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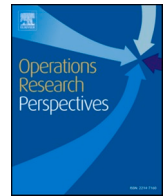
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Analysing the impact of COVID-19 pandemic on the psychological health of people using fuzzy MCDM methods

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ABSTRACT

Recently, a large portion of the world's population has experienced an unprecedented devastating effect of the COVID-19 pandemic. At the time of its outbreak, not much was known about this disease and therefore, quarantine and social distancing were the only ways suggested to prevent its spread among humans. Although the current situation is much better than before however, strict social distancing norms as well as frequent long-lasting lockdowns with stringent guidelines and actions to control the spread in the early days have affected the physical and psychological health of the people. Consequently, this study was carried out to attain the following major objectives: (i) to identify the potential psychological problems/factors that might have been caused due to COVID-19 led social distancing and lockdowns, and (ii) to determine the ranks of the identified psychological factors to reflect their degree of criticality. The first objective was achieved by gathering information about the potential psychological factors from the experts. Data, in terms of linguistic variables, was collected from the experts and analyzed using two fuzzy-based multi-criteria decision-making (MCDM) methods i.e. Fuzzy Best Worst Method (F-BWM) and Fuzzy TOPSIS (F-TOPSIS) which led to the accomplishment of the second objective. The results of this study revealed that anxiety, stress, panic attacks, frustration, and insomnia were the top five critical psychological factors that might have affected people due to this pandemic. Consistency of the results was ensured by comparing the obtained ranks with the ranks found using the Fuzzy WSM and Fuzzy MABAC methods. In addition, the robustness of the results was ascertained by conducting the sensitivity analysis. Based on the findings of the study, the identified factors were categorized into most, average, and least critical psychological factors. This research might help the relevant authorities to understand the extent of the seriousness of the various psychological factors caused by this pandemic, so that an effective strategy may be developed for better management, control, and safety.

1. Introduction

Coronaviruses, discovered during the mid-1960s, were found to infect both human beings and a range of animals including both mammals and birds. Severe Acute Respiratory Syndrome or SARS-CoV emerged in 2003 in southern china, which was known to infect

animals, and also caused a large-scale epidemic in humans. In 2012 another coronavirus-based epidemic, identified as the Middle East Respiratory Syndrome or the MERS-CoV, originated in Saudi Arabia [1]. However, the SARS-CoV-2 discovered in 2019 was not recognized in the human population earlier, and hence it is one of the newest strains of coronaviruses. SARS-CoV-2 belongs to the group of coronaviridae,

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which are the single-stranded RNA viruses that commonly affect birds, mammals, and reptiles [2]. SARS-CoV-2 also called COVID-19 was first traced in the Wuhan city of Hubei province in China in December 2019, after an eruption of pneumonia without an obvious cause [3]. On January 30, 2020, WHO acknowledged this outbreak as a Public Health Emergency on an international scale and it was later given the new name: COVID-19 on February 11, 2020 [4].

COVID-19 was different from the previously identified coronaviruses and in a short period, it caused an international disaster due to its fast spread among humans. One of the main reasons for the fast spread of the disease was the lack of testing process in the initial period. In the initial days RT-PCR, a relatively tedious and time taking, testing process was used to identify the COVID-19-infected persons. However, later on, numerous COVID-19 detection solutions were developed that used CT-scan and X-Ray images of the lungs with a CNN-based model to ease and speed up the detection process [5,6]. At present the COVID-19 situation has significantly improved due to several reasons such as the discovery of the protective vaccines in record time, the vaccination drive at an exponential rate, new testing and diagnostic procedures, awareness among the people about the disease, change in the people's behavior and lifestyle, precautionary measures taken by the people in the form of wearing masks and sanitizing hands frequently, strict norms and guidelines, discovery of new medicines to treat the patient, etc. However, at the time of the outbreak of the pandemic, self-protection by taking precautionary measures was the most effective way to control its spread [7]. Further, quarantine viz. restriction of movement and separation of potentially exposed people to COVID-19 was found to be an efficient way to lessen the risk of infecting others. Although it was an efficient way to deal with the pandemic, it contributed to loneliness which in itself is a recognized risk factor for depression, anxiety, and suicide [8]. It has been established from past research that there is an increase in suicide cases after quarantines were imposed during previous epidemic outbreaks [9]. The impact of quarantine may even be long-lasting with many people continuing to avoidance behavior [10]. In addition, it tends to separate people from their loved ones which causes a loss of freedom, and loneliness that leads to various negative effects on one's psychological health [11]. Further, in some of the countries, the authorities had imposed strict social distancing as well as lockdowns for a prolonged period to mitigate the spread of the virus. However, such measures had a socio-economic and psychological impact on the population. Even in countries like India, the government imposed a nationwide lockdown in the early stage of this outbreak which successfully resulted in a slower growth rate of the number of cases and low mortality rates in the country. However, the extended period of such activities has made physical and mental health professionals concerned about the psychological and emotional impact on the individuals. In addition, financial losses during and after the outbreak not only increased the financial burden but also resulted in anger, frustration, and excessive substance use [12]. Further, statistics suggest that there was an increase in domestic violence during COVID-19 due to increased stress/tension related to economic hardship and childcare [13]. Also, it has been reported that restrictions in movement due to COVID-19 in the early stages resulted in frequent, severe, and dangerous violence at home [14]. Hence, it was realized that the psychological behavior of the people might have been adversely affected due to these distancing measures and there is a need to conduct a study in this direction to analyze the psychological problems/factors to determine their criticality. Further, it is observed from the literature that studies about the identification of the potential psychological problems/factors, especially caused by COVID-19, and their ranking to exhibit their criticality using MCDM (Multi Criteria Decision Making) methods are lacking which indeed motivated the authors to conduct the present study. Keeping this in view, an idea to conduct this study was conceived, and subsequently, systematic planning was done to accomplish the following specific objectives: (i) to identify the potential psychological factors based on experts' opinions, (ii) to implement

