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A Cross-Sectional Study on Mental Health of School Students during the COVID-19 Pandemic in India

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Abstract: The broad objective of the present study is to assess the levels of anxiety and depression of school students during the COVID-19 lockdown phase and their association with students' background, stress, concerns and social support. In this regard, the present study follows a novel two stage approach. In the first phase, an empirical survey was carried out, based on multivariate statistical analysis, wherein a group of 273 school students participated in the study voluntarily. In the second phase, a novel Picture Fuzzy FFA (PF-FFA) method was applied for understanding the dynamics of facilitating and prohibiting factors for three categories of focus groups (FG), formulated on the basis of attendance in online classes. Findings revealed a significant impact of anxiety and depression on mental health. Further, PF-FFA examinedthe impact of the driving forces that steered children to attend class as contrasted to the the impact of the restricting forces.

Keywords: school students; COVID-19; mental health; social support; picture fuzzy force field analysis (PF-FFA); level based weight assessment (LBWA)

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1. Introduction

Childhood is a golden phase in every individual's life. During this phase, children attend schools, befriend other children and enjoy their association, develop good habits, imbibe values from their teachers and move ahead in life for further career growth and development. The lessons which children learn in the school build the foundation for their future career. Cognitive, social and personality development of children take shape through school education. Sadly, education at every level has been adversely affected globally since the outbreak of COVID-19 in January 2020. The impact of continuous lockdown in a phased manner, to arrest the rapid spread of the pandemic, caused psychological distress for school students, such as depression and anxiety, and affected their quality of life [1–6]. Recent evidence highlights that women are more vulnerable to depression and anxiety during adversities [4,6]. It has also been observed that young children, hailing from poor income families, manifest greater risks of mental health challenges [7,8].

Rural students, in developing countries like India, were the worst victims of the situation, with lack of online education, due to lack of internet facilities and/or poor internet connectivity. The Remote Learning Reachability report [9] indicated the widening learning gap owing to the digital divide. Poor economic conditions did not allow a majority of the rural children to buy smartphones and/or laptops, and data cards, for online education. Less than 25 percent of households were reported to be equipped with access to the internet [9], among which more than 80 percent of the students in government schools had no access to any educational material in Odisha, Jharkhand, Bihar, Chattisgarh, and Uttar Pradesh [10]. As a result, cognitive development and nutrition [11] of rural school students in India was more affected, when compared to urban students. Further, social isolation and confinement at home, without much physical activity, caused mental distress for the school students [12].

1.1. Magnitude of School Student Enrolment in India, Computer Facilities and Impact

About 1.49 million schools in India offer education at different levels [13]. Available data highlights that almost 265 million students were taught in the schools during 2019–2020 and only 22% of schools in India had internet facilities [14]. Unfortunately, among the government schools, less than 12% had internet in 2019–2020, while less than 30% had functional computer facilities, which adversely affected online education during the pandemic, especially for students in government schools and in the rural areas. Therefore, it is estimated that closure of educational institutions on account of COVID-19 has affected the education of over 320 million children from pre-primary to tertiary levels [15].

The challenges for urban students during the pandemic were slightly different from rural students, although most urban students got the opportunity for online education. Most of the students in the urban areas of India live in two or three room flats. Therefore, physical mobility was restricted. Attending continuous online classes without much break in between the classes was psychologically distressful and tended to aggravate their miseries. Available evidence indicates that COVID-19 has had an adverse impact on the mental and physical health of people beyond geographical boundaries [16–21], with a high incidence of distress, depression, and anxiety among adolescents and the youth [7,22].

Regarding the efficacy of the online mode of teaching and learning process, a mixed image has been reported. A few studies reported positive outcomes of online teaching and learning processes [23–29], while a few reported the opposite picture i.e., negative outcomes such as poor communication between teachers and students, poor internet connectivity, lack of concentration and so on [30–32].

1.2. Research Objectives

There has been limited research addressing the mental health of school children vis-à-vis COVID-19. Therefore, the present study attempted to examine the status of mental health of Indian school students on account of COVID-19 lockdown, in terms of anxiety and depression. Further, the study assessed the association between the status of mental health, their background, stress, worries and support facilities. The following hypotheses were developed for verification.

Hypothesis 1. *Anxiety and depression of school students differ significantly in terms of gender and grade.*

Hypothesis 2. *There exists an association between feeling stressed for staying at home for a long period during the COVID-19 pandemic, and anxiety and depression.*

Hypothesis 3. *There exists an association between perception about the online teaching mode, and anxiety and depression.*

Hypothesis 4. *There exists an association between social support from family and friends, and anxiety and depression.*

Hypothesis 5. *There exists an association between worries about catching COVID-19 and future career of the students with anxiety and depression.*

Moving further, we were also inquisitive about the dynamics between the facilitating and prohibiting factors that influence the level of participation of the children during online classes. For this purpose, we aimed to carry out an FFA on three focused groups (FG) classified as "Always Attend" (FG-1), "Sometimes Attend" (FG-2) and "Very Rarely and Rarely Attend" (FG-3).

1.3. Contributions of the Paper

The present paper adds value to the extant literature in the following ways.

(a) Within our best possible search, we noticed scanty work related to the mental health of school children. In this regard, our study puts forth a new perspective for the educational leaders, parents and policymakers.
(b) The present paper provides a first of its kind integrated framework of empirical multivariate analysis and PFS based FFA, grounded on a psychological perspective.
(c) A new framework of PF-FFA is proposed in the broad domain of change management.

The rest of the paper is structured as follows. Section 2 describes the research methodology. In Section 3 we present the findings and in Section 4 we include necessary discussions. The concluding remarks and recommendations are provided in Section 5.

2. Materials and Methods

The present research is designed in two stages, i.e., stage 1 (empirical multivariate analysis) and stage 2 (FG opinion based PF-FFA). The stages are interconnected and provide a comprehensive framework for assessment.

2.1. Stage 1

2.1.1. Study Design

An online cross-sectional survey was carried out among Indian school students between 3 June 2020, and 3 August 2020, the period of outbreak of COVID-19.

2.1.2. Sample

A group of 237 school students from Grade IX to XII, aged between 14 to 18 years, participated in the online survey voluntarily.

2.1.3. Study Tools

Semi-structured questionnaire (developed by Deb, 2020): this was developed to understand the school students' perception of the online mode of teaching and their issues and concerns during the COVID-19 pandemic. The questionnaire consisted of five sections, viz.:

Section I: Background Information
Section II: Online Mode of Teaching, Learning and Examinations
Section III: Health
Section IV: Perceived Stress and Coping Strategies
Section V: Mental Health of School Students

Section I consisted of 10 questions pertaining to socio-demographic details, including gender, age, grade, type of family, number of siblings, family monthly income, number of rooms in the house, educational background and occupation of parents, and history of chronic health problems of any family member, while Section II consisted of 20 questions related to school students' perception of online classes, challenges faced by them in attending the online classes, students' perception about online and face to face teaching methods, experience in writing online examinations and so on. Some of the questions related to Section II were as follows:

- Did you attend online classes offered by your school?
- Did you face an internet connectivity problem?
- How did you find the online mode of teaching?
- Could you clarify your doubts, ask questions and get the answers?

Section III comprised seven items related to health concerns of school students, arising due to attending continuous classes, fear of catching COVID-19, physical and leisure time activities. Section IV included six questions related to perceived stress and coping strategies.

The face validity of the interview schedule was ascertained by two experts. A five-point scale was used to capture the response of the subjects to most of the questions while for some questions, a dichotomous mode of response was sought. For example, in a question like 'did you face an internet connectivity problem?', the mode of response was captured by using a 5-point scale (1 = Always: 5 = Never).

(a) Depression Scale:

This brief scale consisted of two items of the Reynolds Adolescent Depression Scale-2nd Edn. (RADS-2), and the items included: (i) I feel that no one cares about me; and (ii) I feel worried. The mode of responses include 'almost never', 'sometimes', 'a lot of the time' and 'all the time'. Score "0" is assigned to "almost never" while score "3" is assigned to "all the time". A high score indicates high depression. The Cronbach's Alpha of RADS-2 short version with the present sample was 0.66.

(b) Anxiety Scale:

The brief Anxiety Scale consisted of six items of the Multidimensional Anxiety Scale for Children (MASC). Some of the items included: (i) I get scared when my parents go away; (ii) I avoid going to places without my family; (iii) I feel restless and on the edge. The mode of responses includes 'never true about me', 'rarely true about me', 'sometimes true about me' and 'often true about me'. Score "0" is assigned to "never true about me" while score "3" is assigned to "often true about me". A high score indicates high anxiety. The Cronbach's Alpha of RADS-2 short version with the present sample was 0.68.

