STATISTICAL ANALYSIS OF PPE WASTE MANAGEMENT BEHAVIOUR AMONG YOUTH IN INDIA DURING

COVID-19

M.Sc. Project

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CERTIFICATE

This is to certify that the project entitled **"STATISTICAL ANALYSIS OF PPE WASTE MANAGEMENT BEHAVIOUR AMONG YOUTH IN INDIA DURING COVID-19 "** is the bonafide project work carriedout by **ARIF P**, Department of Statistics and Applied Mathematics, Central University of Tamil Nadu, Thiruvarur 610 005 during the academic year 2022-2023, in partial fulfilmentof the requirements for the award of the degree of Master of Science in Statistics and Applied Mathematics by the Central University of Tamil Nadu.No part of this report has been submitted elsewhere for the award of any other degree.

Dr. C.VIJAYALAKSHMI

Date: 08/05/2023

Place: Thiruvarur

DECLARATION

I, ARIF P of II year M.Sc Statistics and Applied Mathematics, Department of Statistics and Applied Mathematics, Central University of Tamil Nadu, Thiruvarur, hereby declare that the project work entitled **“STATISTICAL ANALYSIS OF PPE WASTE MANAGEMENT BEHAVIOUR AMONG YOUTH IN INDIA DURING COVID-19 ”** submitted to the Department of Statistics and Applied Mathematics, Central University of Tamil Nadu during the academic year 2022-23 under the guidance of **Dr. C VIJAYALAKSHMI**, Department of Statistics and Applied Mathematics, Central University of Tamil Nadu, Thiruvarur, is a bonafide work done by me. This project work is submitted in partial fulfilment of the requirements for the award of the degree of **“Master of Science”** in Statistics and Applied Mathematics. I further declare that the results of this work have not been submitted for any other degree.

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ABSTRACT:

Personal protective equipment has been globally used by people at the COVID-19 pandemic to protect themselves from infection. According to the research, it was found that young individuals display a high level of apprehension towards contracting infections, and a significant proportion of them resorted to wearing masks as a preventive measure against the spread of the virus. The research investigates how young people in India disposed of Personal Protective Equipment (PPE) waste during the COVID-19 pandemic using the value-identity-personal norm model framework. Data were gathered from 458 Indian youths, using questionnaires, and analysed using Partial Least Square Structural Equation Modelling (PLS-SEM). Six relationships is found in this study (1) Biospheric values are positive in relation with Environmental personal social responsibility (2) Biospheric value is positively associated to environmental self-identity (3) Personal norm is positively correlated to PPE waste management behaviour (4) Environmental self identity is positively related to PPE waste management behaviour(5) Environmental Personal Social responsibility is positively linked to the personal norm (6) Environmental personal social responsibility is positively related to PPE waste management behaviour. Findings indicates that all the relationships are significant. The cluster analysis identified two distinct clusters based the latent factors and are significant.

Keywords: PPE Waste management behaviour, PLS-SEM, Cluster analysis

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CHAPTER 1

INTRODUCTION

The COVID-19 outbreak, commonly referred to as the coronavirus pandemic, started in Wuhan, China, towards the end of 2019. SARS-CoV-2, the virus that's causing the outbreak, mainly transmits by respiratory droplets produced when a person with the infection coughs, sneezes, or talks [5]. The outbreak has significantly impacted public health, the global economy, and daily life for millions. In 2020, the WHO proclaimed the COVID-19 outbreak to be a pandemic.

Public health measures such as social distancing, mask-wearing, and vaccinations have been implemented worldwide to combat the spread of the virus. They are resulting in a considerable rise in the use of PPE body suits, gloves, and masks, among other items of personal protective equipment. PPE is generally made of single-use plastic designed to protect personnel from infection. The public widely uses them to prevent transmission of the COVID-19 virus.

PPE played a vital role in preventing COVID-19 transmission and protected the people throughout the crisis. Nations around the world require face masks as well as gloves when in public. Every day, people all around the world use millions of these personal protective devices. But PPEs are disposable after usage, creating a new type of waste.

The wide usage of such protective equipment created a challenge in managing and disposing of such wastes. Due to the sudden increase in the usage of PPE, existing facilities were unable to handle the situation properly. Since it is a single-use plastic, it creates a massive amount of solid waste and becomes a repercussion for environmental contamination.

Due to the lack of environmental awareness, PPE waste was disposed of improperly. Most of them are thrown into the environment or littered with PPE. Since it is made of plastic and has low biodegradability, it remains in the environment. Mismanagement of PPE leads to serious environmental problems. PPE waste also affects the marine ecosystem directly and indirectly. Some aquatic species may become trapped inside gloves or entangled in the elastic ear loops of facial masks, which may restrict their movement and possibly cause them to starve. Additionally, improper PPE disposal transmits other infectious diseases in addition to polluting the environment.

So human behaviour is an important thing that can impact environmental problems. Lack of awareness of how the plastic will affect environmental stability is a significant reason behind the mismanagement of PPE waste. To prevent environmental pollution caused by PPE, we need to study human behaviour toward PPE waste management. The PPE waste continues to increase day by day. Effective waste management is needed to overcome the scenario. It is essential for ensuring sustainable development. Waste management is not a technical issue but a social issue too, as it is immediately connected with human behaviour.

At the heart of the waste management issue, human behaviour is the primary cause. How we consume, produce, and dispose of it significantly impacts the amount of waste generated [6]. But our disposal practices, such as littering and dumping make worsen the problem by creating additional waste and polluting the environment.

Human behaviour towards waste management can be considered a Value Identity personal Norm model and have different levels such as Biospheric values, Environmental Self-identity, Personal Norms, and Environmental personal social responsibility. The Value identity personal norm model has been used in the past to analyse human pro-environmental conduct among people.

Biospheric values are those values that refer to the ethical, cultural, and spiritual values which are associated with the earth’s ecosystem and the living beings that inhabit it. These values recognize the instinct worth of nature and the importance of preserving it for its own sake, as well as the well-being of humans and other species. It explains positive pro-environmental thoughts.

Environmental Self Identity is the degree to which an individual identifies with environmental values and behaviour. It elicits moral obligations to protect the environment. Individuals who identify strongly with environmentalism are more likely to view waste as a personal responsibility.

Personal norms are the internalized standards and expectations that guide an individual's behaviour in a specific situation. In the context of waste management, personal norms can play an essential role in shaping an individual's behaviour and promoting sustainable waste management practices.

Compared with previous generations' youths, they have more environmental challenges, especially during the COVID-19 pandemic. Youths have started consuming a considerable number of PPEs due to viral transmission and protocol insisted by respective authorities, and we should be noticed their PPE waste management behaviour. It can change their behaviour for some time.

India is a developing country having the majority of youth. 65% of the population is under 35 years old. The pro-environmental behaviour of youth can protect the sustainability of nature and the environment from PPE pollution while protecting themself. Studying the behaviour of a large section of the population can use to picturise how the country is developing and managing its problems.

The study intends to investigate how young people in India handled PPE waste during the COVID-19 pandemic and predict how they would behave in the future using the value identity personal norm model.

The core of statistics includes first-generation multivariate techniques such as multiple linear regression, logistic regression, and analysis of variance. They provide significantly shaped results. However, these methods have three major drawbacks in common such as (1) the postulations of simple model structure, (2) demand that all variables be observable (3) the presumption that every variable being studied must be measured without an error. While observing the relationship measure of theoretical variables, first-generation techniques may not provide proper results. To overcome this, researchers widely use second-generation techniques such as Structural Equation Modelling (SEM). There are primarily two types of SEM: partial least squares (PLS-SEM) and covariance-based (CB-SEM). The main purpose of the CB-SEM is to confirm (or reject) the underlying theories and hypotheses. But PLS-SEM is made as a predictive approach to SEM, which mainly explains the variance of the dependent variable present in the model. For creating and studying the structural relationship, both approaches are equally effective. In contrast to PLS-SEM, which is fairly liberal, CB-SEM places substantial demands on the data [7]. For the study, the PLS-SEM approach is used to validate our hypothesised model. PLS-SEM is changing rapidly as a statistical modelling technique. There have been many introductory articles about this methodology in the past decades. For clustering the individuals based on their behaviour Partition Around Medoid (PAM) is used. Because a medoid is less affected by outliers or other extreme values other than a mean, PAM is more robust even if the outliers are present in the data [4].

