International Journal of Medical Informatics 186 (2024) 105442

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.elsevier.com/locate/ijmedinf

A novel decision support system for proactive risk management in healthcare based on fuzzy inference, neural network and support vector machine

Amine En-Naaoui [a,b,*], Mohammed Kaicer [a], Aicha Aguezzoul [c]

[a] Department of Mathematics, Ibn Tofail University, Kenitra, Morocco
[b] National Institute of Oncology, Ibn Sina University Hospital Center, Rabat, Morocco
[c] IAE Metz, University of Lorraine, France

ARTICLE INFO

Keywords:
Decision support system
FMEA
Fuzzy inference support
Artificial neural network
Support vector machine
Healthcare

ABSTRACT

Background: The nature of activities practiced in healthcare organizations makes risk management the most crucial issue for decision-makers, especially in developing countries. New technologies provide effective solutions to support engineers in managing risks.
Purpose: This study aims to develop a Decision Support System (DSS) adapted to the healthcare constraints of developing countries that enables the provision of decisions about risk tolerance classes and prioritizations of risk treatment.
Methods: Failure Modes and Effects Analysis (FMEA) is a popular method for risk assessment and quality improvement. Fuzzy logic theory is combined with this method to provide a robust tool for risk evaluation. The fuzzy FMEA provides fuzzy Risk Priority Number (RPN) values. The artificial neural network is a powerful algorithm used in this study to classify identified risk tolerances. The risk treatment process is taken into consideration in this study by improving FMEA. A new factor is added to evaluate the feasibility of correcting the intolerable risks, named the control factor, to prioritize these risks and start with the easiest. The new factor is combined with the fuzzy RPN to obtain intolerable risk prioritization. This prioritization is classified using the support vector machine.
Findings: Results prove that our DSS is effective according to these reasons: (1) The fuzzy-FMEA surmounts classical FMEA drawbacks. (2) The accuracy of the risk tolerance classification is higher than 98%. (3) The second fuzzy inference system developed (the control factor for intolerable risks with the fuzzy RPN) is useful because of the imprecise situation. (4) The accuracy of the fuzzy-priority results is 74% (mean of testing and training data).
Conclusions: Despite the advantages, our DSS also has limitations: There is a need to generalize this support to other healthcare departments rather than one case study (the sterilization unit) in order to confirm its applicability and efficiency in developing countries.

1. Introduction

The revolution of artificial intelligence in the last few decades has led to the evolution of healthcare decision-making from humans to machines. Many clinical decisions are supported by intelligent algorithms in different medical disciplines, such as medical imaging, radiotherapy, chemotherapy, surgical interventions, and others. However, the use of The Artificial intelligence (AI) revolution has less impact on the healthcare management field than the clinical field [1]. For this reason, recently, healthcare decision-makers should focus on introducing the AI in the management field.

The improvement of quality and safety of healthcare processes is one of the most important objectives in healthcare management domain. The proactive approach is necessary to achieve this objective because it aims to identify and predict the failure associated with the system before it occurs [2].

Managing potential risks is one of the most proactive devices used to improve the performance and the quality of services delivered to

* Corresponding author.
E-mail addresses: amine.en-naaoui@uit.ac.ma (A. En-Naaoui), mohammed.kaicer@uit.ac.ma (M. Kaicer), aicha.aguezzoul@univ-lorraine.fr (A. Aguezzoul).

https://doi.org/10.1016/j.ijmedinf.2024.105442
Received 17 August 2023; Received in revised form 5 March 2024; Accepted 29 March 2024
Available online 30 March 2024
1386-5056/

patients in medical departments. One of the powerful methods to perform the proactive risk management is the Failure Mode and Effects Analysis (FMEA) [3], which is a proactive method used to identify and assess the risks by analyzing their causes, listing their consequences and assessing their criticalities [4] in order to support decision for quality improvement. The classical FMEA method is effective and appropriate in the healthcare sector [5] for several reasons such as its simplicity and easiness in practice and its effectiveness to assess adverse events before they occur based on human expertise. Nevertheless, the traditional approach of the FMEA has been widely criticized due to several drawbacks. The mean listed drawbacks of the FMEA method are, among others:

(1) The numerical range of RPN is discontinuous [6].
(2) Assessors face difficult decisions due to the risk's vagueness and uncertainty.
(3) Risk criticality does not consider the different importance between O, D and S [7].
(4) Risk criticality does not take into consideration different importance between O, D and S [8].
(5) No scientific method or rule exists for separating tolerance classes [9].

Researchers have published numerous works to surmount the classical FMEA weaknesses by combining FMEA with other techniques such as expert-systems and multi-criteria decision making. The fuzzy inference approach is the most combined with the FMEA in the healthcare sector [5] named fuzzy-FMEA. Numerous studies in the healthcare area propose combinations of FMEA with developed fuzzy inference systems in different hospital departments, such as the sterilization unit [9], the emergency department [10], and the hospital purchasing process [11].

According to the associated literature, the fuzzy-FMEA approach allows the surmounting of some FMEA drawbacks (1), (2), (3), and (4) cited previously. However, the classification problem is still not solved with fuzzy inference alone (weakness number (5)). The classification problem is one of the crucial issues treated by machine learning and deep learning techniques [12]. One of the powerful techniques used for solving classification problems is the Artificial Neural Network (ANN) and the Support Vector Machine (SVM).

The application field of this study is the sterilization unit of a Moroccan university hospital (see Section 2.1: Setting). Limitations of resources and budgets, and the complexity of administrative procedures are among the biggest challenges facing the healthcare sector, specifically in developing countries [13,14]. For this reason, it is necessary to improve the FMEA methodology in order to be adequate to the context of the application area.

The objective of our study is to propose a novel, effective and adapted Decision Support System (DSS) for risk management in healthcare based on improved FMEA, double-fuzzy inference systems, ANN and SVM techniques. To achieve this objective, the present paper is organized as follows: Section 2 highlights the setting, materials used for this study, and the algorithm of the proposed DSS. Section 3 presents and evaluates the obtained results, Section 4 presents discussions of the results, and Section 5 provides some conclusions.

2. Materials and methods

2.1. Setting and participants

The Central Sterilization Unit (CSU) of Ibn Sina Hospital, Rabat, Morocco, is the application field of this study. The principle mission of the CSU is to deliver sterile and packaged Reusable Medical Instruments (RMI) to the medical departments of the largest hospital university (Ibn Sina Hospital) in Morocco. To ensure this mission, the CSU personnel ensure a set of sequential processes, namely:

- Reception and disinfection of used RMIs.
- Packaging of disinfected RMIs.
- Autoclaving packaged RMIs.
- Storage and distribution of RMIs.

A FMEA team is constructed, which includes four members in the identification and the classical FMEA assessment steps: the pharmacist responsible (manager of the unit), the nurse's head, and two quality and safety engineers. The FMEA team has implemented a risk assessment plan based on classical FMEA (Processes identification, failure modes identification, and assessment using classical FMEA (see Section 2.2: Classical FMEA procedure)). One of the quality engineers plays the role of coordinator with the authors of this paper. The other quality engineer has been consulted as an expert at the end of the study to provide his point of view and compare results provided by the classical FMEA and the fuzzy-FMEA (see Section 2.4.1: fuzzy inference system).

2.2. Classical FMEA procedure

The FMEA was developed by the U.S army in the 1940s, used for the first time by aerospace industry in the 1960s and adopted by the healthcare sector in the 1990s [5,15]. The FMEA method is a proactive method used to identify and assess the risks by analyzing the causes as well as their effectiveness [4]. The assessment of each risk using FMEA is performed with the calculation of the risk criticality, named Risk Priority Number (RPN), based on 3 factors: The Occurrence (O), the non-Detection (D) and the Severity (S).

