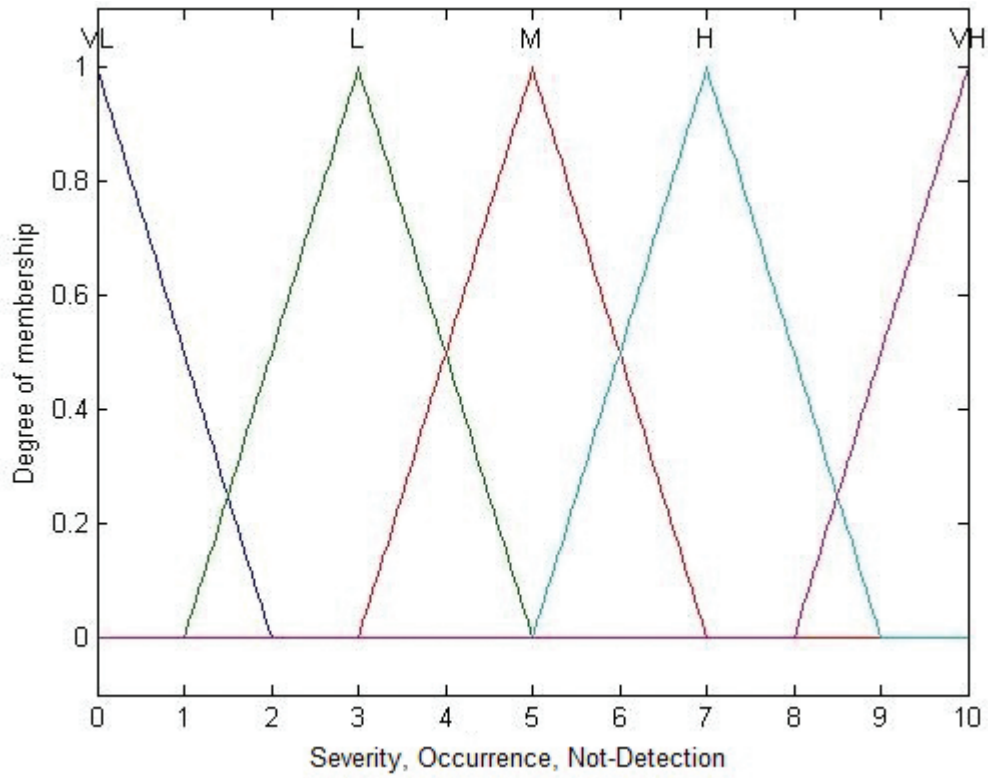
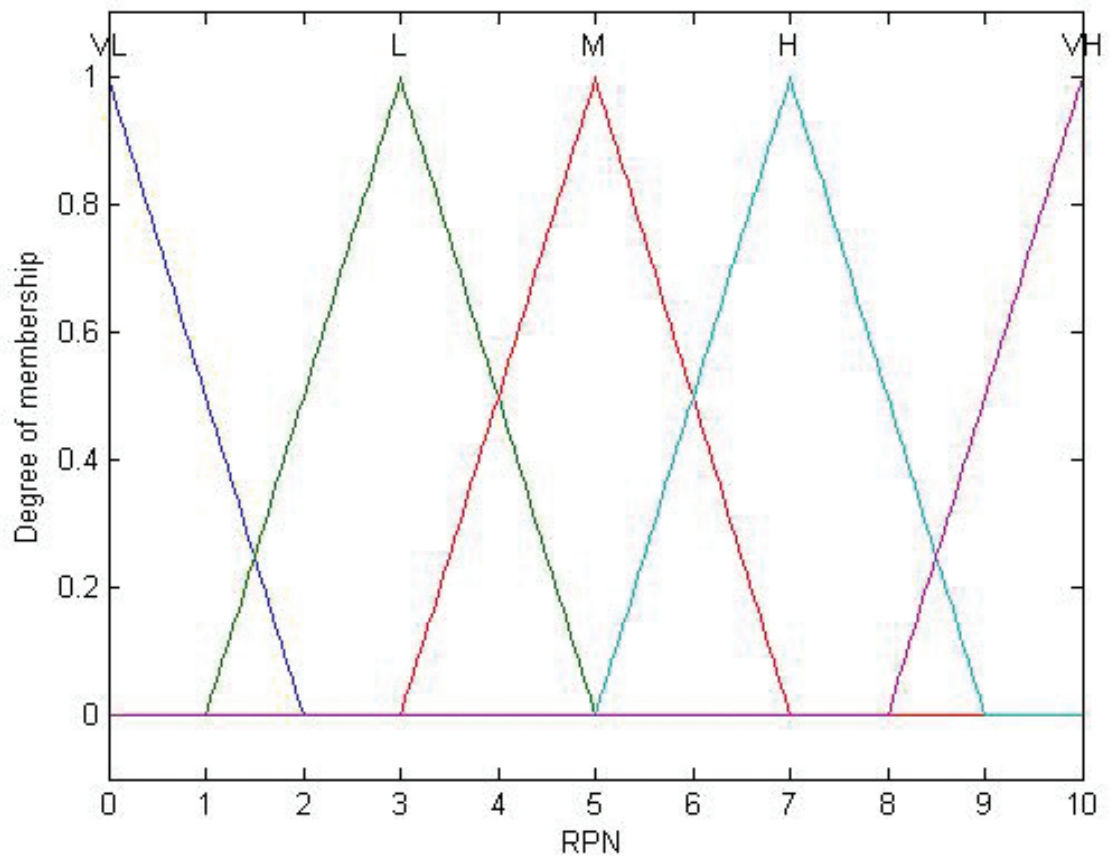**Figure 4** Fuzzy membership functions of the three input parameters