integrated fuzzy MCDM methods i.e. F-BWM and F-TOPSIS to rank the identified psychological factors to estimate their severity, (iii) to ensure consistency and accuracy of the ranking result produced by the implemented fuzzy MCDM methods by comparing it result with the results of other fuzzy MCDM methods i.e. F-WSM and F-MABAC, (iv) to establish robustness and reliability of the ranking results through sensitivity analysis. To accomplish the stated objective, potential psychological factors were first identified utilizing the vast experience of the experts and then they were ranked using Fuzzy based MCDM methods i.e. F-BWM and F-TOPSIS methods. The identified psychological factors were evaluated based on three attributes viz. severity (S), the possibility of occurrence (O), and obscurity of detection (D). F-BWM was used to compute the weights of these attributes. Subsequently, the F-TOPSIS method was employed to rank these psychological factors. Finally, the consistency and robustness of the acquired ranks were confirmed by comparing them with the ranks obtained from two fuzzy-based MCDM methods and performing sensitivity analysis.

The COVID-19 pandemic has not only caused the loss of precious human lives but also has impacted the physical and mental health of people leading to different types of psychological problems. This study has been conducted to gauge the severity of the psychological problems/factors using an integrated fuzzy MCDM method which in the opinion of the authors makes this work distinct and novel. The implemented integrated fuzzy MCDM method determines accurate and robust rank, signifying severity, of the psychological factors/problems caused by the COVID-19 pandemic. The remaining content of the paper is structured as follows: Section 2 describes the selection of experts and the psychological factors. Section 3 explains the methodology used in the present study. Results of the study along with relevant discussion are presented in Section 4 while Section 5, puts forth conclusions of the present study. Section 6 discusses the research implications and Section 7 highlights the limitations of the present study and also makes a few suggestions.

2. Selection of experts and identification of potential psychological factors

The selection of appropriate experts is essentially important to provide the feedback necessary to carry out the study to achieve the set goals. In the present study, five qualified and experienced doctors with an average experience of more than 10 years of practicing in psychiatry in Indian medical colleges and hospitals were selected as experts who suggested the following twelve psychological factors through consensus which were considered in the present study: (i) Stress (PF1), (ii) Loneliness (PF2), (iii) Anxiety (PF3), (iv) Panic attacks (PF4), (v) Insomnia (PF5), (vi) Loss of appetite (PF6), (vii) Depression (PF7), (viii) Frustration (PF8), (ix) Fear of catching disease (PF9), (x) Suicidal tendencies (PF10), (xi) Mood swings (PF11), and (xii) Domestic violence (PF12). Based on the literature, three attributes namely severity (S), the possibility of occurrence (O), and obscurity of detection (D) [15] were selected to evaluate the psychological factors to rank them using fuzzy-based MCDM methods. The requisite data, in terms of linguistic variables, were collected from the experts and were subsequently analyzed using fuzzy-based MCDM methods.

3. Methodology

This study tends to rank the identified psychological factors to reflect their criticality by evaluating them based on three attributes viz. severity (S), the possibility of occurrence (O), and obscurity of detection (D) using F-BWM and F-TOPSIS methods. An attribute can be either beneficial or non-beneficial. An attribute for which maximum value is desired is known as a beneficial attribute. Similarly, an attribute for which minimum value is preferred is termed as a non-beneficial attribute. It is to be mentioned that all three attributes considered in this study i.e. severity (S), the possibility of occurrence (O), and obscurity of detection (D) are of a beneficial type and therefore, their maximum

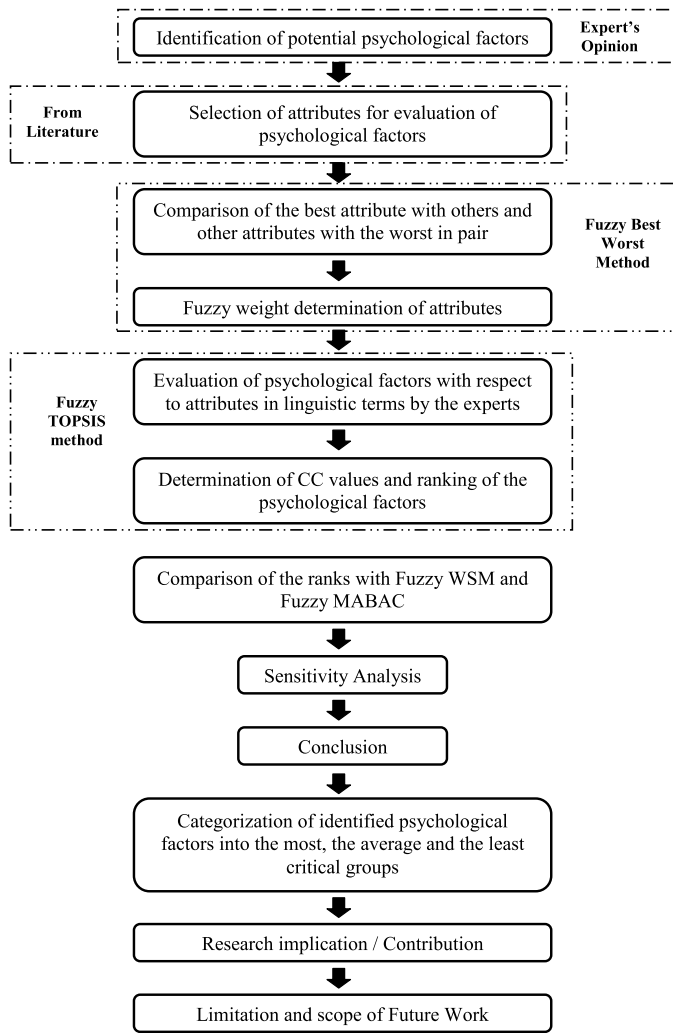


Fig. 1. The adopted research framework.

