Q-Rung Orthopair Fuzzy Sets-Enhanced FMEA for COVID-19 Risk Assessment

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Failure Modes and Effects Analysis (FMEA) is a widely used tool for risk analysis, primarily to identify risk factors affecting system quality. Due to the limitations of the traditional FMEA model, several recent models incorporating advanced fuzzy set extensions have been developed to enhance the reliability of risk assessment outcomes. However, most of these models limit expert flexibility in expressing preferences and often overlook the impact of unequal expert weights and the stability of risk ranking results. This study introduces a new FMEA model based on Q-Rung Orthopair Fuzzy Sets (Q-ROFSs), termed Q-ROFSs-FMEA. Q-ROFSs, an extension of intuitionistic fuzzy sets, introduce a new linguistic term. The Q-ROFSs-FMEA model considers the unequal weights of experts, enabling a dynamic representation of expert preferences. These weights and the linguistic evaluation of risk factors are integrated through an aggregation operator, facilitating consensus among experts. The model is applied to a case study on COVID-19 risk factors, revealing that 'older age' (risk priority number 0.000012) is the highest risk factor, while 'gender' (risk priority number -0.0037) is the lowest. It is found that the ranking of risk factors determined by the Q-ROFSs-FMEA model is obtained as $FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_5 \succ FM_7 \succ FM_8 \succ FM_2$ *. Furthermore, a comparative analysis indicates consistent ranking results across different models, demonstrating the reliability of the proposed model. The case study and comparative analysis validate the effectiveness and applicability of the Q-ROFSs-based risk assessment model.*

Povzetek: Razvili so model FMEA, izboljšan z uporabo Q-rung ortoparnih mehkih množic, za oceno tveganj COVID-19. Model omogoča dinamično izražanje preferenc strokovnjakov z neenakimi utežmi in združuje ocene tveganj prek agregacijskega operatorja. V študiji je bil kot najvišji dejavnik tveganja identificiran 'starejša starost', kot najnižji pa 'spol' (RPN -0,0037).

1 Introduction

Risk assessment is a crucial management tool for reducing project risks and promoting sustainable development. Risk assessment helps us to make the right decision especially when we are confronting problems with several alternatives and criteria [1]. There are numerous models available for determining risks and identifying hazards. The Failure Modes and Effects Analysis (FMEA) is one of the most widely used models since it is straightforward and efficient. It employs a proactive and systematic approach to identifying where and how it may fail [2]. Looking into the detailed part of FMEA, it is the process of analysing as many components, assemblies, and subsystems as possible to discover potential failure modes in a system and their causes and effects. FMEA has been widely applied across various sectors due to its proactive and systematic approach to failure identification. The FMEA is used to assess the relative impact of various failures such as in reducing medical errors [3], analysing the failure modes of nuclear-powered icebreakers, obtaining risk analysis for the textile industry's occupational safety and health [4], among many other applications. When mathematical failure rate models proposed by Tay and Lim [5] were linked with a statistical failure mode ratio database, the FMEA can be a qualitative analysis [6]. Therefore, FMEA is one of the earliest and most meticulously structured methods of failure analysis.

The FMEA was originally used in the aerospace sector in the 1960s, and it has been around for more than 60 years. Unlike other failure-prevention strategies, the FMEA was described in language that was universally understandable by those with minimal technical and/or systems knowledge. These encouraged the use of intelligent linguistic based approaches that are applicable to all enterprises and industries. The FMEA was brought into the mainstream by the automotive sector, which adopted it as the major mechanism for error and risk reduction. In recent years, the FMEA method has been widely used in a variety of fields, including manufacturing [7,8], aerospace [9], information technology risk assessment [10], healthcare risk management, [11,12] food industry [13,14], and maritime risk safety [15,16].

From a theoretical point of view, the FMEA comprises three components, namely the severity of the failure mode (*S*), the occurrence probability of a failure mode (*O*), and the detectability of the failure mode (*D*), which yields the risk priority number (RPN). The larger the RPN, the higher the risk of the related failure mode. The goal of RPN is to prioritise a product's or system's failure modes so that available resources can be appropriately allocated. The RPN can be expressed mathematically as the multiplication of *S*, *O* and *D* where they are risk parameters that are measured using a suitable point scale, such as Likert's scale [17]. According to Balaraju et al. [18] the FMEA team established an action approach based on the risk categories or risk rating level. For example, minor risk means no action is taken, moderate risk means some action is taken. Then, for high risk, corrective action will be taken, and for critical risk, corrective action will be taken, and major adjustments to the process/product will be necessary. However, in recent years it was argued that many types of risk assessments are difficult to obtain by the standard RPN. In an attempt to ease the assessment, Wang et al. [19] introduced the interval two-tuple linguistic representation model in FMEA. A dental manufacturing business uses the suggested linguistic FMEA technique to manufacture medical products. On the other hand, Huang et al. [20] employed probabilistic linguistic terms in FMEA instead of the normal linguistic term sets. The benefit of probabilistic linguistic terms is that they can handle the inherent ambiguity in FMEA team members' risk assessments without losing any information.

Risks are often associated with contradictory, subjective, ambiguous, or unclear information, making them well-suited for analysis using fuzzy set theory. Based on this assumption, the assessment model FMEA was integrated with fuzzy sets. The risk categories in the form of linguistics such as minor, moderate and high are closely related to the memberships of fuzzy set. The use of linguistic expressions to deal with uncertainty is one of the common aspects in fuzzy set-based risk models. For example, linguistics based on Pythagorean fuzzy set was employed in determining the risk performance of logistic service provider [21]. Recently, Huang et al. [22] proposed an integrated T-spherical fuzzy linguistic-FMEA. More works of FMEA that integrated with fuzzy set theory can be retrieved from Nie et al. [23] and Daneshvar et al. [24]. It was noticed that some of these integrated works used trapezoidal fuzzy set, [25, 26] triangular fuzzy set [27], and interval 2-tuple fuzzy linguistic variables [11, 28]. Recently, an integrated fuzzy set-FMEA was proposed by Ouyang et al. [29] where trapezoidal fuzzy numbers are used in defining linguistic variables. The use of linguistics in risk assessment has attracted many researchers because of its ability to deal with subjective and unclear notions.