CHAPTER 2

LITERATURE SURVEY

Name of the paper	Author Name	Journal name	Technique Used
Youth and sustainable waste management: a SEM approach and extended theory of planned behaviour	Ava Heidary, Mahdi Kolahi	Journal of material cycles and Waste management (Volume 20,2018)	SEM, Cluster analysis
Food waste behaviour at the house hold level, A conceptual frame work	Fadi Abdelradi	International Journal of Integrated Waste Management, Science and Technology (Volume 71,2018)	SEM
Determinants of proper dispoal of single-use masks: kwnoledge,perception,behaviour, and intervention measures	Dasina Crina Petrescu, Hamid Rasegari, Ioan Valentin Petrescu-Mag, Ruxandra Malina Petrescu-Mag	PeerJ Publications (Volume 11,2023)	SEM, Cluster analysis
The Machanism of Household Waste Sorting Behaviour-A study of Jiaxing, China	Bora Ly, Romy Ly	International Journal of Environmental Research and Public Health (Volume 19,2022)	SEM
Waste sorting practices of cambodians during covid-19	Bora Ly, Romy Ly	International Journal of Sustainable Engineering (Volume 15,2022)	PLS-SEM
Increased plastic pollution due to COVID-19 pandemic: Challenges and recommendations	Ana L. Patrício Silva, Joana C. Prata ,Tony R. Walker, Armando C. Duarte , Wei Ouyang , Damià Barcelò , Teresa Rocha-Santos	Chemical Engineering Journal (Volume 405,2021)	SEM, Descriptive Statistics

The Thought of Death in a Pandemic Era: Can Anxiety Determine the Nexus between the Accessibility, Availability and Use of Personal Protective Equipment (PPE) for COVID-19 and Work Behaviour among Aviation Workers	Edmund Nana Kwame Nkrumah ,Suxia Liu, David Doe Fiergbor, Linda Serwah Akoto	Healthcare (Volume 10,2022)	SEM
Understanding the Gap between Environmental Intention and Pro-Environmental Behavior towards the Waste Sorting and Management Policy of China	Huilin Wang, Aweewan Magmeechai	International Journal of Environmental Research and Public Health (Volume 18,2021)	SEM
COVID-19 Pandemic: Assessment of Behavior and Attitudes in Medical Waste Management Among Healthcare Workers in Kuwait	Fatimah Al-Dashti , Anwaar Mohammad Alkandari , Shihanah AlMutairi, Ahmed Al-Saber	International Journal of Electronic Government Research (Volume 18, 2022)	SEM

CHAPTER 3

MATERIALS AND METHODS

3.1 Data Collection

The data used to carry out the study was collected from the youth of different parts of India during the COVID-19 pandemic. The questionnaire is made, and the survey is carried out through online mode in order to avoid transmission from person to person. The survey collected samples from 458 persons. The questionnaire contains personal details and their agreement towards each question. A set of questions measures all the variables. Each person's agreement toward the variable is measured on a five-point Likert scale that ranges from "Strongly Agree" to "Strongly Disagree". The questionnaire is mainly explaining five variables that are essential for the study: Biospheric values, Environmental Self Identity, Environmental personal social responsibility, Personal norms and Personal Protective Equipment (PPE) waste management behaviour. Each variable is measured based on a set of questions. Along with variables, each person's basic information is also collected, such as age and gender. The following Table 3.1.1 shows the questionnaire used.

Table 3.1.1 Questionnaire

Determinants	Indicators
Biospheric Values (B)	B1 : We respect nature and coexist peacefully with all other creatures.
	B2 : I feel that I am a part of the nature.
	B3: Environmental protection and preservation are practiced in nature.
	B4 : There is no pollution in the environment or nature.
Environmental Self-Identity (ES)	E1: I handle PPE Waste with eco-friendly manner
	E2: I tend to handle PPE garbage in an environmentally appropriate manner
	E3 : I consider myself to be a PPE waste management person that cares about the environment.
Personal Norm (P)	P1 : I believe I have a moral obligation to properly dispose of PPE trash.
	P2: I would feel bad if I didn't act in an environmentally friendly manner.
	P3 : I'd be a better individual if I behaved in a more environmentally conscious manner.
PPE Waste Management behavior (PPE WMB)	PPE1 : I appropriately dispose of PPE trash (masks, gloves, face shields, hazard suits, etc.) in disposal bins rather than on the ground, in drains, in rivers, etc.

	PPE2 : I separate waste that is recyclable from PPE waste.
	PPE3 : I don't burn PPE trash as a way of disposal.
	PPE4 : When going out is unnecessary, I stay at home to reduce my use of PPE.
Environmental Personal Social Responsibility (EP)	EP1: In my daily life, I pay attention to environmental protection and the usage of PPE.
	EP2 : I make sacrifices to lessen the pollution caused by PPE trash
	EP3 : I don't handle PPE trash in a way that could be harmful to the environment.
	EP4: For environmental concerns, I have ceased all PPE waste mishandling activities.

The demographic characteristics of respondence are described in Table 3.1.2. A total of 458 youths participated in the study; 62.2 % were male, and the remaining were female (37.8%). Most of the respondents belong to the 15-20 (65.9%) age category. And 91% of them have college/university education qualifications.

Table 3.1.2 Demographic characteristics of participants

Factor	**Frequency**	**Percentage**
Age		
15-20	302	65.9
21-25	108	23.6
26-30	30	6.6
31-35	18	3.9
Gender		
Male	285	62.2
Female	173	37.8
Education Qualification		
College/University	389	84.9
Secondary/ High School	69	15.1

Data Pre-Processing

The responses are ordinal. They are converted into numerical numbers ranging from 1- "Strongly disagree" to 5- "Strongly agree" to do the analysis. Then exploratory data Analysis was carried out to clean the data for analysis. Cleaning data includes dealing with missing data, checking for outliers, and dealing with them. And respondence misconducted responses were found and removed by using standard deviation.

2.Structural Equation Modelling

Structural Equation Modelling (SEM) is an integration of many multivariate statistical techniques into a single model framework. It is an integration of

- Measurement Theory
- Factor (latent variable) Analysis
- Path Analysis
- Regression
- Canonical Analysis

It is useful to describe the system of relationships rather than a dependent variable and a set of predictors. It helps to estimate multiple and interrelated dependencies in an integrated model. It also helps to find the mediation and moderation effect of variables on other variables. It can be helpful to analyse the complex relationship that cannot be done using multiple regression.

Here our aim is to study the underlying relationship between latent variable. The hypothesis we are going to verify about the latent variables are listed below

H1 : Biospheric values are positive in relation with the environmental personal social responsibility

H2 : Biospheric value is positively association to environmental self-identity

H3 : Personal norm is positively related to PPE waste management behaviour

H4 : Environmental self identity is positively correlated to PPE waste management behaviour

H5 : Environmental Personal Social responsibility is positively related to personal norm

H6 : Environmental personal social responsibility is positive link to PPE waste management behaviour.

To find the data pattern such that which of the factors are grouping together, exploratory factor analysis was done by the principal component method with varimax rotation. It has confirmed that the factors are correctly classifying to corresponding latent variables.

