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Measurement of Negative Impacts of COVID-19 Pandemic and Lockdown–a Statistical Learning Approach

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Abstract: *Millions were killed due to COVID-19 pandemic. Lock downs were imposed to control this pandemic. In this paper the negative side effects of this pandemic were measured and quantified. Mathematical models using Structural Equation Modeling and Regression Trees were developed. Based on a primary data of 578 households, out of 56 variables of interest, 47 variables were focused. The other nine variables collected general information. Principal Component Analysis was used for variable reduction. Out of these variables it was found that, Information on people suffering from COVID-19, Information on people recovering from COVID-19, I am afraid of COVID-19 outbreak, News and media increase my tension, Afraid of getting COVID-19, Afraid of losing my life and my relative's life and Limited my social life, were major contributors to Degradation of Mental Health. These variables had standardized factor loading greater than 0.7. Similarly, it was found that households from lower income groups were worst affected by mental health degradation and food insecurity. These conclusions with* $p \leq 0.01$*, were made. With the developed models, households were profiled with respect to income and degradation of mental health. What gets measured should also get addressed, was the motivation of this work.*

Keywords: Structural equation modeling, Principal components regression, Regression trees, Structured questionnaire, Statistical learning

1 Introduction

COVID-19 pandemic and lock downs had an adverse effect on the society. Restrictions imposed during this time, resulted in the degradation of mental health, insecurity of food supply, limited physical activity and constricted life style. In Nepal, COVID-19 was first identified in a Nepalese man. He had recently returned from China in January 2020. This patient later recovered and his contacts were also asymptomatic [1]. In May 2023, the World Health Organization (WHO) declared that COVID-19 was no longer a cause of global public health emergency [2].

During this pandemic, Government of Nepal launched a massive campaign. It inoculated the not vaccinated and offered boosters to the front line workers, the elderly and people in densely populated areas[3]. Two doses of COVID-19 vaccine and booster shots were given [4]. Vaccines used were Serum Institute India's Covishield, AstraZeneca's COVID-19, China's Vero Cell, Johnson and Johnson's Janssen and Pfizer-BioNtech [5]. There were three main variants of COVID-19 during the pandemic and lockdown. They were namely Delta and Omicron and Omicron XE [6].

Various issues acted as stress factors during this time. Firstly, the imposition of lock downs hindered the free movement of human beings and goods. As in other countries of the world, Government of Nepal also enforced a lockdown in the year 2020. It was done in order to control the COVID-19 pandemic, rapidly spreading at that time. First strict lockdown was enforced from 24 March 2020. It was the first wave. This lockdown was completely relaxed on 19 September 2020. The second wave of COVID-19 started in April 2021. Then, a lockdown was enforced on 29 April 2021. This lockdown was partially relaxed from 22 June 2021 [7]. From 22 June, the movement of vehicles was partially restricted, according to the odd and even numbers of the number plate. The shops and departmental stores opened till 11:00 A.M. only. With only certain restrictions in place, this lockdown was completely relaxed on 1 Sept. 2021 [8]. Partial lockdown was again enforced by the Government from mid Jan. to the third week of Feb. 2022 [9]. It was done to control the spread of the pandemic and to enable the smooth administration of the COVID-19 vaccination.

Secondly, the first and the second wave was triggered by the Nepalese migrant workers coming back to Nepal. Announcement of lockdown and curfews in different parts of India caused this massive exodus [10]. At that time, COVID-19 positive cases were found among Indian nationals working in Nepal or Nepali workers who had recently returned from India. Nepal and India share an open border. This enables free movement of people across the border. People can also work without work permits [11]. Thousands of workers had returned to Nepal without proper screening. During the first wave as well, many workers were trapped in different parts of India due to lock downs in both countries. Many workers were also stranded in the border [12], [13], [14], [15].

COVID − 19 pandemic resulted in the deprivation of lives of people. Due to the isolation resulting from the lockdown measures, mental health degradation, threat to food security, limitations in physical activity and restrictions in life style were observed. For example, from a sample of 1684 participants from Lebanon, Haidar et al. [24] concluded that eating habits deteriorated during lockdown, in 42.3 % cases. It was also concluded that dietary intake and adherence to Mediterranean diet was sub optimal during this time. Similarly, Rafraf et al. [33] concluded from the sample size of 220 college students from Iran that, quarantine resulted in increased weight gain, screen, sitting, and sleep time, declined physical activity, worse sleep quality, and feeling stress or anxiety. On the basis of 3803 respondents from Wuhan, China, Li et al. [29] concluded that during this time, important correlates of anxiety, depression, and stress scores were namely city of residence, education, marital status, monthly income, level of attention, self-assessed infection risk, impact on daily life and mental health help-seeking quality. Mir et al. [30] concluded that during these times, low family income, physical activity and female gender were the major determinants and predictors linked to anxiety and depression. This conclusion was made on the basis of data collected from 417 university students of Malaysia. For Nepal, Poudel et. al . [32] concluded on the basis of a sample of 354 Nepalese bread winners, that the impact of COVID-19 lockdown on individuals' work, income, education, living standard, lifestyle, and consequently mental health was significant. For the reduction of severe and chronic mental health problems associated with COVID-19, they had certain recommendations. It was namely, understanding, timely monitoring and intervention on lives of risk groups. Similarly, for Bangladesh, Hossain et al. [25] concluded on the basis of 659 COVID-19 positive patients aged 18 and above that, recovery time of these patients was found to be significantly influenced by their family income, the number of co-morbidity, and the location of therapy. Likewise, Yagmaee et al. [35] concluded on the basis of web-based data collected from 1192 participants aged between 18 to 70 years from Iran that, lifestyle behaviors, such as unhealthy diets, inactivity, and sleep quality disturbance, affect the severity and duration of COVID-19.

Structural Equation Modeling (SEM), Principal Components Analysis (PCA), Principal Components Regression (PCR) and Regression Trees are some of the statistical learning techniques. Models developed using these techniques help in the identification of latent variables and their interrelationships. For example, Joshi and Patil [28] used PCR to predict surface roughness by using machine vision. This model predicted unknown roughness values for free hand ground specimens. Similarly, Chen et al. [19] used PCR for effective management of irrigation water consumption system in China. They combined multiple linear regression and principal component analysis to analyze the relationship between irrigation water consumption and influencing factors. Likewise, techniques like Hierarchical Clustering and Principal Components were used to find the most favorable vegetable biomass for the production of bio fuel pellets, by Garcia et al. [23]. Similarly, Bystrzanowska et al. [18] used PCA to find patterns in the dataset and discriminator between cluster of compounds. Briere et al. [17] used SEM in regression of disengaged parenting on child abuse and insecure attachment. Mercedes et al.[31] investigated relationship between oral language, decoding and two component executive function (cognitive flexibility and working memory) and reading comprehension using SEM. Similarly, Jyoti U. Devkota [22], [21] used SEM and Canonical Correlation Analysis to identify the variables playing a critical role in the energy consumption dynamics of rural households of Nepal.

