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Research Article

An emergency response of dyadic intelligent fuzzy decision process to diagnose of Omicron

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The Severe Acute Respiratory Syndrome Coronavirus -2 (SARS-CoV-2) has created a challenging and threatening situation worldwide. The SARS-CoV-2 embodies diverse epidemiological trends, alongside emerging and reemerging pathogenic characteristics, which have raised great public health concerns. This study aims to investigate using this Dyadic Intelligent Fuzzy Decision Process to diagnose the global prevalence, biological and clinical characteristics of younger and middle-aged people more than previous variants. Worldwide health establishment should take immediate preventive measures to stop outbreaks of this emerging and reemerging pathogenic variant across the globe to minimize the disease burden on humanity. The control of spreading of Omicron in emergency situation the entire world is a challenge, and therefore, the aim of this study was to propose a Dyadic intelligent fuzzy decision model for control and diagnosis of Omicron. The emergency event is known to have aspects of short time and data, harmfulness, and ambiguity, and policy makers are often rationally bounded under uncertainty and threat. There are some classic approaches for representing and explaining the complexity and vagueness of the information. The effective tool to describe and reduce the uncertainty in data information is fuzzy set and their extension. Therefore, we used fuzzy logic to develop fuzzy mathematical model for control of transmission and spreading of Omicron. The fuzzy control of early transmission and spreading of coronavirus by fuzzy mathematical model will be very effective. The proposed research work is on fuzzy mathematical model of intelligent decision systems under the Dyadic fuzzy information. In the proposed work, we will develop a newly and generalized technique for Omicron based on the technique for order of preference by similarity to ideal solution (TOPSIS) and complex proportional assessment (COPRAS) methods under extension of Dyadic fuzzy environment. Finally, an illustrative the emergency situation of OMAIGRAN is given for demonstrating the effectiveness of the suggested method, along with a sensitivity analysis and comparative analysis, showing the feasibility and reliability of its results.

Keywords: SARS-CoV-2, COVID-19, OMAIGRAN, emergency response, Critical path problems.

1. Introduction

Since the first case of Severe Acute Respiratory Syndrome Coronavirus (SARS-CoV-2) was reported in Wuhan, China, on November 17, 2019.

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The name (CORONA-19) "coronavirus" comes from the Latin word "corona" which means a "crown, circle of light or nimbus". This virus influences immediately to your lungs. The world has witnessed multiple waves of a global pandemic followed by mass immunization programs. By now, 72.2% of the world's population has received at least one dose of a COVID-19 vaccine to eradicate the disease[1].

Despite tremendous efforts by scientists, researchers, and health practitioners to combat this highly contagious pandemic, just recently, news of an emerging new variant of the coronavirus has jolted the world. This new variant has suddenly appeared after several countries, and their citizens began to have hope for a seemingly normal life.

The new variant of the Coronavirus, B.1.1.529, named "Omicron", was discovered on November 24, 2021, in South Africa, from a patient's specimen sample that was collected on November 9, 2021. This variant was noticed to have a higher number of mutations than any other previous strain of the virus2. SARS-CoV-2 has continued to change its genetic code through mutations. These mutations, mainly on the spike protein of the virus, lead to slightly modified copies of the Omicron variant is a variant of the COVID-19 virus. Omicron variant is the common name used to refer to what is technically known as the B.1.1.529 variant. A variant of a virus is a new strain that has emerged due to a mutation (or mutations) in the virus's genetic structure.

In practical decision making, there are a great quantity of uncertainties, imprecise and vague information several researchers investigated and developed different methods for addressing The Term Omicron sub variant most commonly refers to the BA.2 sub variant (subtype) of the Omicron variant. The BA.2 sub variant is sometimes called stealth Omicron (or the stealth variant) in casual use because it is somewhat more difficult to distinguish from other variants in lab tests. However, this does not mean that it's not detectable at all. (Public health officials and medical experts have cautioned against the use of nicknames like stealth Omicron, which they say can cause panic and misconceptions about such variants.)

The BA.2 variant became the subject of public health scrutiny and media reports in early 2022 due to having replaced the original Omicron variant as the dominant strain in some places. Based on some studies, the BA.2 variants is even more transmissible than the already highly transmissible original Omicron variant. However, there has been no evidence showing that the BA.2 variant causes more severe illness than the original Omicron variant. Early studies have shown that vaccination is just as effective against the BA.2 sub variant as it is against the original form of the Omicron variant.

The BA.2 sub variant is just one of the sub variants of the Omicron variant. These sub variants have additional mutations not found in the original variant, but they are still similar enough not to be considered completely distinct variants.

Mutations are assigned letters and numbers, such as D614G- which indicates that an amino acid changed from a D (aspartate) to a G (glycine) at position number 614 of the viral spike proteins3. The World Health Organization (WHO) has identified 5 VOCs (variants of concern) as Alpha, Beta, Gamma, Delta, and the latest one was added as an Omicron variant. Besides these, two currently designated VOIs (variants of interest) and seven VOM's (variants under monitoring) are being monitored for pathogenicity. The purpose of the multiple criteria decision making (MCDM) frameworks is to prepare an appropriate decision at different levels of health care, such as operational, methodical, and functional. There may be an ideal solution to any difficult decision-making problem, but it is a difficult task to find such a method.

In particular, management decisions are taken by managers or senior management to grow and maintain the organization. In fact, there are contradictions in strategic decisions, possible synergies between different options, and uncertainty in the final result. When strategic decisions are taken, the company shall agree on tactical and operational planning decisions. Strategic, tactical, and operational planning are grouped together as a taxonomy of health planning (Kumar et al. 2017). Disease prevention and control approaches include multiple management roles like as facility preparation, organization and decision making.

MCDM problems with dyadic fuzzy environment took much attention to the real-life problems where the goal is associated for selecting the best alternative in contrast to the values under the different criteria where the evaluation terms are SFNs given by decision experts (DEs). However, in order to process the ambiguity /imprecision in the data,

Theories like as fuzzy set (FS) (Zadeh 1965), intuitionistic FS (IFS) (Attanassov 1986), picture FS (Cuong and Kreinovich 2013), dyadic fuzzy FS (Ashraf and Abdullah 2019), are applied widely. Presently, decision-making is a hot topic in the field of research which includes the following three main steps:

(a) To describe the information, collect the data on an appropriate scale.

(b) Obtain the totally preference value of the object by assigning the various attribute values.

(c) Rank the objects in a transparent process to get the suit- able alternative(s).

Sotirov et al. (2018) introduced the hybrid approach for modular neural network design using inter criteria analysis and intuitionistic fuzzy logic. Sotirov et al. (2016); Castillo et al. (2015) proposed the novel modular neural network preprocessing procedure with intuitionistic fuzzy inter criteria analysis method to tackle the uncertainty in real life DMPs. Although, IFS based models have been successfully implemented in different areas since its appearance, but there are practical situations in real-world which cannot be represented by the traditional IFSs. Recently, (Cuong and Kreinovich 2013) filled these gaps by introducing the neutral membership in Atanassov's IFS theory.

