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Assessing and Comparing COVID-19 Intervention Strategies Using a Varying Partial Consensus Fuzzy Collaborative Intelligence Approach

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Abstract: The COVID-19 pandemic has severely impacted our daily lives. For tackling the COVID-19 pandemic, various intervention strategies have been adopted by country (or city) governments around the world. However, whether an intervention strategy will be successful, acceptable, and cost-effective or not is still questionable. To address this issue, a varying partial consensus fuzzy collaborative intelligence approach is proposed in this study to assess an intervention strategy. In the varying partial consensus fuzzy collaborative intelligence approach, multiple decision makers express their judgments on the relative priorities of factors critical to an intervention strategy. If decision makers lack an overall consensus, the layered partial consensus approach is applied to aggregate their judgments for each critical factor. The number of decision makers that reach a partial consensus varies from a critical factor to another. Subsequently, the generalized fuzzy weighted assessment approach is proposed to evaluate the overall performance of an intervention strategy for tackling the COVID-19 pandemic. The proposed methodology has been applied to compare 15 existing intervention strategies for tackling the COVID-19 pandemic.

Keywords: intervention strategy; COVID-19 pandemic; layered partial consensus; fuzzy analytic hierarchy process

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1. Introduction

The outbreak of COV-19 was identified in Wuhan, China [1]. Since then, the COVID-19 pandemic has severely affected all aspects of our daily lives [2]. Owing to the high infectivity of COVID-19, governments everywhere have adopted various intervention strategies to curb the spread of COVID-19 [3]. For example, many countries closed their borders to avoid the transnational spread of COVID-19, which was even more meaningful as evidence has shown that COVID-19 mutated differently in different regions [4]. Mass gatherings, especially those held indoors, were discouraged to prevent the spread of COVID through contact [5]. For the same reason, public spaces in which people had close contact, such as movie theaters, churches, and pubs, were also locked down [6]. Samanlioglu and Kaya [7] listed the 15 most common intervention strategies for tackling the COVID-19 pandemic. However, asking people to wear masks was not included, although it had been considered as the most effective intervention strategy [8]. To sum up, the following phenomena have been observed so far:

- Intervention strategies adopted by different governments were not the same [9].

- The effects of various intervention strategies were unequal [10].
- Not all these intervention strategies were acceptable or welcome to people [11].

Therefore, assessing intervention strategies for tackling the COVID-19 pandemic becomes a critical task. Based on the assessment results, the top-performing intervention strategies can be recommended to a country (or city) government. So far, very few attempts have been made to fulfill this task. Samanlioglu and Kaya [7] proposed a hesitant fuzzy analytic hierarchy process (hesitant FAHP) approach, in which hesitant fuzzy numbers [12] were adopted to better consider the subjectivity and uncertainty involved in the judgments of a decision maker.

To sum up, the existing methods for similar purposes are subject to the following problems:

- Fuzzy arithmetic averages are applied to aggregate decision makers' judgements, which may lead to unreasonable results [13,14].
- Decision makers may not reach a consensus about the priorities of factors critical to an intervention strategy [15–17].
- The priority of a critical factor is usually modelled with a crisp value, rather than a fuzzy value. As a result, some meaningful information, such as the possibly highest and lowest priorities of a critical factor, is lost [18–21].

To solve these problems, a varying partial consensus fuzzy collaborative intelligence approach is proposed in this study to assess an intervention strategy for tackling the COVID-19 pandemic. Fuzzy collaborative intelligence methods have rarely been applied to fuzzy group decision-making problems [22–24], because the involved set operations are not easy to calculate [20,25,26]. Fuzzy numerical methods—e.g., fuzzy weighted average (FWA) and its variants [23,24]—are prevalent, but may lead to unreasonable results [20].

The varying partial consensus fuzzy collaborative intelligence approach is a fuzzy group decision-making method in which multiple decision makers assess an intervention strategy for tackling the COVID-19 pandemic collaboratively. In the proposed methodology, the layered partial consensus (LPC) approach proposed by Chen and Wu [27] is applied to aggregate most decision makers' partial consensus, if the overall consensus among all decision makers does not exist. However, Chen and Wu [27] applied the LPC approach to forecast the unit cost of a product, which was a supervised learning problem [25,27,28]. On the contrary, in this study the LPC approach is applied to assess an intervention strategy for tackling the COVID-19 pandemic, which is an unsupervised assessment problem [29,30].

Compared to existing methods in this field, the varying partial consensus fuzzy collaborative intelligence approach has the following novelties:

- The priority of a critical factor is modelled with a fuzzy value.
- When the overall consensus among all decision makers is lacking, the partial consensus among most decision makers [15–17,27] is sought instead.
- The number of decision makers that reach a partial consensus varies when the LPC approach is applied to different critical factors, which is called the "varying" property of the proposed methodology.
- A new assessment method, the generalized fuzzy weighted assessment (GFWA) approach, is proposed to assess an intervention strategy for tackling the COVID-19 pandemic.

In the literature, there have been various methods to aggregate decision makers' fuzzy judgments. The differences between the proposed methodology and some existing methods are summarized in Table 1.

This paper is organized in the following manner. In the next section, the varying partial consensus fuzzy collaborative intelligence approach is introduced. In Section 3, the results of applying the varying partial consensus fuzzy collaborative intelligence approach to assess some intervention strategies for tackling the COVID-19 pandemic are presented. Then, there is a discussion of the experimental results. The conclusions of this study are given in the last section.

Table 1. Differences between the proposed methodology and some existing methods.

Method	Application	Consensus Type	Aggregation Method	Number of Decision Makers Reaching Consensus	Assessment Method
Samanlioglu and Kaya [7]	Intervention strategy assessment	Overall consensus	Fuzzy arithmetic mean	All	Fuzzy arithmetic mean
Lin et al. [22]	Smart technology application assessment	Guaranteed overall consensus	Fuzzy Intersection	All	Fuzzy technique for order preference by similarity to ideal solution
Chen and Wu [27]	Cost forecasting	Layered consensus	Partial consensus fuzzy intersection	Maximum number of decision makers with sufficient consensus	Back propagation network
Chen [31]	Price forecasting	Partial consensus	Partial consensus fuzzy intersection	Maximum number of decision makers with consensus	Back propagation network
Chen and Lin [32]	Yield forecasting	Overall consensus	Fuzzy intersection	All	Back propagation network
Gao et al. [33]	Supplier assessment	Overall consensus	Fuzzy weighted average	All	Fuzzy weighted average
The proposed methodology	Intervention strategy assessment	Varying layered partial consensus	Partial consensus fuzzy intersection	Maximum number of decision makers with sufficient consensus for each critical factor	Generalized fuzzy weighted assessment

2. Literature Review

There are two major trends in the development of fuzzy multiple-criteria decision-making methods. One is to fuzzify an existing crisp multiple-criteria decision-making method by modelling the evaluation result of an alternative, the weight (or relative priority) of a criterion, and/or the weight (or authority level) of each decision maker with fuzzy numbers. For example, Chen [34] applied FWA to aggregate the performances of a hotel along various dimensions, and then defuzzified the aggregation result using a back propagation network. Similarly, fuzzy multi-attribute utility theory (MAUT) methods were applied to select intervention strategies to restore an aquatic ecosystem contaminated by radionuclides [35], assess intelligent buildings [36], and recommend suitable clinics to patients [37]. Sevkli [38] proposed a fuzzy elimination and choice expressing the reality (ELECTRE) method for supplier selection. For a similar purpose, Sachdeva et al. [39] applied the fuzzy preference ranking organization method for enrichment evaluations (PROMETHEE) technique instead. Fuzzy measuring attractiveness by a categorical-based evaluation technique (MACBETH) methods are another type of fuzzy multiple-criteria decision-making method that has been widely applied [40,41]. The other is to adopt new types of fuzzy numbers. For example, Faizi et al. [42] fuzzified the traditional characteristic objects method (COMET), in which the evaluation results of alternatives were given in hesitant fuzzy sets (HFSs). A similar methodology was proposed by Faizi et al. [43] who adopted normalized interval-valued triangular fuzzy numbers instead. Compared to the previous method [42], their methodology considered the difficulty in specifying the membership function, and therefore was more flexible and practicable.