values are desired to rank the psychological factors. The research framework adopted to accomplish the objectives of the study is shown in Fig. 1. For a better understanding of the methods used in this work, the F-BWM and F-TOPSIS methods are also briefly described.

3.1. Fuzzy best-worst method (F-BWM)

The conventional BWM has an advantage over other MCDM methods specifically AHP in terms of high consistency and less pairwise comparison required [16]. Integrating the conventional BWM method with fuzzy logic i.e. F-BWM, to take into consideration the inconsistency and vagueness of human thoughts further improve the accuracy of the results. Owing to these advantages of F-BWM, it has been employed in this study to compute fuzzy weights of the attributes. The details of the F-BWM can be found in the literature [17]. However, it is briefly described here for its better understanding.

Step 1: Formulate decision attributes set i.e. $A = \{A_1, A_2, \dots, A_q\}$, where, “ q ” represents several attributes that are essential for the evaluation.

Step 2: Identify the best and the worst attributes

Identify the best attribute (A_B) and worst attribute (A_W) among the decision attribute set. The best and worst attributes are the ones which are the most and the least important, respectively, for the evaluation of the alternatives.

Step 3: Develop fuzzy best-to-others vector (FBO)

Make a pairwise comparison of A_B with other attributes in linguistic terms (LTs) and transform them into fuzzy numbers (FNs) to obtain FBO vector as given by Eq. (1).

$$\widetilde{FBO} = (\widetilde{b}_1, \widetilde{b}_2, \dots, \widetilde{b}_j, \dots, \widetilde{b}_q) \quad (1)$$

where, \widetilde{b}_j represents the fuzzy importance of A_B over j^{th} attribute. It is to be noted that $\widetilde{b}_b = (1, 1, 1)$.

Step 4: Develop fuzzy others to worst vector (FOW)

Determine significance of all the attributes over A_W in LTs which are converted into predefined FNs. The comparison so obtained is known as fuzzy others to worst (FOW) vector as given by Eq. (2).

$$\widetilde{FOW} = (\widetilde{o}_1, \widetilde{o}_2, \dots, \widetilde{o}_j, \dots, \widetilde{o}_q) \quad (2)$$

where, \widetilde{o}_j represents the fuzzy importance of j^{th} attribute over A_W . It is to be noted that $\widetilde{o}_w = (1, 1, 1)$.

Step 5: Determine the fuzzy weights of the attributes

The fuzzy weights of the attributes $\widetilde{w}_j = (w_j^l, w_j^m, w_j^u)$ are obtained by solving a mathematical non-linear optimization problem as given in Eq. (3).

Minimize $Z = \xi$

Subject to :

$$\left| \frac{(w_B^l, w_B^m, w_B^u)}{(w_j^l, w_j^m, w_j^u)} - (b_j^l, b_j^m, b_j^u) \right| \leq (k^*, k^*, k^*)$$

$$\left| \frac{(w_j^l, w_j^m, w_j^u)}{(w_W^l, w_W^m, w_W^u)} - (o_j^l, o_j^m, o_j^u) \right| \leq (k^*, k^*, k^*) \quad (3)$$

$$\sum_{j=1}^q \frac{w_j^l + 4w_j^m + w_j^u}{6} = 1$$

$$w_j^l \leq w_j^m \leq w_j^u$$

$$w_j^l \geq 0$$

$$j = 1, 2, 3, \dots, q.$$

where, $\xi = (k^*, k^*, k^*)$ represents a deviation from full consistency.

3.2. Fuzzy technique for order preference by similarity to ideal solution (F-TOPSIS)

Among several MCDM methods, TOPSIS is the most widely used and most fascinating among researchers due to its effectiveness in solving decision problems in different knowledge domains [18]. Further, it has been observed that this method has a minimum rank reversal problem compared to other MCDM methods specifically AHPs and ELECTRE [19]. Initially, this technique was proposed in 1981 [20] which was further modified and improved over the last decade by many researchers [21,22]. To incorporate the inconsistency and vagueness in the information, the integrated form of fuzzy set theory and TOPSIS method regarded as the F-TOPSIS method has been developed and found to provide better results as compared to the conventional TOPSIS method [23,24]. Due to these advantages, the fuzzy form of TOPSIS i.e. F-TOPSIS method is used in this study. In F-TOPSIS, the comparison between alternatives is made based on its distance from the best (positive) and the worst (negative) ideal solutions. The step-by-step

procedure for implementing the F-TOPSIS method can be found in the literature [25]. However, the steps involved in this method are briefly described below to provide a better understanding [25]:

Step 1: Formulate a fuzzy decision matrix (\widetilde{DM}) by arranging different alternatives and attributes in rows and columns, respectively, where each element of the matrix represents the evaluation of an alternative against a specific attribute in terms of FNs as shown in Eq. (4).

$$\widetilde{DM} = \begin{bmatrix} \widetilde{s}_{1,1} & \dots & \widetilde{s}_{1,q} \\ \vdots & \ddots & \vdots \\ \widetilde{s}_{p,1} & \dots & \widetilde{s}_{p,q} \end{bmatrix}_{A \times B} \quad (4)$$

where, $\widetilde{s}_{p,q}$ represents the fuzzy score for p^{th} alternative for q^{th} attribute. p and q vary from 1 to A and 1 to B , respectively.

