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# Fuzzy Adaptive Resonance Theory Failure Mode Effect Analysis Non-Healthcare Setting for Infectious Disease: Review

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**ABSTRACT**

Fuzzy Adaptive Resonance Theory (ART) is an ART network that is developed as one of the alternative methods to evaluate risk priority number (RPN) in failure mode and effect analysis (FMEA). Not only is FMEA are common technique as an analysis tool in industrials sectors, but also, especially during the global emergency COVID-19 pandemic hits, FMEA is used in prevention and mitigation measures. Many alternative methods have been proposed. However, not many investigations use clustering models such as Fuzzy ART in FMEA. This paper aims to provide a comprehensive review and then propose a model for systematic risk analysis which implement the Fuzzy ART model, named clustering- Transmission Causes and Effects Analysis (c-TCEA), for the prevention and mitigation of infectious diseases.



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## 1. INTRODUCTION

Illnesses brought on by pathogens or their toxic byproducts that are spread from an animal, contaminated things, or even an infected person to a vulnerable host are known as infectious diseases. They have a significant global burden of disease, disproportionately affecting vulnerable populations. Diarrheal diseases, lower respiratory tract infections, malaria, human immunodeficiency virus(HIV)/ acquired immunodeficiency syndrome(AIDS), and tuberculosis (TB) are leading causes of mortality worldwide. Emerging infectious diseases like Middle East Respiratory Syndrome, Extensively Drug-Resistant Tuberculosis (XDR TB), and Zika virus pose new threats. Preventing and controlling infectious diseases requires a thorough understanding of transmission factors, including agent, host, and environmental determinants.

Infectious diseases, such as Coronavirus disease 2019 (COVID-19), still pose life-threatening risks. As of July 2023, there are over 836 million cases of COVID-19 around the world[1]. It is very advantageous to create interventions that will eliminate and stop the spread of a pandemic strain on the human population. However, the rapid spread of the disease gives significant challenges to designing and developing realistic risk assessments in order to contain the emergence of the disease.

According to [2], risk analysis and management have a major role in human history when battling against pandemics or endemic diseases, which have been existing for a long time. In [2] also mentioned that interventions and measures from experts in handling infectious diseases had been placed for centuries. One example is the establishment of policies and laws for isolation and quarantine during emergency periods. These were mentioned as a crucial component for the mitigation and control of infectious diseases and as one of the societal risk management strategies [3], [4].

Modern risk management is seen in practice as a process of risk identification, assessment, and prioritizing, followed by a coordinated and cost-effective deployment of resources to reduce, manage, and control the likelihood or impact of unfavourable events. Therefore, the failure modes and effect analysis (FMEA) are introduced as a method to do risk analysis and management for a broad range of industries. For example, transport and automotive[5], [6], agriculture[7], [8], and medical and healthcare[9]–[11]. Many variations of the FMEA method are accessible in writing. The general FMEA methodology, however, takes into account root causes, failure modes, effect analysis and relationships, as well as corrective actions, when implementing FMEA. A straightforward scoring method that uses three indices—Severity (S), Occurrence (O), and Detection (D)—as inputs and a Risk Priority Number (RPN) as output is used for risk analysis and prioritization.

Risk management in non-healthcare settings for COVID-19 has been the focus [12]. During the pandemic, FMEA is also being implemented in the healthcare setting as well. For example, transferring protocol in the management of COVID-19 patients [13], assessing the COVID-19 protocols of obstetric emergencies[14], and controlling the admission of asymptomatic COVID-19 patients to the emergency department[9]. Despite the numerous FMEA implementations in many application fields and various research on the risks of infectious disease in healthcare settings, a systematic method for regular risk management of infectious disease has not yet been developed. Besides that, according to [15], the transmission of infectious disease cannot be (fully) interrupted by using basic precautions of healthcare alone. Therefore, transmission-based precautions can be adopted. An innovative method in this approach is the transmission-based risk analysis methodology, where Fuzzy ART will be used to rate and prioritize all the risks, which considers recent developments in risk research for the healthcare and non-healthcare environments.

Thus, Fuzzy ART will be used as a tool to explore FMEA from a different approach. The main aim of this paper is to outline step-by-step transmission-based risk analysis and management, where the risk is all rated and prioritized. This paper is organized into several sections. A summary of Fuzzy ART will be in Section 2. Section 3 describes the FMEA and the Fuzzy Adaptive Resonance Theory (Fuzzy ART) algorithm applied to FMEA will be further explained. Section 4 presents the proposed Fuzzy ART-TCEA. Finally, Section 5 concludes the review study purposes.

