Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

Clustering-Transmission Causes and Effects Analysis (c-TCEA): A Fuzzy ART FMEA – Based Approach for Comprehensive Infectious Disease Risk Analysis

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ARTICLE INFO

Article history:
Received 10 March 2025
Received in revised form 21 July 2025
Accepted 14 September 2025
Available online 28 October 2025

Keywords:
Fuzzy ART FMEA; COVID-19; c-TCEA; risk assessment; Infectious disease

ABSTRACT

This paper addresses the critical challenge of comprehensively assessing infectious disease risks, particularly within non-healthcare premises. The existing approaches for infectious disease risk analysis may lack the precision needed to thoroughly understand the complexities of disease transmission. The absence of a unified model that integrates Failure Mode and Effects Analysis (FMEA) with Fuzzy Adaptive Resonance Theory (Fuzzy ART) hinders our ability to adaptively analyse and prioritise risks associated with infectious diseases. To bridge this gap, our research introduces the Clustering-Transmission Causes and Effects Analysis (c-TCEA) model, designed to enhance the precision of risk analysis and provide a deeper understanding of the factors contributing to disease spread and its effects. By focusing on the infectious disease COVID-19, we demonstrate the adaptability of c-TCEA to dynamic disease dynamics and highlight its potential as a robust tool for comprehensive risk assessment. The clustered data output from c-TCEA offers a valuable foundation for prioritising and guiding the implementation of preventive and mitigation strategies.

1. Introduction

Infectious diseases such as COVID-19, mpox, MERS, SARS, and XDR TB, along with other prevalent conditions like diarrheal diseases and HIV/AIDS, will continue to exert a substantial impact on global mortality. This underscores the persistent threat of both established and emerging infectious diseases, emphasizing the critical need for a comprehensive understanding of transmission factors, including agents, hosts, and environmental determinants, to guide effective prevention and control efforts.

There are still threats to one's life associated with infectious diseases like COVID-19. Globally, there were more than 771 million COVID-19 instances as of October 2023 [1]. Developing measures to eliminate and prevent the spread of a pandemic strain among people is highly beneficial. However,

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https://doi.org/10.37934/ard.146.1.4658

because of the disease's rapid spread, it becomes extremely difficult to create and develop realistic risk assessments to contain the emergence of the disease. In human history, risk analysis and management have been crucial in the fight against long-lasting endemic or pandemic diseases, as stated in [2]. It was also indicated in [2] that for centuries, experts in the field of infectious disease control had implemented interventions and strategies. One example is the creation of laws and regulations pertaining to quarantine and isolation during emergencies. These have been pointed out as one of the key elements of societal risk management strategies and as a means of decreasing and preventing infectious diseases [3,4].

In practical terms, modern risk management is the identification, evaluation, and prioritization of risks, followed by the efficient and well-coordinated use of resources to minimize, control, and manage the likelihood or impact of unfavourable events. The Failure Modes and Effect Analysis (FMEA) method has been introduced as a comprehensive tool for risk analysis and management across various industries such as transport, automotive, agriculture, and medical and healthcare. The overall FMEA methodology considers factors such as failure modes, effect analysis, root causes, and relationships, along with corrective measures, during its implementation. A simple scoring approach, utilizing three indices—Severity (S), Occurrence (O), and Detection (D)—as inputs and generating a Risk Priority Number (RPN) as an output, is employed for prioritization and risk analysis.

The emphasis in [5] has centered on non-healthcare settings for COVID-19 risk management, with the implementation of Failure Modes and Effect Analysis (FMEA) expanding to healthcare during the pandemic. An instance of this is when COVID-19 protocols are evaluated in cases of obstetric emergencies. [6]. Despite the wide use of FMEA in diverse fields and extensive research on infectious disease risks within healthcare, there is a recognized need for ongoing development to elevate it into a more valuable foundation. This enhancement aims to position FMEA as a comprehensive and improved tool serving as the basis for prioritizing and guiding the implementation of preventive and mitigation strategies in infectious disease risk management. Consequently, the adoption of transmission-based precautions is recommended. One innovative approach in this area is the transmission-based risk analysis methodology, which rates and ranks all risks using Fuzzy ART while accounting for recent advancements in risk research in both healthcare and non-healthcare settings.