Picture fuzzy set (PFS) in a finite fixed set $\mathfrak{R}$ is written as $\{\langle \partial_\gamma, \widehat{P_b}(\partial_\gamma), \widehat{I_b}(\partial_\gamma), \widehat{N_b}(\partial_\gamma) \rangle | \partial_\gamma \in \mathfrak{R}\}$ where $(\widehat{P_b}, \widehat{I_b}, \widehat{N_b}) \in [0,1]$ with condition that $0 \leq \widehat{P_b} + \widehat{I_b} + \widehat{N_b} \leq 1$. Basically, PFSs can precisely describe a human view, including more responses, such as: "yes", "abstain", "no" and "refusal".

Many researcher (Ashraf et al. 2019, Khan et al. 2019, Wei 2017; Zeng et al. 2019) contribute to the picture FS. Since the introduction of IFS, the theories and applications of IFS have been studied comprehensively, including its' applications in DMPs. These researches are very appropriate to tackle DMPs under PFS environment only owing to the condition $0 \leq \widehat{P_b} + \widehat{I_b} + \widehat{N_b} \leq 1$. However, in practical DMPs, the decision makers provides evaluation value in the form of $(\widehat{P_b}, \widehat{I_b}, \widehat{N_b})$, but it may be not satisfy the condition $0 \leq \widehat{P_b} + \widehat{I_b} + \widehat{N_b} \leq 1$ and beyond the upper bound 1. Aiming at this limitation which PFN cannot handle, (Ashraf and Abdullah 2019) established a new concept of Dyadic fuzzy (DF) set to handle with this situation.

DFS is an extension of PFS by slackening the condition $0 \leq \widehat{P_a}.\widehat{P_b} + \widehat{I_b}.\widehat{I_b} + \widehat{N_b}.\widehat{N_b} \leq 1$. We must also note that the acceptable dyadic orthogonal fuzzy space increases, thus providing more freedom for observers to express their belief in supporting membership. Therefore, DFSs express more extensive fuzzy information; Whilst, DFSs are more maneuverable and more appropriate for dealing with uncertainties information. Several researchers have done quite valuable contributions in the expansion of DF set and its approach to different fields, their results shows the great success of DF set in theoretical and technical aspects. As aggregation operators have a strong role to play in decision-making problems (DMPs), several researchers have done quite valuable contributions to introduce aggregation operators for DF set. Dyadic aggregation operators based on algebraic norms (Ashraf et al. 2019a) dealing with uncertainty and inaccurate information in DMPs. DF set the representation of DF norms (Ashraf et al. 2019b) and TOPSIS methodology introduced for DF information. DF Dombi aggregation operators based on Dombi norm are introduced in Ashraf et al. (2019c). DF Logarithmic aggregation operators based on entropy are proposed in Jin et al. (2019a). Linguistic fuzzy Choquet integral is proposed (Ashraf et al. 2018) for SF information. Cosine similarity measures are presented in Rafiq et al. (2019) to discuss the application in DMPs. Application of DF distance measures are discussed in Ashraf et al. (2019d) to determine the child development influence environmental factors using DF information. In Zeng et al. (2019) proposed the TOPSIS approach based on DF rough Set and discussed their application in DMPs. Gündo˘gdu et. Linguistic SF aggregation operators are presented in Jin et al. GRA methodology based on Dyadic al. (2020b) presented the TOPSIS methodology using DF information and discussed their real life application in DMPs. Gündo˘gdu and Kahraman (2020c) introduced the QFD method and also presented its application to the linear delta robot technology development problem.

Complex Proportional Assessment (COPRAS) (Zavadskas and Kaklauskas 1996) methodology proposed by Zavadskas and Kaklauskas in 1996. Corresponding weights of parameters and the degree of usefulness of alternative. Choosing the appropriate alternative is achieved by focusing at the ideal and anti-ideal solutions. COPRAS claims that the importance and usefulness features under investigation are directly and proportionately dependent on a set of criteria that describes alternatives efficiently and on the criteria's values and weights. COPRAS has many benefits, such as less processing time, a very easy and straightforward method of computing etc., over other MCDM methods such as EVAMIX, VIKOR and AHP. With respect to the advantages of DF set in describing uncertain information, also, regardless of the motivation and inspiration of all the above debate, we enlist the main objectives of the article:

1) Article main objective to provide a new strategy to DF set through emergency group decision making problem (GDMP) for control and prevent the Omicron effectively.
2) In this paper, a new methodology based on TOPSIS approach hybrid with the COPRAS, which can deal much more uncertainties in the form of Omicron fuzzy sets. *Note that*, in comparisons with the classic fuzzy sets, Omicron fuzzy set has more capability to deal the different situations more successfully. In fact, these sets consider opinions of DMs better than classic fuzzy sets. That is why, to use advantages and flexibility of the DF sets, the introduced technique is established under these sets to discourse the uncertainty of real-life in better way.
3) We design an algorithm to tackle emergency decision making problem of Omicron.

4) We shall collect the exact data disaster during the Omicron and then construct the mathematical model of emergency decision support systems for Omicron under generalized structure of Dyadic fuzzy sets and compare to propose technique with existing techniques to shows the validity and effectiveness of the proposed methodology.

To achieve the list of goals the structure of the paper is arranged as follows: In Sect. 1, some basic concepts are introduced. In Sect. 2, proposed the different types of distance between DF numbers. Section 3, gave the main contribution of the paper, and introduced the TOPSIS-COPRAS technique to deal with the uncertainty in DMP using DF information. Section 4, propose the numerical case study of outbreak of Omicron as an emergency decision support problem to demonstrate the applicability and reliability of the proposed technique.

2. Preliminaries

In this section, for better understanding of the Dyadic fuzzy sets, some related basic concepts will be briefly reviewed.

Definition 1:
Zadeh (1965) A fuzzy set ε in fixed set $\mathfrak{R}$ is described as $\varepsilon = \{\langle \partial_\gamma, \widehat{P_b}(\partial_\gamma)\rangle | \partial_\gamma \in \mathfrak{R}\}$,
Where $\widehat{P_b}(\partial_\gamma) \in [0,1]$ called positive membership grade. By $\varepsilon_1 \subseteq \varepsilon_2$ we mean that $\widehat{P_{b1}}(\partial_\gamma) \leq \widehat{P_{b2}}(\partial_\gamma)$ for each, $\partial_\Upsilon \in \mathfrak{R}$. Clearly $\varepsilon_1 = \varepsilon_2$ if $\varepsilon_1 \subseteq \varepsilon_2$ and $\varepsilon_2 \subseteq \varepsilon_1$.
Utilizing (Zadeh 1965), proposed min–max system to define basic operational laws as follows:
(1) $\varepsilon_1 \cap \varepsilon_2 = \left\{min\left(\widehat{P_{b1}}(\partial_\gamma), \widehat{P_{b2}}(\partial_\gamma)\right) \middle| \partial_\gamma \in \mathfrak{R}\right\}$,
(1) $\varepsilon_1 \cup \varepsilon_2 = \left\{max\left(\widehat{P_{b1}}(\partial_\gamma), \widehat{P_{b2}}(\partial_\gamma)\right) \middle| \partial_\gamma \in \mathfrak{R}\right\}$,
Where $\varepsilon_1, \varepsilon_2 \in F\hat{S}(\mathfrak{R})$ and $\partial_\Upsilon \in \mathfrak{R}$.