The FMEA method is a multidisciplinary method used to assess risks of a specific process. The assessment of risks in FMEA consists of calculating the RPN based on three factors: O, D and S. The classical approach of FMEA provides RPNs values using the equation $RPN = O \times D \times S$. The process of the classical FMEA consists of performing the following steps:

- Step 1: determining the studied process.
- Step 2: forming the FMEA team.
- Step 3: identifying potential risks, their causes and consequences.
- Step 4: determining criteria of factors (significations of O, D and point-scales, and tolerance classes).
- Step 5: calculating RPNs values using the formula $RPN = O \times D \times S$.
- Step 6: deciding the tolerance class about each risk.
- Step 7: proposing corrective actions of intolerable risks.

2.3. Improved FMEA

The aim of the FMEA method is to provide decision concerning the tolerance of risks in order to propose corrective actions for intolerable risks. Nevertheless, as cited previously, one of the biggest challenges facing healthcare sector in these countries are the limited of allocated resources and complexity of administrative procedures. For this reason, we propose a novel factor, named Control factor (C), enables to assess the capacity of the feasibility and the easiness of the implementation of the corrective actions. This factor allows to the CSU managers to prioritize intolerable risks and start with the easiest one rather than wasting time and resources for a hard risk. We note that low priority risks are not eliminated but planned later.

2.4. Materials

2.4.1. Fuzzy inference system (FIS)

The FIS is an algorithm based on fuzzy logic theory, which is developed by Lotfi Zadeh in 1965 [16,17]. Briefly, the FIS process is composed on the following phases:

- **The initialization and fuzzification phase:**
  - Definition of the linguistic variables.

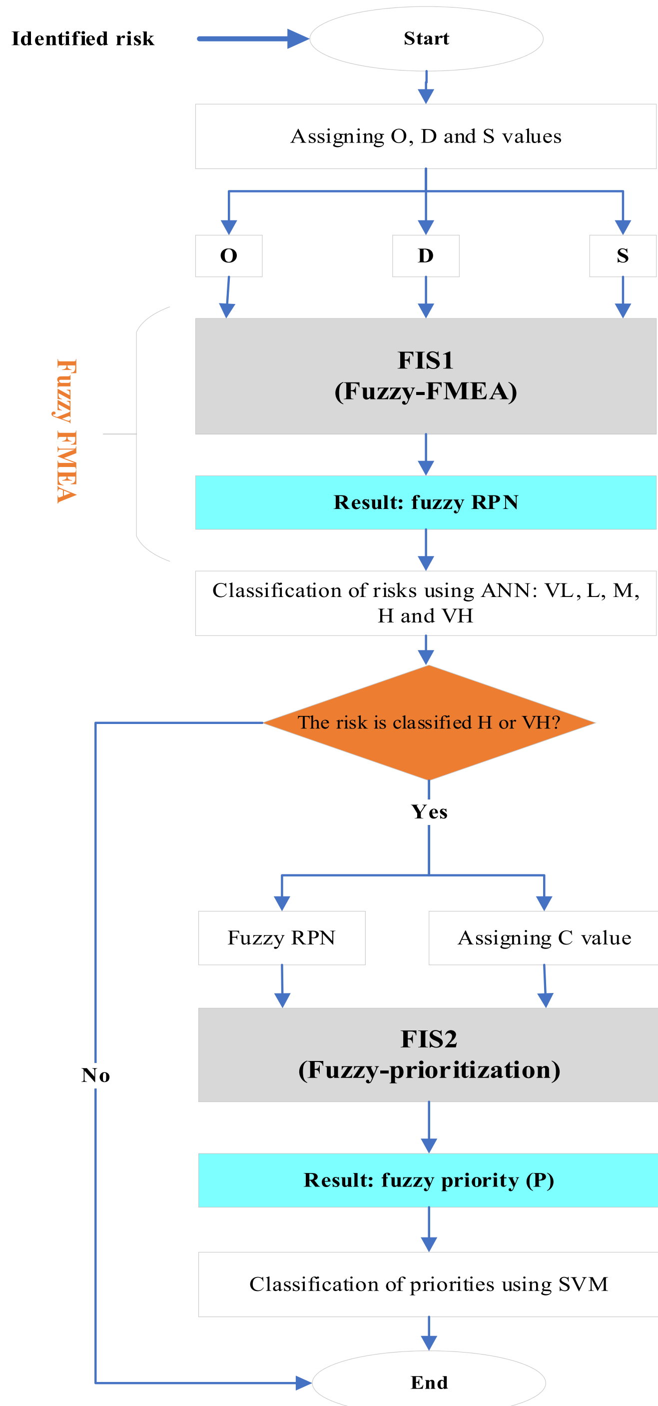


Fig. 1. DSS algorithm.

- Construction of the membership functions.
- Construction of the rule base.
- Conversion of the crisp input data to fuzzy values.

- **The inference engine phase:**
  - Evaluation of the rules in the rule base.
  - Combination of the results of each rule.
- **The defuzzification phase:** Conversion of the output data to non-fuzzy values

2.4.2. *ANN technique*

The ANN is a supervised learning technique that is on simulating the network of neurons of the human brain, allowing the passage of signals from the first to the last neuron [18]. The ANN is a flexible and powerful machine learning technique [19]. It was developed based on the human brain system and how it works. The ANN algorithms are gaining importance in the field of the predictive and classification modelling [20]. Generally, the steps followed to perform the classification using the ANN algorithm are presented as follows:

- Step 1: Preparation of the datasets: the input and the output data.
- Step 2: Definition of data repartition samples of the training, the validation and the testing data.
- Step 3: Determination of the neural network architecture: inputs, hidden layers, output layers and outputs.
- Step 4: Start the training of the ANN algorithm.
- Step 5: Evaluation of the model using the validation and the testing data.

Table 1
Significations of FMEA point-scales factors (O, D and S).

Point scale	Significations		
	Occurrence (O)	Non-Detection (D)	Severity (S)
1	Rare	Easily detectable	Non-significant consequence
2	Low frequency	Detectable	Interruption or disturbance of unity activity
3	Moderate occurrence	Moderately detectable	Client dissatisfaction
4	Medium occurrence	Hardly detectable	Potential failure of instruments sterility
5	High occurrence	No means of detection	Certain danger on patient or professional safety

Table 2
Significations of prioritization point-scales factors (RPN and C).