Thus, this paper uses Fuzzy ART as a tool to investigate FMEA from an alternative perspective. An innovative approach in this context introduces the transmission-based risk analysis methodology. For this method, experts will utilize the FMEA for scoring and determining the three indices (S, O, and D). The values obtained are normalized and fed into the Fuzzy ART algorithm. The outcomes of the Fuzzy ART algorithm are interpreted, enabling the clusterisation of transmission potentials in the area of interest, which in this paper is the educational institution facilities. This information is then further contributed to the prioritisation and guidance of preventive and mitigation strategies. Hence, this paper explores FMEA from a different perspective by employing Fuzzy ART as a tool.

2. Literature Review

2.1 Existing Methods and Models for Infectious Disease Risk Analysis

There are a few techniques used for infectious disease risk analysis besides using fuzzy ART. One of the methods is machine learning (ML)[7]. ML is a generic subset of artificial intelligence (AI) that can recognize patterns in data without the need for programming. To do this, the data is analysed, and predictions are made using the knowledge gained from past events [8]. ML is a field of AI that has been practiced for many years. It incorporates ideas from several other fields, including computer science, statistics, and mathematics [9]. ML algorithms have been effectively implemented in conjunction with the disciplines in several industries, such as marketing, banking, healthcare, and agriculture, due to their accuracy and reliability in diagnosing process [10].

Another current technique implemented in infectious disease risk analysis is sentiment analysis [11]. Sentiment analysis or opinion mining, is a natural language processing (NLP) technique that identifies the sentiment expressed in a text, whether it be positive, negative, or neutral. The objective of this analysis is to understand and extract subjective information from the text so that the author's emotions may be categorized. One of the methods for using this analysis is getting data through social media. These platforms are thought to be the worldwide hub for big data since users use their smartphone apps and spend excessive amounts of time on social media platforms [12]. This is because users usually give out emotions, whether it be happy, sad, surprised, etc, while using their phones [13].

2.2 Limitations and Challenges Faced by Traditional Approaches

However, there are a few challenges faced in using the existing methods or models to detect and diagnose infectious diseases. For the ML technique, the fast and exponential growth of data has created a problem for prediction accuracy. The study of data temporalities involves tracking changes in data throughout time. Since the quality of each dataset differs and the data from various patients may have varied periods, this poses a serious difficulty for disease diagnosis. Besides that, the lack of bigger size samples accessible is a barrier to the development of machine-learning models for infectious diseases. Finding trends in a small dataset that is typical of the entire population frequently produces skewed outcomes [14]. Since there are so few cases worldwide, it is impossible to determine with any degree of accuracy when an individual will get infected. The dataset may be small in size if it contains only a limited number of samples or if a large amount of data is missing. This does not offer a thorough and precise examination of the information.

For sentiment analysis, there are reported problems with data processing that have to do with the idea that data are not relevant or that they come in different forms and formats. The necessity of a large number of analytic processes is recognized, in addition to the opinion of other academics that processing data from social media calls for exceptional processing abilities [15,16]. On the other hand, as social media platforms spread and thus rapidly double the amount of data, gathering information on a user's ideas regarding a particular subject is an enormous burden and complex procedure [15]. The challenge of defining keywords to locate the needed data is another factor contributing to this issue. Other than that, there are also problems and difficulties in the social media platform with integrity and reliability [17]. Other researchers talked about the difficulties in interpreting sentiments on social media platforms due to factors like the frequency of content capability limitations, potential exaggeration, difficulties in understanding different sources, or disease outbreaks [18].

2.3 Introduction of Fuzzy ART and FMEA

In addressing the challenges faced by existing methods for infectious disease risk analysis, our research introduces a synergistic approach by integrating Fuzzy Adaptive Resonance Theory (Fuzzy ART) and Failure Mode and Effects Analysis (FMEA). This section highlights the reasons why the selection of Fuzzy ART within the variety of fuzzy systems and neural network models. Fuzzy ART, a neural network model, is strategically chosen for its exceptional capabilities in pattern identification and classification, particularly when dealing with ambiguous, imprecise, or incomplete data [19]. The adaptability of Fuzzy ART plays a pivotal role in enhancing the precision of risk analysis, making it well-suited for situations where traditional methods may struggle with uncertainty. The algorithm within Fuzzy ART controls the similarity between input values, determining their position in classes while considering the inherent risk parameter. Notably, the simplicity of Fuzzy ART's architecture facilitates a clear interpretation of the neural network's responses to input patterns, offering transparency in decision-making compared to more complex models [20].