2.1.4. Data Collection and Analysis

Data was drawn via an online survey. Data was primarily reported using descriptive statistics. Differences in the prevalence of depression and anxiety across each demographic variable were tested by using independent samples t-test and one-way ANOVA. All the analysis was done by using IBM SPSS version 23.0.

2.2. Stage 2

In the next stage, a FG study was conducted and a PF-FFA was carried out.

2.2.1. Description of the FGs

In the study, the respondents were classified into three categories, such as "Always Attend (AA)", "Sometimes Attend (SA)" and "Very Rarely and Rare Attend (VRA)", based on their attendance during online classes. It was observed that a higher number of students fall under category 1 (AA). According to the size of the three categories, three FGs were formed, following convenient sampling.

- FG 1: The representative sample consists of 20 students belonging to AA category.
- FG 2: In this group 10 students from SA category are included.
- FG 3: 05 (five) students from the VRA category.

2.2.2. Identification of the Factor

An exploratory discussion was carried out with the FGs separately and after accumulating the views, six facilitating factors and six prohibiting factors were finalized, as given in Table 1.

Table 1. Facilitating and Prohibiting Factors.

Facilitating Factors		**Prohibiting Factors**	
S/L	Description of the Factor	S/L	Description of the Factor
P1	Less travelling	N1	Lack of infrastructure
P2	Access to distant courses	N2	Physical health issue
P3	Staying together with family	N3	Difficulty in online learning
P4	Enjoy online class	N4	Worry about Covid-19
P5	Free time	N5	Worry about future
P6	Enjoy online exam	N6	Movement restriction

2.2.3. Force Field Analysis (FFA)

The concept of FFA has its genesis in the seminal work on the three step model of planned organizational change management, proposed by Lewin. Later, Lewin [33] proposed the framework of FFA, which is based on two types of forces, namely, Driving Forces (DF), which favour the change and act as the enablers, and Restraining Forces (RF) which tend to restrict the change from taking place. Given a situation or requirement, FFA analyses the interplay among various RFs and DFs while making a transition from the "As is" state to the "To Be" stage, by embracing the change [34]. FFA helps in formulating dynamic business strategies to withstand strategic regression and market competition, as utilized by Paquin and Koplyay [35].

In the context of psychological analysis and organizational change management, FFA has been applied extensively by the researchers. For instance, Hlalele [36] conducted a vulnerability analysis of drought conditions from the phenomenological perspective, supported by FFA. Youssef and Mostafa [37] extended the application focus of FFA to the area of cloud computing adoption in organizations and utilized a combined model of FFA, along with pairwise comparison and the Delphi method. To understand the DFs and RFs supporting the adoption of environmental strategy by firms involved in the hotel industry of Taiwan, Mak and Chang [38] applied FFA.

In a recent study [39], the authors explored the factors that influenced students and their families regarding online learning and reported that safe home environment, leisure time, food, family bonding, economical aspects and flexibility, are some of the supporting factors, while technical issues such as network glitches, distractions, stress and anxiety, lack of real-life experiences, and social distancing, were the adverse factors. The authors finally advocated for a "blended or hybrid" mode of learning. In a different scenario, Ramos et al. [40] conducted a field study on Small and Medium Enterprises (SME) in the Philippines, to assess their readiness toward adopting the Internet of Things (IoT) and related technologies, based on FFA and causal analysis, using Structural Equation Modelling (SEM).

In this context, it may be noted that FFA has been used for solving various issues related to engineering, management and social sciences, and has been applied in conjunction with other multivariate techniques such as SEM. However, the application of FFA with imprecise information and analysis in an uncertain environment seems to be rare.

2.2.4. PFS

The concept of PFS was developed as an extension of the intuitionistic fuzzy sets (IFS). Unlike IFS, PFS indicates the degree of refusal and brings about better accuracy and granularity in the analysis, which involves a considerable amount of subjectivity and impreciseness in the available information [41]. Due to its potential for superior analysis under uncertainty, PFS has been utilized by various researchers (e.g., [42–48]) in distinct situations, for multi-criteria decision making (MCDM) related problems. In the following section, we mention some of the basic definitions, operations and properties of PFS [49,50]. The preliminary definitions, operations and properties of PFS are given in Appendix A.

2.2.5. LBWA Method

LBWA is an algorithm designed by Žižović & Pamučar [51], to decide criteria weights. LBWA offers a lesser number of pairwise comparisons (only $(n-1)$ number of criteria comparisons) and thus enables operation with a lesser computational complexity. It works efficiently with a large criteria set, to provide better consistency and robustness of results, and equally operates with subjective and objective information. LBWA finds its applications in many complex real-life problems, such as facility location selection [52]; selection of airport ground access mode [53]; military operations [54–56]; healthcare management during crisis [57]; location selection for offshore wind farms [58]; sustainable energy management [59,60]; and social entrepreneurship [42]. The computational steps of the algorithm are described in Appendix B.

2.2.6. The Proposed PF-FFA Method

The algorithm of the proposed PF-FFA method is described below.

Suppose,

C_j, where $j = 1, 2, \ldots n$ (n is finite and ≥ 2): The number of criteria. In our paper, the criteria represent a list of six facilitating/prohibiting factors.

E_t, where $t = 1, 2, \ldots m$ (m is finite and ≥ 2): The number of respondents who have provided their opinions during the study.

Then, for each of the facilitating and prohibiting factors separately, the following steps are followed for computation

Step 1. Formulation of the linguistic rating matrix

$$\varphi^t = \left[\varphi_1^t \ \varphi_2^t \ldots \varphi_n^t\right]$$

Here, φ_j^t is the rating of the factor C_j by the respondent E_t based on the relative importance of the corresponding factor. We use the linguistic expression in terms of Yes (Y) (if the challenging factor is perceived as impactful, i.e., positive membership), No (N) (if the challenging factor is perceived to have very little or no impact, i.e., negative membership), and Can't say (A) (if it is not possible to precisely assess the impact, i.e., neutral view). We do not include the option of refusal as the factors are derived through discussion with the respondents.

Step 2. Formulation of the PF factor weight matrix

The factor weight matrix is represented as $= [_j]_{n\times 1}$. Here, $_j = \left\langle \mu_j, \eta_j, \upsilon_j \right\rangle$ is a PFN representing the importance of the factor C_j considering the responses of all respondents. We follow the demonstration of Jovčić et al. [61] to derive the PFNs.

Step 3. Calculation of the actual scores

The actual scores are calculated using the steps followed in Si et al. (2019) (refer the Equations (A26)–(A31) as given in Appendix A)

The actual scores of all PFNs corresponding to the factors (facilitating/prohibiting factors) are calculated separately.

Step 4. Determination of weights of the factors

We use the computational steps of the LBWA algorithm (as given in the Appendix B) to derive the weights of the factors.

Step 5. Finding out the aggregated scores of the facilitating and prohibiting factors

We use PFWA operator (see Expression (A32) in Appendix A) to calculate the aggregated scores of the facilitating and prohibiting factors separately.

Step 6. Comparison of aggregated scores of the facilitating and prohibiting factors

The aggregate score is obtained through defuzzification (see Expressions (A21) to (A23) in Appendix A).

The decision rule:

If $Score_{Facilitating} > Score_{Prohibiting}$, we conclude that the change is supported;
If $Score_{Facilitating} < Score_{Prohibiting}$, we conclude that the change is dominated and prevented;
If $Score_{Facilitating} = Score_{Prohibiting}$, no adequate evidence to support the movement.

3. Results

In this section, we summarize the results of the data analysis using the methodological steps as described in Section 2. The results are exhibited stage-wise.

3.1. Stage 1

3.1.1. Description of the Sample

Table 2 depicts the description of the sample. Of the 273 participants, 54.9% (150/273) were male and 45.1% (123/273) were female. The majority of the respondents came from single families (74.7%), less than a quarter of the participants (23.4%) were from joint families and 1.8% were living with their relatives. Close to a quarter of the respondents were studying in the 9th grade (24.2%), 18.7% were in their 10th grade, 22.0% were studying in the 11th grade and more than one third of the students were studying in the 12th grade (35.2%).

Table 2. Description of the Sample (*N* = 273).