Point scale	RPN	Level of Control C
1	VL	L
2, 3	L	
4, 5, 6	M	M
7, 8	H	H
9, 10	VH	

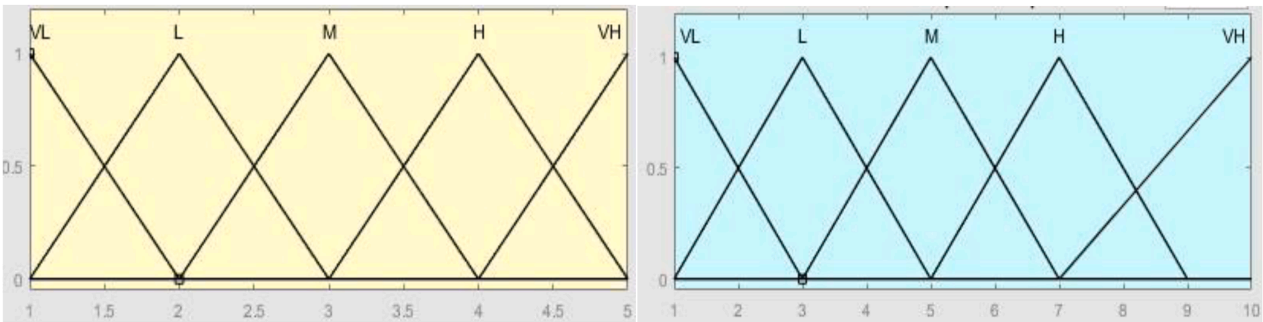
2.4.3. *SVM technique*

The Support Vector Machine (SVM) is a supervised learning method. SVM is a sophisticated and popular machine learning method that was proposed by Vapnik in 1982 and extended to solve classification problems, and has become exceedingly popular for neuroimaging analysis in recent years [21]. It is a supervised learning method used for classifications, which consists of optimizing the linear threshold (called separation hyperplane) between points of the 2 classes. In case of nonlinear separation, the SVM is done using the projection of the dataset to a higher dimensional space where a determined hyperplane (support vector) separates the categories of the training data [22]. Performing the SVM algorithm is performed by following these steps:

- Step 1: Preparation of the datasets: training data and test data.
- Step 2: Selection of the adequate Kernel function: several kernel functions can be used as the linear, the gaussian, the cubic, etc.
- Step 3: Execution of training algorithms (training data).
- Step 4: Classification/prediction of unseen data (test data).
- Step5: Evaluation of the SVM classifiers' performances.

2.5. *The proposed DSS algorithm*

The main objective of this study is to build a DSS effective and adaptable to the context of healthcare sector specifically in developing countries. To achieve this purpose, the DSS algorithm consists of the



(I): membership function assigned to the inputs O, D and S

(II): membership function assigned to the output RPN

Fig. 2. Membership function of inputs O, D and S (I) and the output RPN (II) of the FIS 1.

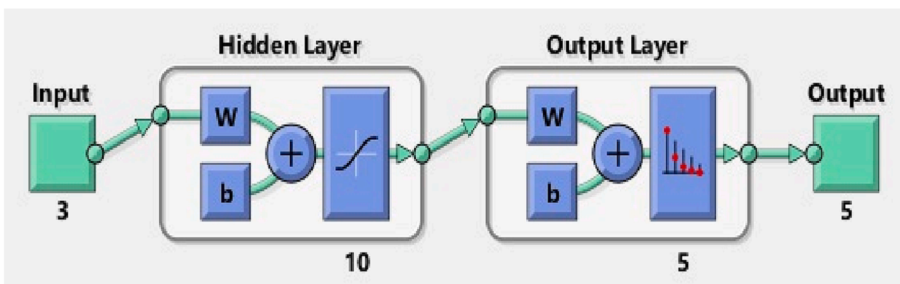
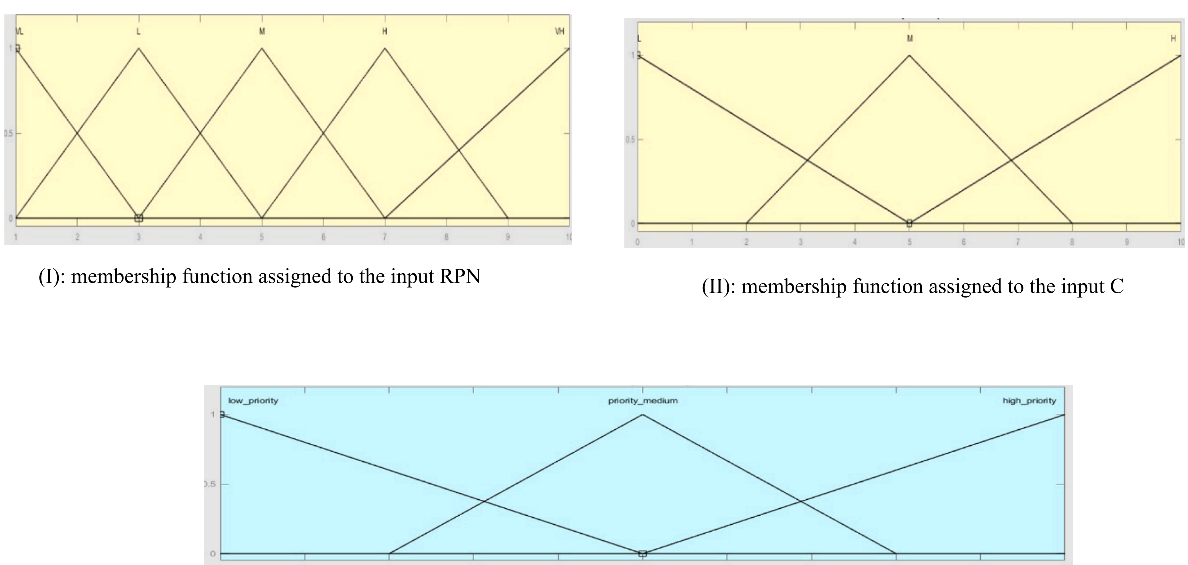


Fig. 3. The ANN model architecture.



(I): membership function assigned to the input RPN

(II): membership function assigned to the input C

(III): membership function assigned to the output P

Fig. 4. Membership function of inputs RPN (I) and C (II), and the output P (III) of the FIS 2.

following steps: (see Fig. 1)

1. Building first FIS process (fuzzy-FMEA) in order to obtain fuzzy RPN value of each identified risk (O, D and S are inputs and RPN is output).

Table 3
Results of the Fuzzy Inference System 1 (FIS 1).

Risk code	Risk description	O	D	S	Fuzzy RPN	fuzzy RPN Classification
R1	Stab wounds	1	5	5	9,03	VH
R2	leaking liquid	2	1	4	5	M
R3	Hygiene rules non-respected	1	3	4	5	M
R4	Putting jewelers in work box	1	1	4	5	M
R5	No respect of protection rules and procedures	3	1	5	9,03	VH
R6	Non-declaration of non-functional RMI	1	4	3	3	L
R7	Inefficient brushing	2	3	5	9,03	VH
R8	Aggressive brushing	2	2	1	1,64	VL
R9	RMI passed with no brush	2	3	5	9,03	VH
R10	Immersion duration not respected	1	5	4	7	H
R11	Dilution concentration not respected	2	4	5	9,03	VH
R12	Small RMI lost in sewers	2	4	3	5	M
R13	Inefficient rinsing	1	1	2	1,64	VL
R14	Inefficient drying	2	1	4	5	M
R15	Error of cycle selection	1	1	3	3	L
R16	Airlock opened from 2 sides	4	1	4	9,03	VH
R17	Inefficient control of wholeness	3	2	4	7	H
R18	Use non-functional box	1	1	4	5	M
R19	Use non-functional paper	2	5	4	7	H
R20	Bad operation of packaging	2	3	4	7	H
R21	Inefficient control of RMI constitution	2	4	3	5	M
R22	Losing RMI or part of RMI	1	2	3	3	L
R23	No applications of indicators	1	1	4	5	M
R24	Inefficient welding	1	1	4	5	M
R25	Error of cycle selection	1	1	4	5	M
R26	Using expired Bowie-Dick test	1	2	3	3	L
R27	Non-functional autoclave machine (breakdown)	3	1	2	3	L
R28	Breakdown of consumables	4	1	2	3	L
R29	Inhomogeneous loading	2	3	4	7	H
R30	Indicators not putted	5	1	4	9,03	VH
R31	Error of cycle selection of sterilization process	2	1	4	5	M
R32	Blocked autoclave machine	2	3	2	3	L
R33	Explosion of autoclave (overpressure of autoclave)	1	5	5	9,03	VH
R34	Burns of autoclave nurse (when getting out RMI package from autoclave)	3	2	5	9,03	VH
R35	Inefficient control of indicators results	5	1	2	3	L
R36	Crushes between RMIs	4	1	5	9,03	VH
R37	Deadlines of sterile RMI not respected	2	2	4	5	M
R38	Client's confusion	3	4	3	7	H
R39	Lateness in delivery of RMI	1	1	3	3	L
R40	Inadequate conditions of transport	2	3	4	7	H
R41	Absence of area cleaning	1	1	5	7	H
R42	Inefficient cleaning	1	1	5	7	H
R43	Ineffective waste management	1	2	5	7	H
R44	Ineffective maintenance intervention	1	1	3	3	L
R45	Non-reactivity for an intervention request	2	1	3	3	L
R46	Non-satisfaction of a procurement demand	5	1	2	3	L