When multiple decision makers are involved, the decision-making problem becomes a group-based one. However, most past studies assumed that there was an overall consensus among all decision makers, and just averaged decision makers' judgements before applying a fuzzy multiple-criteria decision-making method, which was problematic because sometimes it was difficult for decision makers to reach an overall consensus [15–17,27,31]. In addition, the averaging result may be meaningless to decision makers [44]. To address this issue, the partial consensus among some decision makers can be sought instead [15–17]. This study also belongs to this type of research.

3. The Proposed Methodology

3.1. Implementation Procedure

The varying partial consensus fuzzy collaborative intelligence approach is proposed in this study for assessing an intervention strategy for tackling the COVID-19 pandemic. The implementation procedure of the varying partial consensus fuzzy collaborative intelligence approach comprises the following steps:

Step 1. Each decision maker must apply the fuzzy geometric mean (FGM) method [45–47] to evaluate the relative priorities of factors critical to an intervention strategy for tackling the COVID-19 pandemic.
Step 2. Consider the first critical factor.
Step 3. If all the decision makers reached an overall consensus, go to Step 4; otherwise, go to Step 6.
Step 4. Apply fuzzy intersection (FI) [32] to aggregate the relative priorities evaluated by the decision makers.
Step 5. Go to Step 7.
Step 6. Apply the LPC approach to aggregate the relative priorities.
Step 7. If all critical factors have been considered, go to Step 10; otherwise, go to Step 8.
Step 8. Consider the next critical factor.
Step 9. Go to Step 3.
Step 10. Apply the GFWA approach to assess the overall performance of an intervention strategy for tackling the COVID-19 pandemic.
Step 11. Apply the center-of-gravity (COG) method [48,49] to defuzzify the assessment result, so as to generate an absolute ranking of intervention strategies for tackling the COVID-19 pandemic.

A flowchart is provided in Figure 1 to illustrate the implementation procedure of the varying partial consensus fuzzy collaborative intelligence approach.

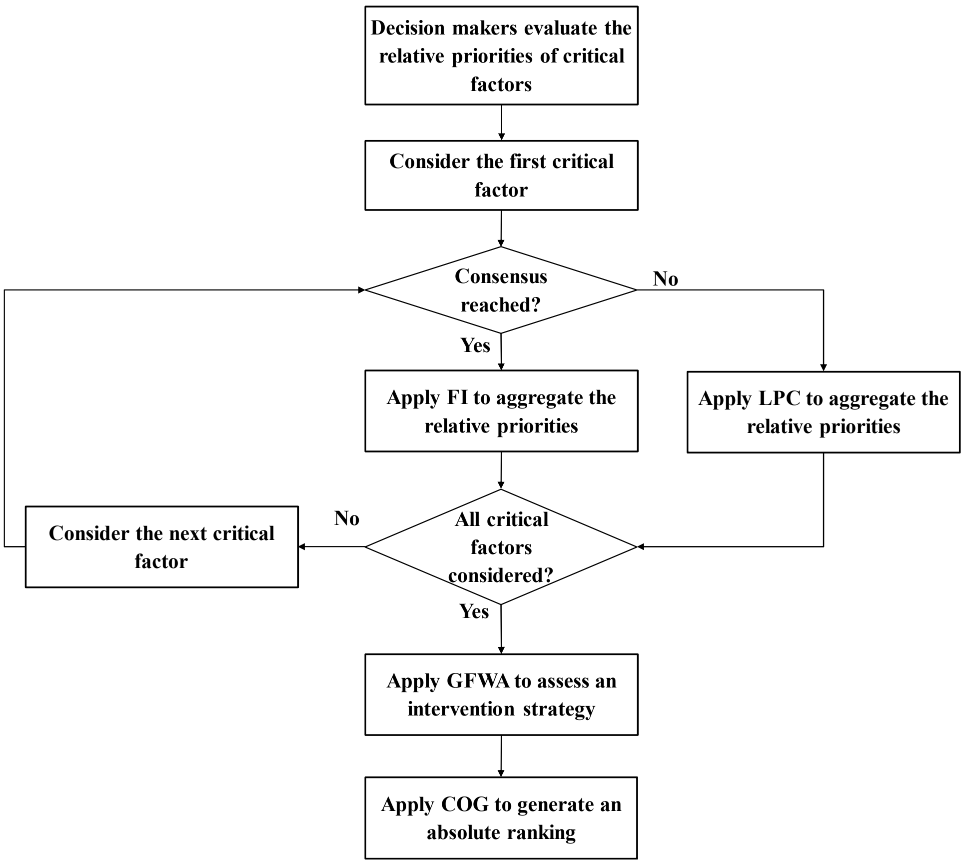


Figure 1. Implementation procedure of the varying partial consensus fuzzy collaborative intelligence approach.

Inputs to the proposed methodology include multiple decision makers' judgments, possible intervention strategies for tackling the COVID-19 pandemic, and critical factors in the intervention strategies. Outputs from the proposed methodology include the relative priorities of critical factors and the ranking result of intervention strategies. The problem structure is illustrated in Figure 2.

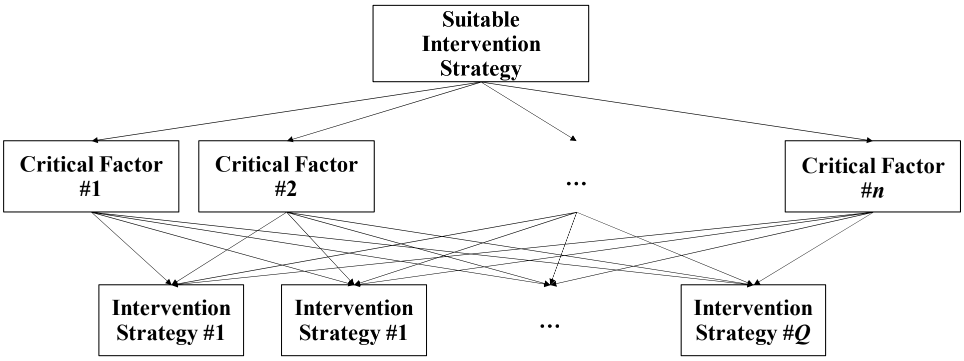


Figure 2. Problem structure.

3.2. FGM Method for Evaluating the Relative Priorities of Critical Factors

In the proposed methodology, first each decision maker evaluates and compares the relative priorities of critical factors in pairs using the FGM method. The comparison results are expressed in linguistic terms such as "as equal as," "weakly more important than," "strongly more important than," "very strongly more important than," "absolutely more important than," etc. A prevalent way is to associate these linguistic terms with triangular fuzzy numbers, as summarized Table 2 [46]. Usually, these triangular fuzzy numbers (TFNs) are within [1,9]. By widening these TFNs, the possibility for decision makers to reach a consensus increases [20]. In addition, restricting these TFNs to be within a narrower range, such as [1,3], elevates the consistency of the pairwise comparison results [7].

Table 2. Linguistic terms for expressing the relative priorities of critical factors.

Symbol	Linguistic Term	TFN
L1	As equal as	(1, 1, 3)
L2	As equal as or weakly more important than	(1, 2, 4)
L3	Weakly more important than	(1, 3, 5)
L4	Weakly or strongly more important than	(2, 4, 6)
L5	Strongly more important than	(3, 5, 7)
L6	Strongly or very strongly more important than	(4, 6, 8)
L7	Very strongly more important than	(5, 7, 9)
L8	Very or absolutely strongly more important than	(6, 8, 9)
L9	Absolutely more important than	(7, 9, 9)

Based on the pairwise comparison results, the fuzzy judgment matrix $\widetilde{\mathbf{A}}_{n\times n} = [\widetilde{a}_{ij}]$ is constructed, in which:

$$\widetilde{a}_{ji} = 1/\widetilde{a}_{ij}. \tag{1}$$

The fuzzy eigenvalue and eigenvector of $\widetilde{\mathbf{A}}$, indicated with $\widetilde{\lambda}$ and $\widetilde{\mathbf{x}}$, respectively, satisfy:

$$det(\widetilde{\mathbf{A}}(-)\widetilde{\lambda}\mathbf{I}) = 0, \tag{2}$$

and

$$(\widetilde{\mathbf{A}}(-)\widetilde{\lambda}\mathbf{I})(\times)\widetilde{\mathbf{x}} = 0, \tag{3}$$

where $(-)$ and $(\times)$ denote fuzzy subtraction and multiplication, respectively.