Step 2: Normalize elements of \widetilde{DM} to convert into a comparable range using Eq. (5).

$$\widetilde{s}_{p,q}^N = \begin{cases} \left(\frac{\widetilde{s}_{p,q}}{\text{MAX}(\widetilde{s}_{p,q})} \right) & \text{for beneficial attribute} \\ \left(\frac{\text{MIN}(\widetilde{s}_{p,q})}{\widetilde{s}_{p,q}} \right) & \text{for non-beneficial attribute} \end{cases} \quad (5)$$

where, $\widetilde{s}_{p,q}^N$ represents normalized value corresponding to the element $\widetilde{s}_{p,q}$.

Step 3: Determine weighted normalized values ($\widetilde{s}_{p,q}^{wN}$) using Eq. (6).

$$\widetilde{s}_{p,q}^{wN} = \widetilde{w}_q \times \widetilde{s}_{p,q}^N \quad (6)$$

where, \widetilde{w}_q represents the weight of attribute q .

Step 4: Determining overall distance from the best (positive) and the worst (negative) ideal solutions using Eq. (7) and Eq. (8), respectively.

$$D_p^+ = \sum_{q=1}^B D(\widetilde{s}_{p,q}^{wN}, \widetilde{p}_q) \quad (7)$$

$$D_p^- = \sum_{j=1}^q D(\widetilde{s}_{p,q}^{wN}, \widetilde{n}_q) \quad (8)$$

where, $\widetilde{p}_q = (1, 1, 1)$ and $\widetilde{n}_q = (0, 0, 0)$. $D(\widetilde{s}_{p,q}^{wN}, \widetilde{p}_q)$ and $D(\widetilde{s}_{p,q}^{wN}, \widetilde{n}_q)$ represents the distance between fuzzy numbers $\widetilde{s}_{p,q}^{wN}$, \widetilde{p}_q and $\widetilde{s}_{p,q}^{wN}$, \widetilde{n}_q , respectively.

Step 5: Compute closeness coefficient (CC_p) as defined by Eq. (9).

$$CC_p = \frac{D_p^-}{D_p^+ + D_p^-} \quad (9)$$

An alternative with the highest CC_p value is regarded as the best among the considered alternatives and ranked first. The remaining alternatives are ranked as per the CC_p values in descending order.

Table 2

Best attribute and pairwise comparison of the best attribute with others.

Expert	Best attribute	Severity	Occurrence	Detection
ex ₁	Severity	EIP	VIP	FIP
ex ₂	Severity	EIP	WIP	VIP
ex ₃	Severity	EIP	VIP	FIP
ex ₄	Severity	EIP	AIP	VIP
ex ₅	Occurrence	EIP	EIP	VIP

ex₁: Expert number 1; ex₂: Expert number 2; ex₃: Expert number 3; ex₄: Expert number 4; ex₅: Expert number 5.

4. Results and discussion

To achieve the research objectives, a well-defined questionnaire was designed, developed, and administered to the experts to take their opinion. The questionnaire consisted of two sections. Its first section was designed according to the BWM where experts were requested to first identify the best attribute and the worst attribute. Subsequently, they were asked to provide their opinion about the significance of the best attribute over others and other attributes over the worst while comparing them in pairs. LTs such as Weakly Important (WIP), Equally Important (EIP), Fairly Important (FIP), Very Important (VIP), and Absolute Important (AIP) were used to indicate the significance of one attribute over another during pairwise comparison. The judgment of the experts for the best attribute and its comparison with other attributes is shown in Table 2. Table 3 shows the worst attributes identified by the experts and the result of a pairwise comparison between other attributes with the worst one.

In the second section of the questionnaire, feedback from the experts for evaluation of different psychological factors was obtained in LTs viz. Very Low (VLW), Low (LW), Medium-Low (MLW), Fair (FR), Medium-High (MHH), High (HH) and Very High (VHH). The judgment of the experts for the evaluation of the psychological factors is shown in Table 4.

Opinion gathered from the experts in LTs, as shown in Tables 2 and 3, was transformed to equivalent TFN. The transformation was performed as follows: (1, 1, 1) for EIP, (2/3, 1, 3/2) for WIP, (3/2, 2, 5/2) for FIP, (5/2, 3, 7/2) for VIP and (7/2, 4, 9/2) for AIP. The transformation resulted in the formulation of FBO and FOW vectors. For example, the calculation for the opinion gathered from expert number 1 (ex₁) is given below.

The fuzzy best to others vector and fuzzy others to worst vector are: FBO = {(1,1,1), (7/2, 4, 9/2), (5/2, 3, 7/2)} and FOW = {(7/2, 4, 9/2), (1,1,1), (5/2, 3, 7/2)}. Then, a non-linear programming model was formulated as defined in Eq. (3). Formulation of the non-linear programming model for the judgments given by the expert (ex₁) is shown in Eq. (10).

Table 3

Worst attribute and pairwise comparison of other attributes with the worst attribute.

Worst attribute →	ex ₁ Occurrence	ex ₂ Detection	ex ₃ Occurrence	ex ₄ Occurrence	ex ₅ Detection
Severity	VIP	VIP	VIP	AIP	FIP
Occurrence	EIP	FIP	EIP	EIP	VIP
Detection	FIP	EIP	FIP	WIP	EIP

Table 4

Judgment of the experts for the evaluation of psychological factors.