The proposed measurement model is as follows

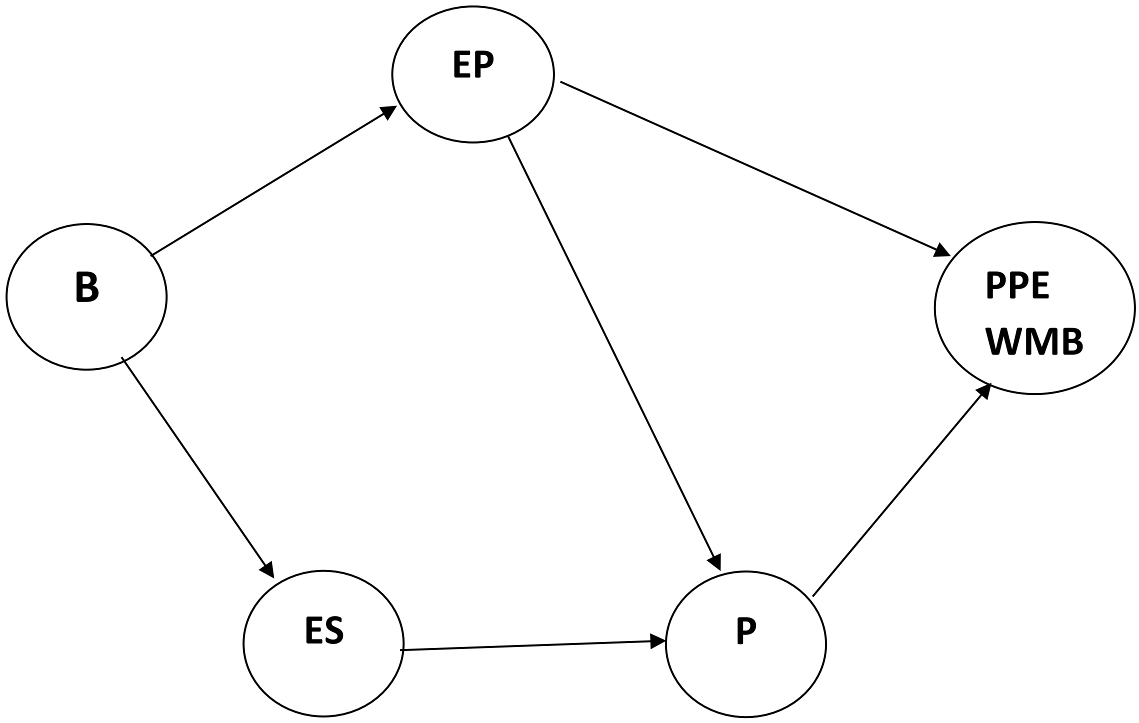


Fig.3.2.1 Proposed model

By assessing the measurement model, the study's construct quality can be determined. By analysing factor loadings and comparing construct reliability and construct validity, one can assess the quality standards.

Factor loading is the correlation between a latent variable and its measured indicators. It is an extent to which how strongly the indicator explains the underlying latent variable. Factor loading varies from the range –1 to +1. The higher value indicates a high correlation indicator with the underlying factor. Recemented value of factor loading is 0.5.

In order to evaluate the multicollinearity among each indicator, the variance inflation factor (VIF) can be used. According to the Hair et al [1], multicollinearity is not a problem for VIF below 5.

Reliability analysis is the degree to which the measured latent factor is stable and consistent. This reliability measurement validates the repeatability, such that if the factor is measured repeatedly by the same indicators, it will yield the same result or not. The Cronbach Alpha and the Composite Reliability are the reliability metrices that are widely employed.

The Cronbach alpha measures the internal consistency to measure the latent variable by means of factors. Thus, it implies how good or bad the measurement accuracy. We can calculate Cronbach alpha by

$$\alpha = \frac{N\bar{k}}{\bar{l} + (N-1)\bar{k}}$$

Were, N- number of items, $\bar{k}$ – Average inter-item covariance between items, $\bar{l}$ – Average variance

Similarly Composite Reliability is the found by

$$CR = \frac{\left(\sum_{I=1}^{k} \theta_i\right)^2}{\left(\sum_{I=1}^{k} \theta_i\right)^2 + \sum_{i=1}^{k} Z(\delta_i)}$$

Where, θ_i = entirely standardized loading for the i^{th} indicator

$Z(\delta_i)$ = the error term variance for the i^{th} indicator

k = number of indicators

For both indications, 0.6 represents adequate reliability while 0.8 or above represents good reliability.

In Construct validity, we have two sections, convergent validity and discriminant validity. The degree to which many attempts to assess the same construct yield the same results is known as convergence validity. One can use the Average Variance Extracted (AVE) metric to assess convergent reliability. One can use the Average Variance Extracted (AVE) metric to assess convergent reliability. AVE is the sum of squared loadings divided by the number of indicators. The observed variable converges to measure the factor if the AVE value is above or equal to 0.50, and convergent validity is confirmed. AVE greater than or equal to 0.5 indicates the 50 percentage or higher the variance of factor is explained.

Here, an indicator from Biospheric values (B4, factor loading = 0.400) and Environmental Self Identity (EP3, factor loading = 0.465) are deleted to achieve the threshold of factor loadings. Generally, outer Loading with 0.4 to 0.7 shall be considered to remove if the deletion result increase in AVE value beyond the threshold. So, to get the threshold value of AVE, an indicator from PPE waste management behaviour (PPE3, factor loading = 0.635, AVE-0.463) is deleted. The remaining factors are satisfying the needed thresholds and are shown in the following table

Table 3.2.1 Factor loading

	B	EP	ES	P	PPE WMB
B1	0.842				
B2	0.778				
B3	0.780				
EP1		0.861			
EP2		0.749			
EP4		0.661			
E1			0.764		
E2			0.836		
E3			0.843		
P1				0.755	
P2				0.766	
P3				0.732	
PPE1					0.671
PPE2					0.736
PPE4					0.746

Table 3.2.2 Multicollinearity statistics (VIF) for indicators

	VIF
B1	1.505
B2	1.226
B3	1.326
E1	1.291
E2	1.807
E3	1.721
EP1	1.329
EP2	1.328
EP4	1.183
P1	1.170
P2	1.279
P3	1.242
PPE1	1.159
PPE2	1.146
PPE4	1.118

Table 3.2.3 Construct Reliability Analysis (Cronbach Alpha and Composite Reliability)

	Cronbach's alpha	Composite reliability
BIOSPHERIC VALUES	0.660	0.812
ENVIRONMENTAL PERSONAL SOCIAL RESPONSIBILITY	0.645	0.804
ENVIRONMENTAL SELF IDENTITY	0.747	0.856
PERSONAL NORM	0.616	0.795
PPE WASTE MANAGEMENT BEHAVIOR	0.537	0.762

Table 3.2.4 Construct Convergent validity (AVE)

	Average Variance Extracted (AVE)
BIOSPHERIC VALUES	0.592
ENVIRONMENTAL PERSONAL SOCIAL RESPONSIBILITY	0.580
ENVIRONMENTAL SELF IDENTITY	0.664
PERSONAL NORM	0.564
PPE WASTE MANAGEMENT BEHAVIOR	0.516

Discriminant validity is the extent to which measures of different constructs are different in nature. The behind is that the valid measure is not strongly associated if two more ideas are unique. Hetrotrait-monotrait ratio (HTMT) is a measure of discriminant validity. The HTMT measures all indicators' correlations across latent variables assessing various latent variables in comparison to the geometric mean of their average correlations across the same latent variable. The required threshold is less than 0.85. Here all the factors have HTMT values less than the required threshold.

Table 3.2.5 Discriminant validity- HTMT criterion

	B	EP	ES	P
BIOSPHERIC VALUES	-			
ENVIRONMENTAL PERSONAL SOCIAL RESPONSIBILITY	0.524	-		
ENVIRONMENTAL SELF IDENTITY	0.455	0.739	-	
PERSONAL NORM	0.403	0.673	0.712	-
PPE WASTE MANAGEMENT BEHAVIOR	0.341	0.813	0.668	0.841

Another way of assessing the discriminant validity is by Fornell & Lacker criterion. By this criterion, discriminant validity attained by correlation with all other latent variables is less than the square root of AVE . Here all the latent variables are achieved the particular threshold

Table 3.2.6 Discriminant validity- Fornell & Lacker criterion

	B	EP	ES	P	PPE WMB
BIOSPHERIC VALUES	***0.770***				
ENVIRONMENTAL PERSONAL SOCIAL RESPONSIBILITY	0.348	***0.761***			
ENVIRONMENTAL SELF IDENTITY	0.330	0.535	***0.815***		
PERSONAL NORM	0.270	0.455	0.491	***0.751***	
PPE WASTE MANAGEMENT BEHAVIOR	0.206	0.516	0.427	0.484	***0.718***

Note: Bold italics represents the square root of AVE

Because the measurement model fits data well, the goodness of fit of the proposed theoretical fame work can be evaluated by the structural model. Path analysis is used to test the hypothesis, such that to confirm the proposed relationships between latent variables. Here, we performed 5000 samples of the PLS-SEM model using the Bootstrapping procedure, and we achieved results for model significance. t-statistics larger than 1.96 indicates that the path coefficients are statistically significant. From the result, we can see that all the latent variables, including Biospheric values, Environmental self-identity, Environmental social responsibility and Personal norms, explain the PPE waste management behaviour. So, it supports the hypothesis H3, H4 and H6. Similarly, the remaining hypothesis is also valid. The following Table 3.2.7 validate the significance of each hypothesis by assessing the path coefficient and t-statistics.