In risk assessment models, fuzzy sets [30] that were represented by the membership functions allow the use of linguistic variables in FMEA to have a value between 0 and 1. However, some argued that a single membership function fails to address dual membership functions. Therefore, the intuitionistic fuzzy set (IFS) was proposed by Atanassov [31] where the total value of membership and non-membership may be greater than 1. However, in some real-world situations, the square sum of its dual memberships is equal to or less than 1 which is in violation of the condition of IFS. To solve the problem, Yager [32] developed the Q-rung Orthopair Fuzzy sets (Q-ROFSs) to overcome the ultimate limitation in which we can change the parameter value q to fulfil the value range requirement in a corresponding risk decision-making environment. The Q-ROFS is developed to deal with increasingly complex challenges where parameter value *q* is the notion of flexibility and variability. The capacity to evaluate a broader membership grade space with the parameter value *q* is the main benefit of these sets [33]. In other word, Q-ROFS is a new set for studying ambiguous information in a system. Compared to fuzzy sets, intuitionistic fuzzy sets, and Pythagorean fuzzy sets, this set is more potent and complete. Due to the inclusion of the parameter value *q*, the space of uncertain information described by the Q-ROFS is found to be enormous and flexible [34]. The current literature serves as the motivation for this paper to propose a novel FMEA model that can successfully address uncertainty issues. Some experts might not appreciate utilising crisp numbers to evaluate the failure modes while employing FMEA. They frequently employ linguistic variables or interval numbers to convey their ideas more effectively. In these circumstances, our suggested method is heavily emphasis the use of FMEA to combine heterogeneous information. Table 1 summarizes related research, highlighting current literature gaps that motivate this paper’s proposed FMEA model to address uncertainty more effectively.

Table 1: Summary of literature review

Authors	Year of publication	Type of sets used	Type of linguistic representation
Wang et al. [19]	2019	NA	Interval two-tuple
Huang et al. [20]	2022	NA	Probabilistic linguistic
Yalcinkaya and Cebi [21]	2022	Pythagorean fuzzy set	NA
Huang et al. [22]	2022	NA	T-spherical fuzzy linguistic
Nie et al. [23]	2018	NA	Multi-granular linguistic
Daneshvar et al. [24]	2020	Triangular and trapezoidal fuzzy set	NA
Wang et al. [25]	2017	Trapezoidal fuzzy set	NA

Wang et al. [26]	2017	Trapezoidal fuzzy set	NA
Testik and Unlu [27]	2022	Triangular fuzzy set	NA
Bhuvanesh Kumar and Parameshwaran [28]	2018	NA	Interval 2-tuple fuzzy linguistic
Ouyang et al. [29]	2021	NA	Trapezoidal fuzzy linguistic
Proposed method		Q-ROFSs	NA

Note: NA is an acronym for Not Available

The development of Q-ROFSs provides a valuable integration with FMEA, as both approaches address uncertainty in risk assessment. This paper proposes a Q-ROFS-FMEA model, where uncertainty is expressed through the linguistic variables of Q-ROFS. In this model, the linguistic variables for severity (*S*), occurrence (*O*), and detectability (*D*) in FMEA are replaced with Q-ROFS memberships, allowing for a nuanced representation of uncertainty. To illustrate the proposed work, a case study of risk factors of Coronavirus disease 2019 (COVID-19) will be implemented. In more detail, our proposed method can convert various assessment data into four-tuple linguistic variables that can be used to compute RPN. As a collective decision tool, FMEA requires input from a group of experts using linguistic terms. The uncertainty of information in FMEA is dealt with appropriately in the proposed model. The novel approach can handle the fuzziness and subjectivity in an uncertain environment, cover the diversity of viewpoints on the FMEA group of experts, and prevent the loss of crucial data throughout the risk assessment process. This method has the advantage of considering heterogeneous information as opposed to information of a single type.

The contributions of this paper are three-fold. First, we define ten linguistic terms for failure modes and develop two equations to transform interval-valued memberships into single-valued memberships and non-memberships within the Q-ROFSs framework. These terms are specifically applied to the *S*, *O*, and *D* components of FMEA. Second, the paper addresses heterogeneous expert input by assigning unequal weights to experts, reflecting differences in their opinions. Third, we demonstrate the model's application by identifying critical failure modes associated with COVID-19 risk factors. This paper is organised as follows. The next section recalls some prerequisite definitions and operations of Q-ROFSs. Section 3 presents the proposed Q-ROFS-FMEA risk assessment model. A case study of the risk factors of COVID-19 is illustrated in Section 4. In this section, detailed computational steps and results are presented. Finally, Section 5 concludes.

2 Preliminary

This section presents the definition of Q-ROFSs and its related operations.

Definition 2.1 Q-Rung Orthopair Fuzzy sets [32].

Let X be the universe of discourse. A Q-ROFSs $\tilde{Q}$ in X is denoted by

$$\tilde{Q} = \left\{ < x, \mu_{\tilde{Q}}(x), v_{\tilde{Q}}(x) > | \, x \in X \right\},$$

where $\mu_{\tilde{Q}} : X \to [0,1]$ and $v_{\tilde{Q}} : X \to [0,1]$ signify the membership degree and the non-membership degree of the element $x \in X$ to the set $\tilde{Q}$, respectively with the limited condition $0 \le \mu_{\tilde{Q}}^q(x) + v_{\tilde{Q}}^q(x) \le 1$. The indeterminacy degree $\pi_{\tilde{Q}}(x) = \sqrt[q]{1 - \mu_{\tilde{Q}}^q(x) - v_{\tilde{Q}}^q(x)}$.