Failure Mode and Effects Analysis (FMEA) is introduced as a complementary methodology, providing a systematic and structured approach to assess potential failure modes in infectious disease transmission scenarios. FMEA is widely recognized for its effectiveness in identifying, evaluating, and ranking risks or failures within systems, processes, or products. By systematically examining failure modes and their associated consequences, FMEA aims to formulate mitigation tactics and enhance overall system reliability. The incorporation of FMEA into infectious disease risk analysis allows for a comprehensive examination of the potential risks and vulnerabilities in transmission dynamics [20]. The combined use of Fuzzy ART and FMEA in infectious disease risk analysis capitalises on the strengths of each methodology. Fuzzy ART's adaptability ensures the precise identification of patterns in infectious disease transmission, considering the inherent uncertainties and complexities. Simultaneously, FMEA provides a structured framework for systematic risk assessment, allowing for the identification, evaluation, and prioritization of potential failure modes. Combining these methodologies enhances the accuracy and effectiveness of infectious disease risk analysis, offering a comprehensive approach to understanding and mitigating transmission potentials. Therefore, implementing the fuzzy ART and FMEA into the infectious disease risk analysis will help make the data more precise and increase the accuracy rate of a specific situation.

3. Conceptual Framework

Clusterisation-based Transmission Cause and Effect Analysis, or known as c-TCEA, is an innovative approach for infectious disease risk analysis. This model integrates Fuzzy ART (Adaptive Resonance Theory) for clusterisation and FMEA (Failure Mode and Effect Analysis) for assessing the causes and effects of disease transmission [21].

FMEA is employed as the initial step in the c-TCEA model for this analysis. It is a systematic methodology for identifying the potential failure modes in a system and assessing their effects. In the c-TCEA model, it focuses on assessing the causes and effects of disease transmission. It considers factors such as the mode of transmission, vectors involved, and environmental factors to identify potential failure modes in the infectious disease transmission process.

After possible failure modes are identified using FMEA, the c-TCEA model uses Fuzzy ART for clustering. Fuzzy ART is a neural network model known for its ability to adaptively learn and categorize patterns in a flexible and fuzzy manner. Fuzzy ART is applied to the pre-processed data to dynamically group similar infectious disease data points into clusters. This process allows for the identification of patterns and relationships in the transmission dynamics, building on the insights gained from the FMEA.

4. Methodology

Fig. 1 illustrates the c-TCEA model's flowchart, featuring two primary phases. In the initial stage, the focus is on identifying potential transmission causes. This involves data collection through observations within the Central Teaching Facilities 1 and 2 at Universiti Malaysia Sarawak (CTF 1 and CTF 2). The collected data serves as input for the c-TCEA model's first part, where collaborative discussions with an expert from the Faculty of Medicine and Health Sciences of UNIMAS are crucial for constructing a TCEA (transmission cause and effect analysis) table. A portion of the constructed TCEA table worksheet, presented in Table 1, emphasizes COVID-19 transmission potentials, effects, and causes.

Significantly, severity, occurrence, and detection scales, detailed in Table 2, Table 3, and Table 4, respectively, assist the expert in assessing the significance of the worksheet's highlights.

After data collection and expert evaluation, the information undergoes input into the Fuzzy ART algorithm for clustering. The Fuzzy ART algorithm proves effective in grouping failure modes (transmission potentials) into clusters, accommodating new failure modes seamlessly [20]. Subsequently, each cluster will be ranked and prioritised accordingly. Examining the risk rankings of different sets of failure mechanisms provides detailed information about the associated risks. This examination goes beyond traditional FMEA table assessments, enabling experts to implement targeted actions swiftly. By focusing on mitigating the risks associated with COVID-19, the results facilitate the development of a rapid and effective mitigation plan.

This section discusses and provides additional details on the Fuzzy ART algorithm that is used with FMEA and RPNs. Fig. 2 shows the modelling FMEA methodology by using Fuzzy ART. It shows that the model's input is xi,j, that the failure mode classes are represented by Cs, and that the weight between Layers 1 and 2 is wi,j. Additionally, it determines whether each input value at Layer 1 belongs to a distinct class at Layer 2.