2. Classifying risk tolerances using a developed ANN algorithm.
3. Proposing corrective actions for intolerable risks: risks that are classified High or Very High are considered as intolerable risks.

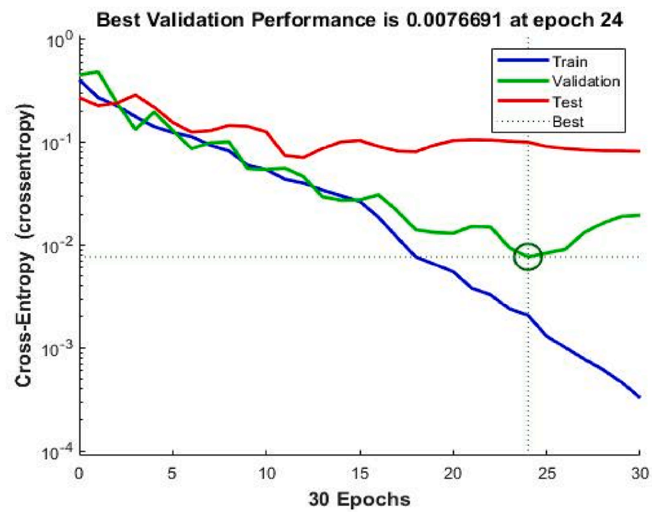


Fig. 5. Neural network training performance.

4. Assigning C (Control factor) to each corrective action to assess its feasibility.
5. Building second FIS process (fuzzy-prioritization) in order to obtain Priority risk (P) (RPN and C are inputs and P is the output).
6. Classifying action priorities using a developed SVM algorithm.

2.5.1. FMEA and prioritization criteria

FMEA team composed from 4 CSU experts (1 professor in sterilization on CSU chief, the CSU workers head and 2 quality and safety engineers) provide 5-point-scales and their significations of O, D, S in Table 1.

5 tolerance classes are proposed to categorize each risk: Very Low (VL); Low (L); Medium (M); High (H); Very High (VH). The FMEA team provides 10-point-scales and their significations of RPN and C in Table 2.

3 Priority classes are proposed for each corrective: Low priority (LP); priority medium (PM); high priority (HP).

2.5.2. FIS 1: fuzzy-FMEA

The selected form of the used membership function in the FIS 1 is the triangular form which is a very popular membership function given by equation A.1 [9–11]. Fig. 2 illustrates the membership functions of the inputs O, D and S (Fig. 2.I), the membership of the output RPN (Fig. 2.II).

The FMEA team has proceeded to the rule base construction using the code: (***If*** O is … ***AND*** D is … ***AND*** S is … ***THEN*** RPN is …). Results of the rule base (125 rules) is provided in the Appendix B.

The inference engine has been performed based on the Mamdani approach. And the Center Of Gravity (COG) technique has been adopted for the defuzzification process, which is expressed with the formula A.2.

2.5.3. Classification of risks using ANN

The architecture of the ANN algorithm is composed from 3 inputs (O, D and S), 10 hidden layers, 5 output layers and 5 outputs (5 classes: VL, L, M, H, VH) as presented in Fig. 3:

The repartition of the dataset is given as follows: 70 % for the training data, 15 % for the validation data and 15 % for the testing data (Fig. 4).

2.5.4. FIS 2: fuzzy-prioritization

The selected form of the used membership function in the FIS 2 is the triangular form membership function given by equation A.1 (the same form selected in FIS 1). Fig. 3 illustrates the membership functions of the inputs RPN (Fig. 3.I), C (Fig. 3.II), the membership of the output P (Fig. 3.III).

Table 4
Results of the Fuzzy Inference System 2 (FIS 2).

Risk code	Risk description	Fuzzy RPN	fuzzy RPN Classification	Level of Control C	P	Prioritization
R1	Stab wounds	9,03	VH	2	8,17	HP
R5	No respect of protection rules and procedures	9,03	VH	8	8,17	LP
R7	Inefficient brushing	9,03	VH	9	8,23	LP
R9	RMI passed with no brush	9,03	VH	8	8,17	HP
R10	Immersion duration not respected	7	H	3	6,15	PM
R11	Dilution concentration not respected	9,03	VH	4	8,22	PM
R16	Airlock opened from 2 sides	9,03	VH	7	7,98	HP
R17	Inefficient control of wholeness	7	H	6	8,22	HP
R19	Use non-functional paper	7	H	4	7,27	LP
R20	Bad operation of packaging	7	H	7	7,98	LP
R29	Inhomogeneous loading	7	H	6	8,22	LP
R30	Indicators not putted	9,03	VH	8	8,17	HP
R33	Explosion of autoclave (overpressure of autoclave)	9,03	VH	8	8,17	LP
R34	Burns of autoclave nurse (when getting out RMI package from autoclave)	9,03	VH	9	8,23	PM
R36	Crushes between RMIs	9,03	VH	4	8,22	HP
R38	Client's confusion	7	H	5	8,37	HP
R40	Inadequate conditions of transport	7	H	1	5	LP
R41	Absence of area cleaning	7	H	9	8,31	LP
R42	Inefficient cleaning	7	H	7	7,98	HP
R43	Ineffective waste management	7	H	6	8,22	LP

The FMEA team has proceeded to rule base construction using the code: (***If*** fuzzy-RPN is … ***AND*** C is … ***THEN*** P is …). The results of the rule base (15 rules) are provided in Appendix C.

The inference engine has been performed based on the Mamdani approach. And the Center Of Gravity (COG) technique has been adopted for the defuzzification process, which is expressed with the formula A.2.

2.5.5. Prioritization of intolerable risks using SVM

Six kernel functions are performed to prioritize actions of intolerable risks: the linear, the quadratic, the cubic, the fine gaussian, the medium gaussian, and the coarse gaussian. The approach adopted for the multi-class problem is the "one-vs-one" approach. The dataset has been divided randomly into two categories: 70 % for training and 30 % for the testing sets.

3. Results

The analysis of the CSU processes led the FMEA team to identify 46 risks. The team assigns O, D, and S levels for each risk. The FIS 1 provides results and classification of the RPN (see Table 3):

The repartition of the dataset is given as follows: 70 % for the training data (32 samples), 15 % for the validation data (7 samples) and 15 % for the testing data (7 samples).

The cross-entropy loss (Fig. 5) shows that 30 iterations has been done to select the appropriate validation (with minimal error rate). The best validation performance provided in the 24th iteration with a minimal error rate equal to 0.76 %.