For convenience, Yager [32] termed $\left(\mu_{\tilde{Q}}(x), v_{\tilde{Q}}(x)\right)$ a Q-rung Orthopair Fuzzy number (Q-ROFN), which is signified as $\ddot{q} = \left(\mu_{\tilde{Q}}, v_{\tilde{Q}}\right)$.

Definition 2.2 Accuracy value $H(\tilde{Q})$ [35].

Let $\tilde{Q} = \left(\mu_{\tilde{Q}}, v_{\tilde{Q}}\right)$ be a Q-ROFN. The score value $S(\tilde{Q})$ of the Q-ROFN $\tilde{Q} = \left(\mu_{\tilde{Q}}, v_{\tilde{Q}}\right)$ is defined as $s(\tilde{Q}) = \mu_{\tilde{Q}}^q - v_{\tilde{Q}}^q$, where $S(\tilde{Q}) \in [-1,1]$ and $q \ge 1$. The accuracy value $H(\tilde{Q})$ of the Q-ROFN $\tilde{Q} = \left(\mu_{\tilde{Q}}, v_{\tilde{Q}}\right)$ is defined as $H(\tilde{Q}) = \mu_{\tilde{Q}}^q + v_{\tilde{Q}}^q$, where $H(\tilde{Q}) \in [0,1]$ and $q \ge 1$.

Definition 2.3 Accuracy values of the Q-ROFNs [35]

Let $\tilde{Q}_1 = \left(\mu_{\tilde{Q}_1}, v_{\tilde{Q}_1}\right)$ and $\tilde{Q}_2 = \left(\mu_{\tilde{Q}_2}, v_{\tilde{Q}_2}\right)$ be any two Q-ROFNs, and let $S(\tilde{Q}_1)$ and $S(\tilde{Q}_2)$ be the score values of the Q-ROFNs $\tilde{Q}_1$ and Q-ROFNs $\tilde{Q}_2$ respectively.

Let $H(\tilde{Q}_1)$ and $H(\tilde{Q}_2)$ be the accuracy values of the Q-ROFNs $\tilde{Q}_1$ and Q-ROFNs $\tilde{Q}_2$, respectively,

(1) If $S(\tilde{Q}_1) > S(\tilde{Q}_2)$, then $\tilde{Q}_1 > \tilde{Q}_2$.

(2) If $S(\tilde{Q}_1) = S(\tilde{Q}_2)$ and $H(\tilde{Q}_1) > H(\tilde{Q}_2)$, then $\tilde{Q}_1 > \tilde{Q}_2$.

(3) If $S(\tilde{Q}_1) = S(\tilde{Q}_2)$ and $H(\tilde{Q}_1) = H(\tilde{Q}_2)$, then $\tilde{Q}_1 = \tilde{Q}_2$

Many scholars have studied and expanded mathematical operations over Q-ROFSs, a fascinating topic with many obstacles. The following are the basic activities outlined by Peng and Luo [36].

(1) Complement, $\ddot{q}^c = (\mu, v)$

(2) Union, $\ddot{q}_1 \cup \ddot{q}_2 = \left(\max\{\mu_1, \mu_2\}, \min\{v_1, v_2\}\right)$

(3) Intersection, $\ddot{q}_1 \cap \ddot{q}_2 = \left(\min\{\mu_1, \mu_2\}, \max\{v_1, v_2\}\right)$

(4) Subset, $\ddot{q}_1 \subseteq \ddot{q}_2 iff \mu_1 \le \mu_2, v_1 \ge v_2$

(5) Addition,

$$\ddot{q}_1 \oplus \ddot{q}_2 = \left(\left(\mu_1^q + \mu_2^q - \mu_1^q \cdot \mu_2^q \right)^{\frac{1}{q}}, v_1 \cdot v_2 \right)$$

(6) Multiplication.

$$\ddot{q}_1 \otimes \ddot{q}_2 = \left(\mu_1 \cdot \mu_2, \left(v_1^q + v_2^q - v_1^q \cdot v_2^q \right)^{\frac{1}{q}} \right)$$

These definitions of concepts and their operations are directly used in the computational implementation of the proposed work.

3 Proposed Q-ROFSs-FMEA

The FMEA is a computational tool that proactively strategized for examining a process whether it might fail. The tool is also used to analyse the relative impact of various failures in which process aspects that need to be altered the most can be identified. This section presents a new proposed Q-ROFS-FMEA where Q-ROFS and FMEA are combined. The computational procedures of fuzzy sets-FMEA method that was proposed by Ouyang et al. [29] become the basis in this work. To make it compatible with Q-ROFSs setting, several innovations to FMEA are made. The first innovation is the use of Q-ROFSs in defining linguistic terms where four-tuple number is used instead of one single number. To recognise the difference in experts' opinions and heterogenous information, unequal relative weight of experts is introduced as the second innovation. Finally, an aggregation operator is introduced to merge expert opinions of which a consensus RPN can be obtained. Details of these innovations are further explained in the computational procedures of the proposed Q-ROFSs-FMEA. The computational procedures of the proposed work are presented as follows.

Step 1: Determine the failure modes

To identify all probable failure modes denoted by $FM = \{FM_1, FM_2, \ldots, FM_m\}$ indicates the m failure modes that results in system failure, the experts $e_k (k = 1, 2, \ldots, l)$ with suitable expertise and experience are invited.

Step 2: Estimate the failure modes by linguistic terms.