The three indices values that make up the RPN value are evaluated separately for every input. FMEA values are evaluated independently utilising severity, detection, and occurrence values instead of a combination of these elements, even though RPN values are equivalent to one another. As a consequence, RPN values make up the inputs, and the system is represented with each input separately as (S, O, D). Effective parameters result from the application of FMEA to test problems present the system with a three-data input (S, O, D) in each event, and related inputs are clustered based on the three indices which are the severity, occurrence, and detection.

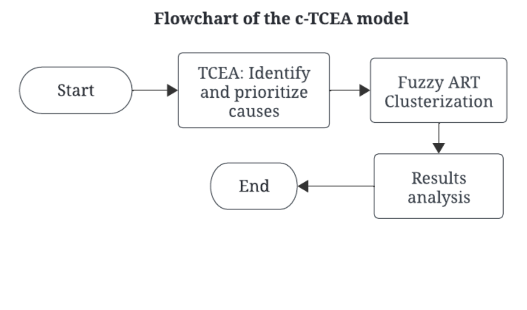

Fig. 1. The c-TCEA model flowchart

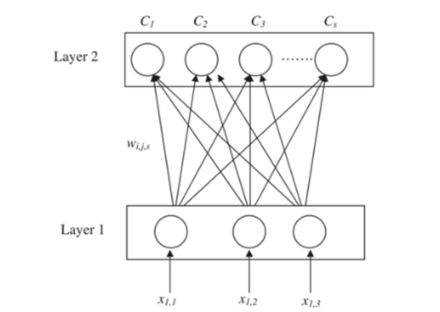

Fig. 2. Modelling FMEA methodology by Fuzzy ART [20]

Fig. 3 shows the flowchart of the Fuzzy ART FMEA methodology. Fuzzy ART FMEA methodology consists of 11 steps. Step 1 is normalisation. Each of the three input values $I_{(i,j)}$, where the S, O, and D, is normalized by using equation (1).

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

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 normalised input value.
Step 2 is where parameters are determined. Following are the parameter intervals for any Fuzzy ART problem:

Vigilance threshold, (ρ): Responsible for the number of classes (0< ρ ≤1).
Choice Parameter, (α): Effective in class selection (0< α ≤ 1)
Learning Rate, (β): Controlling the classification's pace (0< β ≤ 1)

Table 1
Example of the TCEA worksheet

Area	**Functions and description**	**Transmission Potentials**	**ID**	**Transmission Effects**	**SEV**	**Transmission Causes**	**OCC**	**Control/prevention strategy**	**DET**	**RPN**
Bilik Seminar 1-6	Small hall with teaching facilities	Area contamination with infectious agents (eg, tables, chairs, computers, whiteboards and etc.	TP.9	Students, lecturers and CTFs Staffs		•Contamination caused by infected students and staff members		•Provide sanitizing hand rub dispensers at the door entrances •Advise lecture hall users not to change their seats once seated. • Students observe the social distancing rule by sitting in their assigned areas. •Sanitize the area after use.		

The parameters must be defined by the user, and the type of problem will determine which parameters are used. The values of α, ρ, and β parameters in this model are ρ=0.9, β=1, and α=0.002. Step 3 is to determine the initial weights for Fuzzy ART FMEA. Every weight is assigned a value of 1 for this step. Class, C_s number is set as s = 1. For all $jw_{i,j,s}$ (0) =1. Step 4 is the representation of the network's input values. The network is assigned input vector (x), which is the normalised values of the input triple. The input vector (x) is normalised in the range of (0,1].

Next, step 5 is where the choice function value will be computed. The following equation defines the choice function $T_{i,j,s}$.

$$T_{i,s}(NI) = \frac{\sum_{j=1}^{3}(NI_{i,j} \wedge w_{i,j,s})}{\alpha + \sum_{j=1}^{3} w_{i,j,s}} \tag{2}$$

where '^' is fuzzy 'AND' operator and (x ^ y) = min (x,y).
Step 6 is where the maximum choice function value (T*) will get selected. The highest choice function value will be selected.

$$T^{*} = \max\{T_{i,s}: s = 1,2, \dots, m\} \tag{3}$$

Step 7 is the matching test. The matching test in this step establishes the class of the relevant input. The following equation is used to calculate the matching function:

$$M_{i,s}(T^*) = \frac{\sum_{j=1}^{3}(NI_{i,j} \wedge w_{i,j,s})}{\sum_{j=1}^{3} NI_{i,j}} \tag{4}$$