The accuracy of the ANN model of all data (training, validation and testing) is equal to 97.8 %, which means that the developed ANN model is a very good classifier (according to the Kappa agreement, a very good accuracy is between 80 % and 100 % [23]).

Table 4 illustrates assigned control levels of the intolerable risks (H or VH risks) and provides results of prioritizations P using FIS 2:

The six selected SVM classifiers (the linear, the quadratic, the cubic, the fine gaussian, the medium gaussian and the coarse gaussian) are performed to learn the classification. 70 % for the training data (14 samples and 30 % for the testing data (6 samples). According to the results, the most adequate SVM classifier in our case is the fine gaussian, with 70 % accuracy rate in the training phase and 83,3% accuracy rate in the testing phase.

4. Discussion

The implementation of the DSS in healthcare focuses generally on the clinical domain [24]. Many studies have been published that which propose the design of DSSs in different healthcare activities [25–28]. Nevertheless, the focus on the healthcare management domain is lesser. The same for the sterilization units, which do not receive the same attention as the other healthcare departments [29].

The associated literature shows that there is a large number of published works that aim to combine the fuzzy logic and AI techniques with the FMEA in several sectors, such as construction projects [30], industrial sector [31,32], agri-food industries [33], and healthcare [34,35]. These studies aim to create models that can be used to calculate RPN values and decide on tolerance classes. Nevertheless, none of these studies have included the phase of risk treatment, despite the importance of this phase in the decision-making process. These studies did not take into consideration the context of the application fields and their constraints. Our developed DSS provides solutions for these gaps.

The present study shows that the design and implementation of the DSSs specifically those that use the AI techniques present a real opportunity for managers to develop a decision-making process. The results of this study prove a high performance of the developed DSS especially in the context of developing countries. The associated literature shows that the combination of the fuzzy logic with the FMEA provides a more efficient tool than the classic FMEA method [36]. The general accuracy obtained for the risk tolerance classification using the ANN is about 98 %, which is an excellent result. Moreover, the added decision step associated for the risk prioritization to be adapted to the study area constraints also show good performance with more than 83 % accuracy rate in testing phase. Thus, the developed DSS in this study is a high performant tool for developing countries healthcare managers.

5. Conclusion

The present study presents a real demonstration of the real usefulness and the efficiency of the implementation of the intelligent DSS adapted to the context of developing countries (Morocco as example). This paper proposes an original idea to automatize the assessment, the treatment and the monitor of risks using lesser resources. The obtained results have proved the high efficiency of our developed DSS. Therefore, this study presents a real opportunity for researchers and engineers to convict decision-makers to introduce and promote the use of AI in healthcare management field as well as the clinical field.

However, several limitations form barriers for the achievement of this purpose, such as the limitation of the study in one healthcare department (sterilization unit). For this reason, we propose as future works, to implement and applied the proposed DSS in other medical departments such as operating rooms, emergency and diagnosis departments.Summary Table

What was already known on the topic?	What does this study add to our knowledge?
• Computerized-decision support systems which is based on AI techniques is widely used in healthcare sector. • Many published articles propose studies that aims to combine FMEA with fuzzy logic, ANN and SVM algorithms.	• The present study provides a decision support useful for low-income countries (and also high-income countries). • This study covers in addition to the risk assessment process (calculation of RPNs and determination of risk classes), the risk treatment process is also highlighted with the prioritization of intolerable risks. • Treating 2 risk management processes leads us in this paper to use double fuzzy inference systems and 2 artificial intelligence algorithms (ANN and SVM).

CRediT authorship contribution statement

Amine En-Naaoui: Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Mohammed Kaicer:** Methodology, Supervision. **Aicha Aguezzoul:** Validation.

Declaration of competing interest

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

Acknowledgments

We offer our thanks to the central administration of the Ibn Sina University-Hospital Center, to the administration of Ibn Sina Hospital and all workers of the Central Sterilization Unit of Ibn Sina Hospital specifically Pr. J EL HARTI (and the manager of the unit), M. BELESMAK (nurses head) and I. TOOUBOUH (Quality engineer) for supporting us in collecting data provided in this study.

Authors' contributions

Eng. Amine EN-NAAOUI (hospital quality and safety engineer) led the collection of the necessary data, the development of the model, and the initiation of the paper's draft. Dr. Prof Mohammed KAICER (artificial intelligent expert) verified of the approach adopted and the reliability of results. And Dr. Prof Aicha AGUEZZOUL (logistics and quality process expert) verified the compatibility and the harmony of the study.

Authors statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Equations and mathematical formulas

Let X be a nonempty set. Let A be a set in X. And let μ_A be the triangular membership function ($\forall x \in X \mu_A(x) \in [0,1]$). Let a, b, c and d be real numbers ($a < b < c < d$). Then:

$$\mu_A(\mathbf{x}) = \begin{cases} \dfrac{\mathbf{x}-\mathbf{a}}{\mathbf{b}-\mathbf{a}} if a \leq x \leq b \\ \dfrac{\mathbf{b}-\mathbf{x}}{\mathbf{c}-\mathbf{b}} if b \leq x \leq c \\ 0 otherwise \end{cases} \tag{A.1}$$

$$\mathbf{COG} = \frac{\int \mu_A(\mathbf{x})\mathbf{x}d\mathbf{x}}{\int \mu_A(\mathbf{x})d\mathbf{x}} \tag{A.2}$$

Appendix B. Rule base of FIS 1

1. If (Occurrence is VL) and (non-Detection is VL) and (Severity is VL) then (RPN is VL)
2. If (Occurrence is L) and (non-Detection is VL) and (Severity is VL) then (RPN is VL)
3. If (Occurrence is M) and (non-Detection is VL) and (Severity is VL) then (RPN is VL)
4. If (Occurrence is H) and (non-Detection is VL) and (Severity is VL) then (RPN is L)
5. If (Occurrence is VH) and (non-Detection is VL) and (Severity is VL) then (RPN is L)
6. If (Occurrence is VL) and (non-Detection is L) and (Severity is VL) then (RPN is VL)
7. If (Occurrence is L) and (non-Detection is L) and (Severity is VL) then (RPN is VL)
8. If (Occurrence is M) and (non-Detection is L) and (Severity is VL) then (RPN is VL)
9. If (Occurrence is H) and (non-Detection is L) and (Severity is VL) then (RPN is L)
10. If (Occurrence is VH) and (non-Detection is L) and (Severity is VL) then (RPN is L)
11. If (Occurrence is VL) and (non-Detection is M) and (Severity is VL) then (RPN is VL)
12. If (Occurrence is L) and (non-Detection is M) and (Severity is VL) then (RPN is VL)
13. If (Occurrence is M) and (non-Detection is M) and (Severity is VL) then (RPN is L)
14. If (Occurrence is H) and (non-Detection is M) and (Severity is VL) then (RPN is L)
15. If (Occurrence is VH) and (non-Detection is M) and (Severity is VL) then (RPN is L)
16. If (Occurrence is VL) and (non-Detection is H) and (Severity is VL) then (RPN is L)