Definition 2:
(Ashraf and Abdullah 2019)A Dyadic fuzzy set ε in fixed set $\mathfrak{R}$ is described as
$\varepsilon = \{\langle \partial_\gamma, \widehat{P_a}(\partial_\gamma), \widehat{I_a}(\partial_\gamma), \widehat{N_a}(\partial_\gamma)\rangle | \partial_\gamma \in \mathfrak{R}\}$, where $P_b(\partial_\gamma) \in [0,1]$ positive membership, $I_b(\partial_\gamma) \in [0,1]$ neutral membership and , $N_b(\partial_\gamma) \in [0,1]$ negative membership grades, respectively. In addition, it is necessary to $0 \leq \widehat{P_a}.\widehat{P_a}(\partial_\gamma) + \widehat{I_a}.\widehat{I_a}(\partial_\gamma) + \widehat{N_a}.\widehat{N_a}(\partial_\gamma) \leq 1$, for each $\partial_\Upsilon \in \mathfrak{R}$. To what follows, we symbolize the collection of all Dyadic Orthogonal fuzzy sets in $\mathfrak{R}$ by $\in \hat{D}\hat{O}\hat{F}\hat{S}(\mathfrak{R})$. For convenience, the Dyadic fuzzy number (DFN) is symbolized by the triplet
$\varepsilon = (\widehat{P_b}, \widehat{I_b}, \widehat{N_b})$.
Let $\varepsilon_1, \varepsilon_2 \in \hat{S}F\hat{S}(\mathfrak{R})$ .Ashraf and Abdullah (2019) defined the following notions:
(1) $\varepsilon_1 \sqsubseteq \varepsilon_2 \Leftrightarrow$ if $\widehat{P_{b1}}(\partial_\gamma) \leq \widehat{P_{b2}}(\partial_\gamma), \widehat{I_{b1}}(\partial_\gamma) \leq \widehat{I_{b2}}(\partial_\gamma)$ *and* $\widehat{N_{b1}}(\partial_\gamma) \geq \widehat{N_{b2}}(\partial_\gamma)$ for each $\partial_\Upsilon \in \mathfrak{R}$. Clearly $\varepsilon_1 = \varepsilon_2$ if $\varepsilon_1 \sqsubseteq \varepsilon_2$ and $\varepsilon_2 \sqsubseteq \varepsilon_1$.

$$(2)\ \varepsilon_1 \sqcap \varepsilon_2 = \left\{ \begin{array}{l|} min\left(\widehat{P_{b1}}(\partial_\gamma), \widehat{P_{b2}}(\partial_\gamma)\right), \\ min\left(\widehat{I_{b1}}(\partial_\gamma), \widehat{I_{b2}}(\partial_\gamma)\right), \\ max\left(\widehat{N_{b1}}(\partial_\gamma), \widehat{N_{b2}}(\partial_\gamma)\right) \end{array} \partial_\gamma \in \mathfrak{R} \right\}$$

$$(3)\ \varepsilon_1 \sqcup \varepsilon_2 = \left\{ \begin{array}{l|} max\left(\widehat{P_{b1}}(\partial_\gamma), \widehat{P_{b2}}(\partial_\gamma)\right), \\ min\left(\widehat{I_{b1}}(\partial_\gamma), \widehat{I_{b2}}(\partial_\gamma)\right), \\ min\left(\widehat{N_{b1}}(\partial_\gamma), \widehat{N_{b2}}(\partial_\gamma)\right) \end{array} \partial_\gamma \in \mathfrak{R} \right\},$$

(3) $\varepsilon^C{}_1 = \{\widehat{N_{b1}}(\partial_\gamma), \widehat{I_{b1}}(\partial_\gamma), \widehat{P_{b1}}(\partial_\gamma) | \partial_\gamma \in \mathfrak{R}\}$,
Where $\varepsilon_1, \varepsilon_2 \in \hat{D}\hat{O}F\hat{S}(\mathfrak{R})$ and $\partial_\Upsilon \in \mathfrak{R}$.

Definition 3:

(Ashraf and Abdullah 2019) Let

$\varepsilon_1 = \{\widehat{P_{ƀ1}}(\partial_\gamma), \widehat{I_{ƀ1}}(\partial_\gamma), \widehat{N_{ƀ1}}(\partial_\gamma)\}$ and
$\varepsilon_2 = \{\widehat{P_{ƀ2}}(\partial_\gamma), \widehat{I_{ƀ2}}(\partial_\gamma), \widehat{N_{ƀ2}}(\partial_\gamma)\} \in \hat{D}\,\hat{O}\,F\,\hat{N}(\mathfrak{R})$
with $\varpi > 0$. Then, the operational rules are as follows:

(1) $\varepsilon_1 \otimes \varepsilon_2 =$
$\left\{\widehat{P_{ƀ1}}\widehat{P_{ƀ2}}, \widehat{I_{ƀ1}}\widehat{I_{ƀ2}}, \sqrt{\widehat{N_{ƀ1}}.\widehat{N_{ƀ1}} + \widehat{N_{ƀ2}}.\widehat{N_{ƀ2}} - \widehat{N_{ƀ1}}.\widehat{N_{ƀ1}}\ \widehat{N_{ƀ2}}.\widehat{N_{ƀ2}}}\right\}$;

(2) $\varepsilon_1 \oplus \varepsilon_2 =$
$\left\{\sqrt{\widehat{P_{ƀ1}}.\widehat{P_{ƀ1}} + \widehat{P_{ƀ2}}.\widehat{P_{ƀ2}} - \widehat{P_{ƀ1}}.\widehat{P_{ƀ1}}\ \widehat{P_{ƀ2}}.\widehat{P_{ƀ2}}},\ \widehat{I_{ƀ1}}\widehat{I_{ƀ2}}, \widehat{N_{ƀ1}}\widehat{N_{ƀ2}}\right\}$;

(3) $\varepsilon_1.\varpi = \left\{(P_{ƀ1})^{\varpi}, (I_{ƀ1})^{\varpi}, \sqrt{1 - \left(1 - \widehat{N_{ƀ1}}.\widehat{N_{ƀ1}}\right)^{\varpi}}\right\}$;

(3) $\varpi.\varepsilon_1 = \left\{\sqrt{1 - \left(1 - \widehat{P_{ƀ1}}.\widehat{P_{ƀ1}}\right)^{\varpi}}, (I_{ƀ1})^{\varpi}, (N_{ƀ1})^{\varpi},\right\}$.