Variable	*N*	(%)
Gender		
Male	150	54.9
Female	123	45.1
Family Type		
Joint	64	23.4
Single	204	74.7
Staying with relative family	05	1.8
Grade		
9th class	66	24.2
10th class	51	18.7
11th class	60	22.0
12th class	96	35.2
Age		
14 to 15 years	134	49.1
16 to 18 years	139	50.9
Siblings		
Only child	88	32.2
1 sibling	159	58.2
2 siblings and above	26	9.5
Monthly income		
Less than 20,000 INR	48	17.6
20,001 to 50,000 INR	86	31.5
50,001 to 100,000 INR	72	26.4
100,001 to 150,000 INR	42	15.4
150,001 and above INR	25	9.2
How did you find the online mode of teaching?		
Most effective	09	3.3
Effective	59	21.6
Moderately effective	104	38.1
Not so effective	67	24.5
Not at all effective	34	12.5

Table 2. *Cont.*

Variable	N	(%)
Are you worried that you will catch COVID-19?		
Highly worried	41	15.0
Worried	50	18.3
Worried to some extent	75	27.5
Not so worried	54	19.8
Not at all worried	53	19.4
Do you feel stressed from staying at home for a long period during COVID-19 pandemic?		
Highly stressed	118	43.2
Stressed	51	18.7
Moderately stressed	46	16.8
Rarely stressed	27	9.9
Not so stressed	31	11.4
Are you worried about your future career?		
Highly worried	119	43.6
Worried	77	28.2
Worried to some extent	39	14.3
Not so worried	19	7.0
Not at all worried	19	7.0
Do you get emotional support from your family when you need it?		
Always	105	38.5
Most of the time	66	24.2
Sometimes	58	21.2
Rarely	29	10.6
Never	15	5.5
Do you have friends who extend support at times of any crisis or challenge?		
Always	108	39.6
Most of the time	52	19.0
Sometimes	63	23.1
Rarely	23	8.4
Never	27	9.9

Half of the participants were aged 18–20 years (49.1%) and another half were aged 16 to 20 years (50.9%). More than half of the participants had 1 sibling (58.2%), one third of the respondents were the only children (32.2%) and 9.5% had two or more siblings. The monthly income of one third of the sample was 20,001 to 50,000 INR (31.5%), more than a quarter had 50,001 to 100,000 INR (26.4%), less than a quarter had less than 20,000 INR (17.6%), 15.4% had 100,001 to 150,000 INR and 9.2% had 150,001 INR and above monthly familial income.

With respect to online mode of teaching during lockdown, more than one-third of the respondents found it moderately effective (38.1%), a quarter of the participants found it to be not so effective (24.5%), less than a quarter found it effective (21.6%) and more than one-tenth did not find it effective (12.5%). Only 3.3% found it most effective. Less than a quarter of the students were worried about catching COVID-19 (18.3%) while 15% and 27.5% reported being highly worried and worried to some extent.

Regarding stress from staying at home for a long period during COVID-19, nearly half of the participants felt highly stressed (43.2%), less than a quarter felt stressed (18.7%) or moderately stressed (16.8%), 9.9% felt rarely stressed and 11.4% did not feel much stressed. About half of the participants were highly worried about their future career (43.6%) and over a quarter were in the worried category (28.2%).

More than one-third of the participants received emotional support (38.5%) from the family during the lockdown period, while a quarter of the respondents received emotional support most of the time (24.2%). As far as emotional support from friends is concerned, 39.6%, 19% and 23.1% received it always, most of the time and sometimes, respectively (Table 2).

3.1.2. Description of Anxiety and Depression

Data pertaining to description of anxiety and depression is provided in Table 3, indicating the mean anxiety (mean = 8.05; *SD* = 4.10) and depression (mean= 3.10; *SD* = 1.86) levels reported by the students during COVID-19 lockdown, in the range of 0 to 18 and 0 to 6, respectively.

Table 3. Description of anxiety and depression (N = 273).

	Mean	*SD*	Actual Score Range	Possible Score Range
Anxiety	8.05	4.10	0–18	0–18
Depression	3.10	1.86	0–6	0–6

Note: SD = Standard deviation.

3.1.3. Levels of Anxiety among Students during COVID-19 Lockdown

Table 4 highlights the levels of anxiety of school students during COVID-19 lockdown. More than one-third of the participants (37.7%) reported having low levels of anxiety, nearly half of the participants (46.9%) reported moderate levels of anxiety, and over one-tenth of the sample (13.2%) reported high levels of anxiety, while 2.2% of the participants did not report any anxiety.

Table 4. Levels of anxiety (N = 273).

Level	Score Range	*n*	%
No anxiety	0	6	2.2
Low anxiety	1 to 6	103	37.7
Moderate anxiety	7 to 12	128	46.9
High anxiety	13 to 18	36	13.2
Total		273	100

3.1.4. Levels of Depression among Students during COVID-19 Lockdown

Table 5 reflects the levels of depression of students during COVID-19 lockdown. A quarter of the participants (25.3%) reported a low level of depression. Over one-third of the respondents (34.8%) reported a moderate level of depression. More than a quarter of the participants (27.5%) reported high levels of depression and over one-tenth of the samples (12.5%) did not report depression.

Table 5. Levels of depression (N = 273).

Level	Score Range	*n*	%
No depression	0	34	12.5
Low depression	1 to 2	69	25.3
Moderate depression	3 to 4	95	34.8
High depression	5 to 6	75	27.5
Total		273	100

3.1.5. Association of Anxiety and Depression with Demographic Variables

Data provided in Table 6 indicates a significant association between grade and depression [F (3, 269) = 4.15, $p < 0.01$]. Depression was found to be higher among the students of the 11th grade, followed by students of the 12th grade and the 9th grade. Therefore, Hypothesis 1 that is "*Anxiety and depression of school students differ significantly in terms of gender and grade*" is partially accepted, as there was no significant gender difference with respect to anxiety and depression, although grade-wise significant difference was observed.

Regarding the stress resulting from long stay at home during COVID-19 lockdown, among adolescent students, a significant association was found with anxiety [F (4, 268) = 2.48, $p < 0.05$] and depression [F (4, 268) = 8.10, $p < 0.001$]. Students who felt stressed during the lockdown reported significantly higher rates of anxiety, as compared to students who did not feel stressed. The levels of depression were found to be higher among students who felt stressed, followed by those who felt highly stressed, rarely stressed and not so stressed. Hence Hypothesis 2 i.e., "*There exists an association between feeling stressed from staying at home for a long period during COVID-19 pandemic and anxiety and depression*" has been accepted.

A significant association was found between an online mode of teaching during COVID-19 lockdown, and anxiety [F (4, 268) = 4.20, $p < 0.01$] and depression [F (4, 268) = 8.44, $p < 0.001$]. Students who did not find online teaching effective at all reported greater levels of anxiety, followed by those who found online teaching moderately effective and effective. Students who did not find online teaching effective at all reported higher rates of depression, followed by those who did not find online teaching so effective, moderately effective, effective and most effective, respectively. As for Hypothesis 2, Hypothesis 3 i.e., "*There exists an association between perception about the online mode of teaching and anxiety and depression*" has been accepted.

With respect to emotional support from family, a significant association was found with depression only [F (4, 268) = 12.13, $p < 0.001$]. Students who did not receive emotional support from their family demonstrated higher levels of depression, followed by those who received emotional support rarely, sometimes, most of the time and always.

Further analysis of data revealed a significant association between peer group support during COVID-19 lockdown and depression [F (4, 268) = 2.83, $p < 0.05$]. Students who always received support from friends were found to be less depressed than students who never received any support from their friends during times of crisis. Therefore, Hypothesis 4 i.e., "*There exists an association between social support from family and friends and anxiety and depression*" is partially tenable as significant association was found between poor social support and depression only.

Worries of school students about infection with COVID-19 was found to be associated with high levels of anxiety [F(4, 268) = 2.83, $p < 0.05$]. That is, the students who demonstrated worries about catching COVID-19 showed higher anxiety levels than those who were not at all worried.

Similarly, worries of school students about their future career caused higher levels of anxiety [F (4, 268) = 5.66, $p < 0.001$] and depression [F(4, 268) = 6.62, $p < 0.001$]. Students who felt worried about their future reported higher anxiety, followed by those who felt rarely worried and not so worried during the lockdown. Similarly, students who felt worried about their future career demonstrated higher rates of depression, followed by those who felt moderately worried, rarely worried and not so worried.

Looking at the analysis of data, it has been observed that Hypothesis 5 (There exists an association between worries about catching COVID-19 and future career of the students with anxiety and depression) has been tenable in case of association with fears of catching COVID-19 and anxiety, while in the case of worries of the school students about future career, a significant number of school students reported to be suffering from high levels of anxiety and depression.

Table 6. Means, Standard Deviation and t/*F* Scores of Anxiety and Depression (*N* = 273).