The FGM method [25] is applied to evaluate the relative priority of each critical factor ($\widetilde{w}_i$), as:

$$\widetilde{w}_i \cong \frac{\sqrt[n]{\prod_{j=1}^{n} \widetilde{a}_{ij}}}{\sum_{k=1}^{n} \sqrt[n]{\prod_{j=1}^{n} \widetilde{a}_{kj}}}. \tag{4}$$

The fuzzy maximal eigenvalue $\widetilde{\lambda}_{\max}$ can be estimated as:

$$\widetilde{\lambda}_{\max} = \frac{1}{n}\sum_{i=1}^{n} \frac{\sum_{j=1}^{n} (\widetilde{a}_{ij}(\times)\widetilde{w}_j)}{\widetilde{w}_i}. \tag{5}$$

The consistency of the pairwise comparison results can be evaluated in terms of the critical ratio (CR):

$$\widetilde{CR} = \frac{\frac{\widetilde{\lambda}_{\max}-n}{n-1}}{RI}, \tag{6}$$

where RI is the random consistency index [50]. $\widetilde{CR}$ should be less than 0.1 for a small FAHP problem, or less than 0.3 if the problem size is large or the problem is highly uncertain [51,52].

3.3. LPC Approach for Aggregating the Relative Priorities

When there is no overall consensus among all the decision makers, the partial consensus among some of them can be sought instead [32,53].

Definition 1. *The H/M partial consensus fuzzy intersection (PCFI) of the relative priorities derived by M decision makers for the i-th critical factor, indicated with $\widetilde{w}_i(1) \sim \widetilde{w}_i(M)$, is denoted by $\widetilde{PCFI}^{H/M}(\widetilde{w}_i(1), \ldots, \widetilde{w}_i(M))$, such that:*

$$\mu_{\widetilde{PCFI}^{H/M}}(x) = \max_{\text{all } g}(\min(\mu_{\widetilde{w}_1(g(1))}(x), \ldots, \mu_{\widetilde{w}_1(g(H))}(x))), \tag{7}$$

where $g() \in Z^+$; $1 \le g() \le M$; $g(p) \cap g(q) = \emptyset\ \forall\ p \neq q$; $H \ge 2$.

An example is given in Figure 3, showing the relative priorities of a critical factor evaluated by five decision makers. If fuzzy intersection is applied to find the common part of the evaluations, the result will be an empty set. As a result, these decision makers lack an overall consensus, because no value is acceptable to all of them.

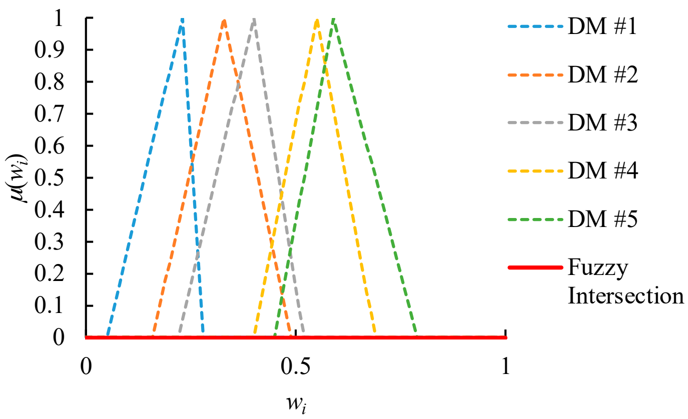


Figure 3. An example.

Nevertheless, (partial) consensus among any four decision makers exists. For illustrating this, the 4/5 PCFI result of the evaluations is derived, as shown in Figure 4. For example, 0.47 is acceptable to decision makers #2, #3, #4, and #5, and has a positive membership. However, the 4/5 PCFI result covers very few possible values.

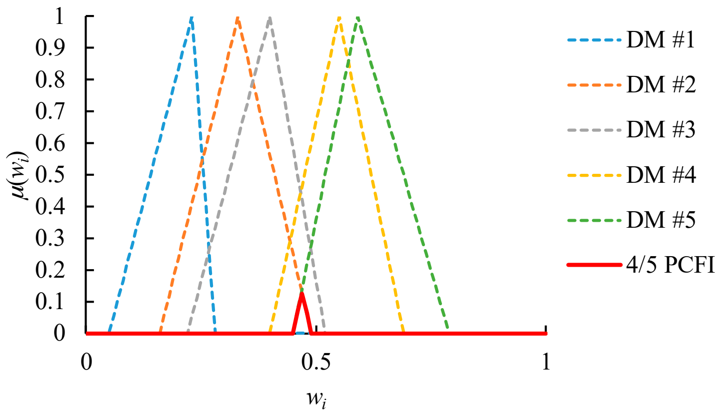


Figure 4. The 4/5 partial consensus fuzzy intersection (PCFI) result.

It is easier to reach a partial consensus among fewer decision makers. For this reason, the 3/5 PCFI result of the fuzzy priorities is derived, as shown in Figure 5. More values are acceptable to three of the five decision makers.

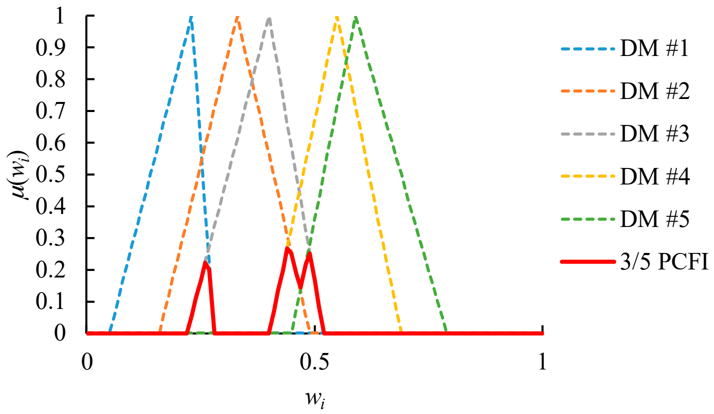


Figure 5. The 3/5 PCFI result.

If the consensus between only two decision makers is sought, there will be much more possible values that are acceptable, as illustrated in Figure 6.

The problem is how to determine the number of decision makers that reach a consensus. According to Chen and Wu [27]:

(1) It is better if more decision makers reach a consensus [54,55].
(2) The PCFI result should cover a sufficient number of possible values: for this purpose, the range of the PCFI result should be wider than a threshold ξ [56].

In the previous example, the ranges of various PCFI results are summarized in Table 3. If ξ is set to 0.3, only the 2/5 PCFI result meets the second requirement, and a partial consensus between any two decision makers will be sought. In contrast, setting ξ to 0.15 makes the 3/5 PCFI result also feasible. In this way, every possible value is acceptable to three decision makers.

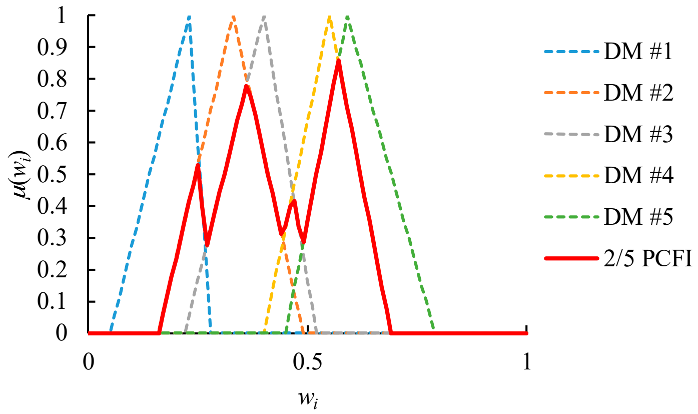


Figure 6. The 2/5 PCFI result.

Table 3. Ranges of various PCFI results.

PCFI	Range
4/5	0.04
3/5	0.18
2/5	0.53

The number of decision makers that reach a partial consensus may vary when the layered partial consensus approach is applied to different critical factors:

$$H_i \neq H_j \; \exists i \neq j, \tag{8}$$

where H_i indicates the number of decision makers that reach a partial consensus, regarding the relative priority of critical factor i.