In face of limited and scarce data of the developing world, the data-based approach is the novelty of this work. The originality of this work lies, in the development of different models in explaining the incidence of COVID-19. In the landscape of a knowledge gap in the developing world, this paper tries to bridge this gap by developing various models using multivariate statistics. This work focuses on the development of various mathematical techniques, that bridge up this gap. Hence this paper is not a generalization of the current state of knowledge. The negative effects of COVID-19 and lockdowns are quantified here. Models are developed using four techniques namely SEM, PCA, PCR and Regression Trees. A large sample size of 578 households is used. Based on the Central Limit theorem, the normality of the data was ensured by this large sample size.

This paper is arranged in the following manner. This Introduction section is followed by the section Materials and Methods. In this section, data and methodology used are explained in detail. This section followed by Results and Discussion. Major results are concluded in the last section of this paper titled Conclusion.

2 Methods

2.1 Data

For data collection, 578 households comprising 2805 individuals, were surveyed online. This questionnaire comprised of 56 questions. From these questions, 47 variables directly related to the objective of study were identified. This paper is based on these 47 variables. Other nine questions were aimed at the collection of general information of the household. The data collection was done by the students, as a part of their course work. The students were trained and were first the interviewee and then interviewers. Snow ball sampling technique was used.

The questionnaire was designed to collect detailed information on variables associated with four major types of degradation, observed during these times. These were mental health degradation, threat to food security, limitations in physical activity and restrictions in life style. Multiple choice options were provided for the responses to each question. These options mostly generated ordinal data scaled from one to five. Here, higher values were associated with the severity of the impact. These questions assessed in detail the impressions of the family with respect to, COVID-19 general information, Food Insecurity, Restrictions on Physical Activity, Degradation of Mental Health and change in Life Style, during COVID-19 pandemic and lockdown.

The data collection was done in three phases. One set of data was recorded in November and December 2020. Another set was collected in March and April 2021. The last set was collected from November 2021 to January 2022. In this way information was gathered on different waves of COVID-19 pandemic and the impact of lockdown executed during this pandemic. Two lockdowns were executed during the first and second waves of COVID-19 infection. The first lockdown was imposed from 24 March 2020 to 19 September 2020 and the second lockdown was imposed from 29 April 2021 to 1 September 2021. There were three waves of pandemic during the entire data collection process.

2.2 Statistical Methods

The data generation and collection, analysis and prediction techniques used, were decided well in advance. The main aim was to conduct a detailed mathematical study of major side effects of COVID-19 pandemic. The sample collected here represents the urban population of Nepal. Thus, conclusion made here can be generalized to this section of the society. The interrelationship between the four major groups (threats) Food Security, Physical Activity, Mental Health and Life Style was explained by Principal Component Regression (PCR), Structural Equation Modelling (SEM), Regression Trees. There were multiple variables in each group, which were reduced by Principal Components Analysis (PCA). The use of these techniques explained below, gives a comparative perspective to the solution of a problem.

PCA: PCA is a dimension reduction technique. In this technique, the interdependence between multiple inter correlated variables is explained by generating orthogonal variables. These uncorrelated orthogonal variables explain maximum variability of the data. The analysis of interrelationship among a large number of variables is done by this statistical method [16].

Suppose we have a set of N variables, a^*_{1j} to a^*_{Nj}, representing the N variables related to the economic and mental health status with respect to COVID-19 lockdown, for each household j. Let us denote it as impact index. Further, let us standardize each variable by its mean and standard deviation. For example,

$$a_{1j} = \frac{(a_1 j^* - a^*_1)}{s^*_1}$$

where a_1^* is the mean of a_{1j}^* across all households and s_1^* is the standard deviation.
These selected variables are expressed as linear combination of a set of underlying components for each household j.

$$\begin{aligned} a_{1j}^* &= v_{11} * A_{1j} + v_{12} * A_{2j} + \quad \cdots \quad + v_{1N} * A_{Nj} \\ &\vdots \\ a_{Nj}^* &= v_{N1} * A_{1j} + v_{N2} * A_{2j} + \quad \cdots \quad + v_{NN} * A_{Nj} \end{aligned} \tag{1}$$

Here $j = 1, \ldots, J$. In Equation (1), A 's are the principal components and v' s are the coefficient on each component for each variable. The "scoring factors" from the model are recovered by inverting the system implied by Equation (1), and yield a set of estimates for each of the N principal components, given below in Equation (2)

$$\begin{aligned} A_{1j} &= f_{11} * a_{1j} + f_{12} * a_{2j} + \quad \cdots \quad + f_{1N} * a_{Nj} \\ &\vdots \\ A_{Nj} &= f_{N1} * a_{1j} + f_{N2} * a_{2j} + \quad \cdots \quad + f_{NN} * a_{Nj} \end{aligned} \tag{2}$$

here $j = 1, \ldots, J$
The impact index expressed in terms of the original (unnormalized) variables, is given below in Equation (3).

$$A_{1j} = f_{11} * \frac{(a_1 j^* - a_1^*)}{s_1^*} + f_{12} * \frac{(a_2 j^* - a_2^*)}{s_2^*} + \ldots + f_{1N} * \frac{(a_N j^* - a_N^*)}{s_N^*} \tag{3}$$

here $j = 1, \ldots, J$
With respect to this study, PCA has been conducted for four groups Food Security, Physical Activity, Mental Health and Life Style separately. So, for Food Security, Physical Activity, Mental Health and Life Style, N is 7, 6, 4, and 6 respectively and J = 578.

SEM: With this technique, complex relationship between observed variables is explained by this technique. This method provides a quantitative test of a theoretical model. This technique determines the extent to which the theoretical model is supported by the sample data [34]. SEM helps in understanding and explaining the complex relationship between the constructs. The theoretical model developed using SEM is also tested here using testing of hypothesis. SEM can be seen as, an expansion of the theory of Multiple Regression, with more than one regression like equation also including latent variables. Here variables can be independent in one equation and dependent in another. These SEM can be explained by path diagrams. The structural model is written in terms of following matrix equations (4), (5) and (6).

$$\eta = B\eta + \Gamma\xi + \zeta \tag{4}$$

Here η is the $m \times 1$ vector of endogenous concepts and ξ is the $n \times 1$ vector of exogenous concepts. B, Γ are $m \times m$ and $m \times n$ matrices of structural coefficients. ζ is $m \times 1$ error vector. The variance – covariance matrix of ξ is ϕ, a $n \times n$ matrix. The variance- covariance of matrix of error ζ is Ψ, a $m \times m$ matrix.