## 2. FUZZY ART (ADAPTIVE RESONANCE THEORY)

Carpenter *et al*. [16] created the algorithm known as fuzzy-adaptive resonance theory (ART). Any binary or analogue data can be clustered using this neural network model. One of the main causes for the development of Fuzzy ART was ART 1's inability to classify analogue data, as well as the Predictive ART architecture based on ART1 modules.

ART is a prime example of how developing artificial intelligence (AI) and comprehending 'the brain' can work together to benefit both fields. ART draws its inspiration from the cortex and deeper learning structures' recurrent organization of information processing. The difficulties of implementing ART on a computer should not be confused with the fact that it was inspired by recurrent brain structures [17]. A new set of principles that have been realized as quantitative systems and can be applied to problems involving prediction, category learning, and recognition have been added to the earlier theory. This has been done through a series of developing ART neural network models.

In order to address clustering and classification problems, ART networks are frequently used. A clustering algorithm takes a set of input vectors as input to generate a set of clusters, along with a mapping from each input vector to each cluster as output. A specific similarity measure should be used to determine which input vectors should be mapped to the same cluster. The interpretation of each input vector mapped to a cluster can be indicated by the labelling of the clusters[16].

There are several classical ART clustering algorithms, such as ART1, ART2, ART2A, ART3, and Fuzzy ART[18]–[20].

ART1: The basic ART network and its cluster binary inputs.

ART2: Clusters real-value input patterns.

ART2A: A fast version of ART2

ART3: An extension of ART that controls the search process with "chemical transmitters" in a hierarchical ART structure.

Fuzzy ART architecture: Fuzzy set theory computations are incorporated into ART1. Instead of the crisp operator, uses the fuzzy AND operator.

ART adapts to input indefinitely. If the environment and the patterns are sufficiently related, new categories can emerge when the environment does not match any of the observed patterns [21]. An output and input layer make up the two layers of a typical ART network. There are no hidden layers. The dynamics of the network are controlled by an orienting subsystem and an attention subsystem. The orienting subsystem chooses whether to accept a winning neuron (or category) proposed by the attention subsystem [22]. According to [23], by replacing the appearance of the logical AND intersection operator (∩) in ART1 with the MIN operator (^) of fuzzy set theory, the generalization of learning both binary and analog input patterns is achieved.

Fuzzy ART is a framework for adaptive resonance that provides a unified architecture for inputs with both binary and continuous values. Fuzzy ART operations only accept binary vectors in ART1 as a special case. According to [23], by replacing the appearance of the logical AND intersection operator (∩) in ART1 with the MIN operator (^) of fuzzy set theory, it is achievable to generalize the learning of both binary and analogue input patterns. In [24], The researcher noted that several modifications to ART1 were made as part of the Fuzzy ART neural network. The first change was that non-binary input vectors could be processed. Secondly, there was a single weight vector connection and finally was applied in addition to the vigilance threshold (ρ). A choice parameter (α) and a learning rate (β) are two additional parameters that had to be specified.

### 2.1. Related Research

Several researchers have looked into applications of fuzzy ART networks. As mentioned in the introduction, which is Section 1, the Fuzzy ART algorithm, was developed by Carpenter *et al.* [16]. Fuzzy ART is known for its incorporation of the computation or ART 1. The major properties of Fuzzy ART were explained in [25]. Template properties, reset access properties, access properties, and properties relating to the number of list presentations required for weight stability were the four categories into which the properties were divided. Next, [26] also explained the properties of learning a Fuzzy ART variant. In this article, they demonstrated that Fuzzy ART's fast training times applied to both large and small values of the choice parameter. A robust pattern recognition model which possesses robust and invariant properties for the Fuzzy ART algorithm was developed by Kim *et al.* [27]. Next, novel geometric concepts adapted from the original architecture of Fuzzy ART and two fuzzy ART Modules ART-a and ART-b linked together via inter-ART Module (Fuzzy ARTMAP) were introduced in [28]. Fuzzy ART categories' geometrical interpretation has yielded important insights, and more recently, the original framework has been expanded to include new geometric ideas. Other than that, a pair of ART modules (ARTMAP neural networks) and Fuzzy ART were also applied to the electric load-forecasting problem [29]. The Fuzzy ART and ARTMAP method have been proven to reduce the processing time and improve the quality of the results, compared to the classical forecasting methods. Fuzzy ART was used in [30] to estimate a high-performance concrete mix proportion model rather than using difficult function approximation methods. Furthermore, Fuzzy ART was also applied as a similarity analysis and clustering of the Failure Mode and Effect Analysis (FMEA) model for solving agriculture problems[31].