Table 3.2.7 Path analysis (Direct effects)

Paths (Direct effect)	Coefficients	Standard deviation (STDEV)	t statistics
B -> EP	0.348*	0.052	6.708
B -> ES	0.330*	0.052	6.307
EP -> P	0.270*	0.042	6.357
EP -> PPE WMB	0.372*	0.055	6.812
ES-> P	0.347*	0.048	7.250
P -> PPE WMB	0.315*	0.056	5.643

Note: *Relationships are significant at p<0.01.

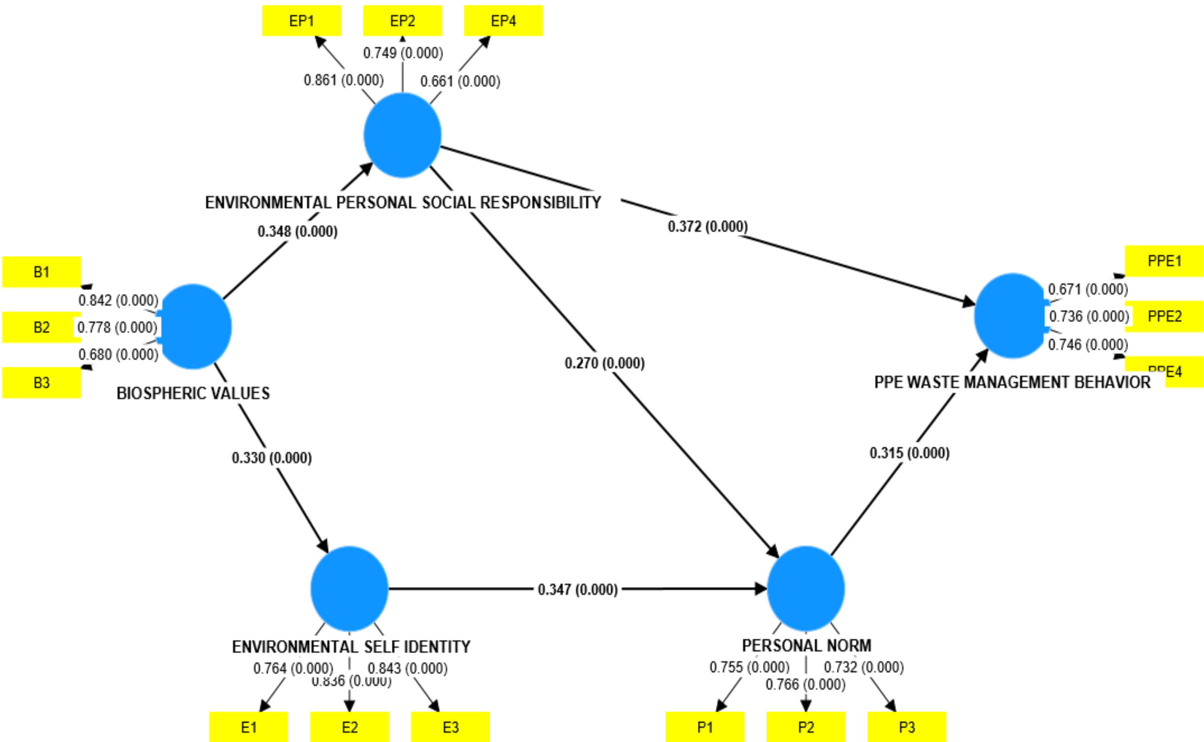


Figure 3.2.2 PLS-Structural Equation Model

Mediation analysis is evaluated to assess the median relationship between latent variables, that is between independent and dependent variables. The following table 3.2.8 shows the significant indirect effects in the proposed model

Table 3.2.8 Path analysis (Indirect effects)

Paths (Indirect effects)	Original sample (O)	Standard deviation (STDEV)	t statistics	P values
B -> ES-> P	0.114	0.026	4.375	0.001
EP-> P -> PPE WMB	0.085	0.020	4.183	0.001
B -> EP -> PPE WMB	0.130	0.029	4.445	0.001
B-> ES-> P-> PPE WMB	0.036	0.012	3.051	0.002
B -> EP -> P-> PPE WMB	0.030	0.009	3.326	0.001
B -> EP -> P	0.094	0.022	4.288	0.001
ES -> P -> PPE WMB	0.109	0.027	4.054	0.001

Here table is describing the possible indirect effects in the model that are significant.

Table 3.2.7 Total effect of proposed PLS-SEM model

Latent Variables	Path	Direct Effect	Indirect Effect	Total Effects
B	ES	0.330		0.330
	EP	0.348		0.348
	P		0.208	0.208
	PPE WMB		0.195	0.195
ES	P	0.347		0.347
	PPE WMB		0.109	0.109
EP	PPE WMB	0.372	0.085	0.457
	P	0.27		0.270
P	PPE WMB	0.315		0.315

Discussing about the suggested structural equation model's explanatory power. R square value is used to interpret the variance explained by the endogenous variable. That is, one or more independent variables can measure a little change in the dependent variable. Additionally, it measures the ability of a model for the explanation. R square has a range of 0 to 1; higher values denote more explanatory ability. According to Falk and Miller (1992) [8] and Cohen, J. (2013) [2], R square values of 0.10 or above are sufficient to explain the endogenous variable. The difference in the R square value caused by the removal of an exogenous variable from the model is known as the f square value. Different variables can affect the variables in a structural model. If an external variable is eliminated, the dependent variable might change.

Q square is a measure the predictive relevance of the structural equation model. It describes the predictive relevance of each endogenous variable. Q square values over zero signify that the model has predictive power.

Here PPE waste management behaviour is moderately explained by the three latent variable environmental self-identity, environmental social responsibility and personal norm. Also, Q square values of latent variables are above the threshold. the model has the explanatory power.

Table 3.2.8 R square value

	R-square	Adjusted R-square
EP	0.133	0.132
ES	0.136	0.134
P	0.295	0.292
PPE WMB	0.355	0.353

Table 3.2.9 f^2 values

	f-square
B -> EP	0.154
B -> ES	0.131
EP -> P	0.070
EP -> PPE WMB	0.183
ES -> P	0.123
P -> PPE WMB	0.119

Table 3.2.10 Q^2 value

	Q^2predict
ENVIRONMENTAL PERSONAL SOCIAL RESPONSIBILITY	0.123
ENVIRONMENTAL SELF IDENTITY	0.106
PERSONAL NORM	0.066
PPE WASTE MANAGEMENT BEHAVIOR	0.143

3.3. Cluster Analysis

As an exploratory statistical technique, cluster analysis is used to identify patterns in the data. In cluster analysis, we are interested in grouping our observations in a manner that all group members are similar, that is, grouping observations with the same features. However, the observations that belong to one group are distinctly different from those that belong to another group.

Since the data are categorical, the K- Medoids clustering method is applied. K-Medoid is also known as Partition Around Medoids (PAM). Since the mean is not defined for ordinal data, we use medoids in such a way that starts from initial set of medoid and iteratively replace with the non-medoid if the replacing improves the total distance of clusters. This method is more robust than K-means to outliers.