17. If (Occurrence is L) and (non-Detection is H) and (Severity is VL) then (RPN is L)
18. If (Occurrence is M) and (non-Detection is H) and (Severity is VL) then (RPN is L)
19. If (Occurrence is H) and (non-Detection is H) and (Severity is VL) then (RPN is M)
20. If (Occurrence is VH) and (non-Detection is H) and (Severity is VL) then (RPN is M)
21. If (Occurrence is VL) and (non-Detection is VH) and (Severity is VL) then (RPN is L)
22. If (Occurrence is L) and (non-Detection is VH) and (Severity is VL) then (RPN is L)
23. If (Occurrence is M) and (non-Detection is VH) and (Severity is VL) then (RPN is L)
24. If (Occurrence is VH) and (non-Detection is VH) and (Severity is VL) then (RPN is M)
25. If (Occurrence is H) and (non-Detection is VH) and (Severity is VL) then (RPN is M)
26. If (Occurrence is VL) and (non-Detection is VL) and (Severity is L) then (RPN is VL)
27. If (Occurrence is L) and (non-Detection is VL) and (Severity is L) then (RPN is VL)
28. If (Occurrence is M) and (non-Detection is VL) and (Severity is L) then (RPN is L)
29. If (Occurrence is H) and (non-Detection is VL) and (Severity is L) then (RPN is L)
30. If (Occurrence is VH) and (non-Detection is VL) and (Severity is L) then (RPN is L)
31. If (Occurrence is VL) and (non-Detection is L) and (Severity is L) then (RPN is VL)
32. If (Occurrence is L) and (non-Detection is L) and (Severity is L) then (RPN is L)
33. If (Occurrence is M) and (non-Detection is L) and (Severity is L) then (RPN is L)
34. If (Occurrence is H) and (non-Detection is L) and (Severity is L) then (RPN is L)
35. If (Occurrence is VH) and (non-Detection is L) and (Severity is L) then (RPN is M)
36. If (Occurrence is VL) and (non-Detection is M) and (Severity is L) then (RPN is L)
37. If (Occurrence is L) and (non-Detection is M) and (Severity is L) then (RPN is L)
38. If (Occurrence is M) and (non-Detection is M) and (Severity is L) then (RPN is M)
39. If (Occurrence is H) and (non-Detection is M) and (Severity is L) then (RPN is M)
40. If (Occurrence is VH) and (non-Detection is M) and (Severity is L) then (RPN is M)
41. If (Occurrence is VL) and (non-Detection is H) and (Severity is L) then (RPN is L)
42. If (Occurrence is L) and (non-Detection is H) and (Severity is L) then (RPN is L)
43. If (Occurrence is M) and (non-Detection is H) and (Severity is L) then (RPN is M)
44. If (Occurrence is H) and (non-Detection is H) and (Severity is L) then (RPN is M)
45. If (Occurrence is VH) and (non-Detection is H) and (Severity is L) then (RPN is M)
46. If (Occurrence is VL) and (non-Detection is VH) and (Severity is L) then (RPN is L)
47. If (Occurrence is L) and (non-Detection is VH) and (Severity is L) then (RPN is M)
48. If (Occurrence is M) and (non-Detection is VH) and (Severity is L) then (RPN is M)
49. If (Occurrence is H) and (non-Detection is VH) and (Severity is L) then (RPN is H)
50. If (Occurrence is VH) and (non-Detection is VH) and (Severity is L) then (RPN is H)
51. If (Occurrence is VL) and (non-Detection is VL) and (Severity is M) then (RPN is L)
52. If (Occurrence is L) and (non-Detection is VL) and (Severity is M) then (RPN is L)
53. If (Occurrence is M) and (non-Detection is VL) and (Severity is M) then (RPN is M)
54. If (Occurrence is H) and (non-Detection is VL) and (Severity is M) then (RPN is M)
55. If (Occurrence is VH) and (non-Detection is VL) and (Severity is M) then (RPN is H)
56. If (Occurrence is VL) and (non-Detection is L) and (Severity is M) then (RPN is L)
57. If (Occurrence is L) and (non-Detection is L) and (Severity is M) then (RPN is L)
58. If (Occurrence is M) and (non-Detection is L) and (Severity is M) then (RPN is M)
59. If (Occurrence is H) and (non-Detection is L) and (Severity is M) then (RPN is M)
60. If (Occurrence is VH) and (non-Detection is L) and (Severity is M) then (RPN is H)
61. If (Occurrence is VL) and (non-Detection is M) and (Severity is M) then (RPN is L)
62. If (Occurrence is L) and (non-Detection is M) and (Severity is M) then (RPN is M)
63. If (Occurrence is M) and (non-Detection is M) and (Severity is M) then (RPN is M)
64. If (Occurrence is H) and (non-Detection is M) and (Severity is M) then (RPN is H)
65. If (Occurrence is VH) and (non-Detection is M) and (Severity is M) then (RPN is H)
66. If (Occurrence is VL) and (non-Detection is H) and (Severity is M) then (RPN is L)
67. If (Occurrence is L) and (non-Detection is H) and (Severity is M) then (RPN is M)
68. If (Occurrence is M) and (non-Detection is H) and (Severity is M) then (RPN is H)
69. If (Occurrence is H) and (non-Detection is H) and (Severity is M) then (RPN is H)
70. If (Occurrence is VH) and (non-Detection is H) and (Severity is M) then (RPN is VH)
71. If (Occurrence is VL) and (non-Detection is VH) and (Severity is M) then (RPN is M)
72. If (Occurrence is L) and (non-Detection is VH) and (Severity is M) then (RPN is M)
73. If (Occurrence is M) and (non-Detection is VH) and (Severity is M) then (RPN is H)
74. If (Occurrence is H) and (non-Detection is VH) and (Severity is M) then (RPN is H)
75. If (Occurrence is VH) and (non-Detection is VH) and (Severity is M) then (RPN is VH)
76. If (Occurrence is VL) and (non-Detection is VL) and (Severity is H) then (RPN is M)
77. If (Occurrence is L) and (non-Detection is VL) and (Severity is H) then (RPN is M)
78. If (Occurrence is M) and (non-Detection is VL) and (Severity is H) then (RPN is H)
79. If (Occurrence is H) and (non-Detection is VL) and (Severity is H) then (RPN is VH)
80. If (Occurrence is VH) and (non-Detection is VL) and (Severity is H) then (RPN is VH)
81. If (Occurrence is VL) and (non-Detection is L) and (Severity is H) then (RPN is M)
82. If (Occurrence is L) and (non-Detection is L) and (Severity is H) then (RPN is M)