The Fuzzy ART algorithm, is known as an unsupervised learning algorithm based on the ART algorithm and fuzzy logic, is used for clustering and pattern recognition. It is capable of processing imprecise and uncertain data and classifying them into different clusters based on their similarity. Fuzzy ART's straightforward and simple architecture makes it simple to explain how the neural network responds to input patterns [23]. This is in contrast to other models that find it difficult to explain the input pattern, generate a specific output, and being able to learn (without disregarding past learning).

## 3. FMEA (FAILURE MODE EFFECT ANALYSIS)

FMEA is a technique and instrument for identifying failure causes and predicting their effects. The main aims of the FMEA are to evaluate the fundamental causes and effects of failure modes in each component, identify potential failure modes, reduce the likelihood of failure modes, and identify what can be avoided. The results of FMEA make an easier risk management decision-making [32]. The RPN has three indices: severity (S), occurrence (O), and detection(D), and it is used in the FMEA method to identify the cause of the failure [33]. Many researchers have used FMEA as a methodology in many applications. In [34], a risk assessment using a more general RPN methodology was proposed for the preventive analysis of the product design and management process. In [6], a model-based design safety analysis system(based on the FMEA method) has provided beneficial results in designing automatic electrical safety analysis tools which have been integrated into the software. Besides that, [5] also proposed a systematic risk assessment approach which combined FMEA and POFIA (pessimistic–optimistic fuzzy information axiom) to evaluate the risk at the railway dangerous goods transportation system. Two different calculation results approaches were compared, and the improved approach was proven to be much more reliable than the traditional FMEA approach. Next, [7] has improved the FMEA traditional method with a genetic-algorithm- based design of fuzzy membership functions and monotone fuzzy rules for risk assessment and analysis the rice production, which indirectly improved food safety in the agriculture sector. Another example in the same sector was the edible bird nest production quality[8]. Fuzzy FMEA was used as a quality and risk assessment tool during the processing of the edible bird nest. In addition, the number of publications regarding the applications of FMEA to healthcare risk analysis is also escalating. For example, in [35], FMEA methodology was used to assess the risks for patients who were undergoing radiotherapy treatment. The RPN values were calculated and determined whether any safety measures should be proposed for safety improvement and process quality. Besides that, FMEA was also used as a tool to anticipate potential failures during the COVID-19 pandemic for the admission and transfer of patients in the emergency rooms for everyone's safety, where a traditional FMEA was implemented[9]. More examples of FMEA applications in healthcare risk analysis were reviewed in [36] to evaluate the improvement of quality and error reduction when employing the FMEA method in the healthcare environment.

However, the traditional FMEA method has many drawbacks in its implementation, as mentioned in several publications, for various reasons[37]–[45]. There are three drawbacks shown below.

i. Risk assessment and prioritization problems
ii. Complex FMEA Worksheet
iii. Complicated application

The first drawback in implementing FMEA is risk-assessment and prioritization problems. The traditional RPN model used in FMEA has a number of drawbacks, including failing to take into account the relative significance of the Detection (D), Occurrence (O), and Severity (S) indices [42], producing similar RPN values for various combinations of D, O, and S with different risk implications [43], and making the three risk indices difficult to accurately estimate [37], [44]. The mathematical formulas used to calculate RPN values also contain uncertainties[41]. The second drawback is related to the complexity of the FMEA worksheet. Due to their large entries, FMEA worksheets can become complex and challenging to construct, interpret, and read, making it difficult for FMEA users to identify the overall structure[45]. The third drawback is that it can be hard to create, interpret, and read the FMEA worksheet. Due to the extensive entries in FMEA worksheets, users are not able to see the overall structure of the worksheets[45].