To carryout PAM algorithm we find the dissimilarity matrix with daisy() command. Dissimilarity matrix is used to find the dissimilarity between the individual, that is how each respondent is dissimilar from each other. It ranges from '0' to '1' such that '0' indicate completely similar and '1' indicate completely dissimilar. For ordinal dissimilarity matrix is calculated by the 'Gower Method' instead of Euclidean distance.

In 'Gower method' the dissimilarity between i^{th} and j^{th} unit is obtained as

$$d(i,j) = \frac{\sum_k \beta_{ijk} d_{ijk} w_k}{\sum_k \beta_{ijk}\, w_k}$$

Where d_{ijk} represent distance between i^{th} and j^{th} component as considering k^{th} variable , w_k is the weight of the k^{th} variable. For ordinal data distance is found by transforming the observation by the

$$g_{ik} = \frac{r_{ik} - 1}{max\,(r_{ik}) - 1}$$

Where r_{ik} is the factor level. Then this new g_i are used to as new observations which are in interval scale and corresponding distance measure can be used

$$d_{ijk} = \frac{|g_{ik} - g_{jk}|}{R_k}$$

Where R_k range of the k^{th} variable.

PAM needs a predetermined number of clusters. By using either a diagnostic approach or domain knowledge, we can figure out the optimum number of clusters. The silhouette approach is used to determine the optimal number of clusters for the given set of data. For ordinal data, the silhouette method is frequently used to determine the optimum number of clusters.

The silhouette method determine a list of cluster sizes by measuring the observations are similar in a cluster against similar they are to observations from other cluster . This method gives scores to ranges from -1 to 1 for each number of clusters. A score of +1 indicates that the clustering is highly effective, whereas a score of -1 indicates poor clustering. Here cluster size with best number of scores is chosen.

```
silhoutte$Best.nc
Number_clusters     Value_Index
          2.00            0.37
```

With the help of multidimensional scaling PAM is plotted in to two-dimensional scale.

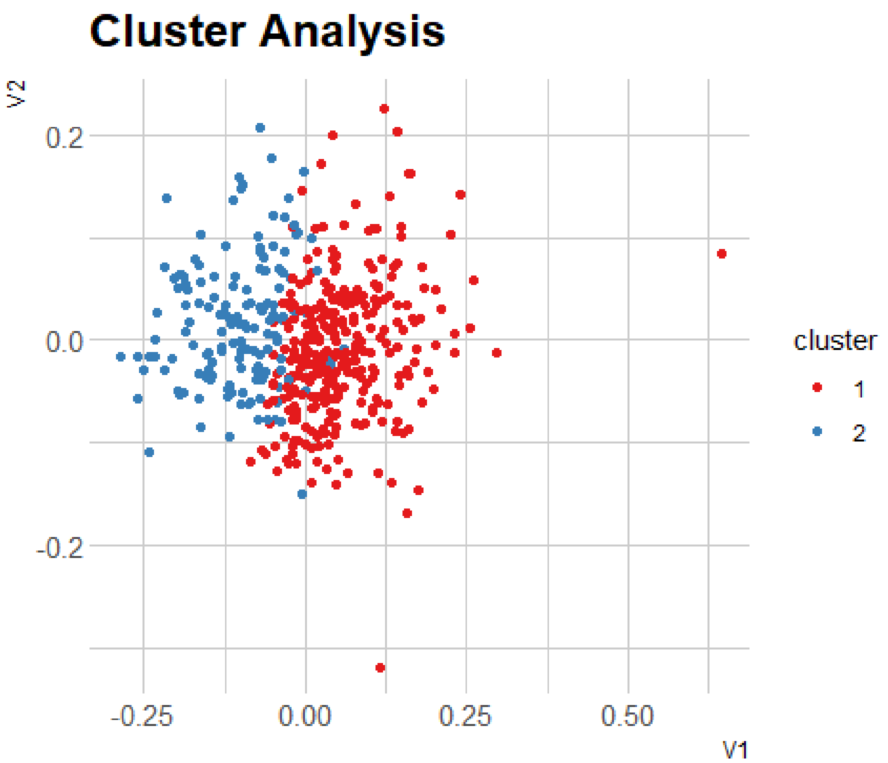


Figure 3.3.1 Plot of individuals based on clusters

From the clusters we can see that individuals are classified based on the responses. The cluster 1 and 2 contain 300 and 158 individuals respectively.

```
clust$clusinfo
           size  max_diss    av_diss    diameter    separation
cluster 1  300  0.6111111  0.1468519  0.7500000  0.04166667
cluster 2  158  0.3750000  0.1414381  0.4861111  0.04166667
```

To access the goodness of clustering we have two indices namely Silhouette width and Dunn index

Silhouette analysis calculates the average distance between the clusters in order to assess how good the data is grouped. The silhouette plot displays the separation between each point in a cluster and each point in its neighboring clusters. The silhouette width is

Silhouette width is found as

$$S_i = \frac{n_i - m_i}{\max(m_i, n_i)}$$

where m_i represents the cluster's average dissimilarity between point i and all other points. n_i is the dissimilarity between i and the point which is in its neighbor cluster, not in the same cluster.

The observations with large S_i are very well grouped. And observations with negative S_i are likely to assign incorrect cluster. When S_i value close to zero, observation is in between the clusters.

Her for PAM clustering the average silhouette width is 0.2. for each cluster the average silhouette width is