83. If (Occurrence is M) and (non-Detection is L) and (Severity is H) then (RPN is H)
84. If (Occurrence is H) and (non-Detection is L) and (Severity is H) then (RPN is VH)
85. If (Occurrence is VH) and (non-Detection is L) and (Severity is H) then (RPN is VH)
86. If (Occurrence is VL) and (non-Detection is M) and (Severity is H) then (RPN is M)
87. If (Occurrence is L) and (non-Detection is M) and (Severity is H) then (RPN is H)
88. If (Occurrence is M) and (non-Detection is M) and (Severity is H) then (RPN is H)
89. If (Occurrence is H) and (non-Detection is M) and (Severity is H) then (RPN is VH)
90. If (Occurrence is VH) and (non-Detection is M) and (Severity is H) then (RPN is VH)
91. If (Occurrence is VL) and (non-Detection is H) and (Severity is H) then (RPN is H)
92. If (Occurrence is L) and (non-Detection is H) and (Severity is H) then (RPN is H)
93. If (Occurrence is M) and (non-Detection is H) and (Severity is H) then (RPN is VH)
94. If (Occurrence is H) and (non-Detection is H) and (Severity is H) then (RPN is VH)
95. If (Occurrence is VH) and (non-Detection is H) and (Severity is H) then (RPN is VH)
96. If (Occurrence is VL) and (non-Detection is VH) and (Severity is H) then (RPN is H)
97. If (Occurrence is L) and (non-Detection is VH) and (Severity is H) then (RPN is H)
98. If (Occurrence is M) and (non-Detection is VH) and (Severity is H) then (RPN is VH)
99. If (Occurrence is H) and (non-Detection is VH) and (Severity is H) then (RPN is VH)
100. If (Occurrence is VH) and (non-Detection is VH) and (Severity is H) then (RPN is VH)
101. If (Occurrence is VL) and (non-Detection is VL) and (Severity is VH) then (RPN is H)
102. If (Occurrence is L) and (non-Detection is VL) and (Severity is VH) then (RPN is H)
103. If (Occurrence is M) and (non-Detection is VL) and (Severity is VH) then (RPN is VH)
104. If (Occurrence is H) and (non-Detection is VL) and (Severity is VH) then (RPN is VH)
105. If (Occurrence is VH) and (non-Detection is VL) and (Severity is VH) then (RPN is VH)
106. If (Occurrence is VL) and (non-Detection is L) and (Severity is VH) then (RPN is H)
107. If (Occurrence is L) and (non-Detection is L) and (Severity is VH) then (RPN is H)
108. If (Occurrence is M) and (non-Detection is L) and (Severity is VH) then (RPN is VH)
109. If (Occurrence is H) and (non-Detection is L) and (Severity is VH) then (RPN is VH)
110. If (Occurrence is VH) and (non-Detection is L) and (Severity is VH) then (RPN is VH)
111. If (Occurrence is VL) and (non-Detection is M) and (Severity is VH) then (RPN is VH)
112. If (Occurrence is L) and (non-Detection is M) and (Severity is VH) then (RPN is VH)
113. If (Occurrence is M) and (non-Detection is M) and (Severity is VH) then (RPN is VH)
114. If (Occurrence is H) and (non-Detection is M) and (Severity is VH) then (RPN is VH)
115. If (Occurrence is VH) and (non-Detection is M) and (Severity is VH) then (RPN is VH)
116. If (Occurrence is VL) and (non-Detection is H) and (Severity is VH) then (RPN is VH)
117. If (Occurrence is L) and (non-Detection is H) and (Severity is VH) then (RPN is VH)
118. If (Occurrence is M) and (non-Detection is H) and (Severity is VH) then (RPN is VH)
119. If (Occurrence is H) and (non-Detection is H) and (Severity is VH) then (RPN is VH)
120. If (Occurrence is VH) and (non-Detection is H) and (Severity is VH) then (RPN is VH)
121. If (Occurrence is VL) and (non-Detection is VH) and (Severity is VH) then (RPN is VH)
122. If (Occurrence is L) and (non-Detection is VH) and (Severity is VH) then (RPN is VH)
123. If (Occurrence is M) and (non-Detection is VH) and (Severity is VH) then (RPN is VH)
124. If (Occurrence is H) and (non-Detection is VH) and (Severity is VH) then (RPN is VH)
125. If (Occurrence is VH) and (non-Detection is VH) and (Severity is VH) then (RPN is VH)

Appendix C. Rule base of FIS 2

1. If (fuzzy-RPN is VL) and (level-of-control is L) then (priority-actions is low-priority)
2. If (fuzzy-RPN is L) and (level-of-control is L) then (priority-actions is low-priority)
3. If (fuzzy-RPN is M) and (level-of-control is L) then (priority-actions is low-priority)
4. If (fuzzy-RPN is H) and (level-of-control is L) then (priority-actions is priority-medium)
5. If (fuzzy-RPN is VH) and (level-of-control is L) then (priority-actions is high-priority)
6. If (fuzzy-RPN is VL) and (level-of-control is M) then (priority-actions is low-priority)
7. If (fuzzy-RPN is L) and (level-of-control is M) then (priority-actions is low-priority)
8. If (fuzzy-RPN is M) and (level-of-control is M) then (priority-actions is priority-medium)
9. If (fuzzy-RPN is H) and (level-of-control is M) then (priority-actions is high-priority)
10. If (fuzzy-RPN is VH) and (level-of-control is M) then (priority-actions is high-priority)
11. If (fuzzy-RPN is VL) and (level-of-control is H) then (priority-actions is low-priority)
12. If (fuzzy-RPN is L) and (level-of-control is H) then (priority-actions is low-priority)
13. If (fuzzy-RPN is M) and (level-of-control is H) then (priority-actions is high-priority)
14. If (fuzzy-RPN is H) and (level-of-control is H) then (priority-actions is high-priority)
15. If (fuzzy-RPN is VH) and (level-of-control is H) then (priority-actions is high-priority)

References

[1] T. Davenport, R. Kalakota, The potential for artificial intelligence in healthcare, Future Healthc. J. 6 (2) (2019) 94–98, https://doi.org/10.7861/futurehosp.6-2-94. PMID: 31363513; PMCID: PMC6616181.

[2] R.G. Bea, Human and organizational factors in reliability assessment and management of offshore structures, Risk Anal. 22 (1) (2002), https://doi.org/10.1111/0272-4332.t01-1-00003.

[3] W. Song, J. Li, H. Li, X. Ming, Human factors risk assessment: an integrated method for improving safety in clinical use of medical devices, Appl. Soft Comput. 86 (105918) (2020) 1568–4946, https://doi.org/10.1016/j.asoc.2019.105918.

[4] J. You, S. Lou, R. Mao, T. Xu, An improved FMEA quality risk assessment framework for enterprise data assets, J. Knowl. Econ. 1 (3) (2022) 141–152, https://doi.org/10.1016/j.jdec.2022.12.001.

[5] H.C. Liu, L.J. Zhang, Y.J. Ping, L. Wang, Failure mode and effects analysis for proactive healthcare risk evaluation: a systematic literature review, J. Eval. Clin. Pract. 26 (4) (2020) 1320–1337, https://doi.org/10.1111/jep.13317.

[6] J. Qin, Y. Xi, W. Pedrycz, Failure mode and effects analysis (FMEA) for risk assessment based on interval type-2 fuzzy evidential reasoning method, Appl. Soft Comput. 89 (106134) (2020) 1568–4946, https://doi.org/10.1016/j.asoc.2020.106134.

[7] J. Balaraju, M.G. Raj, C.S. Murthy, Fuzzy-FMEA risk evaluation approach for LHD machine – a case study, J. Sustain. Min 18 (4) (2019) 257–268, https://doi.org/10.1016/j.jsm.2019.08.002.

[8] H.W. Lo, J.J.H. Liou, A novel multiple-criteria decision-making-based FMEA model for risk assessment, Appl. Soft Comput. 73 (2018) 684–696, https://doi.org/10.1016/j.asoc.2018.09.020.

[9] C. Dağsuyu, E. Göçmen, M. Narlı, A. Kokangül, Classical and fuzzy FMEA risk analysis in a sterilization unit, Comput. Ind. Eng. 101 (2016) 286–294, https://doi.org/10.1016/j.cie.2016.09.015.

[10] N. Chanamool, T. Naenna, Fuzzy FMEA application to improve decision-making process in an emergency department, Appl. Soft Comput. 43 (2016) 441–453, https://doi.org/10.1016/j.asoc.2016.01.007.

[11] M. Kumru, P.Y. Kumru, Fuzzy FMEA application to improve purchasing process in a public hospital, Appl. Soft Comput. 13 (2013) 721–733, https://doi.org/10.1016/j.asoc.2012.08.007.

[12] M. Mangeli, A. Shahraki, F.H. Saljooghi, Improvement of risk assessment in the FMEA using nonlinear model, revised fuzzy TOPSIS, and support vector machine, Int. J. Ind. Ergon. 69 (2019) 209–216, https://doi.org/10.1016/j.ergon.2018.11.004.