Yet, the drawbacks of the traditional FMEA methods can be overcome with improvements by modification of the traditional FMEA method, as mentioned. According to [46], there were five classifications of risk evaluation approaches in FMEA, which are MCDM (multi-criteria decision making, AI (artificial intelligence), MP (mechanical programming), integrated methods, and others. Generally, the MCDM approach interprets S, O, and D as the sub-criteria (or the decision criteria), and decision alternatives were evaluated. In this approach, the S, O, and D values can be precise and imprecise. Meanwhile, the AI approach uses intelligent algorithms, such as a rule base system, fuzzy adaptive resonance (ART), fuzzy rule base system, and fuzzy cognitive map, in FMEA. For the MP approach, the S, O, and D values can be precise or usually imprecise. Examples of the techniques that are used to prioritize failure modes are fuzzy envelopment analysis and fuzzy-ordered weighted geometric averaging. Next, integrated approaches are approaches that aim to combine more than one approach for risk evaluation. For example, fuzzy evidential, fuzzy analytical hierarchical process and grey theory.

In this paper, the focus was on the use of the clustering technique for the analysis of the failure mode in FMEA. Vital to note that in [40] where the use of Fuzzy ART in FMEA is examined and proves the different S, O, and D combinations could result in the same RPN scores. There were several justifications for the benefits of applying clustering techniques to FMEA stated in [31]. Firstly, clustering directly addressed the initial S, O, and D values. Next, comparison or visualization of failure modes as informational clusters in the S, O, and D spaces was made possible by clustering. Additionally, loss or modification of crucial information for decision-making was prevented by using the original S, O, and D scores rather than the S, O, and D scores that have been mapped into a common domain.

There are many popular clustering approaches, such as k-means clustering[47], fuzzy c-means[48], and fuzzy ART[16]. The use of Fuzzy ART for clustering failure modes in FMEA into different groups will be implemented in the proposed implementation, where its adaptive and incremental learning properties and the failure modes will be prioritized.

### 3.1. Fuzzy ART-FMEA

For this section, the Fuzzy ART algorithm that is applied to FMEA and RPNs, will cluster and be further described. The fuzzy art model for FMEA is shown in [40]. In Figure 1, $x_{i,j}$ is the input of the model, $C_s$ represents the failure mode classes and $w_{i,j,s}$ weight between Layers 1 and 2. Additionally, it determines whether each input value at Layer 1 belongs to another class at Layer 2.

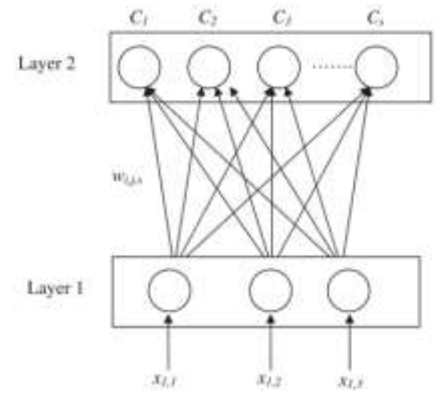


Figure 1. Modelling FMEA methodology by Fuzzy ART [40]

For each input, the severity, occurrence and detection values that compose the RPN value are assessed independently. Although RPN values are equivalent to one another, FMEA values are assessed independently using severity, detection, and occurrence values rather than a multiple of these factors. Hence, RPN values constitute the inputs as a result, and the system is shown with each input individually as (S, O, D). In each event, a three-data input (S, O, D) input is presented to the system by effective parameter results from the application of FMEA to test problems, and related inputs are clustered according to the three indices.

Figure 2 shows the flowchart of the Fuzzy ART FMEA methodology. There are 11 steps in this methodology. Step 1 is normalization. Each of the three input values $I_{(i,j)}$, which are S, O and D, is normalized by using equation (1)

$$NI_{i,j} = \frac{I(i,j)-min(j)}{max(j)-min(j)} \tag{1}$$

Where i: 1→n, n is the maximum failure mode number, j: 1: Severity(S) 2. Occurrence (O), and 3. Detection(D)

$NI_{i,j}$ represents the normalized input value.

Step 2 is determined the parameter. The values of α, ρ and β parameters will be given. Following are the parameter intervals for any Fuzzy ART problem:

i. Vigilance threshold, ρ
Responsible for the number of classes (0< ρ ≤1).

ii. Choice Parameter, α
Effective in class selection (0< α ≤ 1)

iii. Learning Rate, β
Controlling the classification's pace (0< β ≤ 1)

The user defines the parameters, and the choice of parameters is based on the type of problem.