Figure 5 Fuzzy membership function of risk priority number

Table 1   Calculating FRPN index for surgical cancellation factors

Cancellation of surgery	O	D	S	FPRN
Unavailable recovery bed	2	6	5	5
Unavailable ICU bed	8	6	5	5
Improper scheduling	1	6	3	3
Unrealistic operating room	1	3	3	3
Not enough medicine	2	5	3	3
Not enough required instruments & material	2	3	3	3
Unavailable required blood and tissue	2	3	3	3
Surgery cancelled in time, but theatre staff not informed	1	2	3	3
Incomplete/Unavailable notes & consent form	3	4	3	3
Not enough test results	2	4	3	3
Unavailable clinical tests and counseling	2	4	3	3
Fasting	1	5	4	3
Not receiving medication before surgery	1	4	3	3
Shaving	1	2	3	3
Enema	1	2	3	3
No theatre time	2	4	2	3
Unavailability of nurses	1	2	3	3
Unavailability of anesthesia staff	1	2	3	3
Unavailability of other staff	1	2	3	3
Equipment malfunction	1	3	3	3
Unavailable equipment	1	3	3	3
Facility malfunction	1	3	3	3
Unavailable instruments & material	1	2	3	3
Re-sterilization	1	4	2	3
Unavailability of anesthetist	1	3	3	3
High-risk surgery	4	4	3	4
Surgeon unavailable	2	3	3	3
Surgeon not ready	1	2	3	3
Change in treatment plan	1	2	2	3
Cancelled by patient	1	3	2	3
Patient late in arriving	1	3	2	3
No organ for transplant	1	3	3	3
Pyrexia & cold	3	4	2	3
Infection	1	3	2	3
High blood pressure and diabetes	5	2	4	4
Diarrhea	1	3	2	3