Assessment scale of failure modes are made using linguistic terms due to uncertainty and ambiguity of human perceptions and heterogenous information. In this step, a new linguistic term is proposed. The linguistic terms proposed by Jin et al. [37] becomes the basis in this effort. Interval number of memberships in the work of Jin et al. [37] is simplified and transformed into memberships of Q-ROFSs. This transformation is made using Equation (1) and Equation (2) subjected to the condition $0 \le \mu_{\tilde{Q}ROF}^q(x) + v_{\tilde{Q}ROF}^q(x) \le 1$.

$$\left(\mu_{\tilde{Q}ROF}(x)\right) = \left(\left| \frac{\mu_{\tilde{Q}_1}(x) + \mu_{\tilde{Q}_2}(x)}{2} \right| \right) \tag{1}$$

$$\left(v_{\tilde{Q}ROF}(x)\right) = \left(1 - \mu_{\tilde{Q}ROF}\right) \tag{2}$$

where, $\mu_{\tilde{Q}ROF}(x)$ is a membership degree corresponding Q-ROFSs, and $v_{\tilde{Q}ROF}(x)$ is non-membership degrees corresponding Q-ROFSs.

For example, if the interval membership is ([0.99, 0.99], [0.01, 0.01]) then, by using Equation (1), $\left(\mu_{\tilde{Q}ROF}(x)\right) = \left(\left| \frac{0.99 + 0.99}{2} \right| \right) = 0.99$. Then using Equation (2), we have $\left(v_{\tilde{Q}ROF}(x)\right) = (1 - 0.99) = 0.01$. The similar transformations are made for other linguistic terms. Summarily, the new linguistic terms are presented in Table 2.

Table 2: The linguistic terms of Q-ROFSs

Scales	Linguistic terms	Q-ROFSs
0	Exceptionally high	(0.99,0.01)
1	Extremely High	(0.90,0.10)
2	Very High	(0.80,0.20)
3	High	(0.675,0.325)
4	Medium High	(0.525,0.475)
5	Medium	(0.50,0.50)
6	Medium Low	(0.40,0.60)
7	Low	(0.30,0.70)
8	Very Low	(0.175,0.825)
9	Extremely Low	(0.10,0.90)

To measure the risks and to make it compatible with the FMEA model, the linguistic terms are changed to linguistic of Severity (*S*), Occurrence (*O*) and Detection (*D*). Table 3 provides the linguistic terms for *S*, *O*, and *D* with Q-ROFSs.

Table 3: The linguistic terms for Severity (*S*), Occurrence (*O*) and Detection (*D*) with Q-ROFSs

Scale	Severity (*S*)	Occurrence (*O*)	Detection (*D*)	Q-ROFSs
9	Hazardous	Almost certain	Almost impossible	(0.99,0.01)
8	Serious	Very High	Very Remote	(0.90,0.10)
7	Very High	High	Remote	(0.80,0.20)
6	High	Moderately High	Very Low	(0.675,0.325)
5	Moderate	Moderately	Low	(0.525,0.475)
4	Low	Moderately low	Moderate	(0.50,0.50)
3	Very Low	Low	Moderately high	(0.40,0.60)
2	Slight	Slight	High	(0.30,0.70)
1	Very Slight	Remote	Very High	(0.175,0.825)
0	None	Almost Never	Almost certain	(0.10,0.90)

Step 3: Determine the weights of experts

There is an innovation in this step where weights of experts are introduced. Differently from Ouyang et al. [29] where no weight was introduced, this step introduces weights in which these weights are crucial as it represents the difference of human perceptions and heterogenous information.

The weights, λ_k for kth experts, are calculated using Equation (3) with q is a constant. The total weight of experts must equal to one.

$$\tilde{\lambda}_k = \frac{1-((1-\mu_{\tilde{Q}ROF}(x))+v_{\tilde{Q}ROF}(x))/2)}{\sum_{k=1}^{l} 1-((1-\mu_{\tilde{Q}ROF}(x))+v_{\tilde{Q}ROF}(x))/2)} \quad (3)$$

where $\sum_{k=1}^{l} \tilde{\lambda}_k = 1$

The linguistic terms used in finding the weight of experts is presented in Table 4.

Table 4: The weight of expert's preference scale

Scale	Linguistic terms	Corresponding Q-ROFSs
9	Exceptionally Important	(0.99,0.01)
8	Extremely Important	(0.90,0.10)
7	Very Important	(0.80,0.20)
6	Important	(0.675,0.325)
5	Medium Important	(0.525,0.475)
4	Neutral	(0.50,0.50)
3	Medium not Important	(0.40,0.60)
2	Not Important	(0.30,0.70)
1	Very Not Important	(0.175,0.825)
0	Extremely Not Important	(0.10,0.90)

The weights obtained here will be used for the next step of computational procedures.

Step 4: Aggregate the assessment of experts
In this step, the Q-rung Orthopair fuzzy weighted averaging operator (q-ROFWA) proposed by Liu and Wang [35] is used to aggregate the assessment of experts. An aggregated matrix to represent assessments made by k-th experts are calculated using Equation (4).

$$q-ROFWA(E_1, E_2, \ldots, E_l) = \left\langle \sqrt[q]{1-\prod_{k=1}^{l}\left(1-\mu_k^q\right)^{\tilde{\lambda}_k}}, \prod_{k=1}^{l} v_k^{\tilde{\lambda}_k} \right\rangle \quad (4)$$

Differently from Ouyang et al. [29] where no aggregation equation is used, an aggregation is inserted at this step. This aggregation operation is significant as it combines all expert opinions to become a consensus decision.
The q-ROFWA operator is employed because it effectively incorporates the weights of experts, making it well-suited for our context. Its simplicity allows for a balanced aggregation that accurately reflects expert consensus without adding unnecessary complexity. Additionally, the q-ROFWA operator was selected over other averaging methods due to its compatibility with q-ROF numbers, which supports a more precise representation of expert opinions.

Step 5: Determine score function values of failure modes
Score function, $s(\tilde{Q})$ is used for the defuzzification process. Equation (5) is used to find a crisp value.

$$s(\tilde{Q}) = \mu_{\tilde{Q}ROF}(x) - v_{\tilde{Q}ROF}(x) \quad (5)$$

Step 6: Calculate the RPN of failure modes using the multiplication operator of S, O and D (See Equation (6)).

$$RPN = S \times O \times D \quad (6)$$

where S, O, and D are risk parameters.