Step 3 is the determination of initial weights for Fuzzy ART FMEA. First, all weights are assigned a value of 1. Class, $C_s$ number is set as s = 1.

$$w_{i,j,s}(0) = 1 \ and \ s = 1 \ for \ \ \forall i,j \tag{2}$$

Step 4 is the representation of to the network's input values. Input vector (x) (normalized values of input triple) is designated to the network:

$$x: \ \forall i,j \in (0,1) \tag{3}$$

Step 5 is the computation of the choice function value. The following defines the choice function $T_{i,j,s}$.

$$T_{i,s}(NI) = \frac{\sum_{j=1}^{3}(NI_{i,j} \wedge w_{i,j,s})}{\alpha + \sum_{j=1}^{3} w_{i,j,s}} \tag{4}$$

where '∧' is fuzzy 'AND' operator and (x ∧ y) = min (x,y).

Step 6 is the *selection of the maximum choice function value (T*)*: The value with the highest choice function is chosen.

$$T^* = \max\{T_{i,s} : s = 1,2,\dots,m\} \tag{5}$$

Step 7 is the matching test. In this step, the matching test determines the appropriate input's class. The following equation is used to calculate the matching function:

$$M_{i,s}(T^*) = \frac{\sum_{j=1}^{3}(NI_{i,j} \wedge w_{i,j,s})}{\sum_{j=1}^{3} NI_{i,j}} \tag{6}$$

There are a few conditions that need to be followed.

If $M_{i,s} \geq \rho \Longrightarrow T_{i,s}$ is passing the test. Hence, the ith failure mode is added to the existing class $C_s$. Then, go directly to step 9.

If $M_{i,s} < \rho \Longrightarrow T_{i,s}$ is not passing the test. Then, do step 8.

Step 8 is resetting. The choice function value is set as $T_{i,s}$ =-1 and then goes back to step 6. Control the Ti s value that is the next highest. So that all of the $T_{i,s}$ values will undergo the matching test. For the current input, a new class will be created if none of the $T_{i,s}$ pass the test. Hence, *i*th failure mode is added to a new class $C_{s+1}$. Next, repeat step 4 with the next input.

Step 9 is updating weights. The following equation is used to update the input weights of the existing inputs.

$$w_{i,j,s}^{(new)} = \beta\left(NI_{i,j} \wedge w_{i,j,s}^{(old)}\right) + (1-\beta) w_{i,j,s}^{(old)} \tag{7}$$

The algorithm continues with the subsequent input at Step 4 in Step 10, repeating these steps until all the data has been assigned to one or more classes. Step 11 is the prioritization of classes. The failure classes obtained should be prioritized. In prioritization, the arithmetic mean of the input values in each class is used. Classes are ranked by their priority and labeled accordingly. The described methodology will be carried out by a computer program written in MATLAB. This Fuzzy ART FMEA algorithm, ref [40], will be implemented in a non-healthcare setting which is the Central Teaching Facilities, Universiti Malaysia Sarawak. The attention of this implementation is to propose risk management of an infectious disease, which is for COVID-19 management in teaching facilities.