[13] O.O. Oleribe, J. Momoh, B.S. Uzochukwu, F. Mbofana, A. Adebiyi, T. Barbera, R. Williams, S.D. Taylor-Robinson, Identifying Key Challenges Facing Healthcare Systems, In: Africa And Potential Solutions, Int J Gen Med. 6(12) (2019) pp. 395–403. doi:10.2147/IJGM.S223882.

[14] D. Pandey, S. Verma, P. Verma, B. Mahanty, K. Dutta, A. Daverey, K. Arunachalam, SARS-CoV-2 in wastewater: challenges for developing countries, Int. J. Hyg. Environ. Health 231 (2021) 113634, https://doi.org/10.1016/j.ijheh.2020.113634.

[15] Z. Najafpour, M. Hasoumi, F. Behzadi, et al., Preventing blood transfusion failures: FMEA, an effective assessment method, BMC Health Serv. Res. 17 (2017), https://doi.org/10.1186/s12913-017-2380-3.

[16] L.A. Zadeh, Fuzzy sets, Inf. Control 8 (3) (1965) 338–353, https://doi.org/10.1016/S0019-9958(65)90241-X.

[17] J. Ivančan, D. Lisjak, New FMEA risks ranking approach utilizing four fuzzy logic systems, Machines 9 (11) (2021) 292, https://doi.org/10.3390/machines9110292.

[18] C.I. Ossai, N. Wickramasinghe, Intelligent decision support with machine learning for efficient management of mechanical ventilation in the intensive care unit – a critical overview, Int. J. Med. Inf. 150 (2021) 1386–5056, https://doi.org/10.1016/j.ijmedinf.2021.104469.

[19] Z. A. Zhang, Gentle introduction to artificial neural networks, Ann. Transl. Med. 4 (19) (2016) 370. doi:10.21037/atm.2016.06.20. PMID: 27826573.

[20] V. Renganathan, Overview of artificial neural network models in the biomedical domain, Bratisl. Lek. Listy 20 (7) (2019) 536–540, https://doi.org/10.4149/BLL_2019_087.

[21] D.A. Pisner, D.M. Schnyer, Machine learning: methods and applications to brain disorders, in: A. Mechelli, Vieira (Eds.), Support Vector Machine, first ed., Academic press, 2019, pp. 101–121, https://doi.org/10.1016/B978-0-12-815739-8.00006-7.

[22] N.S. Bajaj, A.D. Patange, R. Jegadeeshwaran, S.S. Pardeshi, K.A. Kulkarni, R. S. Ghatpande, Application of metaheuristic optimization-based support vector machine for milling cutter health monitoring, Int. J. Intell. Syst. Appl. 18 (200196) (2023) 2667–3053, https://doi.org/10.1016/j.iswa.2023.200196.

[23] S. Gupta, K. Saluja, A. Goyal, A. Vajpayee, V. Tiwari, Comparing the performance of machine learning algorithms using estimated accuracy, Meas.: Sens 24 (2022) 100432, https://doi.org/10.1016/j.measen.2022.10043.

[24] R.T. Sutton, D. Pincock, D.C. Baumgart, et al., An overview of clinical decision support systems: benefits, risks, and strategies for success, NPJ Digit. Med 3 (17) (2020), https://doi.org/10.1038/s41746-020-0221-y.

[25] A.T.M. Wasylewicz, A.M.J.W. Scheepers-Hoeks. Clinical Decision Support Systems. 2018 Dec 22, in: P. Kubben, M. Dumontier, A. Dekker, Eds. Fundamentals of Clinical Data Science [Internet]. Cham (CH): Springer; 2019. Chapter 11. Available from: https://www.ncbi.nlm.nih.gov/books/NBK543516/. doi: 10.1007/978-3-319-99713-1_11.

[26] S. Katz, J. Suijker, C. Hardt, M.B. Madsen, A.M. Vries, A. Pijpe, S. Skrede, O. Hyldegaard, E. Solligård, A. Norrby-Teglund, E. Saccenti, V.A.P. Martins Dos Santos, Decision support system and outcome prediction in a cohort of patients with necrotizing soft-tissue infections, Int. J. Med. Inf. 167 (2022) 104878, https://doi.org/10.1016/j.ijmedinf.2022.104878.

[27] Y. Du, C. McNestry, L. Wei, A.M. Antoniadi, F.M. McAuliffe, C. Mooney, Machine learning-based clinical decision support systems for pregnancy care: a systematic review, Int. J. Med. Inf. 173 (2023) 105040, https://doi.org/10.1016/j.ijmedinf.2023.105040.

[28] L. Westerbeek, G.J. de Bruijn, H.C. van Weert, A. Abu-Hanna, S. Medlock, J.C. M. van Weert, General practitioners' needs and wishes for clinical decision support systems: a focus group study, Int. J. Med. Inf. 168 (2022) 104901, https://doi.org/10.1016/j.ijmedinf.2022.104901.

[29] A. Kammoun, W. Hachicha, A.M. Aljuaid, Integrating quality tools and methods to analyze and improve a hospital sterilization process, Healt (Basel) 9 (5) (2021) 544, https://doi.org/10.3390/healthcare9050544.

[30] F. ul Hassan, T. Nguyen, T. Le, C. Le, Automated prioritization of construction project requirements using machine learning and fuzzy failure mode and effects analysis (FMEA), Automat. Constr. 154 (2023) 105013, https://doi.org/10.1016/j.autcon.2023.105013.

[31] F. Behnia, H.Z. Ahmadabadi, B.A. Schuelke-Leech, M. Mirhassani, Developing a fuzzy optimized model for selecting a maintenance strategy in the paper industry: an integrated FGP-ANP-FMEA approach, Expert Syst. Appl. 232 (2023) 120899, https://doi.org/10.1016/j.eswa.2023.120899.

[32] M. Gallab, H. Bouloiz, Y. Lamrani Alaoui, M. Tkiouat, Risk assessment of maintenance activities using fuzzy logic, Proc. Comput. Sci. 148 (2019) 226–235, https://doi.org/10.1016/j.procs.2019.01.065.

[33] M. Di Nardo, T. Murino, G. Osteria, L.C. Santillo, A new hybrid dynamic FMECA with decision-making methodology: a case study in an agri-food company, Appl. Syst. Innov. 5 (2022) 45, https://doi.org/10.3390/asi503.

[34] A. En-Naaoui, M. Gallab, M. Kaicer, An intelligent model for improving risk assessment in sterilization units using revised FMEA, fuzzy inference, k-Nearest Neighbors and support vector machine, J. Appl. Res. Technol. 21(5) (2023) 772–786. doi:10.22201/icat.24486736e.

[35] A. En-Naaoui, A. Aguezzoul, M. Kaicer, Improving the quality of hospital sterilization process using failure modes and effects analysis, fuzzy logic, and machine learning: experience in tertiary dental centre, Int. J. Qual. Health Care 35 (4) (2023) mzad078, https://doi.org/10.1093/intqhc/mzad078. PMID: 37757481.

[36] L. Cruz-Rivero, M.L. Méndez-Hernández, C.E. Mar-Orozco, A.A. Aguilar-Lasserre, A. Barbosa-Moreno, J. Sánchez-Escobar, Functional evaluation using fuzzy FMEA for a non-invasive measurer for methane and carbone dioxide, Symmetry 14 (2) (2022) 421, https://doi.org/10.3390/sym14020421.