3.4. GFWA Approach for Assessing an Intervention Strategy

Subsequently, GFWA is proposed to assess an intervention strategy amid the COVID-19 pandemic, for which the varying PCFI result provides the relative weights/priorities of critical factors:

$$\tilde{S}_q = \sqrt[v]{\sum_{i=1}^{n} (\widetilde{PCFI}(\{\tilde{w}_i(m)\})(\times)\tilde{p}_{qi}(-)\tilde{R}_i)^v}, \tag{9}$$

where $\tilde{S}_q$ is the overall performance of the q-th intervention strategy amid the COVID-19 pandemic, $\tilde{p}_{qi}$ is the performance of the q-th intervention strategy in optimizing the i-th critical factor, $\{\tilde{R}_i\}$ is the basis reference point, $(-)$ denotes fuzzy subtraction, and $v \in Z^+$.

Theorem 1. *FWA is a special case of GFWA.*

Proof of Theorem 1. The overall performance of the q-th intervention strategy amid the COVID-19 pandemic can be evaluated using FWA as:

$$\begin{aligned} \tilde{S}_q &= \frac{\sum_{i=1}^{n} \widetilde{PCFI}(\{\tilde{w}_i(m)\})(\times)\tilde{p}_{qi}}{\sum_{i=1}^{n} \widetilde{PCFI}(\{\tilde{w}_i(m)\})} \\ &= \frac{\sqrt[1]{\sum_{i=1}^{n} (\widetilde{PCFI}(\{\tilde{w}_i(m)\})(\times)\tilde{p}_{qi}(-)0)^1}}{\sum_{i=1}^{n} \widetilde{PCFI}(\{\tilde{w}_i(m)\})} \end{aligned}. \tag{10}$$

The divisor can be neglected, since it is constant for all intervention strategies amid the COVID-19 pandemic. As a result,

$$\widetilde{S}_q = \sqrt[1]{\sum_{i=1}^{n} (\widetilde{PCFI}(\{\widetilde{w}_i(m)\})(\times)\widetilde{p}_{qi}(-)0)^1}. \quad (11)$$

which is a special case of GFWA when v = 1. □

Theorem 2. *Fuzzy technique for order preference by similarity to ideal solution (FTOPSIS) is a special case of GFWA.*

Proof of Theorem 2. Using FTOPSIS, the distance between the q-th intervention strategy amid the COVID-19 pandemic and two reference points are measured as:

$$\widetilde{d}_q^- = \sqrt{\sum_{i=1}^{n} (\widetilde{PCFI}(\{\widetilde{w}_i(m)\})(\times)\widetilde{p}_{qi}(-)\widetilde{R}_i^-)^2}, \quad (12)$$

$$\widetilde{d}_q^+ = \sqrt{\sum_{i=1}^{n} (\widetilde{PCFI}(\{\widetilde{w}_i(m)\})(\times)\widetilde{p}_{qi}(-)\widetilde{R}_i^+)^2}. \quad (13)$$

Both are the special cases of GFWA when v = 2. □

However, $\widetilde{PCFI}(\{\widetilde{w}_i(m)\}$ is a polygonal fuzzy number, while $\widetilde{p}_{qi}$ is a TFN. Their combination is not easy to calculate. To tackle such complexity, $\widetilde{PCFI}(\{\widetilde{w}_i(m)\}$ is approximated with a TFN as:

$$\begin{aligned} \widetilde{PCFI}(\{\widetilde{w}_i(m)\} \cong \; & (\min(\widetilde{PCFI}(\{\widetilde{w}_i(m)\}), \\ & 3COG(\widetilde{PCFI}(\{\widetilde{w}_i(m)\}) - \max(\widetilde{PCFI}(\{\widetilde{w}_i(m)\}) - \min(\widetilde{PCFI}(\{\widetilde{w}_i(m)\}), \\ & \max(\widetilde{PCFI}(\{\widetilde{w}_i(m)\}). \end{aligned} \quad (14)$$

In this way, the defuzzified value of the approximating TFN is equal to $COG(\widetilde{PCFI}(\{\widetilde{w}_i(m)\})$, which is calculated as:

$$COG(\widetilde{PCFI}(\{\widetilde{w}_i(m)\}) = \frac{\int_0^1 x\mu_{\widetilde{PCFI}(\{\widetilde{w}_i(m)\}}(x)dx}{\int_0^1 \mu_{\widetilde{PCFI}(\{\widetilde{w}_i(m)\}}(x)dx}. \quad (15)$$

Then, $\widetilde{S}_q$ can be derived using the arithmetic for TFNs. In addition, to generate a crisp ordering of alternatives, the COG method can also be applied to defuzzify $\widetilde{S}_q$.

4. Case Study

Application of the Proposed Methodology

A city government in Taiwan was considering adopting suitable intervention strategies to tackle the COVID-19 pandemic in the city. To this end, the following factors were considered critical:

- Total costs;
- Ease of implementation;
- Acceptability;
- Effectiveness in preventing the spread of COVID-19;
- Irreplaceability by other treatments.

Based on these beliefs, four fuzzy pairwise comparison matrixes were constructed for the decision makers, as shown in Table 4.

Table 4. Fuzzy pairwise comparison matrixes constructed by four decision makers.

Decision maker #1	(1, 1, 1)	(3, 5, 7)	-	-	(5, 7, 9)
	-	(1, 1, 1)	-	-	-
	(2, 4, 6)	(3, 5, 7)	(1, 1, 1)	-	(2, 4, 6)
	(3, 5, 7)	(5, 7, 9)	(3, 5, 7)	(1, 1, 1)	(5, 7, 9)
	-	(1, 3, 5)	-	-	(1, 1, 1)
Decision maker #2	(1, 1, 1)	-	-	-	-
	(3, 5, 7)	(1, 1, 1)	(1, 3, 5)	-	(2, 4, 6)
	(1, 3, 5)	-	(1, 1, 1)	-	(3, 5, 7)
	(2, 4, 6)	(3, 5, 7)	(3, 5, 7)	(1, 1, 1)	(5, 7, 9)
	(1, 3, 5)	-	-	-	(1, 1, 1)
Decision maker #3	(1, 1, 1)	-	-	-	-
	(2, 4, 6)	(1, 1, 1)	(1, 3, 5)	-	(1, 3, 5)
	(3, 5, 7)	-	(1, 1, 1)	-	-
	(5, 7, 9)	(3, 5, 7)	(1, 3, 5)	(1, 1, 1)	(1, 3, 5)
	(1, 3, 5)	-	(1, 3, 5)	-	(1, 1, 1)
Decision maker #4	(1, 1, 1)	-	-	-	-
	(1, 3, 5)	(1, 1, 1)	(1, 3, 5)	-	-
	(1, 3, 5)	-	(1, 1, 1)	-	(1, 3, 5)
	(3, 5, 7)	(2, 4, 6)	(1, 3, 5)	(1, 1, 1)	(1, 3, 5)
	(1, 3, 5)	(1, 3, 5)	-	-	(1, 1, 1)

Each decision maker applied the FGM method to derive the fuzzy maximal eigenvalue and relative priorities from the corresponding fuzzy pairwise comparison matrix. As a result, the derived fuzzy maximal eigenvalues were:

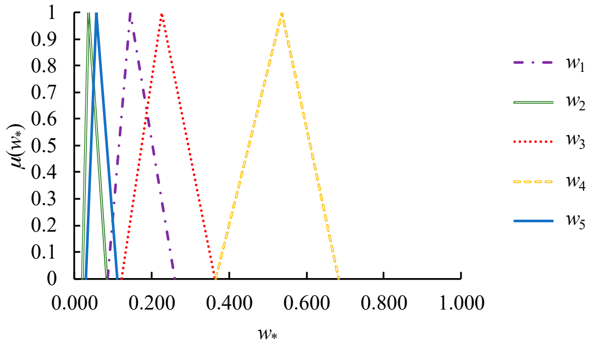
$\widetilde{\lambda}_{\max}(1) = (1.89,\ 5.79,\ 23.61)$,
$\widetilde{\lambda}_{\max}(2) = (1.72,\ 5.73,\ 33.01)$,
$\widetilde{\lambda}_{\max}(3) = (1.48,\ 5.60,\ 46.53)$, and
$\widetilde{\lambda}_{\max}(4) = (1.34,\ 5.87,\ 62.14)$.