Definition 4:

Ashraf et al. (2019a) Let $\varepsilon_k =$
$\{\widehat{P_{ƀk}}(\partial_\gamma), \widehat{I_{ƀk}}(\partial_\gamma), \widehat{N_{ƀk}}(\partial_\gamma)\} \in \hat{D}\,F\,N(\mathfrak{R})$
and DFWA : $DFN^n \longrightarrow DFN$ be a mapping defined as
$DFWA\ (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n) = \sum_{k=1}^{n} \tau k^{\varepsilon}\, k$.
Then, by operational laws of DFNs, we obtained Dyadic fuzzy weighted averaging operator as
$DFWA\ (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n) = \sum_{k=1}^{n} \tau k^{\varepsilon}\, k$.
$=$
$\left\{\sqrt{1 -, \prod_{k=1}^{n}\left(1 - \widehat{P_{ƀk}}.\widehat{P_{ƀk}}\right)^{\tau k}}, \prod_{k=1}^{n}(I_{ƀk})^{\tau k}, \prod_{k=1}^{n}(N_{ƀK})^{\tau k}\right\}$.
Where the weight vector of ε_K ($k \in$ N) With $\tau_k \geq 0$ and $\sum_{k=1}^{n} \tau_k = \{\tau_1, \tau_2, \dots, \tau_n\}$

Definition 5:

Ashraf et al. (2019a) Let $\varepsilon_K =$
$\{\widehat{P_{ƀk}}(\partial_\gamma), \widehat{I_{ƀk}}(\partial_\gamma), \widehat{N_{ƀk}}(\partial_\gamma)\} \in \hat{S}\,F\,N(\mathfrak{R})$
and DFWG : $DFN^n \longrightarrow DFN$ be a mapping defined as
Then, by operational laws of DFNs, we obtained dyadic fuzzy weighted geometric operator as
$DFWG\ (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n) = \sum_{k=1}^{n} \varepsilon_k^{\tau_k}$.
$= \left\{\begin{matrix} \prod_{k=1}^{n}(P_{ƀk})^{\tau_k}, \prod_{k=1}^{n}(I_{ƀk})^{\tau_k} \\ \sqrt{1 - \prod_{k=1}^{n}\left(1 - \widehat{N_{ƀk}}.\widehat{N_{ƀk}}\right)^{\tau_k}}, \end{matrix}\right\}$.Where the weight vector of ε_K ($k \in$ N)With $\tau_k \geq 0$ and $\sum_{k=1}^{n} \tau_k = 1$ is $\tau = \{\tau_1, \tau_2, \dots, \tau_n\}$

3. Distance of Dyadic fuzzy sets

Definition 6:

Let $\varepsilon_1 = \{\widehat{P_{ƀ1}}(\partial_\gamma), \widehat{I_{ƀ1}}(\partial_\gamma), \widehat{N_{ƀ1}}(\partial_\gamma)\}$ and $\varepsilon_2 = \{\widehat{P_{ƀ2}}(\partial_\gamma), \widehat{I_{ƀ2}}(\partial_\gamma), \widehat{N_{ƀ2}}(\partial_\gamma)\} \in \hat{D}\,F\,N(\mathfrak{R})$. Then maximum distance d_{Max} ($\varepsilon_1, \varepsilon_2$) is defined as

$$d_{Max}\ (\varepsilon_1, \varepsilon_2) = \frac{1}{n}\sum_{p=1}^{n} Max\left(\left\{\left|\widehat{P_{ƀ1}}(\partial_{\gamma p}) - \widehat{P_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{I_{ƀ1}}(\partial_{\gamma p}) - \widehat{I_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{N_{ƀ1}}(\partial_{\gamma p}) - \widehat{N_{ƀ2}}(\partial_{\gamma p})\right|\right\}\right)$$

Definition 7:

Let $\varepsilon_1 = \{\widehat{P_{ƀ1}}(\partial_\gamma), \widehat{I_{ƀ1}}(\partial_\gamma), \widehat{N_{ƀ1}}(\partial_\gamma)\}$ and $\varepsilon_2 = \{\widehat{P_{ƀ2}}(\partial_\gamma), \widehat{I_{ƀ2}}(\partial_\gamma), \widehat{N_{ƀ2}}(\partial_\gamma)\} \in \hat{D}\,F\,N(\mathfrak{R})$. Then minimum distance d_{Min} ($\varepsilon_1, \varepsilon_2$) is defined as

$$d_{Min}\ (\varepsilon_1, \varepsilon_2) = \frac{1}{n}\sum_{p=1}^{n} Min\left(\left\{\left|\widehat{P_{ƀ1}}(\partial_{\gamma p}) - \widehat{P_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{I_{ƀ1}}(\partial_{\gamma p}) - \widehat{I_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{N_{ƀ1}}(\partial_{\gamma p}) - \widehat{N_{ƀ2}}(\partial_{\gamma p})\right|\right\}\right)$$

Definition 8:

Let $\varepsilon_1 = \{\widehat{P_{ƀ1}}(\partial_\gamma), \widehat{I_{ƀ1}}(\partial_\gamma), \widehat{N_{ƀ1}}(\partial_\gamma)\}$ and $\varepsilon_2 = \{\widehat{P_{ƀ2}}(\partial_\gamma), \widehat{I_{ƀ2}}(\partial_\gamma), \widehat{N_{ƀ2}}(\partial_\gamma)\} \in \hat{D}\,F\,N(\mathfrak{R})$. Then Hamming distance d_{HD} ($\varepsilon_1, \varepsilon_2$) is defined as

$$d_{HD}\ (\varepsilon_1, \varepsilon_2) = \frac{1}{n}\sum_{p=1}^{n}\left(\left\{\left|\widehat{P_{ƀ1}}(\partial_{\gamma p}) - \widehat{P_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{I_{ƀ1}}(\partial_{\gamma p}) - \widehat{I_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{N_{ƀ1}}(\partial_{\gamma p}) - \widehat{N_{ƀ2}}(\partial_{\gamma p})\right|\right\}\right)$$

Definition 9:

Let $\varepsilon_1 = \{\widehat{P_{ƀ1}}(\partial_\gamma), \widehat{I_{ƀ1}}(\partial_\gamma), \widehat{N_{ƀ1}}(\partial_\gamma)\}$ and $\varepsilon_2 = \{\widehat{P_{ƀ2}}(\partial_\gamma), \widehat{I_{ƀ2}}(\partial_\gamma), \widehat{N_{ƀ2}}(\partial_\gamma)\} \in \hat{D}\,F\,N(\mathfrak{R})$.Then Then Euclidean distance d_{ED} ($\varepsilon_1, \varepsilon_2$) is defined as

$$d_{ED}(\varepsilon_1, \varepsilon_2) = \sqrt{\frac{1}{n}\sum_{p=1}^{n}\left(\left\{\begin{matrix}\left|\widehat{P_{ƀ1}}(\partial_{\gamma p}) - \widehat{P_{ƀ2}}(\partial_{\gamma p})\right| + \\ \left|\widehat{I_{ƀ1}}(\partial_{\gamma p}) - \widehat{I_{ƀ2}}(\partial_{\gamma p})\right| + \\ \left|\widehat{N_{ƀ1}}(\partial_{\gamma p}) - \widehat{N_{ƀ2}}(\partial_{\gamma p})\right|\end{matrix}\right\}\right)}$$