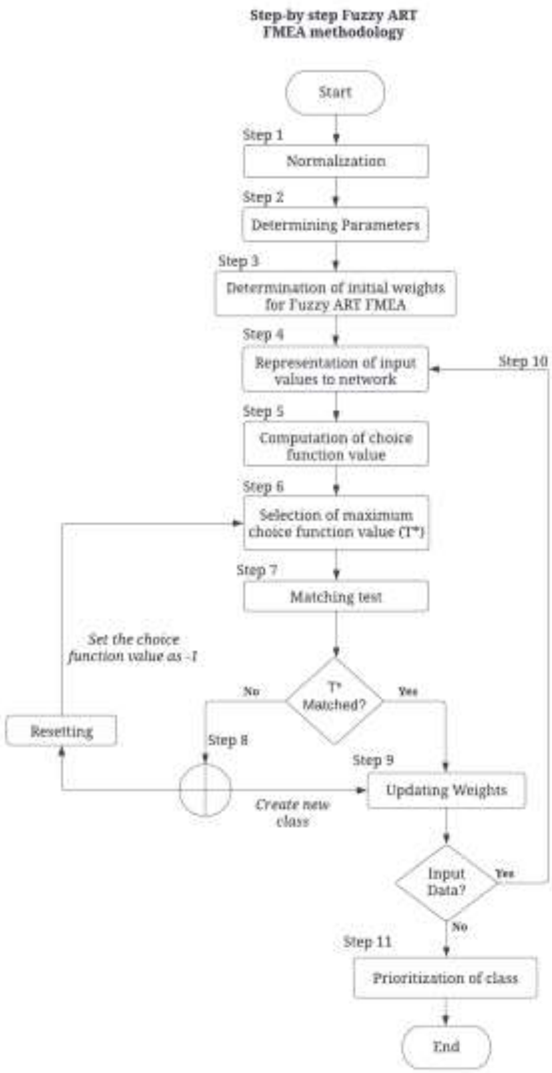


Figure 2. Fuzzy ART-FMEA Methodology

Table 1, Table 2, and Table 3 shows example of the S, O, and D scales for this case study, respectively. There are three columns in each scale table, which consist of "Ranking", Linguistic Term", and "Descriptions". Meanwhile, the score intervals shown in the "Ranking column" are from 1 to 10. This table will be use for the proposed implementation.

Table 1. Ranking of Severity

| Ranking | Linguistic Term | Descriptions |
|---|---|---|
| 1 | Negligible | • Students and staff maintain health practices and standard precautions<br>• All students and staff are fully vaccinated<br>• Frequently cleaning and disinfecting touched objects and surfaces |
| 2-3 | Marginal | • Students and staff maintain health practices and standard precautions<br>• All students and staff are fully vaccinated<br>• Occasionally cleaning and disinfecting touched objects and surfaces |
| 4-6 | Moderate | • Students and staffs occasionally apply health practices and standard precautions<br>• The majority of students and staff are fully vaccinated<br>• Occasionally cleaning and disinfecting touched objects and surfaces |

| | | |
|---|---|---|
| 7-8 | Critical | • Students and staffs rarely apply health practices and standard precautions<br>• A minority of students and staff are fully vaccinated<br>• Rarely cleaning and disinfecting touched objects and surfaces |
| 9-10 | Catastrophic | • Students and staff do not apply health practices and standard precautions<br>• None of the students and staff received vaccines<br>• Cleaning and disinfecting touched objects and surfaces only when required |

The scale table of S is designated to rate the transmission effects based on a risk group with reference to the lifestyle, medical history of COVID-19 interests and crucial health indicators. There are several possible risk factors for morbidity and mortality led by the COVID-19 virus. In [49], [50] stated that the risk factors could be classified into five categories, such as demographic factors, developed comorbidities, pre-existing comorbidities, lifestyle factors and clinical factors.

The scale table of O is designated to rate the likelihood of transmission-cause occurrence. There are two factors taken into account when designing the table of occurrence. First, the degree of confidence in preventing humans, objects or even surfaces that have been exposed to COVID-19 from accessing the CTF1 and 2 premises. Secondly, the assessment of the likelihood that humans, objects, or surfaces may spread the virus to other humans or objects by considering the nature of everyday work activities, social interactions, and environments.

Table 2. Ranking of Occurrence

| Ranking | Linguistic Term | Descriptions |
|---|---|---|
| 1 | Very low | • High confidence that all humans are not infected<br>• High confidence that objects or surfaces are not contaminated<br>• Close communication is avoidable |
| 2-4 | Low | • High confidence that all humans are not infected<br>• High confidence that objects or surfaces are not contaminated<br>• Close communication is hard to be avoided |
| 5-6 | Medium | • Low confidence that all humans are not infected<br>• Low confidence that objects or surfaces are not contaminated<br>• Close communication is hard to be avoided |
| 7-8 | High | • Low confidence that all humans are not infected<br>• Objects or surfaces contamination can hardly be avoided<br>• Close communication is hard to be avoided |
| 9-10 | Very high | • Low confidence that all humans are not infected<br>• Objects or surfaces contamination can hardly be avoided<br>• Crowded places, close-contact settings, confined and enclosed spaces |

Meanwhile, the scale table for D is designated to examine the effectiveness of the suggested strategies. The cleaning and disinfection protocols, the risk and symptom screening protocols, and personal protective equipment are among the aspect that affects the effectiveness of the strategies[51]–[54]. The proposed implementation will be further discussed in the next section.