Psychological factor	Severity	Occurrence	Detection
PF1	(FR, MHH, HH, HH, MLW)	(HH, HH, MHH, FR, HH)	(HH, MLW, LW, FR, LW)
PF2	(MLW, LW, FR, FR, HH)	(FR, LW, FR, MHH, FR)	(LW, LW, LW, FR, LW)
PF3	(MHH, FR, HH, HH, VHH)	(MHH, MHH, FR, FR, VHH)	(LW, LW, LW, MLW, MHH)
PF4	(HH, MHH, HH, VHH, HH)	(FR, FR, LW, HH, FR)	(LW, MLW, LW, FR, LW)
PF5	(FR, LW, MHH, HH, HH)	(MLW, VLW, MHH, MHH, MHH)	(MLW, MLW, LW, FR, MHH)
PF6	(MLW, MLW, MHH, FR, MLW)	(MHH, MLW, HH, FR, LW)	(LW, LW, LW, LW, MLW)
PF7	(FR, LW, HH, HH, FR)	(FR, FR, FR, HH, HH)	(VLW, LW, LW, HH, VLW)
PF8	(MHH, FR, HH, HH, MHH)	(FR, FR, FR, MHH, FR)	(LW, LW, LW, MHH, FR)
PF9	(FR, HH, HH, MLW, VHH)	(LW, FR, FR, MLW, MHH)	(LW, LW, LW, MLW, LW)
PF10	(VHH, LW, VHH, HH, LW)	(LW, LW, LW, MLW, FR)	(MLW, VLW, LW, MLW, LW)
PF11	(VHH, FR, FR, MHH, MHH)	(MHH, MHH, MLW, MHH, MLW)	(MLW, LW, LW, FR, LW)
PF12	(MHH, FR, FR, MHH, VLW)	(MHH, FR, FR, HH, VLW)	(LW, LW, LW, FR, VLW)

Minimize $Z = k^*$

$$\text{Subject to : } \left\{ \begin{array}{l} \left| \frac{w_S^l}{w_O^l} - \frac{7}{2} \right| \leq k^*, \left| \frac{w_S^m}{w_O^m} - 4 \right| \leq k^*, \left| \frac{w_S^u}{w_O^u} - \frac{9}{2} \right| \leq k^* \\ \left| \frac{w_D^l}{w_O^l} - \frac{5}{2} \right| \leq k^*, \left| \frac{w_D^m}{w_O^m} - 3 \right| \leq k^*, \left| \frac{w_D^u}{w_O^u} - \frac{7}{2} \right| \leq k^* \\ \left| \frac{w_D^l}{w_O^l} - \frac{5}{2} \right| \leq k^*, \left| \frac{w_D^m}{w_O^m} - 3 \right| \leq k^*, \left| \frac{w_D^u}{w_O^u} - \frac{7}{2} \right| \leq k^* \\ \frac{1}{6} (w_S^l + 4w_S^m + w_S^u + w_O^l + 4w_O^m + w_O^u + w_D^l + 4w_D^m + w_D^u) = 1 \\ w_S^l \leq w_S^m \leq w_S^u \\ w_O^l \leq w_O^m \leq w_O^u \\ w_D^l \leq w_D^m \leq w_D^u \\ w_S^l, w_O^l, w_D^l \geq 0 \\ k \geq 0 \end{array} \right. \quad (10)$$

where, $\tilde{w}_S = (w_S^l, w_S^m, w_S^u)$, $\tilde{w}_O = (w_O^l, w_O^m, w_O^u)$, $\tilde{w}_D = (w_D^l, w_D^m, w_D^u)$, and \tilde{w}_S , \tilde{w}_O and \tilde{w}_D are the fuzzy weights of the attributes Severity (S), Occurrence (O), and Detection (D), respectively.

Eq. (10) was solved with the help of a computer program developed especially for this purpose using Python 3.0 programming language. The fuzzy weights of the attributes so obtained are $\tilde{w}_S = (0.5264, 0.578, 0.5814)$, $\tilde{w}_O = (0.1323, 0.1448, 0.1461)$,

Table 5

Fuzzy weights of the attributes and consistency ratio.

Attribute	Fuzzy weight	Defuzzified weight	Consistency ratio
Severity (S)	(0.5031, 0.5345, 0.5717)	0.5355	0.03869
Occurrence (O)	(0.231, 0.2565, 0.2896)	0.2578	
Detection (D)	(0.1787, 0.2047, 0.2431)	0.2068	

Table 6

Fuzzy decision matrix.

Psychological factor	Severity	Occurrence	Detection
PF1	(4.6, 6.6, 8.2)	(5.8, 7.8, 9.2)	(2.2, 3.8, 5.6)
PF2	(2.8, 4.6, 6.4)	(2.8, 4.6, 6.6)	(0.6, 1.8, 3.8)
PF3	(6.2, 8.0, 9.2)	(5.0, 6.8, 8.4)	(1.2, 2.6, 4.6)
PF4	(7.0, 8.8, 9.8)	(3.2, 5.0, 6.8)	(0.8, 2.2, 4.2)
PF5	(4.4, 6.2, 7.8)	(3.2, 4.8, 6.6)	(2.0, 3.8, 5.8)
PF6	(2.2, 4.2, 6.2)	(3.2, 5.0, 6.8)	(0.2, 1.4, 3.4)
PF7	(4.0, 5.8, 7.4)	(4.6, 6.6, 8.2)	(1.4, 2.2, 3.6)
PF8	(5.4, 7.4, 9.0)	(3.4, 5.4, 7.4)	(1.6, 3.0, 5.0)
PF9	(5.4, 7.2, 8.4)	(2.4, 4.2, 6.2)	(0.2, 1.4, 3.4)
PF10	(5.0, 6.2, 7.2)	(0.8, 2.2, 4.2)	(0.4, 1.6, 3.4)
PF11	(5.0, 6.8, 8.4)	(3.4, 5.4, 7.4)	(0.8, 2.2, 4.2)
PF12	(3.2, 4.8, 6.6)	(3.6, 5.2, 6.8)	(0.6, 1.6, 3.4)