	Anxiety	Depression
Gender		
Male	7.82 (4.25) 1.04	2.96 (1.90) 1.34
Female	8.32 (3.92)	3.26 (1.80)
Grade		
9th class	7.55 (4.23) 0.66	2.48 (1.73) 4.15 **
10th class	8.53 (4.64)	2.94 (2.0)
11th class	8.31 (3.74)	3.50 (1.84)
12th class	7.96 (3.95)	3.34 (1.79)
Do you feel stressed from staying at home for along period during COVID-19 pandemic?		
Highly stressed	8.34 (4.56) 2.48 *	3.52 (1.73) 8.10 ***
Stressed	9.06 (3.30)	3.57 (1.81)
Moderately stressed	7.37 (3.64)	2.83 (1.83)
Rarely stressed	7.81 (4.19)	2.11 (1.76)
Not so stressed	6.45 (3.62)	1.97 (1.74)
How did you find the online mode of teaching?		
Most effective	6.33 (5.31) 4.20 **	1.11 (1.26) 8.44 ***
Effective	6.92 (4.16)	2.37 (1.82)
Moderately effective	8.04 (3.63)	3.15 (1.77)
Not so effective	8.15 (3.53)	3.42 (1.77)
Not at all effective	10.26 (5.25)	4.06 (1.76)
Do you get emotional support from your family when you need it?		
Always	7.86 (4.51) 0.69	2.43 (1.78) 12.13 ***
Most of the time	7.76 (3.77)	2.92 (1.74)
Sometimes	8.07 (3.39)	3.53 (1.67)
Rarely	8.62 (4.35)	3.97 (1.72)
Never	9.40 (4.73)	5.13 (1.41)
Do you have friends who extend support at times of any crisis or challenge?		
Always	7.90 (4.42) 1.93	2.74 (1.91) 2.83 *
Most of the time	8.52 (3.66)	3.44 (1.78)
Sometimes	7.49 (3.59)	3.24 (1.77)
Rarely	7.17 (4.03)	2.74 (1.79)
Never	9.74 (4.47)	3.81 (1.82)
Are you worried that you will catch COVID-19?		
Highly worried	8.61 (4.21) 3.10 *	3.22 (1.96) 1.36
Worried	9.06 (4.47)	3.30 (1.90)
Worried to some extent	7.88 (4.13)	3.35 (1.66)
Not so worried	8.43 (3.69)	2.72 (1.87)
Not at all worried	6.49 (3.68)	2.83 (1.98)
Are you worried about your future career?		
Highly worried	9.09 (4.31) 5.66 ***	3.62 (1.85) 6.62 ***
Worried	7.95 (3.61)	3.06 (1.79)
Moderately worried	7.21 (3.99)	2.54 (1.59)
Rarely worried	6.32 (3.11)	2.11 (1.70)
Not so worried	5.32 (3.27)	2.05 (1.87)

Note: Figures out of the brackets are the means and those within the brackets are standard deviations; figures after the brackets are t values and F values. Differences in the prevalence across each demographic variable were tested by using independent samples *t*-test and one-way ANOVA. * $p < 0.05$, ** $p < 0.01$ and *** $p < 0.001$.

3.2. Stage 2

We present the findings of the data analysis for the FGs separately. We follow the steps as described in Section 2.

3.2.1. Analysis of the Responses of the FG-1 (i.e., AA Category)

Tables 7 and 8 provide the responses of the respondents of FG 1, related to facilitating and prohibiting factors respectively. Tables 9 and 10 indicate the actual score values and weights (obtained using LBWA) of the factors (facilitating and prohibiting). Tables 11 and 12 show the intermediate calculations of LBWA. However, the decision of PF-FFA largely depends on the weights of the factor and the PFWA calculation. Therefore, sensitivity analysis is of paramount importance here. Sensitivity analysis is carried out to check the stability of the result, obtained by using a MCDM algorithm under the influence of changes in the given conditions, for example, calculation of the criteria weights, changes in the criteria and alternative sets, interplay among the alternatives and criteria among the others [62–68]. In our paper, we change the values of the coefficient of elasticity and examine the changes in the criteria weights. Figures 1 and 2 confirm that the weights obtained using LBWA method are stable with respect to the varying values of the coefficient of elasticity, for the facilitating and prohibiting factors.

Table 7. Rating of the facilitating factors by the respondents of FG-1.

Respondent	Facilitating Factors					
	P1	**P2**	**P3**	**P4**	**P5**	**P6**
R1	Y	A	Y	A	Y	N
R2	Y	A	Y	N	Y	N
R3	Y	A	Y	Y	Y	A
R4	Y	A	Y	Y	Y	Y
R5	A	A	Y	Y	Y	A
R6	A	A	N	A	Y	Y
R7	Y	Y	N	Y	Y	A
R8	N	N	Y	Y	Y	A
R9	N	A	Y	Y	A	Y
R10	A	Y	N	A	N	Y
R11	Y	Y	A	N	N	Y
R12	Y	A	N	Y	Y	Y
R13	N	A	Y	Y	N	N
R14	N	A	A	A	Y	Y
R15	A	A	Y	Y	A	Y
R16	N	Y	N	Y	Y	A
R17	N	A	Y	Y	A	A
R18	N	Y	A	A	N	N
R19	Y	Y	Y	Y	Y	A
R20	N	Y	Y	Y	Y	N
μ	0.4	0.35	0.6	0.65	0.65	0.4
η	0.2	0.6	0.15	0.25	0.15	0.35
ν	0.4	0.05	0.25	0.1	0.2	0.25

Table 8. Rating of the prohibiting factors by the respondents of FG-1.

Respondent	Prohibiting Factors					
	N1	**N2**	**N3**	**N4**	**N5**	**N6**
R1	Y	Y	Y	N	Y	Y
R2	Y	Y	Y	N	N	Y
R3	N	Y	Y	A	A	Y
R4	N	Y	N	N	A	A
R5	A	N	Y	A	A	Y
R6	Y	A	A	N	N	A
R7	Y	N	Y	Y	A	A
R8	N	N	Y	Y	Y	N
R9	N	N	Y	Y	A	N
R10	N	N	N	Y	N	A
R11	N	N	N	N	N	Y
R12	Y	N	Y	A	Y	N
R13	Y	N	Y	N	A	A
R14	Y	Y	Y	N	N	A
R15	N	Y	Y	A	A	N
R16	A	Y	N	A	A	N
R17	N	Y	N	N	N	A
R18	N	Y	N	Y	N	A
R19	N	N	N	N	A	N
R20	Y	Y	A	Y	N	Y
μ	0.4	0.5	0.55	0.3	0.15	0.3
η	0.1	0.05	0.1	0.25	0.45	0.4
ν	0.5	0.45	0.35	0.45	0.4	0.3

Table 9. Actual score values of the facilitating factors.

Factors	PGD	NGD	Abs_Score	Act_Score	Weight	Rank
P1	0.25	0.35	0.40	0.4364	0.1065	6
P2	0.30	0.00	0.70	0.5316	0.1538	4
P3	0.05	0.20	0.75	0.8654	0.1730	3
P4	0.00	0.05	0.95	0.9828	0.2307	1
P5	0.00	0.15	0.85	0.9808	0.1977	2
P6	0.25	0.20	0.55	0.5156	0.1384	5
					Σ = 1.000	

(PIS: <0.65, 0.15, 0.05>; Avg _η = 0.283).

Table 10. Actual score values of the prohibiting factors.

Factors	PGD	NGD	Abs_Score	Act_Score	Weight	Rank
N1	0.15	0.20	0.65	0.7429	0.17300	3
N2	0.05	0.15	0.80	0.9697	0.19771	2
N3	0.00	0.05	0.95	1.0857	0.23066	1
N4	0.25	0.15	0.60	0.5854	0.13840	5
N5	0.40	0.10	0.50	0.4082	0.10646	6
N6	0.25	0.00	0.75	0.6383	0.15377	4
				Σ	1.00000	

(PIS: <0.55, 0.05, 0.03>; Avg _η = 0.225).

Table 11. Weight calculation for facilitating factors (LBWA).

Criteria	C4	C5	C3	C2	C6	C1	
Level	1	1	1	1	1	2	
Integer value	0	1	2	3	4	1	
Function	1.000	0.857	0.750	0.667	0.600	0.462	Σ
Criteria weights	0.2307	0.1977	0.1730	0.1538	0.1384	0.1065	1.00

Table 12. Weight calculation for prohibiting factors (LBWA).

Criteria	C3	C2	C1	C6	C4	C5	
Level	1	1	1	1	1	2	
Integer Value	0	1	2	3	4	1	
Function	1.000	0.857	0.750	0.667	0.600	0.462	Σ
Criteria weights	0.2307	0.1977	0.1730	0.1538	0.1384	0.1065	1.00

Moving ahead, we calculate the aggregate scores of facilitating and prohibiting factors. Tables 13 and 14 show the aggregate scores for facilitating and prohibiting factors.