There are a few conditions that need to be followed. The first condition is that if the input's class value is more than the vigilance threshold value ($M_{i,s} \geq \rho \Longrightarrow T_{i,s}$), the choice function has passed the matching test. Hence, the ith failure mode is added to the existing class C_s. If the condition is satisfied, step 8 will be skipped. However, if the input's class value is less than the vigilance threshold value ($M_{i,s} < \rho \Longrightarrow T_{i,s}$), the choice function has not passed the matching test. Then, step 8 will be carried out.

Step 8 is resetting. The choice function value is set as $T_{i,s}$ =-1, and then goes back to step 6. Maintain control over the next highest $T_{i,s}$ value. 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, ith failure mode is added to a new class C_{s+1}. Then, repeat step 4 with the next input.

The weight gets updated on step 9. The following equation is used to update the input weights of the existing inputs.

$$w_{i,j,s}^{(new)} = \beta \left(NI_{i,j} \wedge w_{i,j,s}^{(old)} \right) + (1-\beta) w_{i,j,s}^{(old)} \tag{5}$$

Once all of the data has been allocated to one or more classes, the algorithm repeats these steps with the next input at step 4 in step 10. Setting class priorities is step 11. Prioritising the failed courses acquired is necessary. The arithmetic mean of the input values for each class is employed in the prioritization process. Classes are labeled and ranked according to priority. A MATLAB computer program will be used to implement the process that has been explained. The Central Teaching Facilities (CTF) at Universiti Malaysia Sarawak, a non-healthcare setting, will be the site of the implementation of this Fuzzy ART FMEA algorithm. The focus of this implementation is to suggest managing the risk of an infectious disease, specifically COVID-19, in educational institutions.

Tables 2, 3, and 4, respectively, display examples of the S, O, and D scales for this case study. Each scale table has three columns: "Ranking", "Descriptions", and "Linguistic Term". In the meantime, the "Ranking column" displays score intervals ranging from 1 to 10. The purpose of the S scale table is to rate the transmission effects according to a risk group by taking into account the lifestyle, medical history, and important health markers of COVID-19 interests. The COVID-19 virus is one of many potential risk factors for morbidity and mortality. Five categories, which are pre-existing comorbidities, demographic factors, lifestyle factors, established comorbidities, and clinical considerations, were identified by [22] and [23] as the risk factors.

The probability of a transmission-cause event is rated using the O scale table. When creating the table of occurrence, two considerations are made. First, the level of assurance regarding the prevention of people, things, or even surfaces exposed to COVID-19 from entering the Central Teaching Facilities 1 and Central Teaching Facilities 2 (CTF1 and CTF2). Second, by taking into account the typical job activities, social contacts, and settings, the assessment determines the probability that persons, items, or surfaces could transfer the virus to objects or other humans.

The purpose of the scale table for D is to assess how well the recommended tactics work. A few factors that influence the efficacy of the methods include the personal protective equipment, the cleaning and disinfection processes, the symptom and risk screening protocols [24-26].