$\tilde{w}_D = (0.2252, 0.2883, 0.3444)$. As $\tilde{b}_W = \tilde{o}_W = (7/2, 4, 9/2)$, the consistency index for the comparisons is 6.69 [24]. The consistency ratio is 0.1043/6.69 = 0.0156, which is very close to zero, and therefore, it indicates high consistency.

Similarly, for each expert, the mathematical model was formulated and solved to obtain fuzzy weights of the attributes and consistency ratio. The final weight of the attributes was computed by taking an average of the weights of each expert. The final fuzzy weight and defuzzified weight of the attributes along with the consistency ratio so obtained is shown in Table 5.

It can be seen from Table 5 that severity (S) is the highest weight (0.5355) attribute which suggests that it is the most important one followed by Occurrence (O) with a weight of 0.2578 and detection (D) having a weight of 0.2068.

Further, LTs for evaluation of psychological factors shown in Table 4

Table 7

D_p^+ , D_p^- , CC_p and rank of the psychological factors.

Psychological Factor	D_p^+	D_p^-	CC_p	Rank
Stress (PF1)	2.2912	0.7579	0.2486	2
Loneliness (PF2)	2.5377	0.519	0.1698	11
Anxiety (PF3)	2.2804	0.766	0.2514	1
Panic attacks (PF4)	2.3033	0.7449	0.2444	3
Insomnia (PF5)	2.3849	0.6665	0.2184	5
Loss of appetite (PF6)	2.5651	0.4973	0.1624	12
Depression (PF7)	2.4152	0.6269	0.2061	7
Frustration (PF8)	2.3334	0.7205	0.2359	4
Fear of catching disease (PF9)	2.4327	0.6194	0.2029	8
Suicidal tendencies (PF10)	2.5261	0.5185	0.1703	10
Mood swings (PF11)	2.39	0.664	0.2174	6
Domestic violence (PF12)	2.5158	0.5322	0.1746	9

Table 8

Ranking results using F-TOPSIS, F-WSM and F-MABAC.

Psychological Factor (PF)	F-TOPSIS	F-WSM	F-MABAC
Stress (PF1)	2	2	3
Loneliness (PF2)	11	11	11
Anxiety (PF3)	1	1	1
Panic attacks (PF4)	3	3	2
Insomnia (PF5)	5	5	6
Loss of appetite (PF6)	12	12	12
Depression (PF7)	7	7	7
Frustration (PF8)	4	4	4
Fear of catching disease (PF9)	8	8	8
Suicidal tendencies (PF10)	10	10	9
Mood swings (PF11)	6	6	5
Domestic violence (PF12)	9	9	10

Table 9

Weight changes in the sensitivity analysis.

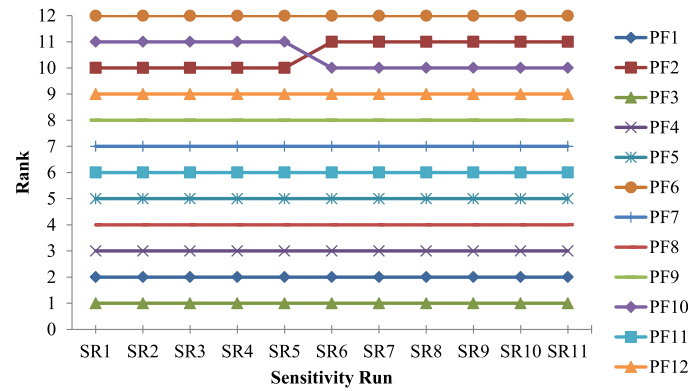
SR	% change	Severity (S)	Occurrence (O)	Detection (D)
SR1	-5%	[0.4779, 0.5078, 0.5431]	[0.2432, 0.27, 0.3049]	[0.1881, 0.2155, 0.2559]
SR2	-4%	[0.483, 0.5131, 0.5488]	[0.2407, 0.2672, 0.3017]	[0.1862, 0.2133, 0.2533]
SR3	-3%	[0.488, 0.5185, 0.5545]	[0.2382, 0.2645, 0.2986]	[0.1842, 0.211, 0.2506]
SR4	-2%	[0.493, 0.5238, 0.5603]	[0.2357, 0.2617, 0.2955]	[0.1823, 0.2089, 0.2481]
SR5	-1%	[0.4981, 0.5292, 0.566]	[0.2333, 0.2591, 0.2925]	[0.1805, 0.2067, 0.2455]
SR6	0%	[0.5031, 0.5345, 0.5717]	[0.231, 0.2565, 0.2896]	[0.1787, 0.2047, 0.2431]
SR7	1%	[0.5081, 0.5398, 0.5774]	[0.2287, 0.254, 0.2868]	[0.1769, 0.2027, 0.2407]
SR8	2%	[0.5132, 0.5452, 0.5831]	[0.2265, 0.2515, 0.2839]	[0.1752, 0.2007, 0.2383]
SR9	3%	[0.5182, 0.5505, 0.5889]	[0.2243, 0.2491, 0.2812]	[0.1735, 0.1988, 0.236]
SR10	4%	[0.5232, 0.5559, 0.5946]	[0.2221, 0.2466, 0.2785]	[0.1718, 0.1968, 0.2338]
SR11	5%	[0.5283, 0.5612, 0.6003]	[0.22, 0.2443, 0.2758]	[0.1702, 0.195, 0.2316]