Table 13. Aggregate score of facilitating factors.

PFWA	μ	η	ν	π
	0.55047	**0.24214**	**0.15894**	**0.04845**
$Score_{Facilitating}$	0.70525			

Table 14. Aggregate score of prohibiting factors.

PFWA	μ	η	ν	Π
	0.41205	**0.14377**	**0.40126**	**0.04292**
$Score_{Prohibiting}$	0.50562			

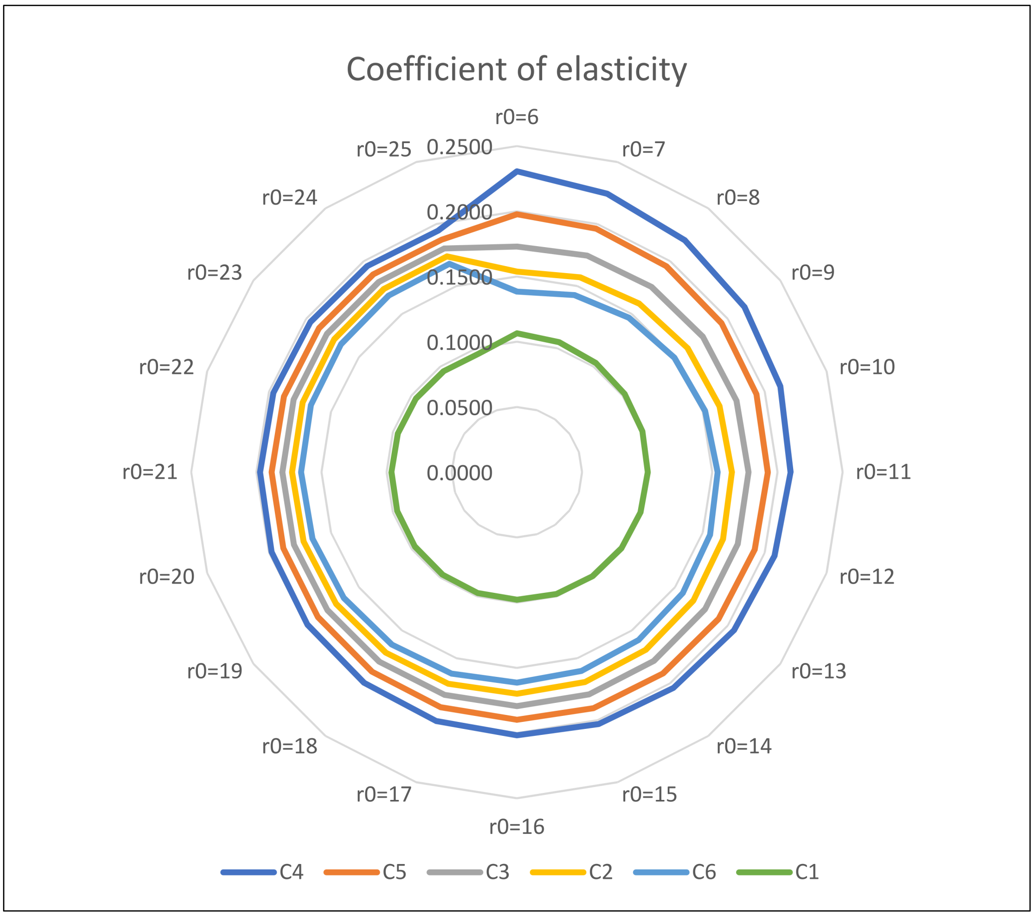

Figure 1. Sensitivity analysis (facilitating actors for FG 1).

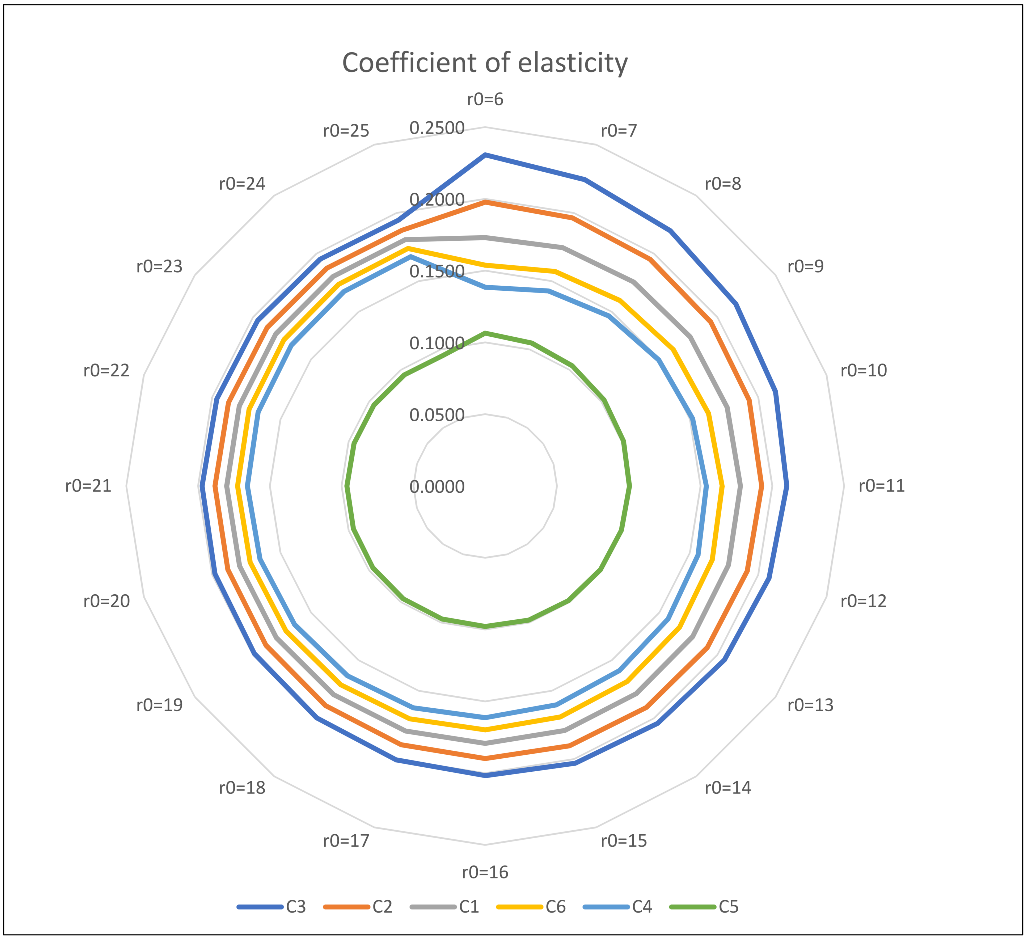

Figure 2. Sensitivity analysis (prohibiting factors for FG 1).

It is observed that $Score_{Facilitating} > Score_{Prohibiting}$ which implies that, for the category of AA, the respondents of FG 1 indicate that there was a stronger driving force as compared to the obstacles. As a result, children found it useful to attend classes regularly.

In a similar way, we carried out the calculations for two other categories, such as SA (represented by FG 2) and VRA (represented by FG 3).

3.2.2. Analysis of the Responses of the FG-2 (i.e., SA Category)

In the similar way (like the previous Section 3.2.1) we carry out the analysis (see Tables 15–20).

Table 15. Rating of the facilitating factors by the respondents of FG-2.

Respondent	Facilitating Factors					
	P1	**P2**	**P3**	**P4**	**P5**	**P6**
R1	Y	A	Y	Y	Y	A
R2	Y	N	Y	N	A	A
R3	N	A	Y	N	N	Y
R4	A	A	Y	Y	Y	A
R5	Y	Y	N	A	Y	N
R6	A	Y	A	Y	N	Y
R7	A	N	A	Y	A	Y
R8	Y	Y	Y	A	Y	Y
R9	N	A	Y	A	N	Y
R10	Y	Y	N	Y	Y	A
μ	0.5	0.4	0.6	0.5	0.5	0.5
η	0.3	0.4	0.2	0.3	0.2	0.4
ν	0.2	0.2	0.2	0.2	0.3	0.1

Table 16. Rating of the prohibiting factors by the respondents of FG-2.