Definition 10:

Let $\varepsilon_1 = \{\widehat{P_{ƀ1}}(\partial_\gamma), \widehat{I_{ƀ1}}(\partial_\gamma), \widehat{N_{ƀ1}}(\partial_\gamma)\}$ and $\varepsilon_2 = \{\widehat{P_{ƀ2}}(\partial_\gamma), \widehat{I_{ƀ2}}(\partial_\gamma), \widehat{N_{ƀ2}}(\partial_\gamma)\} \in \hat{D}\,F\,N(\mathfrak{R})$.Then normalized Hamming distance d_{NHD} ($\varepsilon_1, \varepsilon_2$) is defined as

$$d_{NHD}\ (\varepsilon_1, \varepsilon_2) = \frac{1}{2n}\sum_{p=1}^{n}\left(\left\{\left|\widehat{P_{ƀ1}}(\partial_{\gamma p}) - \widehat{P_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{I_{ƀ1}}(\partial_{\gamma p}) - \widehat{I_{ƀ2}}(\partial_{\gamma p})\right| + \left|\widehat{N_{ƀ1}}(\partial_{\gamma p}) - \widehat{N_{ƀ2}}(\partial_{\gamma p})\right|\right\}\right)$$

Definition 11:

Let $\varepsilon_1 = \{\widehat{P_{ƀ1}}(\partial_\gamma), \widehat{I_{ƀ1}}(\partial_\gamma), \widehat{N_{ƀ1}}(\partial_\gamma)\}$ and $\varepsilon_2 = \{\widehat{P_{ƀ2}}(\partial_\gamma), \widehat{I_{ƀ2}}(\partial_\gamma), \widehat{N_{ƀ2}}(\partial_\gamma)\} \in \hat{D}\,F\,N(\mathfrak{R})$. Then normalized Euclidean distance d_{NED} ($\varepsilon_1, \varepsilon_2$) is defined as

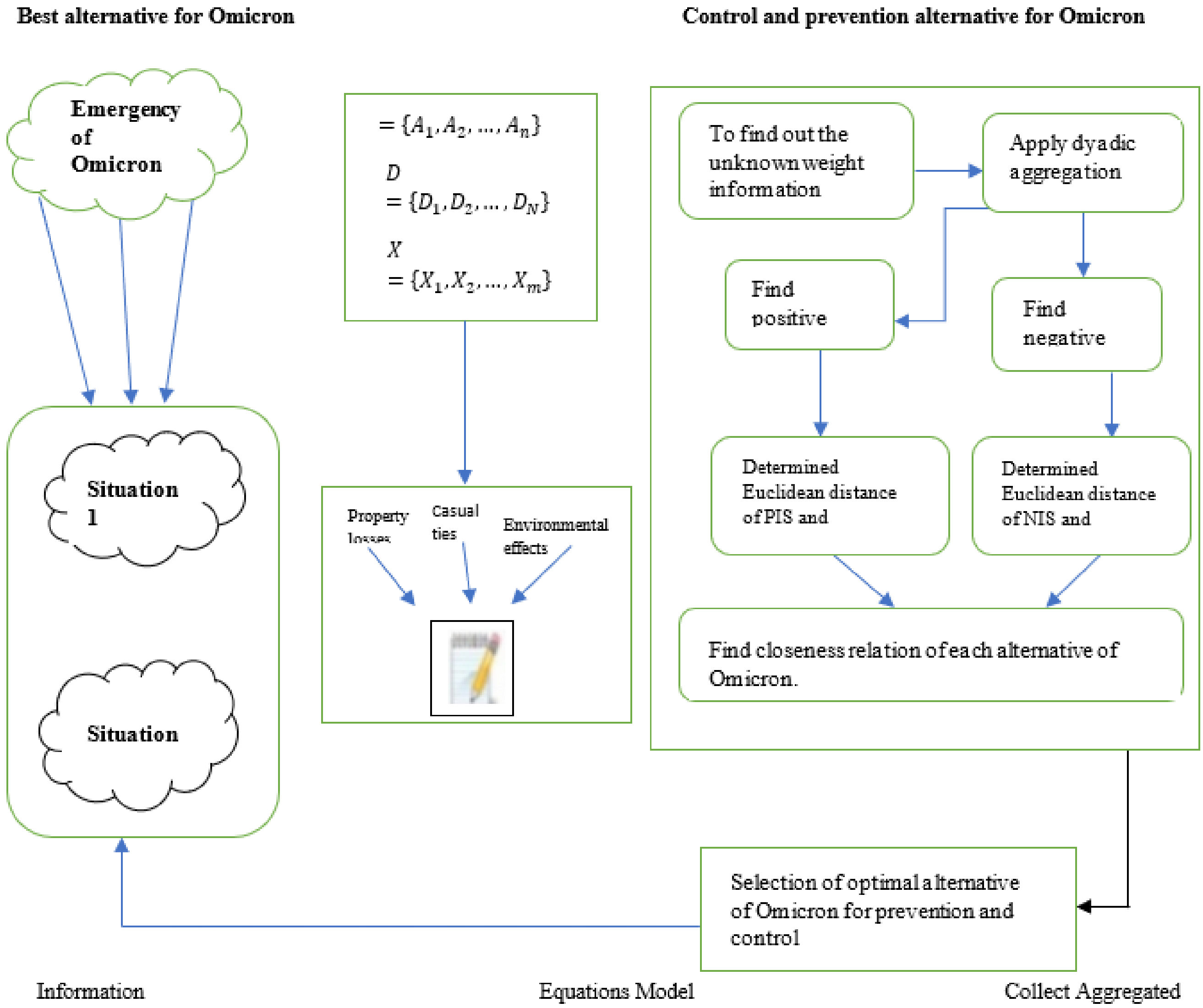
$$d_{NED}(\varepsilon_1, \varepsilon_2) = \sqrt{\frac{1}{2n}\sum_{p=1}^{n}\left(\left\{\begin{matrix}\left|\widehat{P_{ƀ1}}(\partial_{\gamma p}) - \widehat{P_{ƀ2}}(\partial_{\gamma p})\right| + \\ \left|\widehat{I_{ƀ1}}(\partial_{\gamma p}) - \widehat{I_{ƀ2}}(\partial_{\gamma p})\right| + \\ \left|\widehat{N_{ƀ1}}(\partial_{\gamma p}) - \widehat{N_{ƀ2}}(\partial_{\gamma p})\right|\end{matrix}\right\}\right)}$$

4. Proposed Methodology

In this segment, we proposed the methodology to deal with uncertainty and inaccurate information in the form of DFSs in DMPs. The proposed methodology has following steps,

Step1: Data Collection

Judgements of specialists' decision maker (DM) experts on assessments criteria for every activity and each criterion weights are assembled in the shape of initial decision.