The measurement model is represented by equation (2). Latent independent variables are represented by equation (3)

$$Y = \Lambda_Y \eta + \varepsilon \tag{5}$$

Here Y is the $p \times 1$ vector, Λ_Y is the $p \times m$ matrix, η is the $m \times 1$ vector and ε is the $p \times 1$ error vector. The variance – covariance matrix of ε is Θ, a $p \times p$ matrix.

$$X = \Lambda_X \xi + \delta \tag{6}$$

Here X is the $q \times 1$ vector, Λ_X is the $q \times n$ matrix, ξ is the $n \times 1$vector and δ is the $q \times 1$ error vector. The variance – covariance matrix of δ is Θ_δ, a $q \times q$ matrix.

Computation of measurement error as a component of analysis may be involved in SEM. This is a part of broader multivariate perspective.

Regression Trees: These are highly intuitive, practical, and accurate prediction techniques. These techniques can also be used to cluster data. Here each cluster is predicted by a mean of the explanatory variables. This technique splits data into nodes on the basis of data of the explanatory variable. The predicted value at each node is the average target variable value for all observations that fall in that node. These trees recursively partition the data, finding more homogenous groups at each stage. This technique is also suitable for profiling a data set [26]. In particular, linear regression assumes a model of the form

$$f(X) = \beta_0 + \sum_{j=1}^{p} X_j * \beta_j \tag{7}$$

whereas, the regression tree assumes the model of the form

$$f(X) = \sum_{m=1}^{M} c_m * 1_{x \epsilon R_m} \tag{8}$$

where R_1,. . .,R_m represent a partition of feature space [27]. With respect to this study, highly nonlinear complex relationship between the features was seen, so Regression Trees represented by Equation (8) were taken into consideration in this paper.

3 Results and Discussion

The summary statistics of all the variables of this study are given in the annex in Supplementary Table 1. Here, 39 variables are classified on a categorical ordinal scale and seven variables are classified on a ratio scale. These variables are also classified into the groups COVID-19 Information, Mental Health, Food Security and Physical Activity. Data collection on COVID-19 general information, insecurity of food supply, restrictions on physical activity, degradation of mental health and change in life style resulted in formation of these groups.

Supplementary Table 1 shows descriptive statistics for the variables in terms of mean, median, first quartile (Q_1), third quartile (Q_3), skewness and kurtosis. Mean and Median give the center of gravity of each variable across 578 households. SD gives the spread of each variable. Skewness indicates a deviation from symmetry. If the value of kurtosis is less than 3, then that variable is platykurtic. If it is more than 3, then it is leptokurtic. Here the variables: Unable to eat preferred food, Worry about food, Eat limited variety of food, Eat food that you did not want to eat, Eat smaller meal, Eat fewer, No food to eat of any kind, Increased my household food consumption and Increased food shortage, are related to Food Insecurity during the COVID-19 lockdown. The variables, namely, Affected my routine, Limited my social life, Reduced my travelling and Disturbed my sleeping pattern, try to assess the effect of restriction of Physical Activity during this time. Degradation of Mental Health are assessed through the variables: Increased financial uncertainty, Decreased earning and income, Had fears of losing my job, Depressed due to uncertainty, Anxious due to uncertainty, Afraid of getting COVID-19, Afraid of losing my life and my relatives' life, New and Media increased my tension, Stress level anxiety level increased and I am afraid of COVID outbreak. Participation in household chores, Participation in Yoga, Screen and Sitting time has changed, Hours of sleep changed, Quality of sleep changed and Consumption of sweets changed are the variables that assess the change in Life Style due to the physical restrictions imposed by COVID-19 pandemic and lockdown. Here, the higher the value of these variables, the more severe is the impact.

Results obtained during PCA and SEM are given in Table 1. During PCA, it was seen that principal component one denoted by PC 1 has higher loadings to variables related to basic needs of a family. The principal component two denoted by PC 2 has higher loadings on variables related to additional important needs other than basic needs. This holds true for all groups. For the group Food Security, PC 1 has higher loading on anxiety related basic food needs during the pandemic and lockdown. PC 2 has higher loading on eating preferred food and its scarcity. These two principal components together account for 59.67% of the total variance. Similarly for the group Physical Activity, PC 1 has higher loadings on basic needs of unrestricted physical movements of an individual. PC 2 has higher loadings on variables related to the side effects of restriction in physical movements. These are increased food shortage and increased food consumption. These two components together explain 56.62% of the total variance. Likewise for the group Mental Health, PC 1 has higher loadings on the basic fears related to the outbreak of COVID-19 and the information on radio and television about the havoc created by this pandemic. PC 2 has higher loadings on fears related to losing one's life and relatives' lives. Here, 82.27% of the total variance is explained by these two components together. Finally for the group Life Style, PC 1 has higher loadings on quantity and quality of sleep. PC 2 is related to time spent in front of television and computer screen. In this case, the two components together explain 47.77% of the variance.

The standardized values of first predicted variable for the groups Food Security, Physical Activity, Mental Health and Life Style respectively, are classified into five quintiles. This first predicted variable is obtained by using all the principal components. The standardization is done by subtracting from the mean and dividing by the standard deviation. This standardization facilitates comparison between different groups. Then ordinal data in the scale of one to five is generated on the basis of the 20 th, 40 th, 60 th and 80th quantile values. This is done after arranging the standardized first predicted variable into ascending order of magnitude. The resulting variables are represented by catPcaFS, catPcaPA, catPcaMH and catPcaLS for Food Security, Physical Activity, Mental Health and Life Style respectively. The variables thus created are used for generating Regression trees.

Two SEM models are also summarized in Table 1. These are without the intercept terms because the endogenous and exogenous variables are actually differences from their means. The physical interpretation of an increase or decrease of exogenous or endogenous variables implies an increment and decrement from their mean values. Several models and exogenous and endogenous variable combinations were explored, in quest of suitable SEM model [20]. The objective here was to have a holistic view of the true interrelationships between these variables. From Table 1, Model I it can be seen as SEM with five latent variables, namely COVID-19 Information, Insecurity of Food, Restriction in Physical Activity, Deterioration in Mental Health and Change in Lifestyle. Model II on the other hand, have four latent variables, namely COVID-19 Information, Insecurity of Food, Restriction on Physical Activity, Deterioration of Mental Health. In Model II, the latent variable Change in Lifestyle is not taken into consideration. The efficiency of these two models is explained with the help of χ^2, p value, RMSEA, CFI, TLI and χ^2/df.