cluster	Size	Average silhouette width
1	300	0.18
2	158	0.23

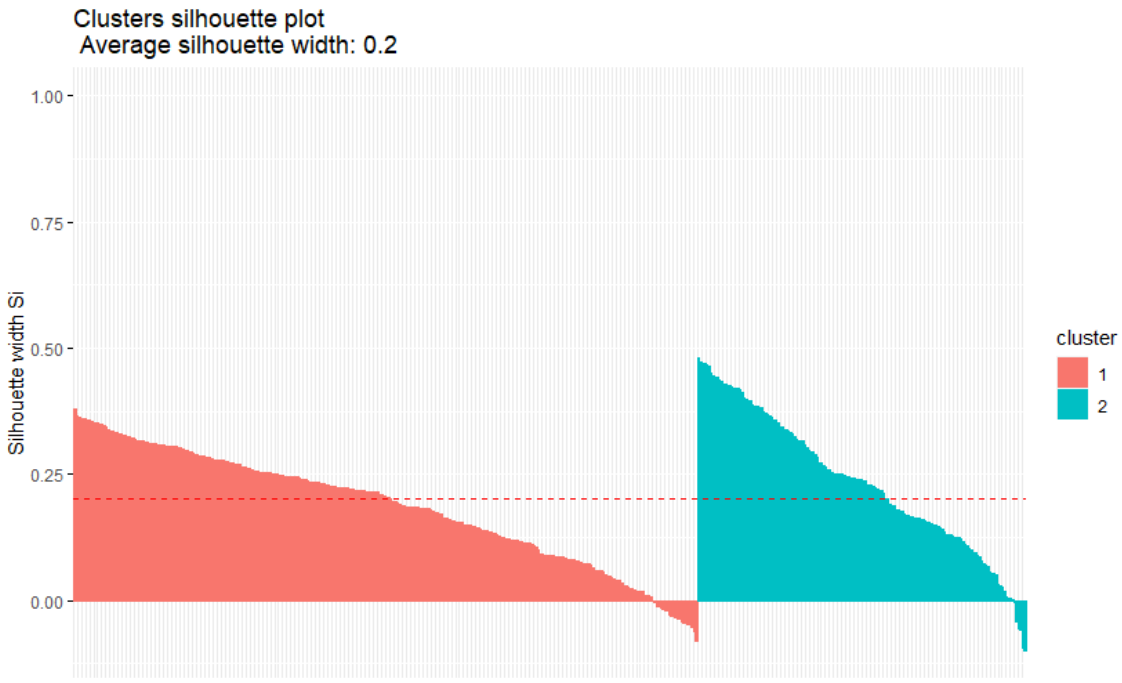


Figure Silhouette plot of PAM cluster

Other measures are

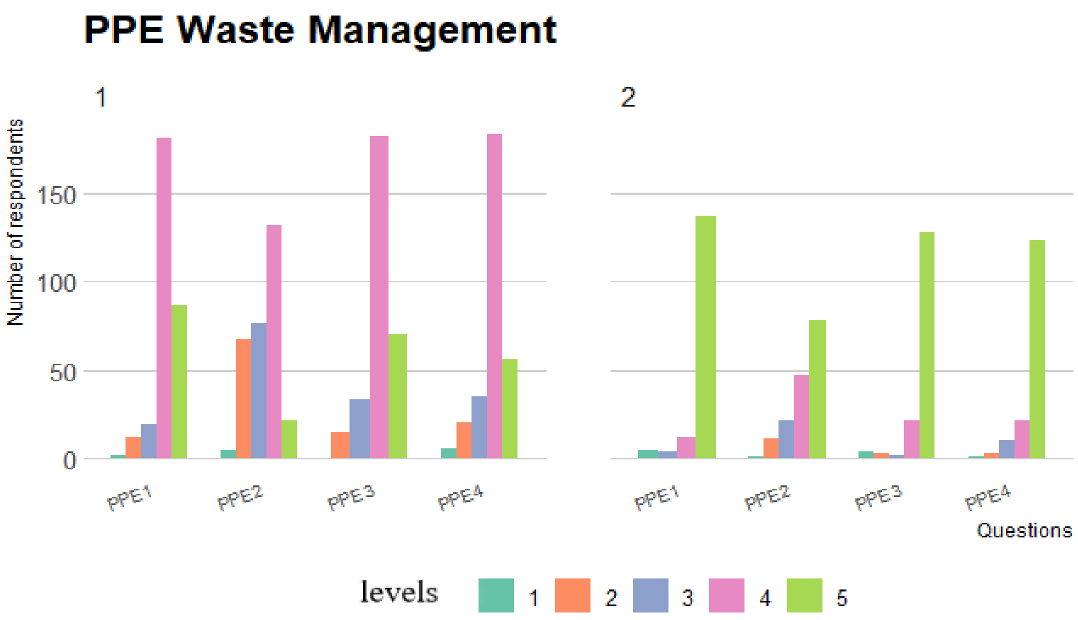
	Scores
Connectivity	152.979
Dunn Index	0.1021

The misclassified observations can be found by negative silhouette value. There are 28 individuals incorrectly clustered. And are listed below

Observation Position	cluster	neighbour	sil_width
5	1	2	-0.0805
21	1	2	-0.0313
32	1	2	-0.03221
33	2	1	-0.09856
36	1	2	-0.01898
66	1	2	-0.04652
85	1	2	-0.00325
100	2	1	-0.05783
114	1	2	-0.04768
127	2	1	-0.04047
145	1	2	-0.00054
189	1	2	-0.01047
199	2	1	-0.00247

211	2	1	-0.09272
228	1	2	-0.02081
229	1	2	-0.05981
243	1	2	-0.01727
247	1	2	-0.03749
344	1	2	-0.03664
353	1	2	-0.04451
392	1	2	-0.02714
393	1	2	-0.04271
422	1	2	-0.04377
430	1	2	-0.03134
438	2	1	-0.05618
439	1	2	-0.01276
449	1	2	-0.05333
455	1	2	-0.01505

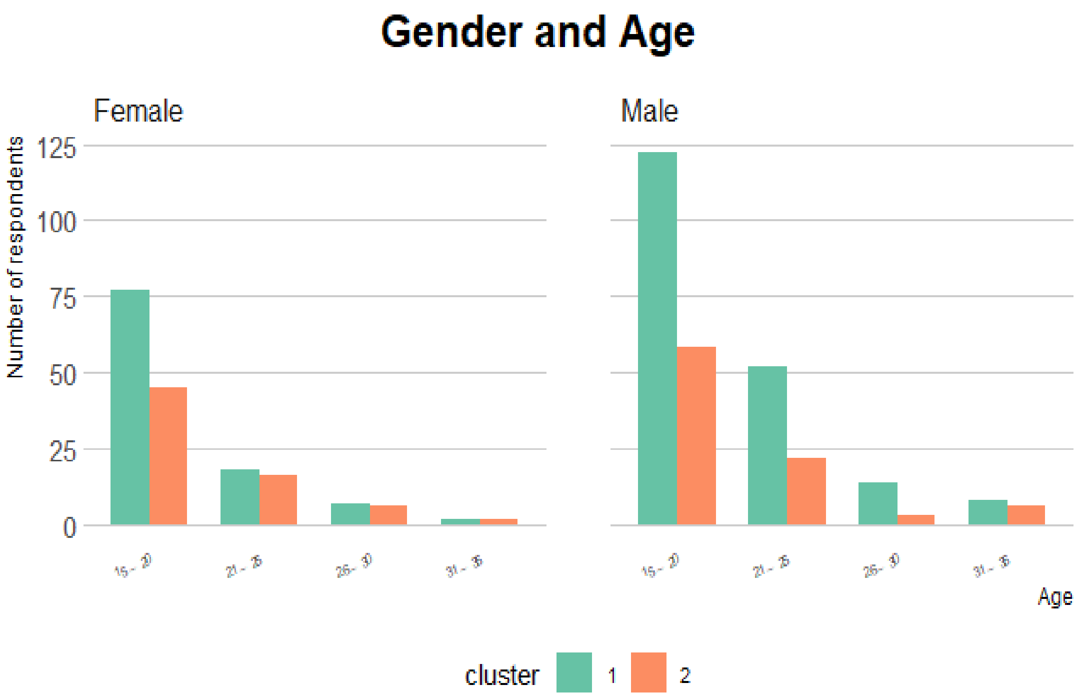
From the results and graphs, individuals from cluster 2 have high waste management behaviour, and the cluster is made on the basis of having the respondents strongly agreeing towards the PPE waste management behaviour. Cluster 2 is made by taking the clustering centre as strongly agreeing towards PPE waste management. Cluster 1 is the cluster containing moderate PPE waste managing people made by taking cluster centre as "agree".



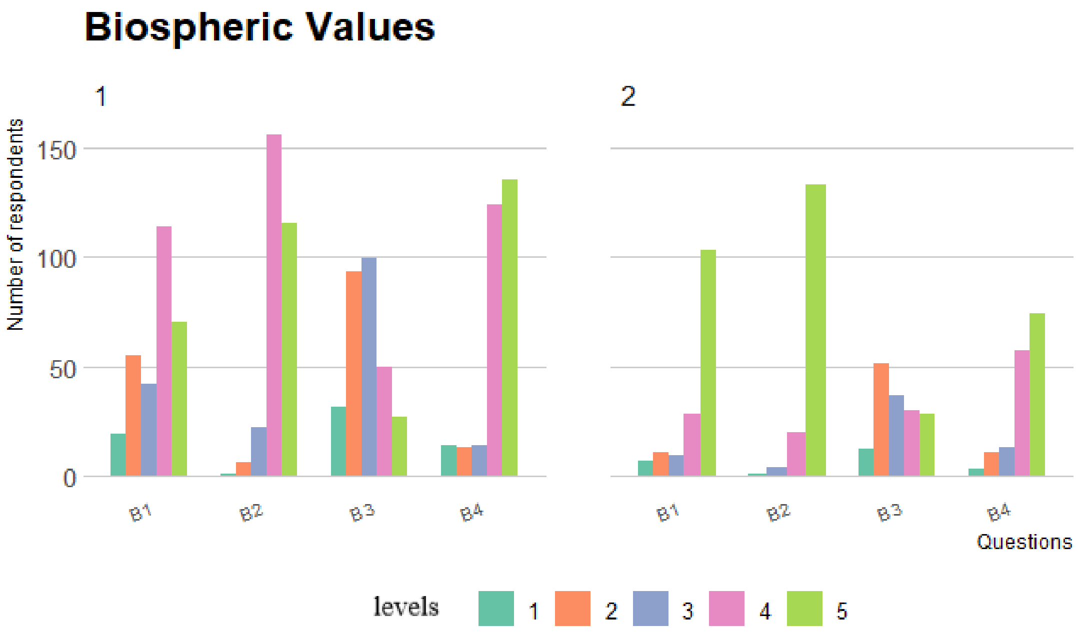
The demographic features of each cluster are shown in the table