Results and Discussion

In this paper, a risk-management-based approach to identifying and ranking surgical cancelation factors is introduced. Table 2 presents FRPN values computed using the hybrid fuzzy FMEA method. As seen, four factors including in-
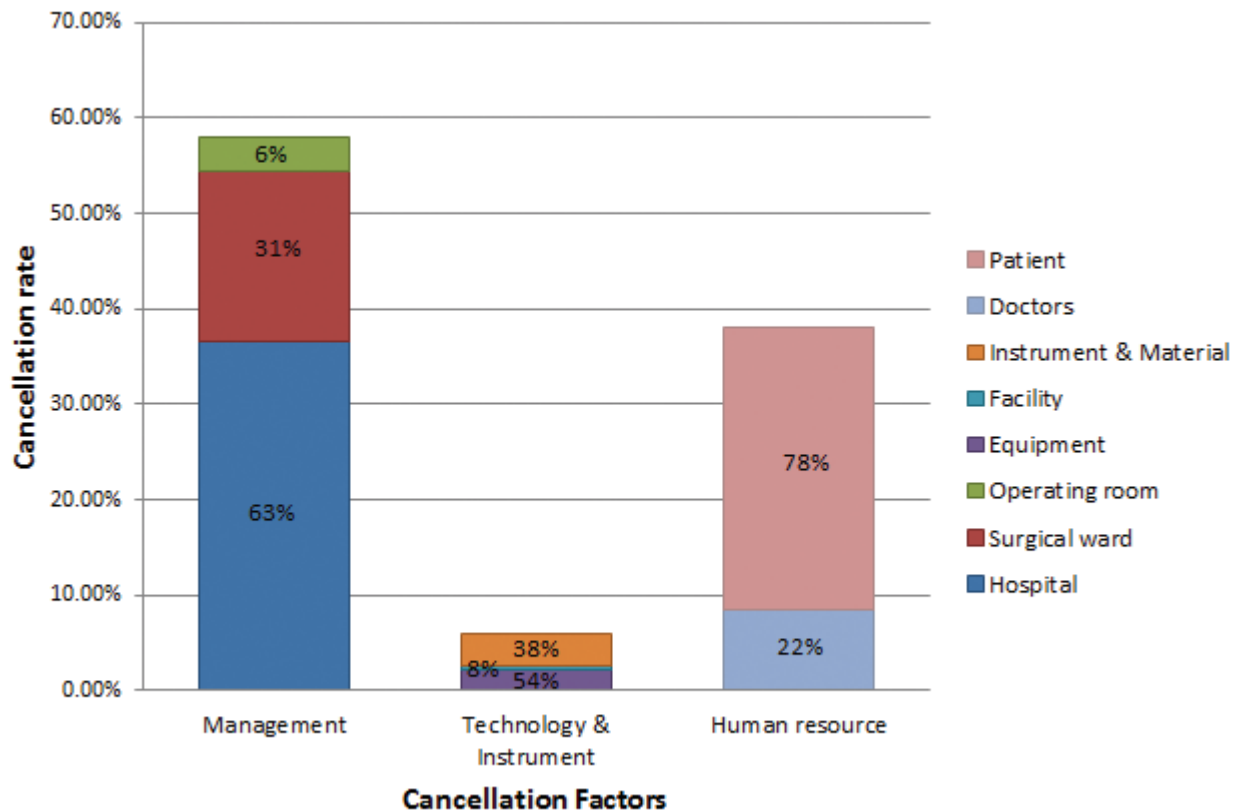
Figure 6 Distribution of surgical cancellation over abstract cancellation factor

adequacy of recovery beds, inadequacy of ICU beds, high-risk surgery, and high blood pressure and diabetes are identified as having the major contribution to the surgical cancelation.

Surgical cancelation rate is an important indicator of operating room inefficiency [3]. Reduction of surgical cancelation rate is one of the major priorities of hospital management [3]. Our results indicated that fuzzy FMEA can serve as an assisting tool to anticipate and the risk factors of surgical cancellation. While this study was limited to prioritizing surgical cancellation factors, identifying the potential of fuzzy FEMA in exploring the risk factors in other healthcare services is an interesting ground for future studies.

Conclusions

In this study, we introduced a fuzzy FMEA framework to ranking factors contributing to surgical cancellation and examined its performance. Inadequacy of recovery bed, inadequacy of ICU bed, high-risk surgery, and high blood pressure and diabetes were found to be the major factors potentially leading to surgical cancellation. Our result was validated against the opinion of operating room experts. The agreement between experts' opinion and the results of fuzzy FMEA calculations indicated the potential of this framework in valid prioritization of surgical cancellation factors.

While this study was limited to examining fuzzy

FMEA performance in prioritizing risk factors of surgical cancellation, future studies can examine the usefulness and performance of this method in prioritizing sources of failure mode in other healthcare services.

Abbreviations

(FMEA): Failure Mode and Effect Analysis; (RPN): Risk Priority Number; (FRPN): Fuzzy Risk Priority Number

Competing Interests

The authors declare no competing interests.

Authors Contributions

RK, MMS and TK jointly designed the study. RK contributed to data collection and analysis, interpretation of results, and editing the draft manuscript. TK was involved in editing the draft manuscript. RK, MMS and TK contributed to revising the manuscript. All authors read and approved the final manuscript.

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