The corresponding consistency ratios were:

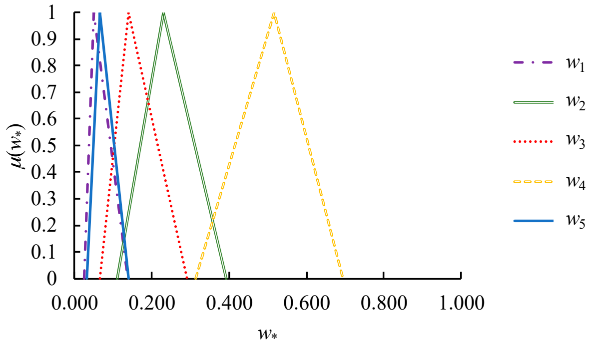
$\widetilde{CR}(1) = (-0.67,\ 0.18,\ 4.15)$,
$\widetilde{CR}(2) = (-0.73,\ 0.16,\ 6.25)$,
$\widetilde{CR}(3) = (-0.79, 0.13,\ 9.27)$, and
$\widetilde{CR}(4) = (-0.82, 0.19,\ 12.75)$.

These show certain levels of consistency. In addition, the relative priorities evaluated by the decision makers are summarized in Figure 7.

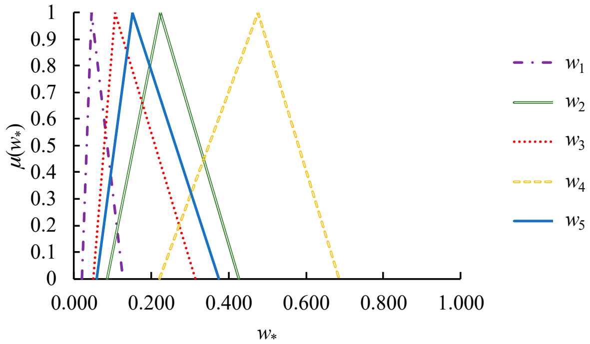
The overall consensus reached by all the decision makers, represented by the FI results of the relative priorities derived by them, are summarized in Figure 8. Obviously, all the decision makers reached an overall consensus regarding the values of $\widetilde{w}_1$ and $\widetilde{w}_3 \sim \widetilde{w}_5$. However, an overall consensus regarding the value of $\widetilde{w}_2$ was lacking, because the FI result was an empty set. As a result, the existing fuzzy group decision making methods assuming the existence of an overall consensus, such as Chen and Lin [32], Lin et al. [22], Gao et al. [33], Samanlioglu and Kaya [7], and Chen [57], were logically not applicable. To solve this problem, a partial consensus among some of the decision makers was sought instead. For this purpose, the PCFI result of the relative priorities was derived.



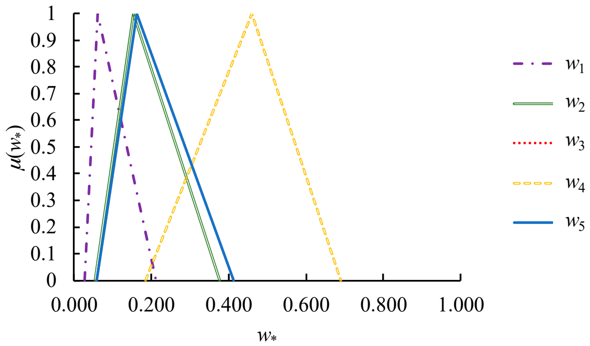
(**a**) Decision Maker #1



(**b**) Decision maker #2



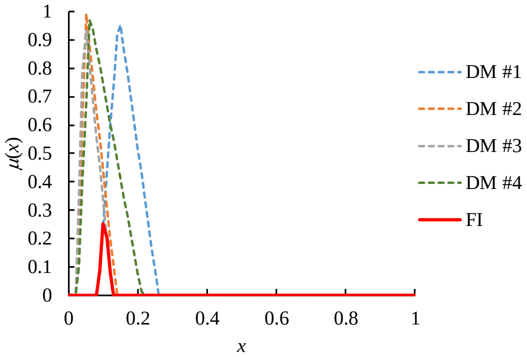
(**c**) Decision maker #3



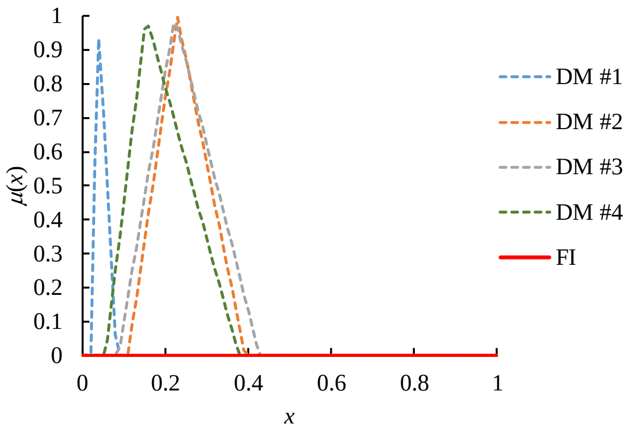
(**d**) Decision maker #4

Figure 7. The derived relative priorities.

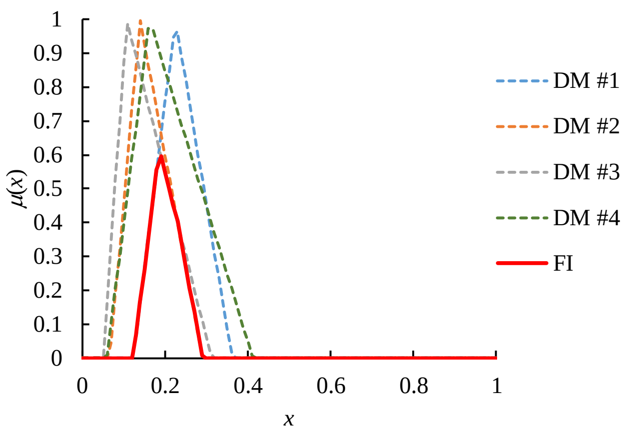
However, the number of decision makers that reached a partial consensus for each critical factor needed to be determined. To this end, the threshold for the range of the PCFI result, ξ, was set to 0.15—i.e., the range of the PCFI result had to be wider than 0.15 for the partial consensus to be significant. In addition, the decision makers that reached a partial consensus had to be as many as possible. As a result, the number of decision makers that reached a partial consensus for each critical factor was determined, as presented in Table 5. The PCFI results are summarized in Figure 9.