Table 3.3.1 Demographic features of Clusters

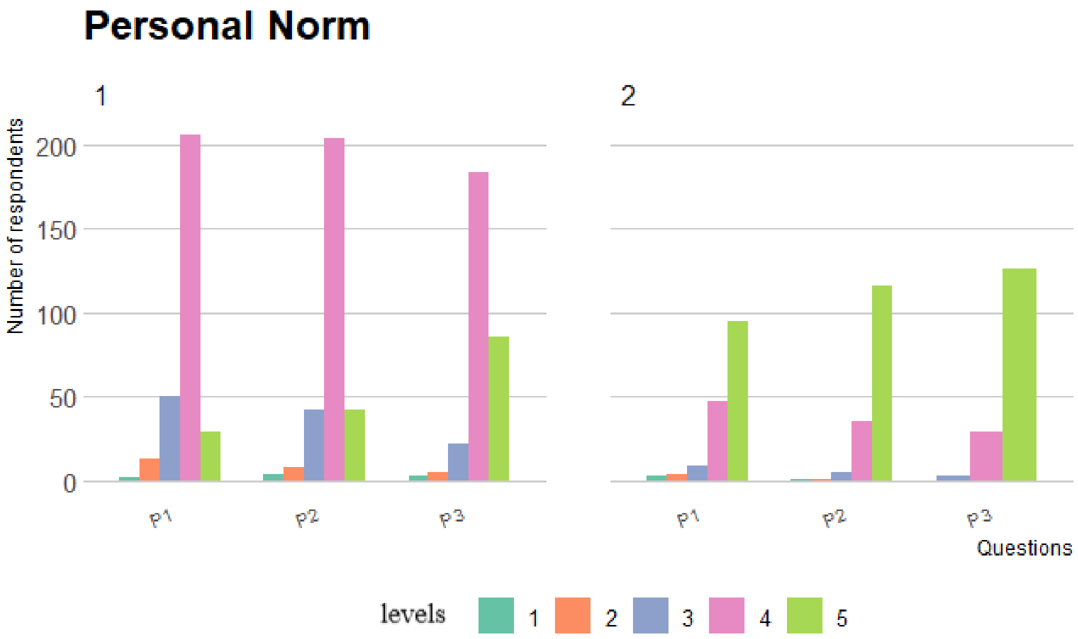
Demographics		Cluster 1,n	Cluster 2, n
Age			
	15-20	199	103
	21-25	70	38
	26-30	21	9
	31-35	10	8
Gender			
	Male	196	89
	Female	104	69

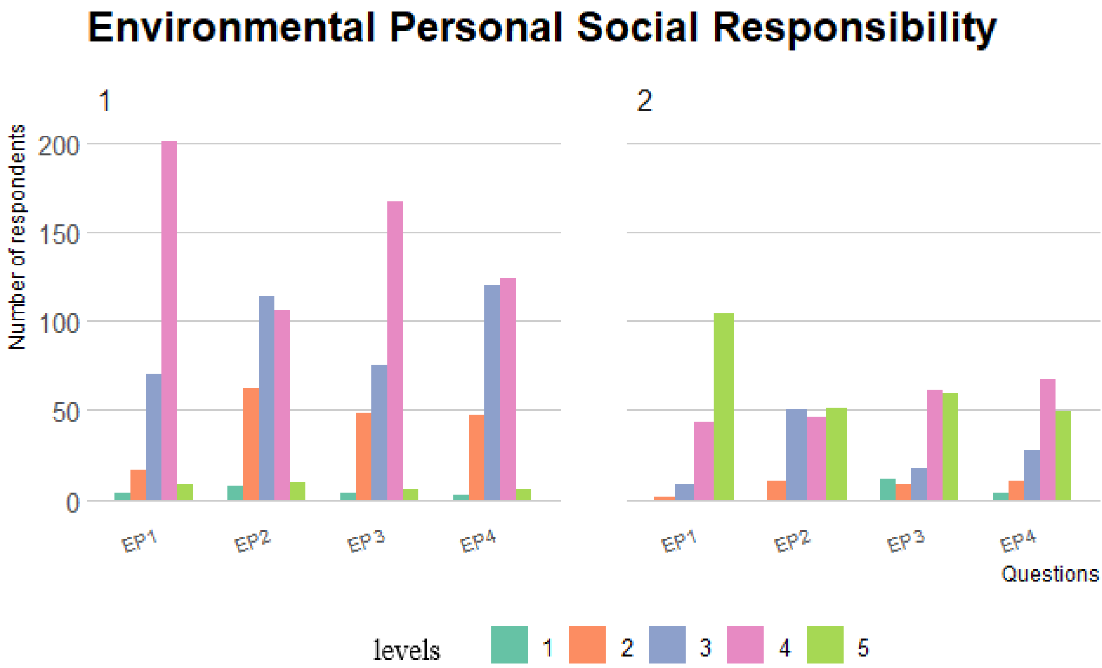


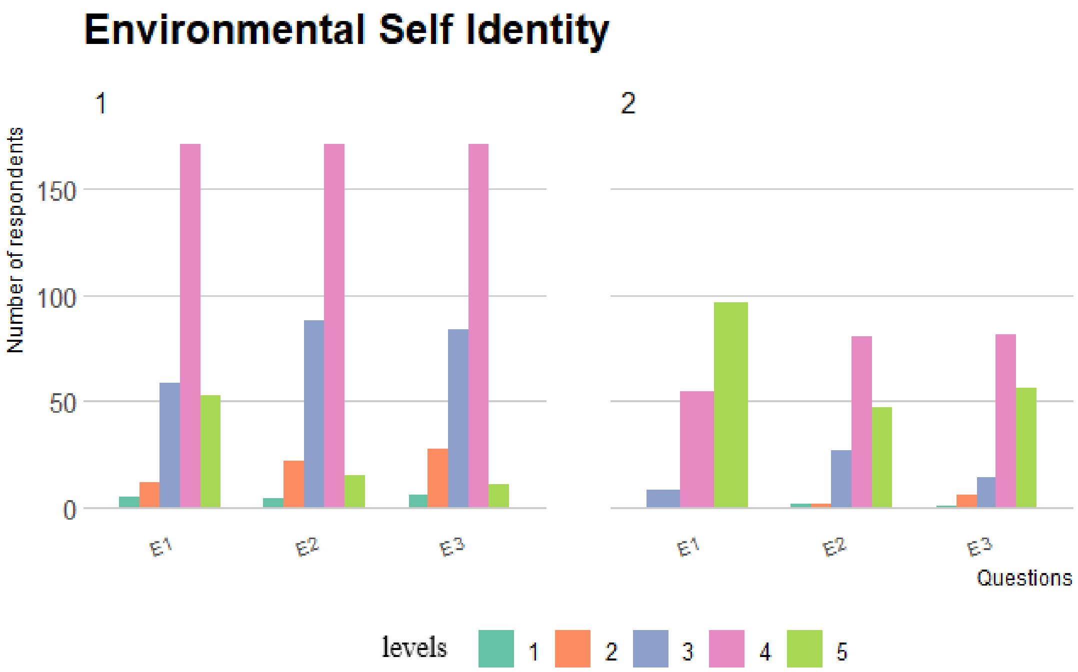
For Biospheric values, cluster 1 contains those who responded to Biospheric values as "Agree" and have moderate Biospheric values. In the second cluster, individuals have Biospheric values.



Similarly, in cluster 1, individuals having moderate environmental self-identity, Environmental personal social responsibility and Personal norm are clustered. But in cluster 2, individuals having a high attitude towards factors are clustered.