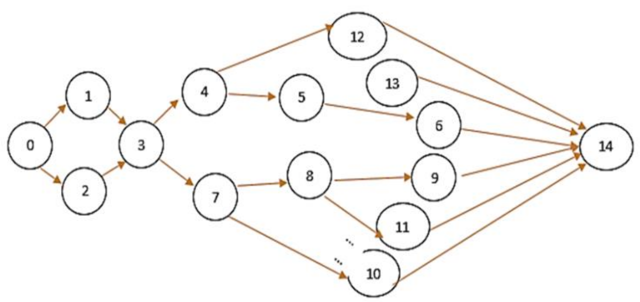


Fig.1. Critical Path Strategy

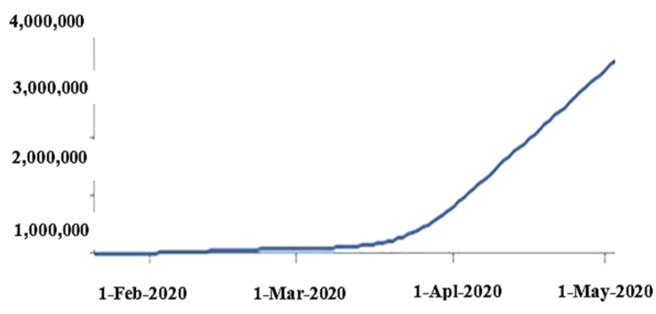


Fig.2. Flow chart of the COVID-19

Table.1 Prevalence of Omicron variant of COVID-19 in various countries worldwide

Name of the Country	Cases on	Dec 3, 21	Dec 9, 21
United Kingdom		22	568
Denmark		4	569
South Africa		77	397
Portugal		13	37
France		1	37
India		2	23
Israel		4	21
Botswana		19	23
Norway		2	33
Netherlands		16	36
United States		2	47
Australia		7	42
Germany		9	15
Canada		6	65
Iceland			20
South Korea		5	60
Austria		1	17
Belgium		1	30
Italy		9	13
Finland		1	9
Spain		2	14
Sweden		3	13
Brazil		2	6
Hong Kong		4	4
Japan		2	4
Nigeria		3	6
Latvia		0	5
Nepal		0	2
Romania		0	2
Russia		0	2
Argentina		0	1
Croatia		0	3
Czech Republic		1	2
Fiji		0	2
Greece		0	3
Ireland		0	1
Saudi Arabia		1	1
Switzerland		0	13
Thailand		0	1
Tunisia		0	1
UAE		1	1
Zambia		0	3
Total confirmed cases		**220**	**2152 (53.34%)**

Table.2 Information of each activity on criteria

A-E	Amount			Period			Reputation		
(a)	1	2	3	1	2	3	1	2	3
0-1	H	MH	VH	H	MH	VH	H	MH	VH
1-3	MH	M	H	MH	M	L	H	ML	H
3-4	M	ML	MH	VL	ML	L	MH	VL	L
4-5	ML	L	M	H	VH	MH	VH	L	H
5-6	ML	L	M	MH	M	VH	H	M	MH
6-14	M	M	H	M	H	MH	L	MH	ML
0-2	H	ML	MH	H	VH	M	L	VH	M
2-3	H	MH	VH	MH	MH	M	M	H	MH
3-7	MH	MH	VH	M	ML	H	M	M	M
7-8	M	VH	H	ML	VH	L	VH	M	MH
8-9	ML	M	ML	MH	L	L	ML	L	H
9-14	MH	H	L	M	H	L	MH	L	MH
10-14	MH	VH	M	H	L	M	M	M	L
11-14	ML	H	M	L	H	M	L	ML	M
12-14	M	M	L	VL	ML	ML	VH	MH	L
13-14	L	ML	ML	MH	MH	MH	H	VL	H

Table.3 Linguistic variables with corresponding DFNs

Very low (VL)	(0.9.0.01.0.01)
Low (L)	(0.9.0.3.0.2)
Medium low(ML)	(0.8.0.2.0.5)
Medium(M)	(0.6.0.2.0.6)
Medium high (MH)	(0.4.0.2.0.8)
High (H)	(0.2.0.3.0.9)
Very high (VH)	(0.01.0.01.0.9)

$$D^* = \begin{bmatrix} 0.21 & 0.16 & 0.76 & 0.21 & 0.16 & 0.85 & 0.22 & 0.18 & 0.86 & 0.36 & 0.21 & 0.65 & 0.61 & 0.11 & 0.36 \\ 0.41 & 0.22 & 0.75 & 0.62 & 0.24 & 0.54 & 0.41 & 0.25 & 0.76 & 0.61 & 0.21 & 0.62 & 0.52 & 0.22 & 0.66 \\ 0.61 & 0.21 & 0.62 & 0.85 & 0.18 & 0.24 & 0.74 & 0.16 & 0.36 & 0.21 & 0.18 & 0.87 & 0.51 & 0.17 & 0.51 \\ 0.75 & 0.21 & 0.14 & 0.51 & 0.27 & 0.64 & 0.36 & 0.21 & 0.61 & 0.62 & 0.21 & 0.62 & 0.54 & 0.24 & 0.66 \\ 0.75 & 0.24 & 0.42 & 0.66 & 0.24 & 0.54 & 0.41 & 0.24 & 0.76 & 0.75 & 0.14 & 0.38 & 0.56 & 0.17 & 0.45 \\ 0.45 & 0.21 & 0.71 & 0.42 & 0.22 & 0.75 & 0.71 & 0.24 & 0.51 & 0.71 & 0.24 & 0.47 & 0.54 & 0.24 & 0.66 \\ 0.47 & 0.24 & 0.72 & 0.55 & 0.25 & 0.55 & 0.51 & 0.18 & 0.56 & 0.75 & 0.24 & 0.42 & 0.41 & 0.22 & 0.76 \\ 0.21 & 0.16 & 0.85 & 0.45 & 0.21 & 0.72 & 0.41 & 0.22 & 0.78 & 0.45 & 0.24 & 0.72 & 0.56 & 0.06 & 0.46 \\ 0.27 & 0.12 & 0.82 & 0.52 & 0.22 & 0.65 & 0.61 & 0.21 & 0.61 & 0.55 & 0.25 & 0.57 & 0.54 & 0.22 & 0.55 \\ 0.26 & 0.16 & 0.81 & 0.87 & 0.25 & 0.31 & 0.34 & 0.14 & 0.78 & 0.58 & 0.11 & 0.55 & 0.72 & 0.15 & 0.45 \\ 0.75 & 0.20 & 0.53 & 0.74 & 0.27 & 0.41 & 0.64 & 0.25 & 0.54 & 0.34 & 0.14 & 0.77 & 0.21 & 0.16 & 0.86 \\ 0.51 & 0.26 & 0.63 & 0.57 & 0.25 & 0.55 & 0.55 & 0.24 & 0.61 & 0.46 & 0.13 & 0.65 & 0.45 & 0.14 & 0.66 \\ 0.34 & 0.14 & 0.75 & 0.55 & 0.27 & 0.57 & 0.71 & 0.24 & 0.46 & 0.64 & 0.16 & 0.48 & 0.64 & 0.25 & 0.54 \\ 0.52 & 0.24 & 0.65 & 0.57 & 0.25 & 0.56 & 0.75 & 0.24 & 0.44 & 0.56 & 0.18 & 0.54 & 0.65 & 0.16 & 0.46 \\ 0.55 & 0.25 & 0.55 & 0.82 & 0.14 & 0.34 & 0.42 & 0.18 & 0.64 & 0.54 & 0.25 & 0.65 & 0.41 & 0.24 & 0.76 \\ 0.84 & 0.24 & 0.41 & 0.41 & 0.21 & 0.81 & 0.42 & 0.21 & 0.61 & 0.51 & 0.18 & 0.55 & 0.51 & 0.16 & 0.56 \end{bmatrix}$$