were transformed into fuzzy numbers by considering (0, 0, 1) for VLW, (0, 1, 3) for LW, (1,3,5) for MLW, (3,5,7) for FR, (5,7,9) for MHH, (7, 9, 10) for HH and (9, 10, 10) for VHH. The aggregated fuzzy decision matrix so obtained is given in Table 6.

Table 6 was normalized using Eq. (5) to obtain the normalized fuzzy decision matrix. Further, Eqs. (6-8) were employed to compute the distance of alternatives (psychological factors) from the best ideal and the worst ideal solutions. Subsequently, the closeness coefficient (CC_p) value for each psychological factor was determined using Eq. (9). The CC_p values were used to determine the ranking of the psychological factors as shown in Table 7.

It is evident from Table 7 that the most critical psychological factor is anxiety (PF3) as its rank is 1. The next in the row is stress (PF1) followed by panic attacks (PF4), frustration (PF8), insomnia (PF5), mood swings (PF11), depression (PF7), fear of catching disease (PF9), domestic violence (PF12), suicidal tendencies (PF10), loneliness (PF2), and loss of appetite (PF6).

Further, it was imperative to examine the consistency and robustness of the derived ranks to draw meaningful conclusions. Consistency of the results was examined by comparing the derived ranks with those obtained from the Fuzzy weighted sum method (F-WSM) and Fuzzy multi attributive border approximation area comparison (F-MABAC) method. Since, these methods were used to validate the ranks of the psychological factors and therefore, discussions about these methods are not given in this paper. However, the computational steps and application of these methods can be found in the literature [26,27]. Table 8 exhibits the

**Fig. 2.** Results of sensitivity analysis.

ranks of the psychological factors obtained from F-TOPSIS, F-WSM, and F-MABAC. It is evident from Table 8 that the ranking result obtained using F-WSM is identical to that of the F-TOPSIS method. Further, a rank change of order 1 in some of the factors viz. PF1, PF4, PF5, PF10, PF11, and PF12 between F-TOPSIS and F-MABAC is also observed in Table 8. A small difference in the ranks given by different methods is attributed to the inherent characteristics of the methods. Hence, from the comparison shown in Table 8, it can be inferred that the ranking results obtained in this study are consistent.

Sensitivity analysis is found as the most widely accepted method to examine the robustness of the ranking results [28,29]. Several approaches to performing sensitivity analysis are available in the literature among which the most common one is to examine variation in the ranks of alternatives with change in weights of the attributes. This work employs one at a time (OAT) method to perform sensitivity analysis as it requires less computation and is easy to implement [30,31]. According to this method, a viable range of weight deviation is specified and the weight of the highest weight attribute is altered from - 5% to 5%. Further, the weights of other attributes are altered in proportion to the highest weight attribute. Table 9 exhibits the change in fuzzy weights of the attributes over all the sensitivity runs (SRs). It may be noted that SR6 is the base sensitivity run.

Subsequently, the ranking procedure used in the study i.e. F-TOPSIS was employed for each of the sensitivity runs. Fig. 2 shows the ranks of the psychological factors so obtained in the sensitivity analysis.

It can be observed from Fig. 2 that the rank of the psychological factor does not change over all the sensitivity runs except for a rank reversal of order 1 for PF2 and PF10. Hence, it can be deduced that the ranking results of the present study are robust.

Multiple reasons may contribute to the increased incidence of stress, anxiety, panic attacks, frustration, and other psychological factors and those with pre-existing psychological disorders are especially vulnerable. For instance, loneliness, loss of freedom, restriction of movement, being away from loved ones, fear of infection, and financial loss with extended distancing at all places are the major reasons. Anxiety, though a normal phenomenon tends to increase in such situations. Therefore, increased anxiety is naturally to be the most prominent psychological characteristic. Subsequently, unfavorably affected financial conditions of middle and lower-class income groups due to prolonged social distancing and lockdowns could be the reason behind stress being the second critical psychological factor. Moreover, self-isolation, loss of freedom, and lifestyle changes will undoubtedly increase stress levels. Anxiety may also trigger stress or vice-versa. Anxiety when becomes difficult to cope with may sometimes lead to an episode of a panic attack. The results of the present study are supported by the findings of the studies available in the literature [32,33] in which the researchers also considered psychological factors, anxiety, and stress, to analyze the impact of COVID-19-led social distancing on mental health and they found these factors to be the most critical.

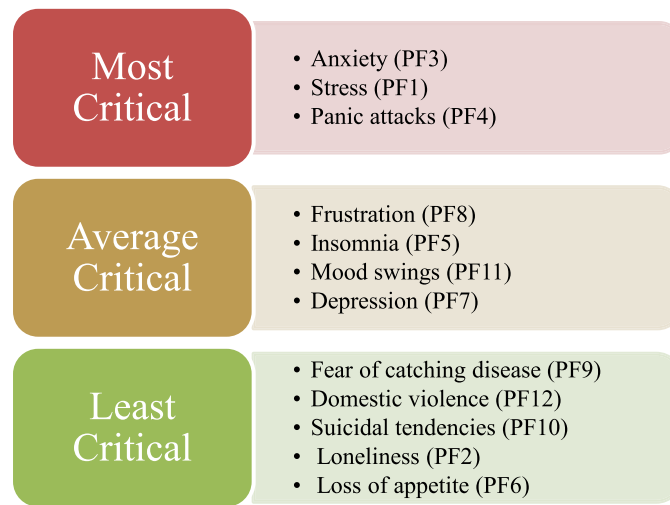


Fig. 3. Categorization based on the ranks of the psychological factors.