Respondent	Prohibiting Factors					
	N1	**N2**	**N3**	**N4**	**N5**	**N6**
R1	N	Y	Y	Y	A	Y
R2	N	Y	Y	A	A	A
R3	A	Y	N	N	A	Y
R4	Y	N	Y	N	A	N
R5	Y	N	Y	N	A	Y
R6	Y	A	A	Y	N	A
R7	Y	N	A	A	Y	N
R8	A	Y	N	N	A	A
R9	Y	Y	Y	Y	Y	N
R10	N	Y	Y	N	Y	Y
μ	0.5	0.6	0.6	0.3	0.3	0.4
η	0.2	0.1	0.2	0.2	0.5	0.3
ν	0.3	0.3	0.2	0.5	0.2	0.3

Table 17. Actual score values of the facilitating factors (FG 2).

Factors	PGD	NGD	Abs_Score	Act_Score	Weight	Rank
P1	0.10	0.10	0.80	0.8000	0.1701	3
P2	0.20	0.10	0.70	0.6364	0.1276	6
P3	0.00	0.10	0.90	1.0000	0.2187	1
P4	0.10	0.10	0.80	0.8000	0.1531	4
P5	0.10	0.20	0.70	0.7778	0.1392	4
P6	0.10	0.00	0.90	0.8182	0.1914	2

(PIS: <0.6, 0.2, 0.1>; Avg _η = 0.3).

Table 18. Actual score values of the prohibiting factors (FG 2).

Factors	PGD	NGD	Abs_Score	Act_Score	Weight	Rank
N1	0.10	0.10	0.80	0.8421	0.17300	3
N2	0.00	0.10	0.90	1.0588	0.23066	1
N3	0.00	0.00	1.00	1.0526	0.19771	2
N4	0.30	0.30	0.40	0.4211	0.10646	6
N5	0.30	0.00	0.70	0.5600	0.13840	5
N6	0.20	0.10	0.70	0.6667	0.15377	4

(PIS: <0.6, 0.1, 0.2>; Avg _η = 0.25).

Table 19. Aggregate score of facilitating factors (FG 2).

PFWA	μ	H	ν	π
	0.51261	**0.28441**	**0.18532**	**0.01765**
$Score_{Facilitating}$	0.66653			

Table 20. Aggregate score of prohibiting factors (FG 2).

PFWA	μ	η	ν	π
	0.49253	**0.20594**	**0.27641**	**0.02512**
$Score_{Prohibiting}$	0.61077			

It may be noted that the criteria weights are decided using the LBWA method, following the usual calculations. One such type of calculation is already shown in detail for FG 1. Like FG 1, here also we observe stability in the results obtained by using the LBWA approach.

In case of FG 2 (i.e., SA category) we observe that $Score_{Facilitating}$ is marginally greater than $Score_{Prohibiting}$ was reflected in their participation level during online classes. Now, we move towards the FG 3 (i.e., VRA category).

3.2.3. Analysis of the Responses of the FG-3 (i.e., VRA Category)

Here also we use the LBWA method, following the usual calculations (see Tables 21–26).

Table 21. Rating of the facilitating factors by the respondents of FG-3.

Respondent	Facilitating Factors					
	P1	**P2**	**P3**	**P4**	**P5**	**P6**
R1	A	N	A	N	Y	N
R2	N	N	A	A	Y	N
R3	A	N	N	N	A	N
R4	Y	A	A	Y	N	A
R5	Y	Y	Y	N	Y	Y
μ	0.4	0.2	0.2	0.2	0.6	0.2
η	0.4	0.2	0.6	0.2	0.2	0.2
ν	0.2	0.6	0.2	0.6	0.2	0.6

Table 22. Rating of the prohibiting factors by the respondents of FG-3.

Respondent	Prohibiting Factors					
	N1	**N2**	**N3**	**N4**	**N5**	**N6**
R1	Y	Y	Y	Y	A	Y
R2	Y	A	N	N	Y	N
R3	N	Y	A	N	N	A
R4	A	N	N	A	Y	A
R5	Y	Y	Y	Y	Y	Y
μ	0.6	0.6	0.4	0.4	0.6	0.4
η	0.2	0.2	0.2	0.2	0.2	0.4
ν	0.2	0.2	0.4	0.4	0.2	0.2

Table 23. Actual score values of the facilitating factors (FG 3).

Factors	PGD	NGD	Abs_Score	Act_Score	Weight	Rank
P1	0.20	0.00	0.80	0.7273	0.2867	2
P2	0.40	0.40	0.20	0.2222	0.0683	4
P3	0.40	0.00	0.60	0.4615	0.1593	3
P4	0.40	0.40	0.20	0.2222	0.0652	5
P5	0.00	0.00	1.00	1.1111	0.3583	1
P6	0.40	0.40	0.20	0.2222	0.0623	6

(PIS: <0.6, 0.2, 0.2>; Avg _η = 0.3).

Table 24. Actual score values of the prohibiting factors (FG 3).

Factors	PGD	NGD	Abs_Score	Act_Score	Weight	Rank
N1	0.00	0.00	1.00	1.0345	0.21870	1
N2	0.00	0.00	1.00	1.0345	0.19136	2
N3	0.20	0.20	0.60	0.6207	0.13917	5
N4	0.20	0.20	0.60	0.6207	0.12757	6
N5	0.00	0.00	1.00	1.0345	0.17010	3
N6	0.20	0.00	0.80	0.6857	0.15309	4

(PIS: <0.6, 0.2, 0.2>; Avg _η = 0.2333).

Table 25. Aggregate score of facilitating factors (FG 3).

PFWA	μ	η	ν	π
	0.42535	**0.29061**	**0.24798**	**0.03606**
$Score_{Facilitating}$	0.59188			

Table 26. Aggregate score of prohibiting factors (FG 3).

PFWA	μ	η	ν	π
	0.52577	**0.22239**	**0.24062**	**0.01122**
$Score_{Prohibiting}$	0.64418			

Now, here (for FG 3 i.e., VRA category) we notice that $Score_{Facilitating} < Score_{Prohibiting}$. The level of participation in online classes is also rare, which clearly justifies the findings of the PF-FFA for FG 3.

4. Discussion

The present online study is successful in understanding the level of anxiety and depression among school students in India during the COVID-19 lockdown phase and its association with their background, stress, worries, and social support facilities.

A total of 273 school students participated voluntarily in the online study. Almost equal numbers of male and female school students (male 54.9% vs. female 45.1%) participated in the study, and they were in grades IX to XII; there was similar interest among students of both genders to participate in the study and share their views and concerns. Attending online classes was enjoyable initially but gradually, students perceived it to be challenging because of various reasons, like internet connectivity problems, power problems and sitting in front of a computer for an extended period. Therefore, students' perception of the online mode of teaching was examined. About one-fifth of the students perceived the online teaching mode as most effective and effective while about-two-fifths perceived it to be moderately effective. The rest found it not so effective and not at all effective. This might be due to various factors, such as not being able to follow classes properly, a hectic time table without any break between the classes, internet connectivity problems, ineffective methods of teaching and also boredom on the part of teachers, thereby leading to a casual method of disseminating knowledge. A study on school students in Romania revealed that the availability of equipment for accessing the internet and the ability of the teaching staff were crucial in effectiveness of online education [69]. Some of the previous studies corroborate our findings, i.e., internet connectivity problems and lack of physical interactions for clarification of academic queries caused a lot of anxiety among students [2,23,27].

Further, through our newly proposed PF-FFA methodology, we ascertain that the dynamics between the facilitating and prohibiting factors determine the intentions of the children regarding attending online classes.

Human beings prefer to remain connected with others, to and share their personal feelings and thinking, which enhances their subjective experience of happiness [70]. School children get maximum happiness while interacting with their classmates in the school. Therefore, social isolation causes high stress for school students [71], as demonstrated by our findings. The findings of the present study indicate that more than half of the school students viewed school suspension as highly stressful.

Uncertainty about the situation, i.e., when the school will reopen, caused worries for a large number of students (about 70%) especially for grade X and XII students, as the final board examinations are very important for every child, for their future growth and prospects. Jung, Horta, and Postiglione [72] showed that unexpected occurrences during the pandemic led to unprepared decisions and psychological disruptions in the education sector. Emotional support at times of crisis or pandemic is very helpful to cope with the situation [73]. In the present study, more than three-fifths of school students were reported to have received emotional support from their family members and friends which can positively impact an individual's personal resilience [74].