(**a**) $\tilde{w}_1$

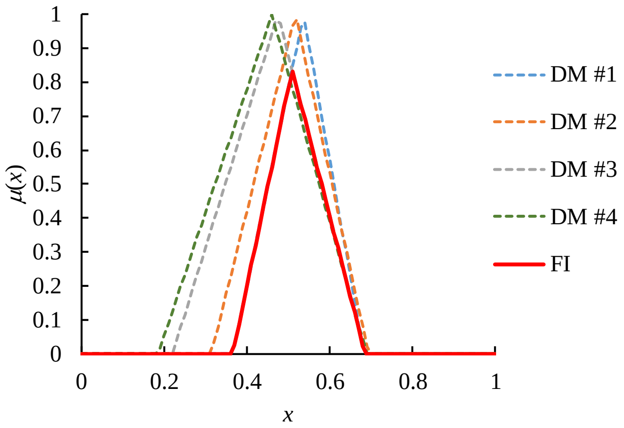


(**b**) $\tilde{w}_2$

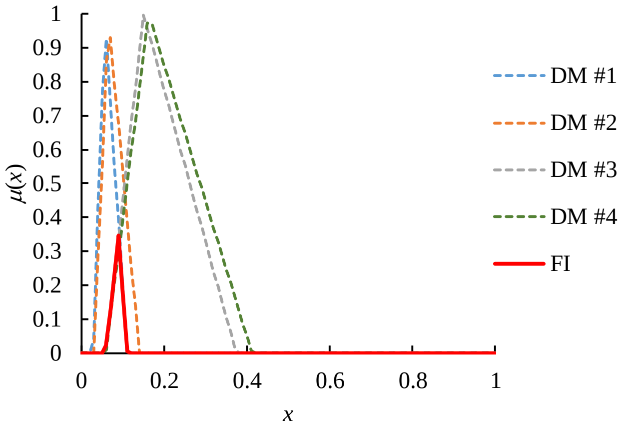


(**c**) $\tilde{w}_3$

Figure 8. *Cont.*

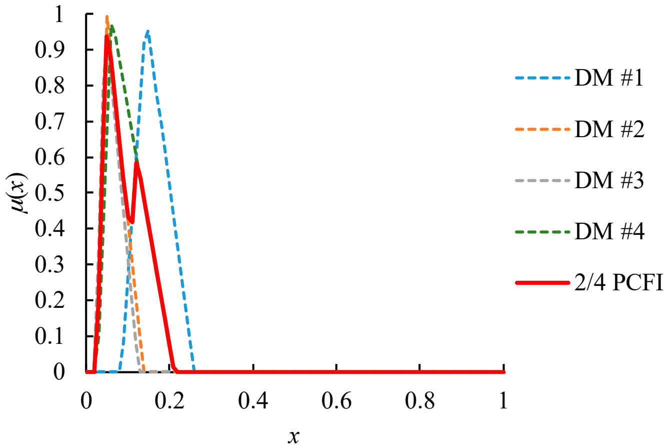


(**d**) $\tilde{w}_4$



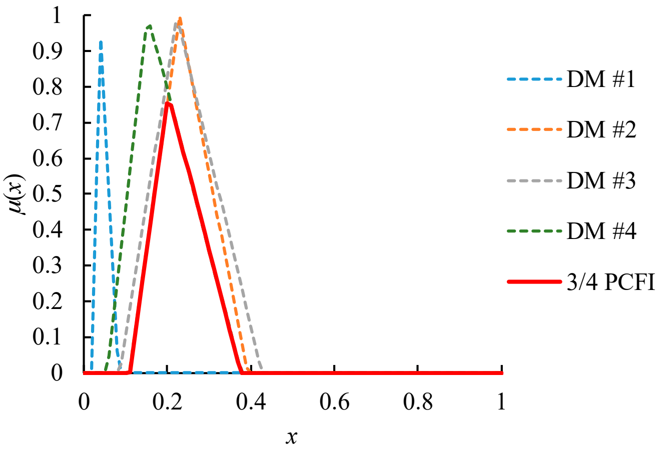
(**e**) $\tilde{w}_5$

Figure 8. The fuzzy intersection (FI) results of the relative priorities.

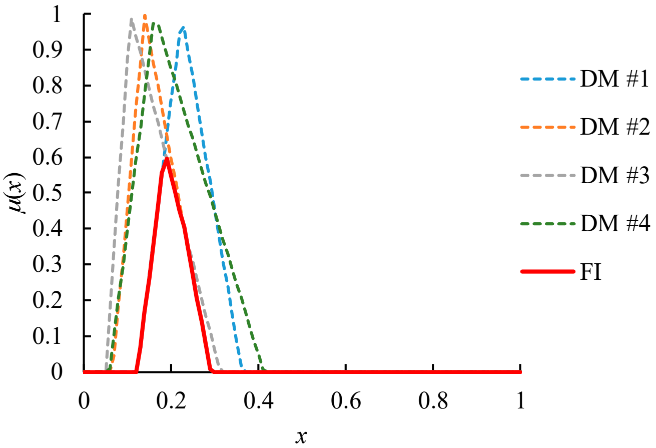


(**a**) $\tilde{w}_1$

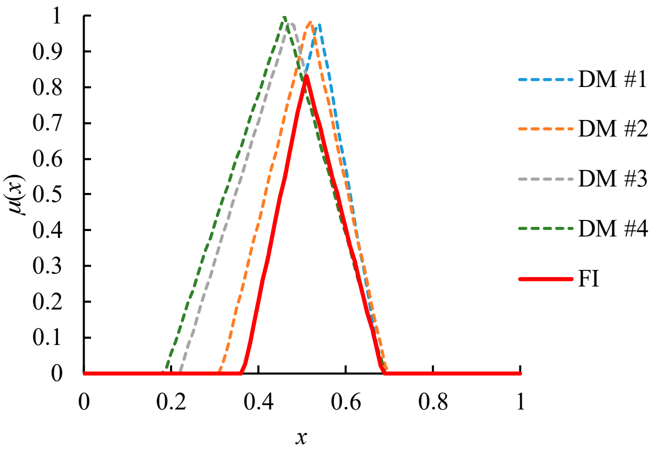
Figure 9. *Cont.*



(**b**) $\tilde{w}_2$

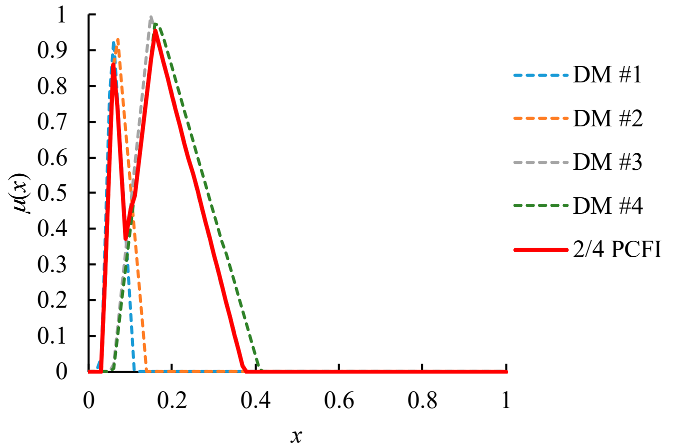


(**c**) $\tilde{w}_3$



(**d**) $\tilde{w}_4$

Figure 9. *Cont.*



(e) $\tilde{w}_5$

Figure 9. The partial consensus fuzzy intersection (PCFI) results.

Table 5. The number of decision makers achieving a partial consensus for each critical factor.

Critical Factor	Number of Decision Makers	Range of the PCFI Result
$\widetilde{w}_1$	2	0.18
$\widetilde{w}_2$	3	0.26
$\widetilde{w}_3$	4 (overall consensus)	0.16
$\widetilde{w}_4$	4 (overall consensus)	0.31
$\widetilde{w}_5$	2	0.33

To facilitate the subsequent calculation, the PCFI results were approximated with TFNs according to Equation (14). The approximation results are shown in Figure 10.

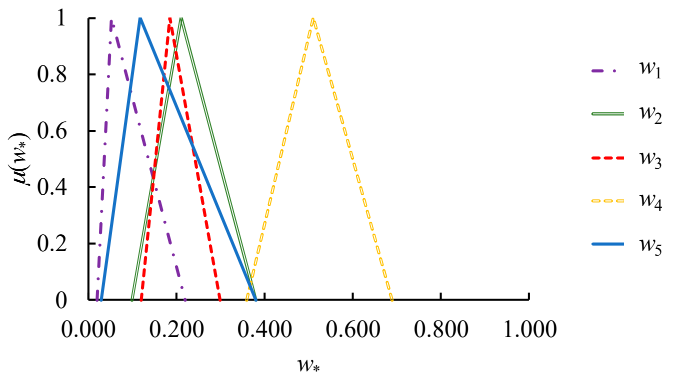


Figure 10. Approximating the partial consensus fuzzy intersection (PCFI) results with triangular fuzzy numbers (TFNs).

Among the five critical factors, only "total costs" was the-lower-the-better performance, whereas the others were the-higher-the-better performances. The performances in optimizing these critical factors were evaluated according to the rules depicted in Table 6.

Table 6. Rules for evaluating the performances in optimizing the critical factors.