In this study, various psychological factors affecting the mental health of people during the initial period of COVID-19 were considered. Many psychological factors like depression, panic attacks, and suicidal tendencies need immediate identification and treatment. Other psychological factors like frustration, fear of catching an illness, and loneliness can be managed with simple counseling and behavioral modification. This study may be helpful for society, mental health professionals, and policymakers to understand the criticality of the potential psychological factors which may lead to better management.

5. Conclusions

No doubt, the COVID-19 pandemic was a catastrophe that had been never experienced by people for over a century. During the initial stages of the pandemic, social distancing measures including lockdowns for a prolonged period were the first and most effective way to decelerate the spread of the disease. Due to these, people were confined to their homes and lost the freedom to lead their lives in the same way as they used to in the pre-pandemic period. The lifestyle changed by almost 180 degrees due to which many people might have suffered from anxiety, depression, stress, loneliness, panic, and several other psychological problems. Further, psychological problems might even have led to suicidal thoughts and many people might have harmed themselves. This paper identified the various psychological factors based on the experts' opinions and demonstrated the application of two fuzzy-based MCDM methods (F-BWM and F-TOPSIS) to rank them to reflect their criticality in the event of COVID-19 outbursts. The foremost conclusions of the study are listed as under:

- Out of three attributes used for evaluation of the psychological factors, severity (S) was the most important attribute as its weight was maximum (0.5355), followed by detection (D) with a weight of 0.2578 and occurrence having a weight of 0.2068.
- Among the several psychological factors considered in the present study, anxiety was the most affected factor due to COVID-19 led strict social distancing measures. On the other hand, the loss of appetite was the least affected psychological factor.
- The psychological factors in decreasing order of importance concerning their criticality were: anxiety > stress > panic attacks > frustration > insomnia > mood swings > depression > fear of catching disease > domestic violence > suicidal tendencies > loneliness > loss of appetite.

It has been seen that after any disaster, war, or pandemic mental

health problems pose a great risk for the affected populations. WHO has predicted a significant increase in mental health problems after and during this COVID-19 pandemic. Many eminent psychiatrists are already seeing an increase in the number of patients reporting anxiety and stress-related problems. This study may help them to make triage for their preferences. Most of the patients are having mild anxiety symptoms which can be tackled by counseling. Some of them will have more serious problems like depression and suicidal tendencies which needed more concern.

Based on the ranking of the identified psychological factors, reflecting their criticality, derived in the present study, they might be grouped into three categories viz. the most critical, the average critical, and the least critical groups. This categorization was done according to the ABC rule of ranking where the top 20% are categorized into the most critical, the next 30% into the average critical, and the last 50% into the least critical psychological factors [34]. In this regard, anxiety (PF3), stress (PF1), and panic attacks (PF4) are considered the most critical; frustration (PF8), insomnia (PF5), mood swings (PF11), and depression (PF7) as average critical and fear of catching disease (PF9), domestic violence (PF12), suicidal tendencies (PF10), loneliness (PF2) and loss of appetite (PF6) as least critical psychological factors. The categorization of the psychological factors into three groups is depicted in Fig. 3.

6. Research implications/contribution

COVID-19 has immensely affected the physical and mental health conditions of people apart from causing the death of a large number of persons across the globe. The pandemic might have caused different psychological problems among the survivors as a result of several factors such as the loss of precious lives of loved ones, loss of jobs, reduction in salaries, financial loss in business, etc. The contribution of the present study is that it has analyzed the potential psychological factors using the integrated fuzzy MCDM method and ranked them to signify their criticality. In addition, based on the ranks of the psychological factors they have also been grouped into the most, the average, and the least critical categories. This study may help the medical fraternity and other relevant authorities to understand the criticality of the various psychological factors caused by this pandemic which may help them in formulating effective strategies for better management, control, and treatment. Further, the categorization of the psychological factors done in the study may help the doctors in designing specific protocols to handle patients suffering from psychological problems according to their criticality.

7. Limitations and scope of future work

Every study has its limitations due to various constraints which opens the doors for making suggestions that may be implemented in future studies. Like other studies, the limitation of this study is that it utilized the information/data provided by five Indian experts (doctors) based on which analysis was carried out using F-BWM and F-TOPSIS methods to assess the impact of strict social distancing measures and lockdowns on psychological characteristics of people. Therefore, the results of this study may not be generalized to represent the impact of COVID-19 on the criticality of the various psychological factors of the entire population across the affected countries as psychological characteristics of the population vary with demography and personal attributes of individuals. Consequently, it is suggested that similar studies may be carried out in different countries affected by COVID-19, and analysis based on the data provided by the experts of the respective countries may be performed to explore the impact of strict social distancing measures on the psychological factors of the population. The results derived from these studies may be compared with those of the present study. Further, a similar but relatively bigger study may be conducted in which experts from different affected countries may be involved and their feedback may be analyzed to probably arrive at a generalized conclusion. In addition, the psychological factors that have not been included in the present study, especially given the current improved COVID-19 situation, may also be considered in future studies.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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