$$LD^* = \begin{bmatrix} 0.02 & 0.01 & 0.7 & 0.02 & 0.02 & 0.7 & 0.01 & 0.02 & 0.7 & 0.01 & 0.02 & 0.2 & 0.01 & 0.01 & 0.01 \\ 0.2 & 0.2 & 0.4 & 0.5 & 0.1 & 0.2 & 0.1 & 0.2 & 0.4 & 0.3 & 0.2 & 0.4 & 0.1 & 0.1 & 0.4 \\ 0.3 & 0.2 & 0.4 & 0.5 & 0.02 & 0.03 & 0.5 & 0.02 & 0.01 & 0.02 & 0.01 & 0.7 & 0.02 & 0.01 & 0.01 \\ 0.6 & 0.2 & 0.2 & 0.2 & 0.2 & 0.2 & 0.01 & 0.01 & 0.2 & 0.4 & 0.2 & 0.5 & 0.2 & 0.2 & 0.5 \\ 0.5 & 0.3 & 0.2 & 0.3 & 0.2 & 0.3 & 0.2 & 0.4 & 0.6 & 0.5 & 0.01 & 0.02 & 0.01 & 0.02 & 0.01 \\ 0.1 & 0.2 & 0.2 & 0.2 & 0.3 & 0.5 & 0.4 & 0.2 & 0.1 & 0.5 & 0.2 & 0.3 & 0.2 & 0.3 & 0.4 \\ 0.2 & 0.1 & 0.4 & 0.2 & 0.2 & 0.1 & 0.01 & 0.01 & 0.2 & 0.4 & 0.2 & 0.1 & 0.2 & 0.01 & 0.3 \\ 0.01 & 0.01 & 0.7 & 0.3 & 0.2 & 0.7 & 0.2 & 0.1 & 0.6 & 0.2 & 0.2 & 0.1 & 0.01 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.7 & 0.2 & 0.2 & 0.5 & 0.5 & 0.2 & 0.6 & 0.1 & 0.2 & 0.1 & 0.2 & 0.1 & 0.2 \\ 0.01 & 0.02 & 0.4 & 0.7 & 0.2 & 0.2 & 0.01 & 0.01 & 0.6 & 0.01 & 0.1 & 0.2 & 0.4 & 0.01 & 0.02 \\ 0.5 & 0.2 & 0.3 & 0.4 & 0.2 & 0.1 & 0.2 & 0.1 & 0.2 & 0.02 & 0.1 & 0.6 & 0.1 & 0.01 & 0.7 \\ 0.3 & 0.2 & 0.3 & 0.2 & 0.3 & 0.2 & 0.3 & 0.2 & 0.2 & 0.03 & 0.01 & 0.4 & 0.01 & 0.1 & 0.4 \\ 0.01 & 0.01 & 0.5 & 0.2 & 0.1 & 0.2 & 0.5 & 0.2 & 0.1 & 0.2 & 0.1 & 0.1 & 0.1 & 0.2 & 0.1 \\ 0.2 & 0.1 & 0.4 & 0.2 & 0.1 & 0.2 & 0.3 & 0.2 & 0.1 & 0.1 & 0.02 & 0.1 & 0.1 & 0.1 & 0.02 \\ 0.1 & 0.1 & 0.1 & 0.6 & 0.1 & 0.2 & 0.01 & 0.1 & 0.1 & 0.2 & 0.1 & 0.4 & 0.2 & 0.2 & 0.4 \\ 0.8 & 0.2 & 0.2 & 0.4 & 0.2 & 0.8 & 0.2 & 0.01 & 0.01 & 0.01 & 0.01 & 0.2 & 0.01 & 0.01 & 0.2 \end{bmatrix}$$

$$RD^* = \begin{bmatrix} 0.3 & 0.2 & 0.8 & 0.3 & 0.5 & 0.7 & 0.3 & 0.2 & 0.7 & 0.7 & 0.1 & 0.7 & 0.4 & 0.2 & 0.7 \\ 0.5 & 0.4 & 0.7 & 0.7 & 0.4 & 0.6 & 0.6 & 0.2 & 0.9 & 0.6 & 0.2 & 0.8 & 0.3 & 0.2 & 0.9 \\ 0.7 & 0.1 & 0.6 & 0.8 & 0.2 & 0.4 & 0.6 & 0.3 & 0.7 & 0.4 & 0.2 & 0.7 & 0.7 & 0.1 & 0.7 \\ 0.6 & 0.4 & 0.7 & 0.7 & 0.2 & 0.7 & 0.6 & 0.4 & 0.9 & 0.7 & 0.2 & 0.8 & 0.9 & 0.3 & 0.7 \\ 0.8 & 0.2 & 0.5 & 0.6 & 0.5 & 0.6 & 0.7 & 0.4 & 0.8 & 0.9 & 0.3 & 0.6 & 0.8 & 0.1 & 0.7 \\ 0.7 & 0.2 & 0.7 & 0.5 & 0.2 & 0.7 & 0.8 & 0.4 & 0.8 & 0.7 & 0.4 & 0.7 & 0.7 & 0.3 & 0.7 \\ 0.6 & 0.4 & 0.9 & 0.7 & 0.5 & 0.7 & 0.7 & 0.2 & 0.7 & 0.9 & 0.1 & 0.6 & 0.7 & 0.1 & 0.7 \\ 0.5 & 0.4 & 0.7 & 0.5 & 0.6 & 0.5 & 0.5 & 0.3 & 0.9 & 0.6 & 0.3 & 0.7 & 0.8 & 0.2 & 0.7 \\ 0.5 & 0.4 & 0.8 & 0.6 & 0.2 & 0.7 & 0.5 & 0.1 & 0.5 & 0.9 & 0.1 & 0.9 & 0.7 & 0.1 & 0.8 \\ 0.5 & 0.2 & 0.8 & 0.7 & 0.2 & 0.4 & 0.7 & 0.3 & 0.9 & 0.6 & 0.2 & 0.7 & 0.8 & 0.2 & 0.8 \\ 0.6 & 0.3 & 0.7 & 0.6 & 0.4 & 0.6 & 0.6 & 0.2 & 0.6 & 0.6 & 0.3 & 0.9 & 0.6 & 0.1 & 0.8 \\ 0.6 & 0.4 & 0.8 & 0.5 & 0.5 & 0.7 & 0.7 & 0.2 & 0.8 & 0.7 & 0.2 & 0.5 & 0.7 & 0.2 & 0.8 \\ 0.7 & 0.3 & 0.7 & 0.7 & 0.4 & 0.7 & 0.7 & 0.4 & 0.7 & 0.9 & 0.2 & 0.9 & 0.5 & 0.2 & 0.8 \\ 0.7 & 0.2 & 0.8 & 0.5 & 0.2 & 0.8 & 0.7 & 0.2 & 0.6 & 0.7 & 0.3 & 0.6 & 0.7 & 0.3 & 0.8 \\ 0.8 & 0.2 & 0.7 & 0.7 & 0.3 & 0.4 & 0.6 & 0.2 & 0.7 & 0.8 & 0.2 & 0.9 & 0.7 & 0.2 & 0.7 \\ 0.6 & 0.2 & 0.5 & 0.3 & 0.5 & 0.7 & 0.7 & 0.2 & 0.8 & 0.7 & 0.2 & 0.7 & 0.7 & 0.1 & 0.7 \end{bmatrix}$$