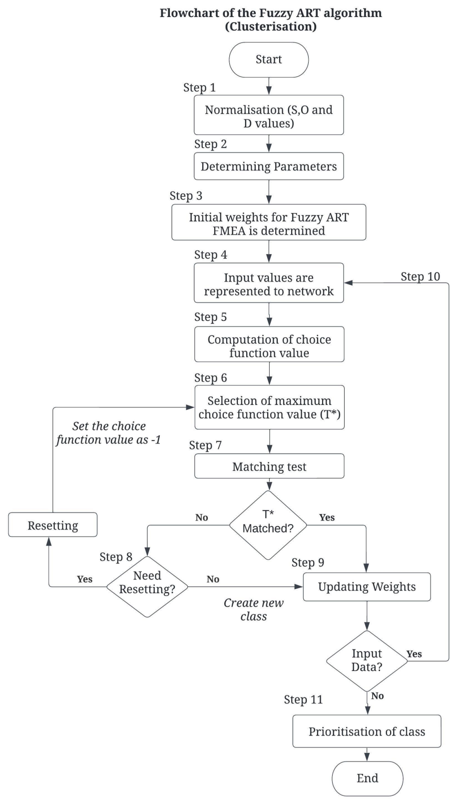

Fig. 3. Fuzzy ART-FMEA methodology

Table 2
Ranking of severity

Ranking	Description	Linguistic Term
1	Staff and students adhere to appropriate safety procedures and health practices All staff and students are vaccinated Regularly sterilizing and sanitation surfaces and items that are touched	Negligible
2-3	Staff and students adhere to appropriate safety procedures and health practices All staff and students are vaccinated Occasionally sterilizing and sanitation surfaces and items that are touched	Marginal
4-6	Staff and students occasionally implement appropriate safety procedures and health practices The majority of staff and students are vaccinated Occasionally sterilizing and sanitation surfaces and items that are touched	Moderate
7-8	Staff and students rarely implement appropriate safety procedures and health practices A minority of staff and students are vaccinated Rarely sterilizing and sanitation surfaces and items that are touched	Critical
9-10	Staff and students do not apply health practices and standard precautions None of the staff or students have received vaccines Cleaning and disinfecting touched objects and surfaces only when required	Catastrophic

Table 3
Ranking of occurrence

Ranking	Description	Linguistic Term
1	• High confidence that there is no infection in humans • High degree of certainty that surfaces or objects are uncontaminated • Close contact can be avoided	Very low
2-4	• High confidence that there is no infection in humans • High degree of certainty that surfaces or objects are uncontaminated • Close contact is hard to avoid	Low
5-6	• Low confidence that there is no infection in humans • Low confidence that objects or surfaces are not contaminated • Close communication is hard to avoid	Medium
7-8	• Low confidence that there is no infection in humans • Difficulty preventing contaminating objects or surfaces • Close contact is hard to avoid	High
9-10	• Low confidence that there is no infection in humans • Difficulty preventing contaminating objects or surfaces • Crowded areas, close-contact settings, small, enclosed areas	Very high

Table 4
Ranking of detection

Ranking	Description	Linguistic Term
1-2	• Extremely likely that COVID-19 transmission will be discovered	Very high
3-5	• A high possibility of detecting COVID-19 transfer	High
6-8	• The moderate likelihood that COVID-19 transmission will be discovered	Medium
9	• Minimal possibility of detecting COVID-19 transfer	Low
10	• Extremely unlikely (or zero) that COVID-19 transmission will be discovered	Very low

5. Results and Discussion

The c-TCEA model is applied in this paper to manage the risk of infectious disease, specifically COVID-19 in educational facilities. The area is Central Teaching Facilities 1 and 2, Universiti Malaysia Sarawak (CTF 1 and CTF 2). The c-TCEA team, including the experts, has found 14 transmission risk potentials that might be the possibilities of the infectious disease to be rapidly spread. One of the transmission potentials is shown in Table 1. The possible causes and effects of the COVID-19 outbreak in the targeted area are contamination of the area, maintenance of the building, human interactions, and many more.

After the evaluation scoring from the expert has been normalized, the value will be inputted into the algorithm. A normalisation process is needed to scale the scoring to a common range, in which the range is between 0 and 1. For this model, this process is crucial because Fuzzy ART algorithms rely on input values that are comparable and consistent, allowing for a fair and unbiased contribution of each related variable to the clustering process.

A graphical interpretation of data is illustrated in Fig.4. In Fig.4, the graph's y-axis represents the normalized value of O, which represents the occurrence of the transmission potentials. Meanwhile, the x-axis shows the normalized S value, which shows the severity of the transmission potentials. In the graph, 8 clusters were created according to the 14 transmission potentials. A summary of which data points are included in each cluster is shown in Table 5. Cluster 2 has the greatest number of data points in a cluster that consists of six data points: TP.2, TP.3, TP.5, TP.7, TP.8, and TP.10. Followed by

Cluster 3 which clusters two data points. Also, in Fig. 4, Cluster 1, Cluster 4, Cluster 5, and Cluster 8 are at the upper part of the graph, while others are at the lower part of the graph.