As seen from Table 1, the χ^2 value is 2774.571 of goodness of fit of Model I with a p value of 0.000. Model II has the χ^2 value of 1479. 264 with a p value of 0.000. These values are statistically significant at $\alpha = 0.05$ for both the samples. But with the large sample size of 578, this is normally the case even for good models. Among these two most suitable models, Model II is the best with the highest values of TLI and CFI. It is also parsimonious and gives stable results during the model validation [34]. This model satisfies the criteria of a good model with respect to the values of model efficiency parameters. The criteria of model efficiency parameters are namely, CFI > 0.95 and TLI > 0.95 [34](. Model II is the improved versions of Model I. Model I is explaining the regression of latent variable Degradation in Mental Health on latent variables COVID-19 Information, Insecurity of Food, Restriction in Physical Activity and Change in Lifestyle. The standardized factor loadings of these latent variables are also given in Table 1. This regression is given by the following multiple regression.

Degradation in Mental Health = 0.212*COVID-19 Information + 0.027*Insecurity of Food
+ 0.259*Restriction on Physical Activity + 0.242*Change in Lifestyle This implies that as COVID-19 Information increases by one, the Degradation in Mental Health increases by 0.212. As Insecurity of Food increases by one, the Degradation in Mental Health increases by 0.027. As Restriction on Physical Activity increases by one, the Degradation in Mental Health increases by 0.259. As Change in Lifestyle increases by one the Degradation in Mental Health increases by 0.242. All the regression coefficients of the latent variable are highly significant at $p < 0.05$, except for the variable Insecurity of Food. These regression coefficients are standardized. We see from the standardized regression coefficients that the variable Restriction of Physical Activity has highest effect on the Degradation of Mental Health. Model I is more cumbersome and out of a total of 30 parameters, only 23 are significant at 5%level of significance.

Similarly, from Table 1 we see that, Model II can be expressed as following regression equation. This model has given the best results in terms of model efficiency parameters [34].

Degradation in Mental Health = 0.288*COVID-19 Information+0.076*Insecurity of Food
+ 0.242*Restriction on Physical Activity

This implies that as COVID-19 Information increases by one, the Degradation in Mental Health increases by 0.288. As Insecurity of Food increases by one, the Degradation in Mental Health increases by 0.076 units. As Restriction on Physical Activity increases by one, the Degradation in Mental Health increases by 0.242 units. These regression coefficients except Insecurity of Food are highly significant with $p \leq 0.05$ From the standardized regression coefficients it can be seen that COVID-19 Information has the highest effect on the degradation of Mental Health followed by the Restriction in Physical Activity.

In this Model II, as seen from Table 1, the latent variable COVID-19 Information has highest loadings on Information on people dying from COVID-19. The latent variable Restriction on Physical Activity has the highest loading on the variable Affected My Routine. The Latent variable Deterioration in Mental Health has the highest loadings on variables, Afraid of COVID-19 outbreak. This is followed by the loadings on I am afraid of getting COVID-19, News and media increase my tension and Afraid of Losing my Life and my Relative's Life. All these variables have standardized loadings > 0.7. These factor loadings are tested at 5% level of significance. All of the 16 factor loadings and two regression coefficients of Model II are highly statistically significant at p < 0.05.

The variables in Model II, with standardized factor loadings > 0.7, arranged in descending order of their factor loadings, are the following. As seen from Table 1, Affected my Routine has the highest factor loading of 0.967, followed by Information on people dying from COVID-19 with a loading of 0.879, I am afraid of COVID-19 outbreak with 0.866 factor loading, News and media increase my tension with a loading of 0.809, Eat Food that you didn't want to Eat with a loading of 0.801, Afraid of losing my life and my Relative's life with a loading of 0.791, Unable to Eat preferred Food with a loading of 0.725, Eat smaller Meal with a loading of 0.723 and Limited my social life with a loading of 0.702. This shows that these variables have a maximum impact on the degradation of mental health during COVID-19 pandemic and COVID-19 lockdown. This result is highly significant with a p ≤ 0.01.

Model II was validated on four random samples of size 400 each. It has shown excellent results with very high values of model efficiency parameters.

Covariances given in Table 1 show the direction of relationships. For example, there is a negative covariance between Food Insecurity and Household Income of -0.168. This implies that, as household income increases, food insecurity decreases. Similarly, there is a negative covariance of -0.137 between Household Income and the latent variable Deterioration in Mental Health. This means that, as household income increases, the deterioration in mental health decreases. So, it can be concluded at 5% level of significance that people from economically weaker sections of society are most affected by food insecurity and degradation in mental health during COVID-19 pandemic and lockdown. Similarly, as the latent variable Restriction on Physical Activity increases, latent variable Food Insecurity increases with a covariance of 0.251. This conclusion can be made with a p value, p ≤ 0.01

Pseudo R^2 of Model II is 0.995. This shows that there is a high degree of correspondence between the observed values and the predicted values of the variance covariance matrix. It is calculated from the variance covariance matrix used in Model II. This model is based on 17 variables; so, the variance covariance matrix is of order 17×17. This matrix comprises of $17 \times 17 = 289$ elements. The value of pseudo R^2 is calculated below in the Equation (9).

The cross - correlation between the variables Income Group, catPcaFS, catPcaPA, catPcaMH and catPcaLS are given in Table 2. The p values are given in the parenthesis. It can be seen that all the correlations are significant with $p < 0.05$, except for the correlation between Income Group and Physical Activity and Mental Health and Life Style. It can be seen from this table that there is a negative correlation between Income Group and catPcaFS, catPcaMH and catPcaLS respectively. This implies that as Income Group increases the degradation in Food Security, Mental Health and Life Style decreases. That is, if a family is in higher income group or is affluent then the negative impact of COVID-19 pandemic and lockdown decreases. These are with respect to the Food Security, Life Style and Mental Health. These correlations are significant with $p < 0.05$.

$$R^2 = \frac{SSR}{SST} = \frac{\Sigma_{i=1}^{17}\Sigma_{j=1}^{17}(\hat{y_{i,j}} - \bar{y_{..}})^2}{\Sigma_{i=1}^{17}\Sigma_{j=1}^{17}(y_{i,j} - \bar{y_{..}})^2} = \frac{8839.483}{8887.513} = 0.995 \tag{9}$$