As far as anxiety of school students in a pandemic like COVID-19 is concerned, the findings of the study disclosed that half of the students reported experiencing moderate levels of anxiety while 13.2% suffered from high levels of anxiety. Under normal circumstances, students go to school and gain knowledge by attending regular classes and clarifying their academic queries. Attending regular classes is essential to complete the syllabus, so that they can write the examinations with maximum effectiveness. In a country like India, where students' performance is assessed based on the results of written examinations, suspension of classes because of the pandemic-induced lockdown, caused a lot of anxiety, although online classes were arranged. Online teaching does not help to clarify all the queries and sometimes teaching is also not clear, due to poor connectivity. Monotony and/or stress on the part of the teachers, while taking continuous online classes, affect the quality of teaching. However, individual coping capacity plays an important role in dealing with various crisis situations. The study also revealed that more than one-third (34.8%) and one-fourth (27.5%) of students were suffering from moderate and high levels of depression, respectively. Continuous social isolation and worrying about the future, fear of getting COVID-19 and exposure to media information on deaths caused by COVID-19, were depressing for the school students. Interaction with classmates in the school campus helps students share their personal feelings and issues with their peers. Since students were effectively under house arrest and unable to meet their friends, they were emotionally upset.

Cross analysis of data highlights an association between grade and depression, i.e., grade XI students were more victims of depression, followed by grade XII students. The school students who perceived social isolation stress were more vulnerable to anxiety and depression. Perception about the online mode of teaching is also associated with anxiety, i.e., the students who reported that the online mode of teaching was not effective have been suffering from more anxiety and depression. Similarly, social support from family and friends were found to be beneficial when dealing with crisis situations. In fact, emotional support helped school students to remain emotionally stable and happy, despite prolonged lockdown, and they utilized their time effectively in studies, and with their family members. The findings of the present study with respect to the benefits of social support are similar to the outcomes of some of the previous studies [17,18,25].

5. Conclusions and Recommendations

In conclusion, it might be stated that COVID-19 caused great anxiety and depression to a large number of school students, mostly because of social isolation and discontinuation of the physical mode of the teaching–learning process. The study revealed that 13.2%, 46.9% and 37.7% of the students were suffering from high, moderate and low levels of anxiety, while 27.5%, 34.8% and 25.3% have been assessed to be suffering from high, medium and low levels of depression. Female school students were suffering from more depression and anxiety, as compared to their male counterparts. Further, a significant association was found between grade, social isolation, feeling of stress, ineffective mode of teaching, worries about catching COVID-19, worry about future career, lack of social support, anxiety, and depression. In addition, the PF-FFA analysis provides a visible understanding of the interplay of the facilitating and prohibiting factors (i.e., DFs and RFs) that steer the children and determine their behavioural intentions in response to the changing scenario of learning, as imposed by COVID-19.

It is recommended for school administration to arrange online mental health support services urgently for school students who exhibit high anxiety and depression, in addition to organizing online parent and teacher interaction meetings, for offering school-based family counseling for parents, to deal sensitively with children's emotions.

The questionnaire was distributed online to students via the school administration in different states of India. Since the study took place relatively early during the lockdown months in India and students were still getting accustomed to the online education system, the percentage of response has been low. We recommend using longitudinal research to understand the trajectory of mental health issues among students through the pandemic, especially as the pandemic continues to surge in waves globally. Larger sample size is likely to enhance the generalizability of the studies. Though online education can itself have varied impacts on students, being infected by the virus once or multiple times during the course of the pandemic can hinder a student's academic progress and impact wider aspects of students' education. However, understanding that the pandemic is common for all can assist in coping with the associated distress. Controlling for these factors would provide additional confirmatory information.

Further, in this paper we have used PFS based analysis for FFA. The calculation of weights plays a central role in determining the outcome of FFA. The present paper uses the LBWA method with which we have carried out the sensitivity analysis. The result of sensitivity analysis shows that there is a stability in the weight calculation process. However, a further study may check the consistency aspect for validation purposes. An algorithm such as the Full Consistency Method (FUCOM) may be used to find the weights using PFNs. A comparison of the weights calculated by using both FUCOM and LBWA may be made for further validation. There may a further study using Spherical Fuzzy Sets (SFS), a generalization of PFS, to conduct the FFA. Subsequently, the outcomes (by using PFS and SFS) may be compared. Nevertheless, the present paper has its own usefulness and we believe that this paper may add value to the growing literature in the stated field.

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Institutional Review Board Statement: The authors declare that the present study was subjected to ethical approval and obtained the clearance (Ref.No.RGNIYD/ADMIN/20-21/SEC/001). All the procedures performed while collecting data from the participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration. Participation in the study was voluntary and participants were assured of the confidentiality of information. Prior consent was taken from the participants and/or their legal guardian(s) after explaining the purpose and modality of the study.

Informed Consent Statement: Prior consent was taken from the participants and/or their legal guardian(s) after explaining the purpose and modality of the study.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author for maintaining confidentiality of the respondents. However, necessary information for carrying out the analysis is provided.

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Conflicts of Interest: Authors declare no conflict of interest in the publication of this research.

Appendix A. Preliminaries of PFS

Appendix A.1. Definition

Let $\widetilde{A}$ denote a PFS on a universe of discourse U. Then, $\widetilde{A}$ is defined as

$$\widetilde{A} = \langle x,\ \mu_{\widetilde{A}}(x), \eta_{\widetilde{A}}(x), v_{\widetilde{A}}(x) \rangle \tag{A1}$$

where, $x \in U$; $\mu_{\widetilde{A}}(x), \eta_{\widetilde{A}}(x), v_{\widetilde{A}}(x) \in [0,\ 1]$ are the degrees of positive, neutral and negative membership of x in $\widetilde{A}$ respectively such that

$$0 \le \mu_{\widetilde{A}}(x) + \eta_{\widetilde{A}}(x) + v_{\widetilde{A}}(x) \le 1\ \forall\ x \in U \tag{A2}$$

Here, if $\eta_{\widetilde{A}}(x) = 0$ then it becomes the intuitionistic fuzzy set (IFS) and if both $\eta_{\widetilde{A}}(x) = v_{\widetilde{A}}(x) = 0$, $\widetilde{A}$ becomes a traditional fuzzy set.

The degree of refusal ($\pi_{\widetilde{A}}\,(x)$) is defined as

$$\pi_{\widetilde{A}}\,(x) = 1 - \left(\mu_{\widetilde{A}}\,(x) + \eta_{\widetilde{A}}\,(x) + v_{\widetilde{A}}\,(x)\right)\ \forall\ x \in U \tag{A3}$$

For a given element x in U, a PFN is represented as

$$A = \{\{\mu_A, \eta_A, v_A \in [0,1] and\ 0 \leq \mu_A + \eta_A + v_A \leq 1\ \}\} \tag{A4}$$

Appendix A.2. Properties

Let $\widetilde{A} = \langle x,\ \mu_{\widetilde{A}}\,(x), \eta_{\widetilde{A}}\,(x), v_{\widetilde{A}}\,(x)\ \rangle$ and $\widetilde{B} = \langle x,\ \mu_{\widetilde{B}}\,(x), \eta_{\widetilde{B}}\,(x), v_{\widetilde{B}}\,(x)\ \rangle$ be two PFS $\forall\ x \in U$, and then the following properties are defined

$$\widetilde{A}\ \cup\ \widetilde{B} = \{x \in U\} \tag{A5}$$

$$\widetilde{A}\ \cap\ \widetilde{B} = \{x \in U\} \tag{A6}$$

$$\widetilde{A}^{\,c} = \{x \in U\} \tag{A7}$$

$$\widetilde{A}\ \subseteq\ \widetilde{B}\,if\ \left(\mu_{\widetilde{A}}\,(x) \leq \mu_{\widetilde{B}}\,(x),\ \eta_{\widetilde{A}}\,(x) \leq \eta_{\widetilde{B}}\,(x),\ v_{\widetilde{A}}\,(x) \geq v_{\widetilde{B}}\,(x)\ \forall\ x \in U\right) \tag{A8}$$

$$\widetilde{A} = \widetilde{B}\,if\ \widetilde{A}\ \subseteq\ \widetilde{B}\,and\ \widetilde{B}\ \subseteq\ \widetilde{A} \tag{A9}$$

$$\widetilde{A}\ \subseteq\ \widetilde{B}\,and\ \widetilde{B}\ \subseteq\ \widetilde{C}\ \Rightarrow\ \widetilde{A}\ \subseteq\ \widetilde{C} \tag{A10}$$

$$\left(\widetilde{A}^{\,c}\right)^{c} = \widetilde{A} \tag{A11}$$

Appendix A.3. Basic Operations

Let $A = (\mu_A, \eta_A, v_A\ )$ and $B = (\mu_B, \eta_B, v_B\ )$ be any two PFNs. The following are some of the basic operations.