Table 3. Ranking of Detection

| Ranking | Linguistic Term | Descriptions |
|---|---|---|
| 1-2 | Very high | • Very high probability that transmission of COVID-19 will be detected |
| 3-5 | High | • High probability that transmission of COVID-19 will be detected |
| 6-8 | Medium | • The moderate probability that transmission of COVID-19 will be detected |
| 9 | Low | • Low probability that transmission of COVID-19 will be detected |
| 10 | Very low | • Very low (or zero) probability that transmission of |

| | |
|---|---|
| | COVID-19 will be detected |

## 4. PROPOSED c-TCEA (Clustering-Transmission Cause Effect Analysis)

Figure *3* shows the flowchart of the proposed c-TCEA. Meanwhile, Figure 4 shows the summary flowcharts of the proposed c-TCEA. The data will be collected by observing the implementation area of the case study, which is the Central Teaching Facilities 1 and 2, Universiti Malaysia Sarawak (CTF 1 and CTF 2). The data will act as input into the c-TCEA system, where discussion and brainstorming with an expert from the Faculty of Medicine and Health Sciences of UNIMAS is needed to construct an FMEA table. A part of the constructed FMEA table worksheet is shown in

Table 4. Transmission of the COVID-19 virus spreads rapidly when health practices and standard precautions are not taken seriously. Hence, this research is carried out to understand the transmission of COVID-19 and manage any possible risks. The highlights of the worksheet are the COVID-19 transmission potentials, effects, and causes. The scale table for Severity, Occurrence and Detection is shown in the previous section in Table 1, Table 2, and Table 3, respectively. This scales table act as an aid for the experts in determining the rate of the highlights point in the worksheet.

After the information has been gathered and evaluated by the experts, it will be inputted by using the Fuzzy ART algorithm in order for the data to be clustered, as mentioned in the previous section. The fuzzy ART algorithm allows the failure modes (transmission potentials) to be clustered into different groups effectively, even if a new failure mode(s) is included. Each group of failure modes (transmission potentials) is ranked and prioritized according to its arithmetic mean. Additionally, the risk ranking of several sets of failure mechanisms will be examined. The examination tries to offer more details, such as if one group of failure modes poses a greater risk than another group of failure modes. In contrast to relying solely on the traditional FMEA table assessment, the examination results will allow the expert to implement targeted actions aimed at minimizing the risks associated with the COVID-19 disease, leading to a more quick and effective mitigation plan.

Table 4. Example of the worksheet

| **Area** | **Functions and description** | **Transmission Potentials** | **ID** | **Transmission Effects** | **SEV** | **Transmission Causes** | **OCC** | **Control/prevention strategy** | **DET** | **RPN** |
|---|---|---|---|---|---|---|---|---|---|---|
| Dewan Kuliah | Large hall with teaching facilities | Social interaction at a close distance, which involves 2 and more students and staff members | TP.1 | Students, lecturers and CTFs Staffs | | •Close-distance conversation without wearing a facemask<br>•Physical and social interaction e.g., handshakes<br>•Fail to take serious precautionary measures | | •Restrict unnecessary conversation among students and staff members without wearing a mask.<br>•Students sit at their designated place, which applies the social distancing rule.<br>• Make sure no symptoms taking the body temperature daily (<37.5°C) | | |