$$\bar{y_{..}} = \frac{y_{i,j}}{17 \times 17} = 1.0767$$

Table 1: SEM and PCA results based on 578 households

	SEM - Model 1		SEM - Model II		PCA	
χ^2	2774.571		1479.264		PC1 and PC2	
df	286		112			
$\frac{\chi^2}{df}$	9.701		13.208			
P value	0.000		0.000			
RMSE	0.123		0.146			
SRMR	0.093		0.087			
CFI	0.956		0.97			
TLI	0.950		0.963			
Number of Observations	578		578			
	Factor Loadings Standardized	P Value	Factor Loadings Standadrdized	P Value	Factor Score PC1	PC2
Latent Variables						
COVID-19 Information measured by						
Household Income	0.114					
Information on people suffering from COVID-19	0.641	0.009*	0.670			
Information on people recovering from COVID-19	0.649	0.009*	0.677	0.000*		
Information on people dying from COVID-19	0.919	0.006*	0.879	0.000*		
Insecurity of food measured by						
Worry about food	0.523		0.483		0.386	-0.225
Unable to eat preferred food	0.720	0.000*	0.725	0.000*	0.351	-0.564
Eat limited variety of food	0.660	0.000*	0.661	0.000*	0.371	-0.238
Eat food that you did not want to eat	0.796	0.000*	0.801	0.000*	0.384	-0.251
Eat smaller meal	0.710	0.000*	0.723	0.000*	0.392	0.464
Eat fewer meal	0.709	0.000*	0.688	0.000*	0.410	0.474
No food to eat of any kind	0.710	0.000*			0.478	0.269
Restrictions of Physical Activity measured by						
Affected my routine	0.926		0.967		0.499	-0.120
Limited my social life	0.683	0.000*	0.702	0.000*	0.467	-0.380
Reduced my travelling	0.456	0.000*	0.444	0.000*	0.457	-0.236
Increased my household food consumption	0.391	0.000*			0.341	0.428
Increased food shortage	0.421	0.000*			0.262	0.776
Disturbed my sleeping pattern	0.488	0.000*			0.372	-0.010
Deterioration in mental health measured by						
Afraid of getting COVID-19	0.823		0.832		0.499	0.288
Afraid of losing my life and my relatives' lives	0.796	0.000*	0.791	0.000*	0.493	0.672
News and media increase my tension	0.823	0.000*	0.809	0.000*	0.505	-0.370
I am afraid of COVID-19 outbreak	0.857	0.000*	0.866	0.000*	0.502	-0.574
Change in lifestyle measured by						
Participation in yoga and aerobics	0.174				-0.056	0.429
Change in sitting and screen time	0.114	0.081			-0.283	0.418
Hours of sleep changed	-0.270	0.000*			-0.662	-0.038
Quality of sleep changed	-0.365	0.000*			-0.643	-0.261
Stress level and anxiety level changed	-0.365	0.000*			-0.643	-0.261
Participation in household chores					-0.218	0.544
Regression						
Detrioration in Mental Health on						
COVID-19 Information	0.212	0.012*	0.288	0.000*		
Insecurity of food	0.027	0.59	0.076	0.105		
Restriction on Physical Activity	0.259	0.000*	0.242	0.000*		
Change in life style	0.242	0.000*				
Covariance						
Food Insecurity with Household Income	-0.220	0.000*	-0.168	0.001*		
Deterioration in mental health with Household Income	-0.141	0.011*	-0.137	0.016*		
Lifestyle with Household Income	-0.216	0.000*				
COVID-19 Information with Food Insecurity	0.263	0.006*	0.274	0.000*		
COVID-19 Information with Restriction on Physical Activity	0.240	0.006*	0.251	0.000*		
COVID-19 Information with Change in Lifestyle	0.325	0.008*				
Food Insecurity with Restriction in Physical Activity	0.432	0.000*	0.303	0.000*		
Food Insecurity with Change in Lifestyle	0.140	0.010*				
Restriction on Physical Activity with Change in Lifestyle	0.371	0.000*				

$*p < 0.05$

Here,
SSR = Variation explained by Model II,
SST = Total variation in the data given in the variance covariance matrix,
$y_{i,j}$ is the element occupying the i th row and j th column of the variance covariance matrix.
$\hat{y_{i,j}}$ is the predicted values of the element occupying the i th row and j th column of the variance covariance matrix.
The value is predicted using Model II. Here $i = 1, 2, \ldots 17$ and $j = 1, 2, \ldots 17$

Model II is also explained with the help of path diagram given in Figure 1. Here COVID-19 Information, Insecurity of Food, Restriction in Physical Activity, Restriction in Life Style and Deterioration in Mental Health are the latent variables. The factor loading of these latent variables are also given in the figure. These factor loading are highly significant with $p \leq 0.01$. The latent variable, Deterioration in Mental Health, is regressed on COVID-19 Information, Insecurity of Food and Restriction in Physical Activity. All the regression coefficients are significant with $p < 0.05$.

The Regression Tree of Income is given in Figure 2. It was found that, the root mean squared error (RMSE) for this regression tree is 0.599. This regression tree predicts Income (group) on the basis of negative impacts of Food Security, Physical Activity, Life Style and Mental Health. The effect of wave has been seen to be insignificant in both regression trees. Regression Tree given in Figure 3 measures the regression of Mental Health on Income, Physical Activity, Life Style and Food Security. In this case the RMSE is 1.578. Thus, Figure 2 has lower RMSE than Figure 1. These regression trees were trained and tested on 289 households each. This was done in order to test the validity of results. A random sample of size 289 each was drawn from the total data, to generate this test and train data. The RMSE for the Regression Tree Figure 2, was 0.557 for training data set and 0.631 for testing dataset. For the Regression Tree Figure 3, the training RMSE is 1.321 and the testing RMSE is 1.335. In both the figures, the testing RMSE is slightly higher than training RMSE. Thus, the regression tree in Figure 2 has been most successful in depicting the negative impact of COVID -19 pandemic and lockdown. Further, for the Regression Tree in Figure 2, the minimum average value of the Income Group is 2.850. These are the worst affected groups with degradation of Mental Health more than 1.5, decrease in Food Security more than 1.5 and restriction in Life Style more than 2.5. Similarly, the maximum average value of the Income Group is 3.217. In this group the degradation of Mental Health is more than 1.5, the decrease in Food Security is less than 1.5. Similarly, it can be seen from the Regression Tree given in Figure 3 that, the maximum average value of Mental Health is 4.051. This is when Physical Activity and Food Security take values more than 4.5. The minimum average value of Mental Health on the other hand is 2.259. This is when the restriction in Physical Activity takes values less than 1.5. All these values are in the scale of 1 to 5. Here higher values imply higher level of degradation.