Step 7: Rank the failure modes using RPN results.
The final RPN results can be ranked in ascending order and the highest failure mode can be identified. The proposed computational procedures will be implemented in a case study investigating risk factors of COVID-19. Detailed computations and results will be discussed in the following section.

4 A case study of COVID-19 failure modes

This section describes the failure modes of COVID-19, the experts who are giving their assessment, and the proposed computational model used to implement the computation.

4.1 Failure modes

The list of failure modes for COVID-19 disease is defined. Table 5 shows the failure modes considered in this study and their respective literature sources.

Table 5: Selected failure modes of COVID-19

No.	Failure mode	Source of Literature
1	Older age (FM_1)	Rashedi, et al. [38] and Jordan et al. [39]
2	Gender (FM_2)	Gebhard et al. [40], Rashedi, et al. [38] and Ambrocino et al. [41]
3	Individual medical condition (FM_3)	De Sousa Lima et al. [42]
4	Occupational factors (FM_4)	Leso et al. [43]
5	Poor ventilation (FM_5)	Rashedi, et al. [38]
6	Low education (FM_6)	Rashedi, et al. [38]
7	Transmissibility (FM_7)	Rashedi, et al. [38]
8	Viral load COVID-19 and its receptor, ACE2 (FM_8)	Rashedi, et al. [38]

4.2 Experts' information

Five experts were invited to contribute their insights in assessing COVID-19 failure modes. A summary of their profiles is provided in Table 6.

Table 6: Biographical data of experts

Expert	Designation	Experience (year)	Academic
E_1	Senior Nurse	10	B,Sc Nursing, Community Health Nursing Certification
E_2	Senior Nurse	19	B,Sc Nursing, Community Health Nursing Certification
E_3	Public Health Expert	16	MBBS, MPH
E_4	Public Health Expert	11	MBBS, MPH
E_5	Nurse	5	B,Sc Nursing, Community Health Nursing Certification

The experts provide an assessment of failure modes and then analyse using FMEA.

4.3 Data

Specifically, eight failure modes for COVID-19, denoted as $(FM_1, FM_2, FM_3, FM_4, FM_5, FM_6, FM_7, FM_8)$ were evaluated by a group of experts $(E_1, E_2, E_3, E_4, E_5)$. Each expert assessed the failure modes based on severity, occurrence, and detection using a scale from zero to nine. To ensure consistency and minimize subjective bias, the experts were provided with Table 3, which outlines the numerical scale alongside its corresponding linguistic terms. Additionally, a brief training session was conducted to standardize the experts' understanding of these linguistic terms, enhancing alignment throughout the evaluation process.

Table 7: Assessment of severity, occurrence, and detection

Expert	FM	Severity (S)	Occurrence (O)	Detection (D)
E_1	FM_1	8	8	8
	FM_2	0	0	0
	FM_3	8	7	7
	FM_4	8	9	5
	FM_5	7	9	5
	FM_6	2	4	8
	FM_7	8	9	3
	FM_8	9	9	1
E_2	FM_1	9	9	8
	FM_2	8	6	1
	FM_3	9	7	8
	FM_4	9	8	6
	FM_5	7	9	4
	FM_6	3	8	8
	FM_7	9	9	3
	FM_8	9	9	2
E_3	FM_1	9	9	8
	FM_2	6	2	0
	FM_3	9	9	9
	FM_4	9	9	4
	FM_5	9	9	0
	FM_6	7	9	8
	FM_7	9	9	2
	FM_8	9	9	2
E_4	FM_1	9	9	8
	FM_2	6	2	2
	FM_3	9	9	6
	FM_4	9	9	6
	FM_5	9	9	0
	FM_6	9	7	9
	FM_7	9	9	3
	FM_8	9	9	3
E_5	FM_1	7	6	8
	FM_2	1	1	3
	FM_3	8	8	5
	FM_4	8	5	6
	FM_5	6	6	5
	FM_6	7	5	6
	FM_7	8	7	4
	FM_8	6	8	1

The heterogenous information from the above table are regarded as the input data in which these data are then computed in accordance with the proposed Q-ROFSs-FMEA (see Section 3).

4.4 Computation and results

The Q-ROFSs-FMEA method is implemented for the case of failure modes of COVID-19 disease. This subsection presents the detailed computations of the input data using the Q-ROFSs-FMEA method.

Step 1: Determine the failure modes
The list of COVID-19 failure modes is provided in Section 4.1, and the experts' biographical information is detailed in Section 4.2.

Step 2: Estimate the failure modes by using linguistic terms.
The linguistic 0-9 scales from Table 7 are converted to matrix form in Q-ROFSs information and the resulting $\ddot{S}, \ddot{O}, \ddot{D}$ matrices are shown as,

$$\ddot{S} = \begin{bmatrix} \langle 0.900, 0.100 \rangle & \langle 0.990, 0.010 \rangle & \cdots & \langle 0.800, 0.200 \rangle \\ \langle 0.100, 0.900 \rangle & \langle 0.900, 0.100 \rangle & \ldots & \langle 0.175, 0.825 \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle 0.990, 0.010 \rangle & \langle 0.990, 0.100 \rangle & \cdots & \langle 0.675, 0.325 \rangle \end{bmatrix}_{8\times 5}$$

$$\ddot{O} = \begin{bmatrix} \langle 0.900, 0.100 \rangle & \langle 0.990, 0.010 \rangle & \cdots & \langle 0.675, 0.325 \rangle \\ \langle 0.100, 0.900 \rangle & \langle 0.675, 0.325 \rangle & \ldots & \langle 0.175, 0.825 \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle 0.990, 0.010 \rangle & \langle 0.990, 0.010 \rangle & \cdots & \langle 0.900, 0.100 \rangle \end{bmatrix}_{8\times 5}$$

$$\ddot{D} = \begin{bmatrix} \langle 0.900, 0.100 \rangle & \langle 0.900, 0.100 \rangle & \cdots & \langle 0.900, 0.100 \rangle \\ \langle 0.100, 0.900 \rangle & \langle 0.175, 0.825 \rangle & \ldots & \langle 0.400, 0.600 \rangle \\ \vdots & \vdots & \ddots & \vdots \\ \langle 0.100, 0.900 \rangle & \langle 0.300, 0.700 \rangle & \cdots & \langle 0.175, 0.825 \rangle \end{bmatrix}_{8\text{x}5}$$

Step 3: Determine the weights of experts.
The linguistic terms defined in Table 4 are used to determine the weights of experts. The importance of experts is represented by a linguistic term and its corresponding Q-ROFSs. Table 8 shows the linguistic terms and their respective Q-ROFSs which reflect the importance of experts.