Environmental Personal Social Responsibility
1
2
Number of respondents
200
150
100
50
0
EP1
EP2
EP3
EP4
Questions
levels
1
2
3
4
5


Environmental Self Identity
1
2
Number of respondents
150
100
50
0
E1
E2
E3
Questions
levels
1
2
3
4
5

The clustering centres for each cluster are shown below

Table 3.3.2 Cluster centres

Cluster	B1	B2	B3	B4	E1	E2	E3	P1	P2	P3
1	3	4	3	4	4	4	4	4	4	4
2	5	5	3	4	5	4	4	5	5	5

Cluster	PPE1	PPE2	PPE3	PPE4	EP1	EP2	EP3	EP4
1	4	4	4	4	4	3	4	3
2	5	5	5	5	5	3	5	4

Where rating scale is 1-“Strongly disagree”, 2- “Disagree”, 3- “Neither agree nor disagree”, 4- “Agree”, 5-“Strongly agree”.

3.4 Garett ranking method

Garret's Ranking techniques is helps to rank the factors based on the responses. For this method respondent were asked to give their ranks about the all factors and it will return with ranking score among with them. The following formula helps to convert

$$Percent\ position = \frac{100(H_{ik} - 0.5)}{N_{ik}}$$

Where H_{ik} = k^{th} respondent's ranking for i^{th}

N_{ik} = Number of variables ranked by the k^{th} person

By comparing the values of percentage position with the Garett's table will provide the score for each rank. After that, each person's score for every factor is added and the total and mean value of scores are computed. The factors having the highest mean value will consider as most important factor and then factors can be ranked based on the mean value obtained.

Since for each factor here we are having a set of questions that explaining factors, we ranked the questions by Garrets ranking based on the response they given to the questions. The responses are rated on a five-point Likert scale, with "Strongly agree" being the highest and "Strongly disagree" being the lowest. For each Factor garret's ranking is found and they are mentioned in the table

Table 3.4.1 Garret's Ranking

	Strongly disagree, n	Disagree, n	Neither agree nor disagree, n	Agree, n	Strongly Agree, n	Rank
B1	26	66	51	142	173	2
B2	2	6	26	176	248	1
B3	43	144	136	80	55	3
B4	209	181	27	24	17	4
E1	5	12	67	225	149	1
E2	6	24	115	251	62	3
E3	7	34	98	252	67	2
EP1	4	18	79	244	113	1
EP2	8	73	164	152	61	4
EP3	16	57	92	228	65	2
EP4	7	58	147	191	55	3
P1	5	12	59	253	124	3
P2	5	9	47	239	158	2
P3	3	5	25	213	212	1

PPE1	7	12	23	193	223	1
PPE2	6	78	97	178	99	4
PPE3	4	18	35	203	198	2
PPE4	7	23	45	204	179	3

For Biospheric values, the question "*I feel that I am a part of the nature*." is having high rank amongst them. Similarly for Environmental self-identity – "*I handle PPE Waste with eco-friendly manner*", Personal norms – "*In my daily life, I pay attention to environmental protection and the usage of PPE*.", Environmental Person Social Responsibility – "*I'd be a better individual if I behaved in a more environmentally conscious manner*".and for PPE Waste management behaviour – "*I appropriately dispose of PPE trash (masks, gloves, face shields, hazard suits, etc.) in disposal bins rather than on the ground, in drains, in rivers, etc.*" are having the highest rank in their corresponding factors.

As a result of this method, the highest-ranked questions can be used to explain the corresponding latent variable instead of using more than one.

CHAPTER 4

CONCLUSION

The goal of the study is to identify the factors that affect youth's waste management practises for personal protective equipment during the COVID-19 pandemic in India, Based on the value identity personal norm model. The study concluded that the factors Biospheric values, Environmental self-identity, Environmental Personal Social Responsibility and Personal norms are significant and positively affect the PPE Waste management behaviour among youth. Most people of the young age category widely use PPE because of high social activity. The attitude towards waste management among this group of people is crucial for the environment on a worldwide scale. The model evaluated through the PLS-SEM algorithm shows that all relationship is significant. We found six relationships in this study (1) Biospheric values are positively related to Environmental personal social responsibility (2) Biospheric value is positively related to environmental self-identity (3) Personal norm is positively related to PPE waste management behaviour (4) Environmental Self identity is positively related to PPE waste management behaviour(5) Environmental Personal Social responsibility is positively related to the personal norm (6) Environmental personal social responsibility is positively related to PPE waste management behaviour.

Environmental personal social responsibility and PPE waste management practises have the largest relationship, while environmental personal social responsibility and Biospheric values are second. Least relationship is Environmental personal social responsibility and Personal norms.

The cluster analysis gives insight about data, the individuals are clustered into two groups. People in Cluster 1 who manage PPE very well and those in Cluster 2 who manage waste more moderately. Each factor is sufficiently helping to cluster into two groups. Cluster 1 is made of individuals whose having moderate behaviour towards each factor. Cluster 2 is made with a high degree of positive attitude toward the factors.

This study sheds light on how young people handled PPE trash during the COVID-19 epidemic and what factors should be taken into account to improve their environmentally friendly PPE waste management practises. According to the study, raising an individual's Biospheric values improves their Environmental self-identity, Personal norms, Environmental personal social responsibility, and eventually influences how they handle PPE waste.

CHAPTER 5

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CHAPTER 6

APPENDIX

R code for Cluster analysis

```
library(cluster)
library(hrbrthemes)
library(tidyverse)
library(NbClust)
library(factoextra)
data1<-data.frame(sem_3[,c(-3,-2,-1)])
data1
d<-daisy(data1,metric = "gower")
n<-NbClust(data1,diss = d,distance=NULL, min.nc = 2,max.nc = 10,method =
"median",index = "silhouette")
n$Best.nc
clust<-pam(d,diss = TRUE,k=2)
clust$isolation
m<-data1[clust$medoids,]
m
plot(clust)
summary(clust)
clust$medoids
clust
clusters<- as.data.frame(cmdscale(d,2))
clusters
clusters$cluster <- as.factor(clust$clustering)
clusters$cluster
ggplot(clusters,aes(x=V1,y=V2,color=cluster)) +
  geom_point() + theme_ipsum() +
  labs(title="Cluster Analysis") +
  scale_color_brewer(palette="Set1")


data1$cluster <- clusters$cluster
```

```
data1
e<-c(1,2,3,4,5)
levels<-as.ordered(e)
language_domains_social_solidarity <- data1 %>%
  dplyr::select(E1,E2,E3,cluster)
names(language_domains_social_solidarity) <-c("E1","E2","E3","PAM cluster")
language_domains_social_solidarity_gathered <- language_domains_social_solidarity %>%
  gather(key="data1",value="e",-"PAM cluster")

ggplot(language_domains_social_solidarity_gathered,
       aes(x=data1,fill=levels)) +
  geom_bar(stat="count",position="dodge",width=0.7)  +
  theme_ipsum(grid="Y") + scale_fill_brewer(palette="Set2") +
  labs(title="Environmental Self Identity") +
  xlab("Questions")+ theme(axis.text.x =
                         element_text(angle = 20,hjust=1,size=8),
                       legend.position="bottom",
                       legend.text=element_text(size=10))+
  ylab("Number of respondents") + facet_grid(~`PAM cluster`)



ggplot(demos,aes(x=Age,fill=cluster)) +
  geom_bar(stat="count",position="dodge",width=0.7)  +
  theme_ipsum(grid="Y") + scale_fill_brewer(palette="Set2") +
  labs(title=" Age",
       subtitle="") +
  xlab("Age")+
  ylab("Number of respondents")

ggplot(demos,aes(x=Gender,fill=cluster)) +
  geom_bar(stat="count",position="dodge",width=0.7)  +
  theme_ipsum(grid="Y") + scale_fill_brewer(palette="Set2") +
```

```
  labs(title=" Gender", ) +
  xlab("Gender")+
  ylab("Number of respondents")

ggplot(demos,aes(x=Age,fill=cluster)) +
  geom_bar(stat="count",position="dodge",width=0.7)  +
  theme_ipsum(grid="Y") + scale_fill_brewer(palette="Set2") +
  labs(title=" Gender and Age",
    ) + theme(axis.text.x = element_text(angle = 20,hjust=1,size=5),
              legend.position="bottom",
              legend.text=element_text(size=8)) +
  xlab("Age")+
  ylab("Number of respondents") + facet_grid(~Gender)
x<-data.frame(demos[,c(3,22)])
filter(x,Age=="26 – 30",cluster==1)
```