Table 2: Cross Correlation between Income Group, catPcaMH, catPcaFS, catPcaPA, carPcaLS

Correlation	Income Group	catPcaMH	catPcaFS	catPcaPA	catPcaLS
Income Group	1	-0.103 (0.013*)	-0.131 (0.0017*)	0.012 (0.775)	-0.083 (0.046*)
catPcaMH	-0.103 (0.013*)	1	0.157 (0.0002*)	0.258 (0.000*)	0.055 (0.1837)
catPcaFS	-0.131 (0.0017*)	0.157 (0.0002*)	1	0.281 (0.000*)	0.153 (0.0002*)
catPcaPA	0.012 (0.775)	0.258 (0.000*)	0.281 (0.000*)	1	0.113 (0.0065*)
catPcaLS	-0.083 (0.046*)	0.055 (0.1837)	0.153 (0.0002*)	0.113 (0.0065*)	1

$*p < 0.05$

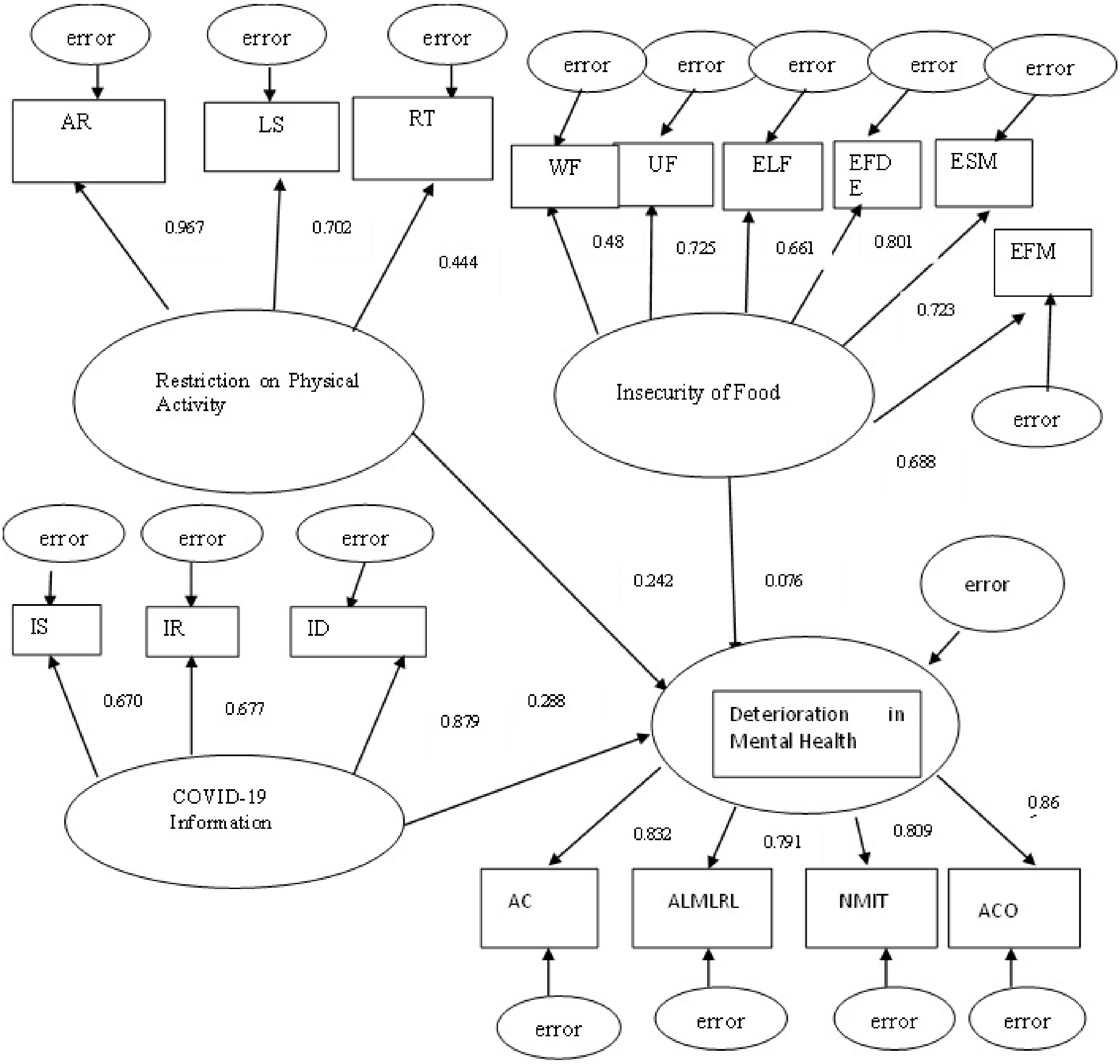

Figure 1: Path diagram of SEM Model III with all the path coefficients significant with $p < 0.01$.

AR: Affected my routine, LS: Limited my social life, RT: Reduced my travelling, IS: Information on people suffering from COVID-19, IR: Information on people recovering from COVID-19, ID: Information on people dying from COVID-19, WF: Worry about food, UF: Unable to eat preferred food, ELF: Eat limited variety of food, EFDE: Eat food that you didn't want to eat, ESM: Eat smaller meal, EFM: Eat fewer meal, AC: Afraid of getting COVID-19, ALMLRL: Afraid of losing my life and my relative's life, NMIT: News and media increase my tension, ACO: I am afraid of COVID-19

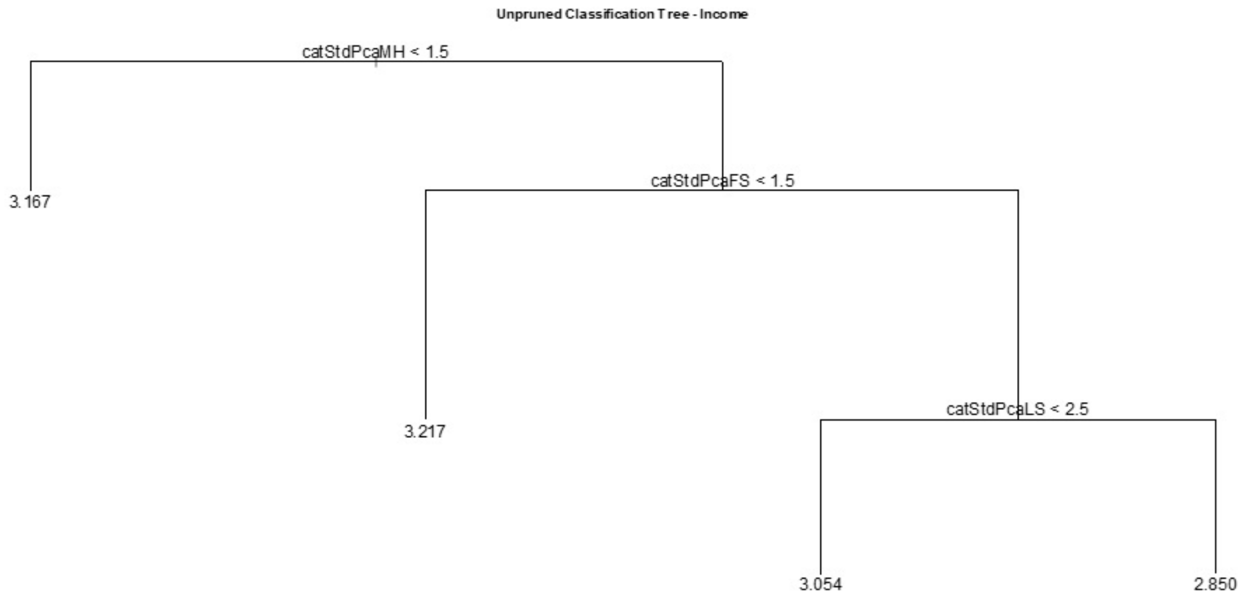

Figure 2: Regression tree of Income based on the whole data.