Critical Factor	Rule
Total costs	$\widetilde{p}_{q1}(x_q) = \begin{cases} (0,0,1) & \text{if } 0.1\cdot\min\limits_r x_r + 0.9\cdot\max\limits_r x_r \le x_k \text{ or data not available} \\ (0,1,2) & \text{if } 0.35\cdot\min\limits_r x_r + 0.65\cdot\max\limits_r x_r \le x_k < 0.1\cdot\min\limits_r x_r + 0.9\cdot\max\limits_r x_r \\ (1.5,2.5,3.5) & \text{if } 0.65\cdot\min\limits_r x_r + 0.35\cdot\max\limits_r x_r \le x_k < 0.35\cdot\min\limits_r x_r + 0.65\cdot\max\limits_r x_r \\ (3,4,5) & \text{if } 0.9\cdot\min\limits_r x_r + 0.1\cdot\max\limits_r x_r \le x_k < 0.65\cdot\min\limits_r x_r + 0.35\cdot\max\limits_r x_r \\ (4,5,5) & \text{if } x_k < 0.9\cdot\min\limits_r x_r + 0.1\cdot\max\limits_r x_r \end{cases}$ x_q is the estimated total costs.
Ease of implementation	$\widetilde{p}_{q2}(x_q) = \begin{cases} (0,0,1) & \text{if } x_k = \text{very difficult} \\ (0,1,2) & \text{if } x_k = \text{difficult} \\ (1.5,2.5,3.5) & \text{if } x_k = \text{moderate} \\ (3,4,5) & \text{if } x_k = \text{easy} \\ (4,5,5) & \text{if } x_k = \text{very easy} \end{cases}$ x_q is the ease of implementation.
Acceptability	$\widetilde{p}_{q3}(x_q) = \begin{cases} (0,0,1) & \text{if } x_k = \text{very unacceptable} \\ (0,1,2) & \text{if } x_k = \text{unacceptable} \\ (1.5,2.5,3.5) & \text{if } x_k = \text{neutral} \\ (3,4,5) & \text{if } x_k = \text{acceptable} \\ (4,5,5) & \text{if } x_k = \text{very acceptable} \end{cases}$ x_q is the acceptability.
Effectiveness in preventing the spread of COVID-19	$\widetilde{p}_{q4}(x_q) = \begin{cases} (0,0,1) & \text{if } x_k = \text{very ineffective} \\ (0,1,2) & \text{if } x_k = \text{ineffective} \\ (1.5,2.5,3.5) & \text{if } x_k = \text{moderate} \\ (3,4,5) & \text{if } x_k = \text{effective} \\ (4,5,5) & \text{if } x_k = \text{very effective} \end{cases}$ x_q is the effectiveness in preventing the spread of COVID-19.
Irreplaceability by other treatments	$\widetilde{p}_{q5}(x_q) = \begin{cases} (0,0,1) & \text{if } x_k = \text{very low} \\ (0,1,2) & \text{if } x_k = \text{low} \\ (1.5,2.5,3.5) & \text{if } x_k = \text{moderate} \\ (3,4,5) & \text{if } x_k = \text{high} \\ (4,5,5) & \text{if } x_k = \text{very high} \end{cases}$ x_q is the irreplaceability.

Based on the derived relative priorities, the 15 intervention strategies mentioned by Samanlioglu et al. [7] were compared:

(1) Quarantining patients and those suspected of infection;
(2) Internal border restrictions—i.e., reducing the ability to move/transport freely within a city/country;
(3) Social distancing;
(4) Health monitoring;
(5) Public awareness campaigns;
(6) Restriction of nonessential businesses;
(7) Restrictions of mass gatherings;
(8) External border restrictions—i.e., reducing the ability to exit or enter a city/country;
(9) Closure of schools;
(10) Enhanced control of the country's health resources (materials and health workers);
(11) Formation of an emergency response team;
(12) Common health testing (independent of suspected infection);
(13) Curfew;
(14) Restriction of nonessential government services;
(15) Declaration of emergency.

Samanlioglu et al. [7] did not investigate the critical factors in an intervention strategy, but directly compared all the intervention strategies in pairs using a FAHP approach, which was a rough analysis and limited by too much subjectivity. In contrast, in this study the performances of each intervention strategy in optimizing the critical factors were evaluated. Table 7 presents the evaluation results.

Table 7. Evaluation results.

Intervention Strategy	Total Costs	Ease of Implementation	Acceptability	Effectiveness in Preventing the Spread of COVID-19	Irreplaceability by Other Treatments
Quarantining patients and those suspected of infection	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(3, 4, 5)	(4, 5, 5)	(4, 5, 5)
Internal border restrictions	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)	(0, 1, 2)
Social distancing	(4, 5, 5)	(4, 5, 5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)
Health monitoring	(3, 4, 5)	(4, 5, 5)	(4, 5, 5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)
Public awareness campaigns	(3, 4, 5)	(1.5, 2.5, 3.5)	(4, 5, 5)	(0, 1, 2)	(1.5, 2.5, 3.5)
Restriction of nonessential businesses	(0, 1, 2)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(0, 1, 2)
Restrictions of mass gatherings	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(0, 1, 2)	(1.5, 2.5, 3.5)	(0, 1, 2)
External border restrictions	(0, 1, 2)	(4, 5, 5)	(1.5, 2.5, 3.5)	(3, 4, 5)	(1.5, 2.5, 3.5)
Closure of schools	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(0, 1, 2)
Enhanced control of country's health resources	(1.5, 2.5, 3.5)	(3, 4, 5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)
Formation of an emergency response team	(4, 5, 5)	(4, 5, 5)	(4, 5, 5)	(0, 1, 2)	(3, 4, 5)
Common health testing	(0, 1, 2)	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(4, 5, 5)	(0, 1, 2)
Curfew	(1.5, 2.5, 3.5)	(1.5, 2.5, 3.5)	(0, 0, 1)	(1.5, 2.5, 3.5)	(0, 0, 1)
Restriction of nonessential government services	(1.5, 2.5, 3.5)	(3, 4, 5)	(3, 4, 5)	(1.5, 2.5, 3.5)	(0, 0, 1)
Declaration of emergency	(0, 0, 1)	(0, 1, 2)	(0, 0, 1)	(1.5, 2.5, 3.5)	(0, 0, 1)

Subsequently, the overall performance of an intervention strategy was assessed using the GFWA approach, for which v was set to 3 and for $\widetilde{R}_i$ was set to $\min_q(\widetilde{PCFI}(\{\widetilde{w}_i(m)\})(\times)\widetilde{p}_{qi})$. The assessment results are summarized in Table 8. The defuzzification results of the overall performances are also shown in the same table.

According to the experimental results, the following discussion was made:

(1) Intervention strategies with higher overall performances should be adopted earlier than those with lower overall performances. In the experiment, "quarantining patients and those suspected of infection", "common health testing", and "external border restrictions" were the top three intervention strategies. The three intervention strategies have been widely adopted by a number of countries/cities, including the city that the decision makers were located. For example, Taiwan's Center for Disease Control and Prevention monitors all people who travelled to Wuhan within 14 days and developed symptoms of fever or upper respiratory tract infection.

(2) During the peak of the COVID-19 pandemic, as many intervention strategies should be adopted as possible. For guiding this, a threshold for the overall performance could be established—e.g., 1.2. Then, the intervention strategies with overall performances higher than the threshold could be taken, which involved eight intervention strategies.

(3) The overall performances of the intervention strategies were ranked, as shown in Figure 11. For comparison, the ranking result by Samanlioglu et al. [7] was also presented in the same figure. There were considerable differences between the ranking results using the two methods. One possible reason for this was that different national conditions have led to a gap in the preferences of decision makers. Another possible reason was that the ranking result by

Samanlioglu et al. [7] was based on subjective comparisons only, while that using the proposed methodology took the objective performances of intervention strategies into account.

(4) A sensitivity (or parametric) analysis has been conducted by varying the order of the objective function (v) in the GFWA approach, so as to observe changes in the ranking result. The results are summarized in Figure 12. Obviously, the ranking result changed as the value of v varied. Nevertheless, "quarantining patients and those suspected of infection" was always the most suitable intervention strategy. In addition, when v was greater than 5, the ranking result was no longer affected by the value of v, showing the stability of the GFWA approach.

(5) Two more existing methods, FGM-FGM-FWA [14] and FGM-FGM-FTOPSIS [58], have been applied to compare these intervention strategies for tackling the COVID-19 pandemic. In FGM-FGM-FWA, the decision makers' judgments were aggregated using FGM. Then, the relative priorities of the critical factors were also derived from the aggregation result using FGM. Subsequently, FWA was applied to assess the overall performance of each intervention strategy. In FGM-FGM-FTOPSIS, the overall performance of an intervention strategy was assessed using FTOPSIS instead. The ranking results using various methods are compared in Table 9.