$$A \oplus B = (\mu_A + \mu_B - \mu_A\mu_B,\ \eta_A\eta_B,\ v_Av_B) \tag{A12}$$

$$A \otimes B = (\mu_A\mu_B,\ \eta_A + \eta_B - \eta_A\eta_B,\ v_A + v_B - v_Av_B) \tag{A13}$$

$$\lambda A = \left(1 - (1-\mu_A)^{\lambda},\ \eta_A{}^{\lambda},\ v_A{}^{\lambda}\right);\ \lambda > 0 \tag{A14}$$

$$A^{\lambda} = (\mu_A{}^{\lambda},\ 1 - (1-\eta_A)^{\lambda},\ 1 - (1-v_A)^{\lambda};\ \lambda > 0 \tag{A15}$$

$$A \oplus B = B \oplus A \tag{A16}$$

$$A \otimes B = B \otimes A \tag{A17}$$

$$\left(A^{\lambda 1}\right)^{\lambda 2} = A^{\lambda 1 \lambda 2} \tag{A18}$$

$$\lambda\ (A \oplus B) = \lambda A \oplus \lambda B \tag{A19}$$

$$(A \otimes B)^{\lambda} = A^{\lambda} \otimes\ B^{\lambda} \tag{A20}$$

Appendix A.4. Defuzzification

The defuzzification of a PFN A is done in the following steps [75,76]:
Step 1. Defining new positive and negative memberships

$$\mu_{\acute{A}} = \mu_A + \frac{\eta_A}{2} \tag{A21}$$

$$v_{\acute{A}} = v_A + \frac{\eta_A}{2} \tag{A22}$$

Step 2. Calculation of defuzzication value

$$\gamma_A = \mu_{\acute{A}} + \pi_A \left(\frac{1 + \mu_{\acute{A}} - \upsilon_{\acute{A}}}{2} \right) \tag{A23}$$

Appendix A.5. Score and Accuracy Functions

The score function of any PFN is calculated as

$$S_A = \mu_A - \upsilon_A \tag{A24}$$

The accuracy function is defined as

$$H_A = \mu_A + \eta_A + \upsilon_A \tag{A25}$$

Rule for comparison

$$If\ S_A \prec S_B,\ then\ A \prec B$$
$$If\ S_A \succ S_B,\ then\ A \succ B$$
$$If\ S_A = S_B,\ H_A \prec H_B,\ then\ A \prec B$$
$$If\ S_A = S_B,\ H_A \succ H_B,\ then\ A \succ B$$
$$If\ S_A = S_B,\ H_A = H_B,\ then\ A = B$$

Appendix A.6. Absolute and Actual Score

Computational steps [77] are described below.
Step 1. Identification of the positive ideal solution (PIS)
For a set of n number of PFNs, PIS is given as

$$Z^{+} = (\mu^{+}, \eta^{+}, \upsilon^{+}) = \mu_i, \eta_i, \upsilon_i), \text{ where } i = 1, 2, \ldots n \tag{A26}$$

Step 2. Find out goal differences for each PFN
Positive goal difference (PGD):

$$\mu_{i+} = \mu^{+} - \mu_i \tag{A27}$$

Negative goal difference (NGD):

$$\upsilon_{i-} = \upsilon_i - \upsilon^{+} \tag{A28}$$

Step 3. Find out the average neutral degree (Avg_ η)

$$\underline{\eta} = \frac{1}{n} \sum_{i=1}^{n} \eta_i \tag{A29}$$

Step 4. Calculation of the absolute score for each PFN

$$S_{i(abs)} = (1 - \mu_{i+}) - \upsilon_{i-} \tag{A30}$$

Step 5. Derive the actual score for each PFN

$$S_{i(act)} = \frac{S_{i(abs)}}{1 - (\underline{\eta} - \eta_i)} \tag{A31}$$

Here, the following rules are applicable

$$\text{If } S_{A(act)} \succ S_{B(act)} \text{ then } A \succ B$$

$$\text{If } S_{A(act)} = S_{B(act)} \text{ then if } \mu_A > \mu_B \text{ and } \eta_A \geq \eta_B \text{ then } A \succ B$$

If $S_{A(act)} = S_{B(act)}$ and $\mu_A \geq \mu_B$ and $\eta_A < \eta_B$ then if $\upsilon_A \leq \upsilon_B$ then $A \succ B$, otherwise $A \prec B$

As $\left(\underline{\eta} - \eta_i\right) \neq 1$, $S_{i(act)}$ is always finite.

Appendix A.7. Aggregation Operator

Let $A_j = \left(\mu_j, \eta_j, v_j\right)$ $(j = 1, 2, \ldots n)$ be a collection of PFNs. Then the Picture Fuzzy Weighted Average (PFWA) is defined as [78]

$$PFWA_w(A_1,\ A_2, A_3 \ldots . A_n) = \oplus_{j=1}^{n}\ (w_j A_j) == \left(1 - \prod_{j=1}^{n}\left(1 - \mu_{A_j}\right)^{w_j}, \prod_{j=1}^{n}\left(\eta_{A_j}\right)^{w_j}, \prod_{j=1}^{n}\left(\nu_{A_j}\right)^{w_j}\right) \tag{A32}$$

Here, w_j is the corresponding weight of A_j $(j = 1, 2, \ldots n)$ with the conditions that

$$w_j > 0;\ \sum_{j=1}^{n} w_j = 1$$

In this paper, w_j is derived using the LBWA method based on actual scores as used by Biswas et al. [42].

Appendix B. Computational Steps of LBWA Algorithm

Let the criteria set be given by $\mathbb{C} = \{C_1, C_2, C_3 \ldots \ldots C_n\}$. Let the i^{th} criterion ($C_i \in \mathbb{C}$) be the most important one as opined by the respondents.

Step 1: Formation of subsets of criteria by grouping, based on level of significance.

The grouping process is described below.

Level L_1: Group the criteria and form the subset with the criteria that are having equal to or up to twice as less as the significance of the criterion C_i

Level L_2: Group the criteria and form the subset with the criteria having exactly twice as less as the significance of the criterion C_i or up to three times as less as the significance of the criterion C_i

Level L_3: Group the criteria and form the subset with the criteria having exactly three times as less as the significance of the criterion C_i or up to four times as less as the significance of the criterion C_i

——————————————————————————————-

Level L_k: Group the criteria and form the subset with the criteria having exactly 'k' times as less as the significance of the criterion C_i or up to 'k + 1′ times as less as the significance of the criterion C_i

Hence,

$$L = L_1 \cup L_2 \cup L_3 \ldots \ldots . \cup L_k \tag{A33}$$

If $s(C_j)$ is the significance of the j^{th} criterion, we note that

$$L_k = \left\{C_j \in L : k \leq s(C_j) \leq k + 1\right\} \tag{A34}$$

Also, the following condition holds good to appropriately define the grouping,

$$L_p \cap L_q = \varnothing;\ \text{where } p, q \in \{1, 2, \ldots k\} \text{ and } p \neq q \tag{A35}$$

Step 2: Comparison of factors according to the significance within the subsets

Based on the comparison, each criterion $C_j \in L_k$ is assigned with an integer value $I_{C_j} \in \{0, 1, 2 \ldots \ldots . r\}$; where, r is the maximum value on the scale for comparison and is given by:

$$r = \max\{|L_1|, |L_2|, |L_3| \ldots \ldots |L_k|\} \tag{A36}$$

Conditions used in this context are as follows.

The most important criterion is assigned with an integer value of zero. In other words,

$$I_{C_i} = 0 \tag{A37}$$

If C_p is more significant than C_q then

$$I_{C_p} < I_{C_q} \tag{A38}$$

If C_p is equally significant with C_q then

$$I_{C_p} = I_{C_q} \tag{A39}$$

Step 3: Find out the elasticity coefficient

The elasticity coefficient r_0 is defined as any real number with the condition $r_0 > r$ and $\tau \in \mathbb{R}$; Where $\mathbb{R}$ represents a set of real numbers

Step 4: Calculate the influence function of the criteria

For a particular criterion, $C_j \in L_k$; the influence function can be defined as $f : L \rightarrow R$

It is calculated as

$$f(C_j) = \frac{r_0}{\delta\, r_0 + I_{C_j}} \tag{A40}$$

Here, ∂ is the number of level or subset to which C_j belongs and $I_{C_j} \in \{0, 1, 2 \ldots\ldots r\}$ is the value assigned to the criterion C_j within that level

Step 5: Calculation of the optimum values of the priority weights of the criteria

For most significant criterion:

$$w_i = \frac{1}{1 + f(C_1) + f(C_2) + \ldots + f(C_n)} \tag{A41}$$

where, $i \in j; j = 1, 2, \ldots,\ n,$ the number of criteria

For other factors:

$$w_{j \neq i} = f(C_j)\, w_i \tag{A42}$$

Decision rule: rank the criteria in descending order of criticality based on the weight values.

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