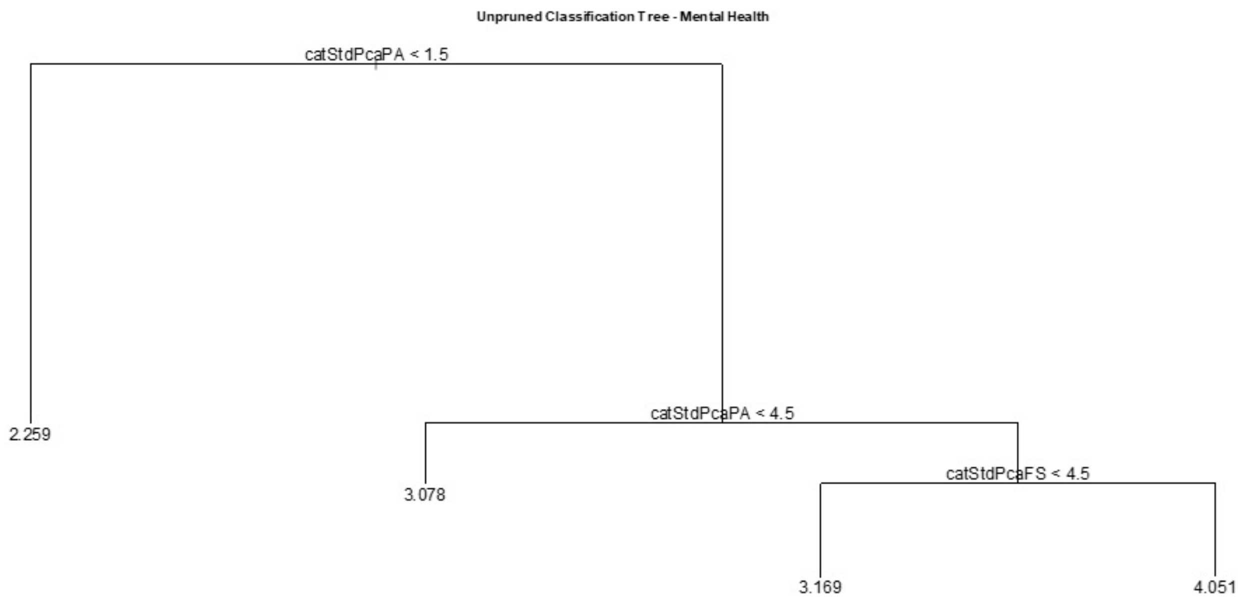

Figure 3: Regression tree of Mental Health based on the whole data.

4 Conclusion

This paper gives a data-based insight to the policy makers and planners on the side effects of a pandemic to an urban population. Evidence-based conclusions made are not a generalization of current trends, but an in depth multivariate analysis. The results obtained here are based on a sample of 578 households, collected using the snow ball sampling technique. The analysis is based on the response of a household on 56 questions. It is an original work, that explains the negative impacts of COVID-19, by developing several models. In this pandemic, death and disease was obvious, but there were various latent negative effects as well. PCA, SEM and Regression Trees used here, give a complete view of the interplay of these latent variables. Here 47 main variables from 56 questions, are classified into groups namely, COVID-19 Information, Mental Health, Food Security, Physical Activity and Life Style. Out of these variables, 39 variables are classified on ordinal scale. Seven variables are classified on ratio scale.

PCA was done on the groups Mental Health, Food Security, Physical Activity and Life Style separately. It was seen for all these four groups, that PC 1 represents basic needs. PC 2 represents needs other than basic needs.

Out of several SEM models explored, two models, Model I and Model II are discussed in great detail. Model II is parsimonious in terms of parameters. It has also given the best results in terms of model efficiency parameters.

Major deductions made from SEM are the following. Of all the variables considered, the following variables were the major contributors to variable Degradation of Mental Health. They are namely, Information on people suffering from COVID-19, Information on people recovering from COVID-19, I am afraid of the COVID-19 outbreak, News and media increase my tension, afraid of getting COVID-19, Afraid of losing my life and my relative's life, and limited my social life. These variables have standardized factor loadings > 0.7. The impact of these variables has to be minimized, if the mental health of people in such a pandemic has to be improved. This conclusion is made with $p \leq 0.05$. It can also be concluded from the direction of covariance that households from lower income groups are worst affected by mental health degradation and food insecurity. This conclusion can be made with a p value $p \leq 0.01$. If another pandemic of this magnitude occurs, then these variables should be given a special attention.

Two Regression Trees exhibited highly nonlinear interrelationship between Income Group, Mental Health, Food Security, Physical Activity and Life Style. In first Regression Tree, Income Group of the household was predicted on the basis of different values measuring the degradation of Mental Health, Food Security, Physical Activity and Life Style. This tree predicted the mean value of Income with very low RMSE of 0.599. This was on the basis of entire data of 578 households. RMSE was 0.557 and 0.631 for training and testing data of 289 households each. Likewise, the second Regression Tree predicted the degradation of Mental Health on the basis of Income Group, Food Security, Physical Activity and Life Style. The RMSE for the total data was 1.578. For training and testing data it was 1.321 and 1.335 respectively.

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A Appendix: Supplementary Table 1: Descriptive Statistics

Sr. No	Variables	Type of Data	Labels and Values	Mean	Median	Q_1	Q_3	SD	Range	Skewness	Kurtosis
Categorical Data											
1	Age of the head in years	Ordinal	1 - 16 to 29 2 - 30 to 49 3 - 50+	2.536	3	2	3	0.592	2	-0.872	2.767
2	Education of the Head	Ordinal	1 - Class 8 or below 2 – Class 9 to 12 3 - Bachelors studying or completed	2.701	3	2	4	0.991	3	-0.185	1.970
3	Occupation	Nominal	1 – Blue collared 2 – Unemployed 3 – White collared 4 - Student								
4	Household Income	Ordinal	1 – Quintile 1 2 - Quintile 2 3 - Quintile 3 4 - Quintile 4 5 - Quintile 5	3.017	3	3	3	0.617	4	-0.364	6.112
5	Wave	Ordinal	1 - Nov. 2020 - April 2021 2 - Nov. 2021– Dec. 2021 3 - Jan. 2022	1.678	2	1	2	0.733	2	0.584	2.054
6	Household savings	Ordinal	1 – No 2 – Yes	1.747	2	1	2	0.435	1	-1.139	2.297
7	Mother's Occupation	Ordinal	1 – Employed 2 – Housewife 3 - Retired	1.438	1	1	2	0.55	2	0.749	2.473
8	Residential Status	Ordinal	1 – Rental 2 - Owner 3 - Other	2.811	3	3	3	0.438	2	-2.250	7.428
9	Gender of the head	Ordinal	1 – Male 2 - Female	1	1	1	1	0.301	1	2.660	8.077
10	Worry about food	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	2.028	2	1	3	1.035	4	0.659	2.644
11	Unable to eat preferred food	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	2.251	2	1	3	1.032	4	0.242	2.091
12	Eat a limited variety of food	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	2.441	2	2	3	1.111	4	0.311	2.287
13	Eat foods that you did not want to eat	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 – Always	2.211	2	1	3	1.02	4	0.393	2.421
14	Eat smaller meals	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	1.796	1	1	2	0.994	4	1.031	3.145
15	Eat fewer meals in a day	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	1.689	1	1	2	0.931	4	1.197	3.702