Table 8: Importance of experts in Q-ROFSs

Expert	Linguistic term	Q-ROFSs
E_1	Neutral	$\langle 0.500, 0.500\rangle$
E_2	Very Important	$\langle 0.800, 0.200\rangle$
E_3	Important	$\langle 0.675, 0.375\rangle$
E_4	Neutral	$\langle 0.500, 0.500\rangle$
E_5	Medium not Important	$\langle 0.400, 0.600\rangle$

With the assumption that weights of experts are unequal, then Equation (3) is used to compute relative weights of experts. Given the information in Table 8, weight for the first expert, $\tilde{\lambda}_1$ for example is computed as

$$\tilde{\lambda}_1 = \frac{1-((1-0.500^3)+0.500^3)/2)}{\left[\begin{array}{l}\left(1-((1-0.500^3)+0.500^3)/2)\right)+\left(1-((1-0.800^3)+0.200^3)/2)\right)\\ +\left(1-((1-0.675^3)+0.375^3)/2)\right)+\left(1-((1-0.500^3)+0.500^3)/2)\right)+\\ \left(1-((1-0.400^3)+0.600^3)/2)\right)\end{array}\right]}$$

$$\tilde{\lambda}_1 = 0.178$$

Similarly, the weights for other experts are calculated and summarised in Table 9.

Table 9: Weight of experts

Expert	Weights
E_1	0.178
E_2	0.268
E_3	0.224
E_4	0.178
E_5	0.151

Step 4: Aggregate the evaluation from different experts using q-ROFWA aggregation operator of matrices, $\bar{S},\bar{O},\bar{D}$. The aggregated matrices to represent assessments made by *k-th* experts are calculated using Equation (4). For example, the aggregated value of FM_1 is computed as follows.

$$\bar{s}_{FM_1} = \left\langle \sqrt[3]{1-\prod_{k=1}^{l}\left[\begin{array}{l}\left((1-0.900^3)^{0.178}\right)\left((1-0.990^3)^{0.268}\right)\left((1-0.990^3)^{0.224}\right)\\ \left((1-0.990^3)^{0.178}\right)\left((1-0.800^3)^{0.151}\right)\end{array}\right]}, \prod_{k=1}^{l}\left[\left(0.100^{0.178}\right)\left(0.010^{0.268}\right)\left(0.010^{0.224}\right)\left(0.010^{0.178}\right)\left(0.200^{0.151}\right)\right] \right\rangle$$
$$= \langle 0.9771, 0.0237\rangle$$

$$\bar{o}_{FM_1} = \left\langle \sqrt[3]{1-\prod_{k=1}^{l}\left[\begin{array}{l}\left((1-0.900^3)^{0.178}\right)\left((1-0.99^3)^{0.268}\right)\left((1-0.99^3)^{0.224}\right)\\ \left((1-0.99^3)^{0.178}\right)\left((1-0.675^3)^{0.151}\right)\end{array}\right]}, \prod_{k=1}^{l}\left[\left(0.1^{0.178}\right)\left(0.01^{0.268}\right)\left(0.01^{0.224}\right)\left(0.01^{0.178}\right)\left(0.325^{0.151}\right)\right] \right\rangle$$
$$= \langle 0.9758, 0.0255\rangle$$

$$\bar{d}_{FM_1} = \left\langle \sqrt[3]{1-\prod_{k=1}^{l}\left[\begin{array}{l}\left((1-0.900^3)^{0.178}\right)\left((1-0.900^3)^{0.268}\right)\left((1-0.900^3)^{0.224}\right)\\ \left((1-0.900^3)^{0.178}\right)\left((1-0.900^3)^{0.151}\right)\end{array}\right]}, \prod_{k=1}^{l}\left[\left(0.100^{0.178}\right)\left(0.100^{0.268}\right)\left(0.100^{0.224}\right)\left(0.100^{0.178}\right)\left(0.100^{0.151}\right)\right] \right\rangle$$
$$= \langle 0.90, 0.10\rangle$$

It is good to note that while parameter value q can be varied, in this computation q=3 is chosen as to cushion the impact of non- membership with negation of membership. The aggregated matrices $\bar{S},\bar{O},\bar{D}$ are shown as

$$\bar{S} = \begin{array}{c}\langle 0.977, 0.0237\rangle\\ \langle 0.732, 0.327\rangle\\ \langle 0.979, 0.021\rangle\\ \langle 0.979, 0.021\rangle\\ \langle 0.941, 0.065\rangle\\ \langle 0.844, 0.197\rangle\\ \langle 0.979, 0.021\rangle\\ \langle 0.984, 0.017\rangle\end{array} \quad \bar{O} = \begin{array}{c}\langle 0.976, 0.026\rangle\\ \langle 0.471, 0.611\rangle\\ \langle 0.949, 0.054\rangle\\ \langle 0.969, 0.033\rangle\\ \langle 0.984, 0.017\rangle\\ \langle 0.01, 0.114\rangle\\ \langle 0.985, 0.016\rangle\\ \langle 0.986, 0.014\rangle\end{array}$$

$$\bar{D} = \begin{array}{c}\langle 0.9, 0.1\rangle\\ \langle 0.255, 0.791\rangle\\ \langle 0.905, 0.106\rangle\\ \langle 0.623, 0.383\rangle\\ \langle 0.438, 0.623\rangle\\ \langle 0.924, 0.079\rangle\\ \langle 0.403, 0.604\rangle\\ \langle 0.299, 0.719\rangle\end{array}$$

Step 5: Determine score function values of $\bar{S},\bar{O},\bar{D}$.
Score function is used for the defuzzification process (see Equation (5)). The score function values of $\bar{S},\bar{O},\bar{D}$ are shown in Table 10.