(6) Carnero [59] proposed the potentially all pairwise rankings of all possible alternatives (PAPRIKA) method for the failure mode and effects analysis (FMEA) [60] of a waste segregation system. In the PAPRIKA method, the failure rates and weights of risk factors were evaluated with intuitionistic fuzzy numbers (IFNs) that had both membership and nonmembership function values. Then, the intuitionistic fuzzy weighted averaging (IFWA) operator was applied to aggregate the decision makers' evaluation results. However, in Carnero's study, it was assumed that the decision makers reached an overall consensus, while in this study only some decision makers reached a partial consensus. In addition, in Carnero's study, the weights of the decision makers were predetermined and remained unchanged within the decision-making process. In contrast, in the proposed methodology the weights of decision makers varied within the decision-making process. Decision makers that reached a partial consensus about each critical factor had equal weights, while the others had zero weights. For example, when determining the relative priority of "total costs", the weights of the two decision makers who reached a partial consensus were both 0.5. When determining the relative priority of "ease of implementation", three decision makers reached a partial consensus, and their weights were all 0.33.

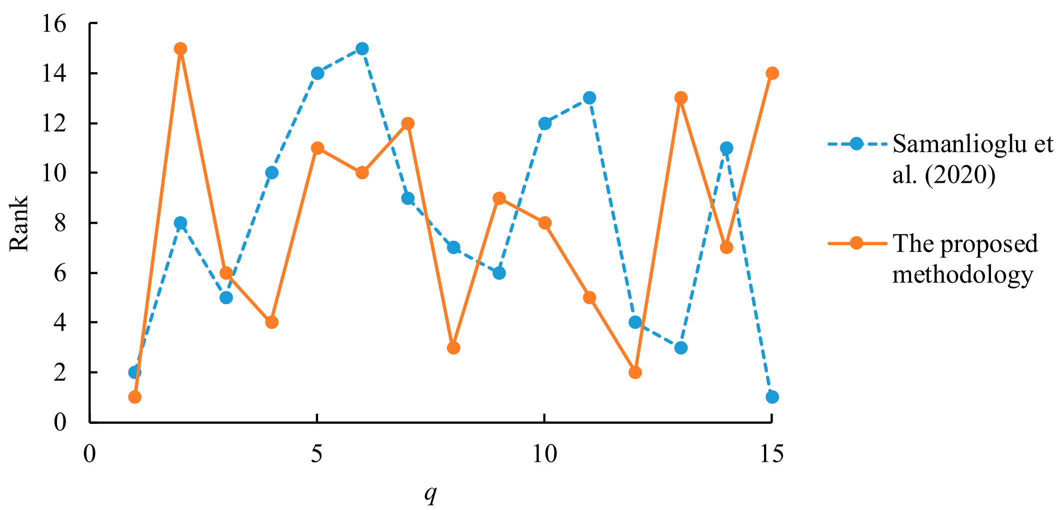


Figure 11. Ranking result.

Table 8. The assessment results.

Intervention Strategy	Overall Performance	Defuzzification Result
Quarantining patients and those suspected of infection	(0.08, 2.09, 3.78)	1.98
Internal border restrictions	(0, 0.2, 1.56)	0.59
Social distancing	(0, 1.06, 2.95)	1.34
Health monitoring	(0.18, 1.23, 3.04)	1.48
Public awareness campaigns	(0.18, 0.95, 2.29)	1.14
Restriction of nonessential businesses	(0, 0.83, 2.63)	1.15
Restrictions of mass gatherings	(0, 0.79, 2.6)	1.13
External border restrictions	(0, 1.63, 3.72)	1.78
Closure of schools	(0, 0.83, 2.64)	1.16
Enhanced control of country's health resources	(0, 0.94, 2.92)	1.29
Formation of an emergency response team	(0.18, 1.14, 2.76)	1.36
Common health testing	(0.06, 2.05, 3.56)	1.89
Curfew	(0, 0.78, 2.57)	1.12
Restriction of nonessential government services	(0.06, 1.03, 2.92)	1.34
Declaration of emergency	(0, 0.77, 2.45)	1.07

Table 9. Ranking results using various methods.

Intervention Strategy	FGM-FGM-FWA	FGM-FGM-FTOPSIS	The Proposed Methodology
Quarantining patients and those suspected of infection	1	1	1
Internal border restrictions	15	15	15
Social distancing	5	6	6
Health monitoring	2	4	4
Public awareness campaigns	9	9	11
Restriction of nonessential businesses	11	11	10
Restrictions of mass gatherings	12	12	12
External border restrictions	3	2	3
Closure of schools	10	10	9
Enhanced control of country's health resources	7	8	8
Formation of an emergency response team	4	5	5
Common health testing	6	3	2
Curfew	13	13	13
Restriction of nonessential government services	8	7	7
Declaration of emergency	14	14	14

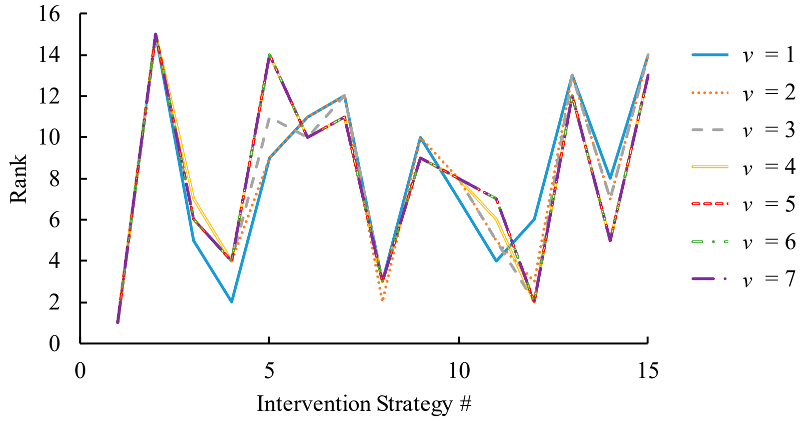


Figure 12. Ranking results with various values of v.

5. Conclusions and Future Research Directions

The COVID-19 pandemic has severely impacted our daily lives. To tackle the COVID-19 pandemic, country (or city) governments around the world have adopted various intervention strategies. Not all intervention strategies will be successful, acceptable, and/or cost-effective. For this reason, the varying partial consensus fuzzy collaborative intelligence approach is proposed in this study to assess an intervention strategy, so that a country (or city) government can choose the top-performing intervention strategies to create synergy. In the varying partial consensus fuzzy collaborative intelligence approach, multiple decision makers express their beliefs on the relative priorities of factors critical to an intervention strategy. If an overall consensus is lacking among the decision makers, the LPC approach is applied to derive a partial consensus among most of the decision makers for each critical factor. Subsequently, the GFWA approach is proposed to evaluate the overall performance of an intervention strategy for tackling the COVID-19 pandemic. Finally, the top-performing intervention strategies can be adopted by or recommended to the country (or city) government to tackle the COVID-19 pandemic.

The proposed methodology has been applied to compare 15 existing intervention strategies for tackling the COVID-19 pandemic to illustrate its applicability. After analyzing the experimental results, the following conclusions were drawn:

(1) Five factors, "total costs", "ease of implementation", "acceptability", "effectiveness in preventing the spread of COVID-19", and "irreplaceability by other treatments", were considered critical to an intervention strategy.
(2) "Quarantining patients and those suspected of infection", "common health testing", and "external border restrictions" were the top three intervention strategies, while "internal border restrictions" performed the worst.
(3) The number of decision makers that reached a partial consensus differed from one.

The proposed methodology has the following advantages over the existing methods:

(1) The proposed methodology does not assume the existence of an overall consensus among all decision makers, which is more practical.
(2) The partial consensus among some decision makers may not be obvious using existing methods, such as Wang and Chen [15], Lin and Chen [16], and Chen et al. [17]. In contrast, the proposed methodology varies the number of decision makers that reach a partial consensus to ensure that the partial consensus is obvious enough.

However, the proposed methodology is also subject to some limits. For example, the partial consensus among decision makers may not be obvious enough, even if the number of decision makers is minimized.

Some future research directions are provided as follows. First, it is difficult to know for how long the COVID-19 pandemic will persist. Therefore, the same analysis needs to be conducted again to see whether the experimental results obtained in this study are still applicable. In addition, intervention strategies for tackling the COVID-19 pandemic can be classified before being compared [61–64]. These constitute some topics for future investigation.

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