Sr. No	Variables	Type of Data	Labels and Values	Mean	Median	Q_1	Q_3	SD	Range	Skewness	Kurtosis
Categorical Data											
16	No food to eat of any kind in my households	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	1.246	1	1	1	0.613	4	2.911	12.293
17	Affected my routine activities	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	3.464	4	3	4	1.150	4	-0.54	2.639
18	Limited my social life	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	3.519	4	3	4	1.18	4	-0.532	2.461
19	Reduced my travelling	Ordinal	1 – Never 2 – Rarely 3-Sometimes 4 – Often 5 - Always	4.163	4	4	5	0.964	4	-1.234	4.225
20	Increased my household food consumption	Ordinal	1 – Never 2 – Rarely 3-Sometimes 4 – Often 5 - Always	3.175	3	2	4	1.22	4	-0.205	2.136
21	Increased food shortage	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	2.067	2	1	3	1.097	4	0.804	2.931
22	Disturbed my sleeping pattern	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	2.948	3	2	4	1.353	4	-0.032	1.802
23	Increased financial uncertainty of my household	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	2.561	3	2	3	1.176	4	0.251	2.236
24	Decreased earning/income of my household	Ordinal	1 – Never 2 – Rarely 3 – Sometimes 4 – Often 5 - Always	2.957	3	2	4	1.297	4	-0.068	1.915
25	I had fears of losing my job	Ordinal	1 – Never 2 – Rarely 3-Sometimes 4 – Often 5 – Always	1.756	1	1	2	1.219	4	1.441	3.867
26	Depressed due to uncertainty created by outbreak	Ordinal	1 – Never 2 – Rarely 3-Sometimes 4 – Often 5 - Always	2.576	3	2	3	1.173	4	0.238	2.252
27	Anxious due to uncertainty	Ordinal	1 – Never 2 – Rarely 3-Sometimes 4 – Often 5 - Always	2.825	3	2	4	1.199	4	0.11	2.18

Sr. No	Variables	Type of Data	Labels and Values	Mean	Median	Q_1	Q_3	SD	Range	Skewness	Kurtosis
Categorical Data											
28	Afraid of getting COVID-19	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	3.384	3	3	4	1.219	4	-0.316	2.254
29	Afraid of losing my life and my relatives' life due to COVID-19	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	3.54	4	3	5	1.201	4	-0.401	2.277
30	All the news about COVID-19 increased my tension	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	3.434	4	3	4	1.154	4	-0.392	2.377
31	I am most afraid of COVID-19 recent outbreak in Nepal	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	3.216	3	2	4	1.183	4	-0.210	2.264
32	How often should the lockdown be imposed?	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	2.882	3	2	3	0.987	4	-0.0338	2.808
33	How has the participation in aerobic exercise/yoga changed?	Ordinal	1– Significantly Decreased 2 – Slightly Decreased 3 - Grossly Similar 4 – Slightly Increased 5 – Significantly Increased	3.386	3	3	4	1.127	4	-0.434	2.643
34	How has the participation in leisure and household chores changed?	Ordinal	1 – Significantly Decreased 2 – Slightly Decreased 3 - Grossly Similar 4 – Slightly Increased 5 – Significantly Increased	4.01	4	4	5	1.032	4	-1.121	3.967
35	How has the sitting time and screen time changed?	Ordinal	1 – Significantly Decreased 2 – Slightly Decreased 3 - Grossly Similar 4 – Slightly Increased 5 – Significantly Increased	4.329	5	4	5	0.833	4	-1.296	4.397
36	How have your hours of sleep changed?	Ordinal	1 – Significantly Decreased 2 – Slightly Decreased 3 - Grossly Similar 4 – Slightly Increased 5 – Significantly Increased	3.514	4	3	4	1.089	4	-0.471	2.740

Sr. No	Variables	Type of Data	Labels and Values	Mean	Median	Q_1	Q_3	SD	Range	Skewness	Kurtosis
Categorical Data											
37	How has your quality of sleep changed?	Ordinal	1 – Significantly Decreased 2 – Slightly Decreased 3 - Grossly Similar 4 – Slightly Increased 5 – Significantly Increased	3.221	3	3	4	1.061	4	-0.014	2.517
38	How have your stress and anxiety levels changed?	Ordinal	1 – Significantly Decreased 2 – Slightly Decreased 3 - Grossly Similar 4 – Slightly Increased 5 – Significantly Increased	3.708	4	3	4	0.881	4	-0.599	3.668
39	How has your consumption of sweets/ candies/ chocolate/ sugar sweetened beverages changed?	Ordinal	1 – Significantly Decreased 2 – Slightly Decreased 3 - Grossly Similar 4 – Slightly Increased 5 – Significantly Increased	3.066	3	3	4	1.026	4	-0.209	2.864
40	Increased financial uncertainty of my household	Ordinal	1 – Never 2 – Rarely 3 - Sometimes 4 – Often 5 - Always	2.561	3	2	3	1.176	4	0.251	2.236
Ratio Data											
41	Number of family members	Ratio		4.853	4	4	4.853	1.83	17	2.337	12.202
42	Number of employed	Ratio		2.081	2	1	3	1.120	6	0.85	1.15
43	Number of female children	Ratio		1.216	1	1	2	1.058	10	1.784	11.703
44	Number of male children	Ratio		1.256	1	1	2	1.094	18	6.833	98.483
45	Suffered from COVID - 19	Ratio		5.152	3	0	7	7.528	69	3.70	24.880
46	Recovered from COVID-19	Ratio		4.63	3	0	6	6.37	69	3.385	24.117
47	Deaths from COVID-19	Ratio		0.6118	0	0	1	3.091	69	19.112	417.851