Step 6: Calculate the RPN of failure modes using the product of S, O, D using Equation (6). For example, RPN of FM_1 in the last column of Table 10 can be calculated as

$$RPN_{FM_1} = 0.953 \times 0.95 \times 0.8$$
$$= 0.725$$

The similar operation is implemented to other failure modes.

Step 7: Rank the failure modes using RPN results.

The ranking of failure modes using Q-ROFS-FMEA method is obtained as shown in Table 10.

Table 10: The score function of $\bar{S}, \bar{O}, \bar{D}$, RPN and ranking

FM	Score function $\bar{S}$	Score function $\bar{O}$	Score function $\bar{D}$	RPN	Rank
FM_1	0.953	0.950	0.800	0.725	1
FM_2	0.405	-0.140	-0.536	0.030	5
FM_3	0.958	0.895	0.800	0.686	2
FM_4	0.958	0.936	0.240	0.216	4
FM_5	0.876	0.967	-0.185	-0.157	6
FM_6	0.647	0.787	0.845	0.430	3
FM_7	0.958	0.969	-0.201	-0.187	7
FM_8	0.967	0.972	-0.420	-0.395	8

The above result shows the RPN of each failure modes in which eventually can portray the rank of RPN. It indicates that *FM_1* (older people) is the highest risk factor and *FM_2* (gender) is the lowest risk factor of COVID-19. The final results are subjected to comparative analysis of which will be explained in the following section.

5 Comparative analysis

The same data used to determine the ranking using the proposed Q-ROFSs-FMEA is then computationally reiterated using the existing FMEA methods such as crisp FMEA, Triangular Fuzzy Number FMEA (TFN-FMEA), and Intuitionistic Fuzzy Set FMEA (IFS-FMEA). It is good to note here that the existing FMEA method is the method used without considering the Q-ROFSs. Table 11 shows the comparison ranking of failure modes based on Q-ROFS-FMEA method alongside other FMEA methods.

Table 11: The ranking of failure modes

FM	RPN FMEA	RPN TFN-FMEA	RPN IFS-FMEA	RPN Q-ROFS-FMEA
FM_1	450.378(1)	0.846 (1)	0.572 (1)	0.725 (1)
FM_2	91.456(8)	0.021 (8)	0.006 (5)	0.030 (5)
FM_3	437.326(2)	0.696 (2)	0.393 (2)	0.686 (2)
FM_4	412.574(3)	0.559 (3)	0.212 (3)	0.216 (4)
FM_5	235.316(7)	0.231 (6)	-0.220 (6)	-0.157 (6)
FM_6	381.611(4)	0.419 (4)	0.033 (4)	0.430 (3)
FM_7	369.809(5)	0.246(5)	-0.222 (7)	-0.187 (7)
FM_8	334.708(6)	0.174 (7)	-0.331 (8)	-0.395 (8)

It can be seen that the RPN values obtained from FMEA are much higher compared to the RPN obtained from TFN-FMEA, IFS-FMEA and Q-ROFSs-FMEA. The main reason behind this big difference is because the type of numbers used. In the FMEA method, assessments are made using real numbers from 0 to 9, whereas fuzzy numbers between 0 and 1 are utilized in TFN-FMEA, IFS-FMEA, and Q-ROFS-FMEA. The RPN values in Q-ROFS-FMEA are significantly lower due to the use of four-tuple values, which represent the membership degrees within Q-ROFSs.

Furthermore, the RPNs obtained from the methods are used to compare the ranking of risk factors (*FMs*). The comparison of these ranks and their respective RPNs can be seen in Figure 1.

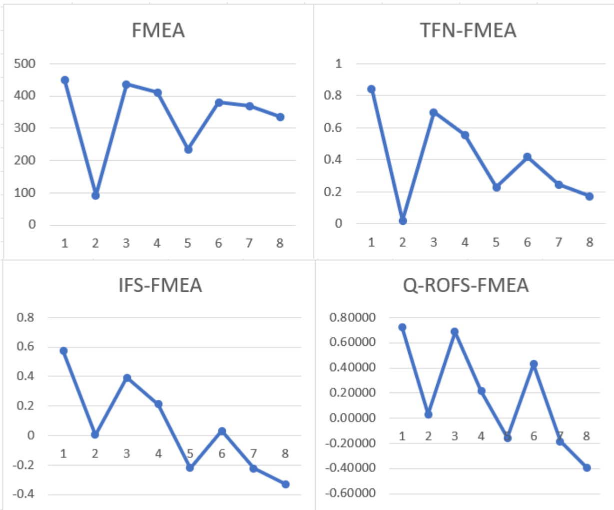

Figure 1: Comparison of RPN values obtained using Q-ROFS- FMEA versus other methods

The ranks of failure modes of COVID-19 obtained using the proposed Q-ROFS-FMEA and some existing FMEA methods are shown in Figure 2.