Calculated aggregated Dyadic matrix for paths by using addition rule of Dyadic fuzzy set are evaluated in table 4(a), (b).

Table 4 Aggregated information in paths

(a)

Paths	**Amount**
0-1-3-4-12-14	(0.296,0.001,0.194)
0-1-3-4-5-13–14	(0.414,0.0012,0.05)
0-1-3-4-5-6-14	(0.47,0.01,0.045)
0-1-3-7-10-14	(0.13,0.001,0.424)
0-1-3-7-8-11-14	(0.177,0.01,0.263)
0-1-3-7-8-9-14	(0.251,0.10,0.128)
0-2-3-4-12-14	(0.318,0.021,0.174)
0-2-3-4-5-13-14	(0.41,0.0012,0.047)
0-2-3-4-5-6-14	(0.371,0.001,0.33)
0-2-3-7-10-14	(0.152,0.0011,0.353)
0-2-3-7-8-11-14	(0.253,0.06,0.249)
0-2-3-7-8-9-14	(0.272,0.02,0.122)

Reputation	**Safety**
(0.393,0.00,0.016)	(0.371,0.00,0.011)
(0.424,0.00,0.007)	(0.376,0.00,0.015)
(0.357,0.012,0.138)	(0.312,0.01,0.152)
(0.444,0.0013,0.043)	(0.319,0.01,0125)
(0.479,0.03,0.021)	(0.315,0.03,0.062)
(0.535,0.0023,0.014)	(0.438,0.0021,0.013)
(0.428,0.0022,0.024)	(0.424,0.01,0.036)
(0.435,0.01,0.004)	(0.238,0.01,0.028)
(0.373,0.031,0.105)	(0.40,0.021,0.056)
(0.467,0.008,0.003)	(0.373,0.02,0.050)
(0.519,0.0012,0.020)	(0.367,0.07,0.035)
(0.515,0.0001,0.371)	(0.371,0.0002,0.045)

(b)

Path	**Specialty**
0-1-3-4-12–14	(0.323,0.013,0.156)
0-1-3-4-5-13-14	(0.482,0.001,0.066)
0-1-3-4-5-6-14	(0.422,0.001,0.021)
0-1-3-7-10-14	(0.363,0.005,0.003)
0-1-3-7-8-11-14	(0.421,0.012,0.023)
0-1-3-7-8-9-14	(0.406,0.001,0.027)
0-2-3-4-12-14	(0.356,0.021,0.141)
0-2-3-4-5-13-14	(0.389,0.001,0.060)
0-2-3-4-5-6-14	(0.454,0.001,0.018)
0-2-3-7-10-14	(0.513,0.012,0.014)
0-2-3-78-11-14	(0.525,0.001,0.037)
0-2-3-7-8-9-14	(0.448,0.001,0.032)

Ranking of the proposed technique seems to differ little. This model is more efficient than most because. In decision making methods, dyadic fuzzy set increases grade space and can variate according to the emergency situation.

5. Superiority of suggested methodology and comparison with other frameworks

Fuzzy set, intuitionistic FS, picture FS have some space limitation on their grades, dyadic FS fills this gap in the literature and offers significant space than dyadic FS, intuitionistic FS, picture FS. The suggested framework enhances existing approaches and the decision-maker can choose the grades freely by using the condition $0\leq \widehat{p_b}\widehat{p_b} + \widehat{I_b}\widehat{I_b} + \widehat{N_b}\widehat{N_b} \leq 1$.

6. Limitations

The limitation of this analysis is that the developed model determines the best alternative in a single setting based on the input of considered experts.

7. Conclusions

The novel 2019 coronavirus, SARS-CoV-2 (COVID-19). Originated in the city of Wuhan in the People`s Republic of China’s Hubei Province towards the end of 2019 and has spread very quickly in a very short time to the world. This article aimed to analyze the pandemic trajectory using mathematical modeling based on the information used by fuzzy decision-making methodology to select the best alternative using critical path strategy.

Dyadic fuzzy set plays a vital role in solving emergency decision making in the emergency situation of COVID-19 As they can optimal describe a preference when there is vague or uncertain information. In this study, the new variant of SARS-CoV-2, Omicron, has involved 57 countries and has resulted in 2152 confirmed cases from the first re- ported case of Omicron, November 24, 2021, to December 9, 2021 integrated approach is established to handle emergency MCGDM problems with unknown weight information.

The presented approach simultaneously considers a DMS` limiting rationality and interdependence among criteria. The objective weight vectors are obtained by using the distance measure and were combined with subjective weights in the Dyadic fuzzy MCGDM model. Moreover, the operating of the proposed method is thoroughly explained with the assistance of a numerical example on the basis of the TOPSIS-COPRAS method. We testified the effectiveness and rationality of the proposed MCGDM approach, its output is compared with other MCGDM problems to make a comparison. The proposed MCGDM approach can also be used to other complicated problems like risk evaluation, emerging technology, uncertain decision-maker project installation, site selection etc.

The approach proposed in this paper will be extended in future research to other ambiguous fields, such as linguistic term sets, probabilistic linguistic term sets, hesitant Spherical fuzzy sets etc. The suggested approach can also be extended to other fields, such as medical diagnosis of nutrition, sustainable choice of suppliers, pattern recognition and so on.

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