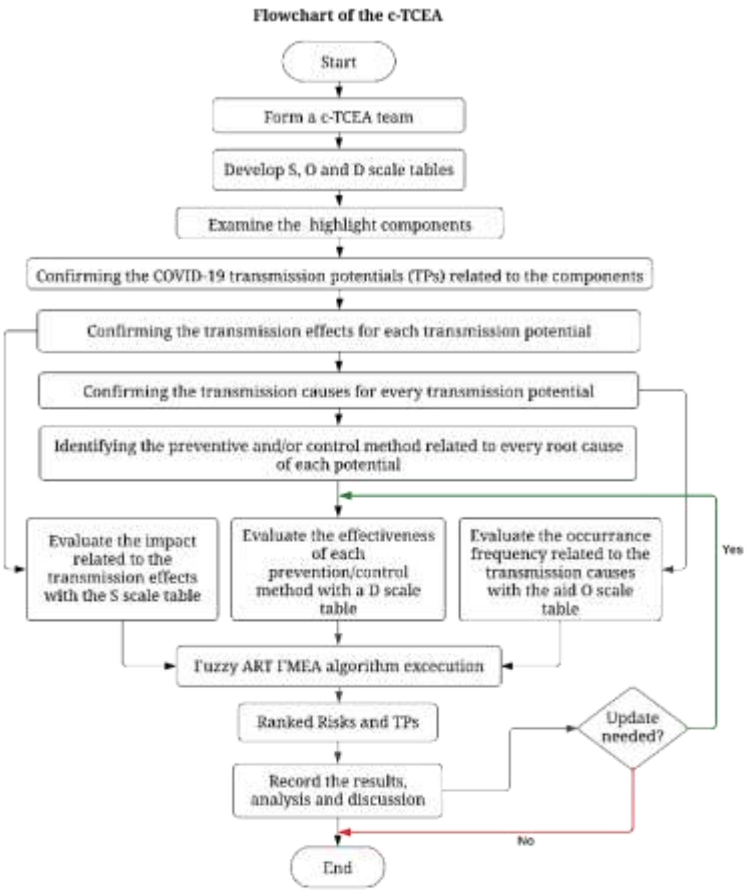


Figure 3. c-TCEA Flowchart

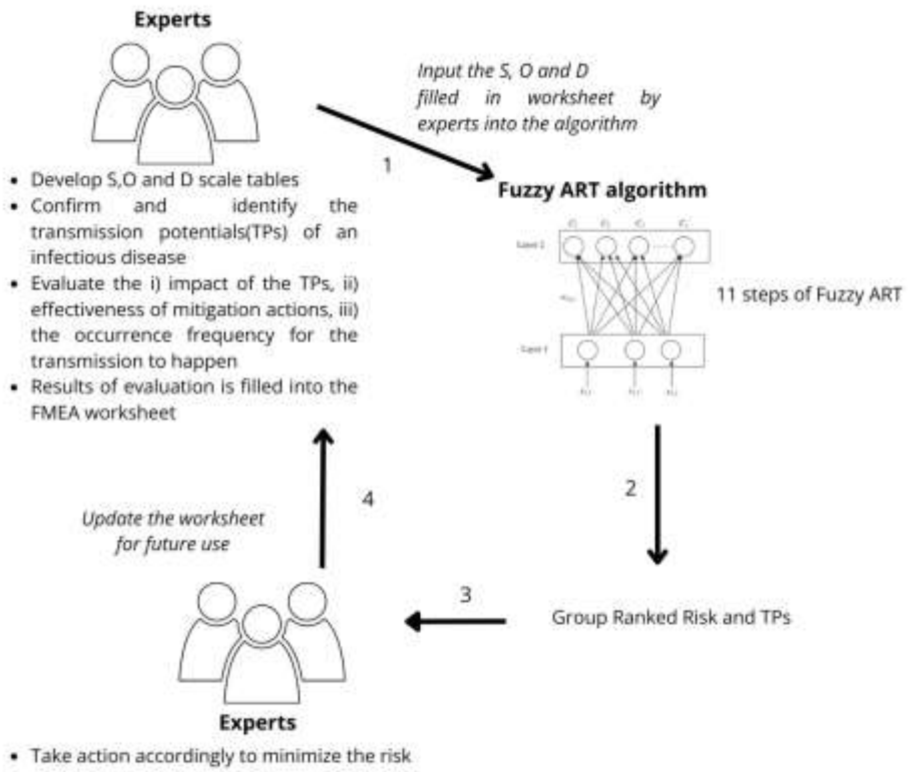


Figure 4. Summary charts of proposed c-TCEA

## 5. CONCLUSION

In conclusion, this study discusses the use of fuzzy ART for clustering failure modes within Failure Modes and Effects Analysis (FMEA). Fuzzy ART is used to improve the effectiveness and adaptability of the failure mode classification, allowing it to easily accommodate new failures. The drawbacks of traditional FMEA techniques are expected to be successfully addressed by this method. Additionally, the fuzzy ART FMEA framework that has been proposed shows promising for improving risk management tactics for infectious diseases like COVID-19. The parameters of the algorithm for infectious disease risk assessment could be adjusted, comparisons to traditional FMEA could be made, such as real-time risk assessment during outbreaks could be explored, and ethical issues could be addressed. Additionally, including a wide range of data sources could improve the fuzzy ART FMEA framework's predictive abilities and make it applicable to a variety of scenarios.

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