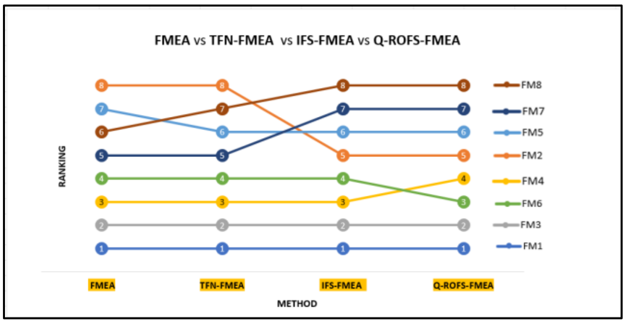

Figure 2: Comparison of *FM* ranking obtained using Q-ROFS- FMEA versus other methods

The rankings of failure modes across these four methods show a high level of consistency. Both the first FM_1 (older age) and second FM_3 (individual medical condition) ranks are the same across all methods. Minor shifts are observed in the third and fourth ranks, but there are significant changes from the fifth rank onward among the methods. Unlike other methods, the traditional FMEA approach does not account for fuzziness or uncertainty, while TFN-FMEA only considers the membership degree and omits the non-membership aspect of the problem. IFS-

FMEA, on the other hand, incorporates both membership and non-membership degrees and can partially address hesitancy. The proposed Q-ROFS-FMEA generates ranking results closely aligned with IFS-FMEA, primarily due to its ability to manage uncertainty. However, Q-ROFS-FMEA offers an advantage by introducing the *q* parameter, which provides enhanced flexibility not available in IFS-FMEA. Although IFS-FMEA includes both non-membership and hesitancy degrees, it has been criticized for limitations in practical applications, as its dual memberships must sum to one or less, which can restrict its adaptability.

Applying Q-ROFS to FMEA offers greater flexibility, as the parameter *q* can be adjusted to meet the specific requirements of various risk decision-making contexts. The Q-ROFS framework is especially well-suited to handle complex scenarios, with the parameter *q* providing added adaptability. This ability to adjust membership grade space via *q* is a significant advantage, as it enhances Q-ROFS's capacity for analyzing ambiguous information. Compared to crisp sets, fuzzy sets, and intuitionistic fuzzy sets, Q-ROFS is more robust and comprehensive. With the inclusion of *q*, the range of uncertain information captured by Q-ROFS is notably extensive and flexible, making it a powerful tool for addressing uncertainty in diverse applications. To assess the robustness of the parameter *q* in the Q-ROFS-FMEA method, a sensitivity analysis is conducted, with the results presented in Table 12.

Table 12: Sensitivity analysis of Q-ROFS-FMEA method with different values of *q*

q	Ranking
1	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_7 \succ FM_5 \succ FM_8$
2	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
3	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
4	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
5	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
6	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
7	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
8	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
9	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$
10	$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_2 \succ FM_5 \succ FM_7 \succ FM_8$

Based on Table 12, the sensitivity analysis results indicate that QROFS-FMEA is a robust method, as variations in the parameter *q* do not affect the overall ranking outcomes, except when *q=1*. At this specific value, a minor shift occurs between the sixth and seventh ranks compared to the other tested *q* values.

It is recalled that the objective of this paper is to identify the most critical failure modes of the risk factor COVID-19 using the proposed Q-ROFSs-FMEA. It is unveiled that FM_1 (older age) is the highest risk among the other failure modes. The relative risks of all factors are obtained as

$$FM_1 \succ FM_3 \succ FM_6 \succ FM_4 \succ FM_5 \succ FM_7 \succ FM_8 \succ FM_2$$

where the lowest failure mode in combating with the COVID-19 disease is FM_2 (gender). Therefore, this study suggests that the factor of 'gender' is not the main risk in estimating the likelihood of COVID-19 diseases. However, the failure mode FM_1 'older age' should be given the highest priority for risk mitigation of COVID-19. It is also good to mention here that the top two worst failure modes of the risk factor of COVID-19 are FM_1 and FM_3. This research sees the 'older age' and 'individual medical condition' failure modes are the most at-risk groups compared to other failure modes. This result is in line with the findings of Rod et al. [44], who found that the two main failure modes for COVID-19 disease are age and comorbidities.

6 Conclusion

Since 2019, the world has grappled with the profound impact of COVID-19. Numerous efforts have been undertaken to prevent its spread, yet questions remain as to whether these measures are truly sufficient to minimize the risk of infection. Moreover, many of the failure modes remain inconclusive and vague. Therefore, this research is conducted to identify the most critical failure modes of risk factors COVID-19. To meet this objective, the risk evaluation model, Q-ROFS-FMEA is proposed. The input data was elicited from a group of experts in public health who have been active in treating COVID-19 patients. Data were computed using the proposed Q-ROFS-FMEA where weights of experts and aggregation operators are the new features in the proposed method. This research indicates that the failure mode 'older age' is identified as the most-at-risk group. The result also shows that the failure mode 'gender' is the weakest risk factor. To validate these findings, a comparative analysis is presented where the results obtained from Q-ROFS-FMEA is compared to the results of the conventional FMEA, TFN-FMEA and IFS-FMEA. The comparative analysis demonstrates that the proposed Q-ROFS-FMEA method is similar to the IFS-FMEA; however, it yields different rankings when compared to the TFN-FMEA and FMEA methods. Notably, the top two highest risk factors for COVID-19 identified across all four methods are consistent: older age and individual medical conditions. This study provides an essential contribution to the medical field to mitigate the spread of the COVID-19 disease. However, the findings need further investigation as there are several limitations surrounded this study. The first limitation is on the data input. Since the data was collected from a group of experts, additional validations on the expert selection and data triangulation are required. Second limitation is on the ranking results where the results are obtained using the proposed works. Future research could benefit from incorporating insights from other studies, such as Gams and Kolenik [45], who highlighted exponential technological progress and its role in addressing human challenges, and Janco et al. [46], who investigated key cultural, developmental, and travelrelated factors in pandemic spread. Expanding the methodological scope by utilizing alternative risk evaluation models such as the Risk Expected Value (REV) method, Data Envelopment Analysis, Monte Carlo Risk Analysis, and Fuzzy Bayesian Network could further enrich the understanding of COVID-19 risk factors and refine predictive accuracy.

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Conflicts of interest
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Availability of data and materials
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Ethics approval and consent to participate
Not applicable

Consent for publication
Not applicable

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