Artificial intelligence (AI) techniques are more adept at handling complexity and uncertainty than "traditional methods" because they are designed to replicate human decision-making more closely. This c-TCEA model is an example, as an alternative to conventional methods for risk mitigation, and successful results are required. One of the contributions of c-TCEA is its clustering ability. The severity and occurrences of transmission potentials of COVID-19 mentioned are categorised by similarity degrees between them. Not only categorises them, but it also clusters them through a matching function. The cluster number is not defined manually. It is formed mathematically according to the matching process in step 7. Another contribution of c-TCEA is this model is flexible and can be executed whatever the data size. The application of this model does not require any expertise field (depending on the applications and situation); with the aid of a small computer program can be easily used in practice. Therefore, the c-TCEA model that is introduced in this study can easily group and prioritise which transmission potentials to be taken, and suitable action can be taken accordingly to prevent and minimise the spread of the disease.

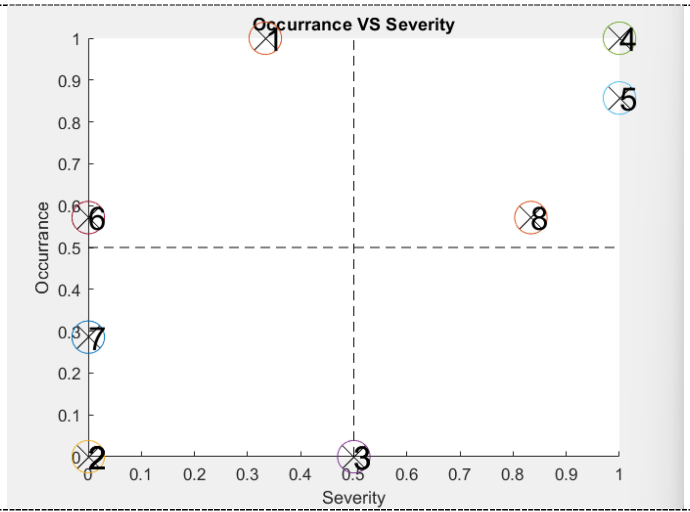

Fig. 4. Graphical Result of Occurrence vs Severity

Table 5
Results summary

Cluster	Transmission Potentials	Number of data points
1	TP.1	1
2	TP.2, TP.3, TP.5, TP.7, TP.8, TP.10	6
3	TP.4, TP.9	2
4	TP.6	1
5	TP.11	1
6	TP.12	1
7	TP.13	1
8	TP. 14	1

6. Conclusion

In conclusion, the COVID-19 pandemic within Universiti Malaysia Sarawak's Central Teaching Facilities 1 and 2 has presented a robust and adaptable approach to addressing the challenges presented by the Clustering-Transmission Causes and Effects Analysis (c-TCEA) model, implemented for the management of infectious diseases. The model, integrating Fuzzy Adaptive Resonance Theory (Fuzzy ART), adeptly identifies and clusters 14 transmission risk potentials associated with the rapid spread of the infectious disease.

The initial phase involves the meticulous identification of potential transmission vectors, ranging from environmental factors like contamination to human interactions. Expert evaluation scores are then normalised, a critical step ensuring equitable contributions of each variable during the subsequent clustering process. The graphical representation in Figure 4 vividly illustrates the clustering results, with eight distinct clusters formed based on the severity and occurrence of transmission potentials. c-TCEA is distinguished by its distinct clustering capability, which categorises and groups transmission potentials according to the degrees of similarity between them. The model exhibits remarkable flexibility by being able to accommodate different data sizes and requiring no specialised knowledge to implement, making it useful in a variety of scenarios. Because of its versatility and ability to form clusters, c-TCEA is a valuable tool for decision-makers looking for efficient ways to stop the spread of infectious diseases. The success of the study highlights the usefulness of artificial intelligence methods in managing the risks associated with infectious diseases, especially Fuzzy ART. The c-TCEA model shows promise as a strong substitute for conventional techniques by using mathematical formulations to form clusters objectively and without the need for human intervention. In summary, the c-TCEA model represents a significant advancement in infectious disease risk mitigation. Its ability to cluster, categorize, and prioritise transmission potentials, coupled with its user-friendly application and adaptability, positions it as a valuable asset for decision-makers striving to implement proactive measures against the spread of diseases within specific environments.

Acknowledgment
This work was supported by Ministry of Higher Education, Malaysia through Fundamental Research Grant Scheme (FRGS) under Project ID FRGS/1/2022/TK08/UNIMAS/02/11. The authors thank Universiti Malaysia Sarawak (UNIMAS) for the research support with Project ID NAT/F02/FRGS/85440/2022.

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