RESEARCH PAPER

Analysis of Factors for the Knowledge Component on Biomedical Waste Management among Health Professionals: A Hospital Based Study

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ABSTRACT
Biomedical Waste is a worldwide problem. Currently there is a steady increase in its generation associated with increasing demand of healthcare, thus leading to establishment of more Health Care Centres. Biomedical waste generated contains infectious and hazardous materials. It is crucial on the part of the health care workers to know the hazards of the biomedical waste in the work environment and make its disposal effective and scientific manner. It is critical that the different professionals working in the healthcare sector have adequate Knowledge with respect to biomedical waste management.
The study aims at identifying factors that can bring about changes in the knowledge levels of the health care personnel
When the analysis was carried out in SPSS software and R factor software, 2 factors were identified and extracted which will probably help the authorities to formulate training plan in the organisation and also accordingly plan the strategies according to the cadres and also better the practices.
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INTRODUCTION

Biomedical waste (BMW) is a type of garbage that is generated daily in India and contains infectious and harmful materials. It is critical for personnel to understand the hazards of biological waste in the workplace and to dispose of it efficiently and scientifically. The many personnel working in the healthcare industry must have sufficient knowledge about biomedical waste management.

Health-care professionals with sufficient knowledge of biological waste management rules and regulations, as well as a grasp of segregation, will be able to dispose of waste competently in their respective businesses.(Kini.B.S et al ,2014, Rao D et al 2018) [1,2] Acceptable biomedical waste management starts with waste generation and continues with waste segregation at the source, storage on site, disinfection, and transfer to the final disposal site. As a result, an adequate understanding of the staff of healthcare institutions is critical.(Rao D et al 2018, Pattnaik S, Reddy MV ,2010, Prem Nath A et al,2010, Mathur V et al ,2010) [2, 3, 4,5]

Factor analysis' main goal is to synthesize data so that relationships and patterns may be easily evaluated and comprehended. It's typically used to organize variables into a small number of clusters based on their shared variance. As a result, it aids in the separation of constructs and concepts. (An Gie Yong and Sean Pearce, 2013) [6].

To uncover patterns in a group of variables, factor analysis employs mathematical approaches for the simplification of associated measures (Child, 2006), [7]. Parsimony refers to the process of attempting to find the simplest approach of

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interpreting observable data, which is what factor analysis is all about. (Harman, 1976)[8].

Exploratory factor analysis (EFA) is a widely used and broadly applied statistical approach in information systems, social science, education, and psychology. Recently, exploratory factor analysis was applied for a wide range of applications, developing an instrument for the evaluation (Lovett and Zeiss 2002)[9],as well as in other fields.

Factor analysis is a technique for condensing a huge number of variables (factors) into a reasonable quantity. It also develops underlying dimensions between measurable parameters and latent constructs, allowing for theory construction and refinement. It also shows that self-reporting scales have construct validity.(Gorsuch 1983; Hair, Anderson et al. 1995a; Tabachnick and Fidell 2001, Thompson 2004).[,10,11,12,13]

Dimensionality Assessment of Ordinal Variables: an exploratory factor analysis of polychoric correlations

Researchers in the social sciences are primarily interested in investigating the inherent (latent) - observable (dormant) characteristics that are the determinants of observed behavior. [14] (Bollen, 2002) Motives, sentiments, and aptitudes are examples of latent variables that can describe a wide range of behavioral processes with a small number of constructs. (Hoyle & Duvall, 2004,) [15]. The underlying variables or components are random, and their characteristics must be explained using statistical models that link the inherent variables to manifest as observed variables. This is thought to be the outcome of at least one or more components, which are investigated using factor analysis. (Mulaik and Millsap, 2000, p. 15)[16] . The factor analysis is a primary statistical approach for explaining the relationships between a potentially large number of observed variables using a smaller number of factors that represent the underlying processes. (Browne &Cudeck, 1993; Hoyle & Duvall, 2004) [15,17]. Though both principal components analysis and factor analysis are used to reduce bigger variables into a smaller number of factors or components, they are essentially different methodologies.

Factor analysis is used to reveal if there are any hidden variables and to explain the link between the present variables. Principal components analysis is a technique for generating new variables (called principal components) that are uncorrelated and linear composites of the original variables. Pearson[18] presented Principal Component Analysis as part of the multivariate approach in 1901, which was independently developed by Hotelling in 1933.[19]

PCA is mainly used as a variable reduction method to decrease the number of variables without losing the information from the available data set.

- The main objectives of principal component analysis are to decrease the larger number of variables from the initial data to a lesser number of principal components and also provide for a regression equation for the basic underlying process by using the predictor variables.
- PCA technically delivers proportionately a small set of variables termed as principal components, which explains the maximum variance in the initial data set.

The purpose of the rotation is to analyze and simplify the data format. Rotations help in selecting, retaining the correct number of factors and can also in the explanation of the result. The Kaiser criterion, in software packages, is used to retain all factors with Eigenvalues greater than one.

AIMS AND OBJECTIVES

The main aim of the study was to assess the knowledge of healthcare personnel and also identify factors that play an important role in biomedical waste management in selected hospitals of Mysore city.

The objectives of the present study:

To assess the knowledge of the various cadres of hospital-based staff working in ten selected hospitals across Mysore city.

2. To determine the number of factors with ordinal variables from a set of factors

3. To develop an appropriate set of factors to assess the knowledge about the biomedical waste management

METHODOLOGY

A basic hypothesis of EFA is that there are m common 'latent' factors to be discovered in the dataset, and the goal is to find the smallest number of common factors that will account for the correlations (McDonald, 1985)[20].

Model

- The knowledge scores of the study respondents from the different cadres of staff viz: doctors, postgraduates, interns, nurses, technicians, and house-keeping staff from the ten hospitals were entered into an MS Excel sheet and used for the analysis. The SPSS and the R factor software were used for the analysis.
- The main objective of the PCA method is the construction of a given set of variables

Xj's (j=1,2.3,…..k) of new variables (pi) are called principal components which are linear combinations of the Xs .

PCjk = ajiXki+aj2Xk2+aj1Xk1+….+ajnXkn ………………………. (1)

where "PCjk" is the score for object "k" on component "j",

"aji" is the loading of a variable "I" on component "k",

"ki" is the measured value of a variable "I" on object "k" and

"n" is the original number of variables.

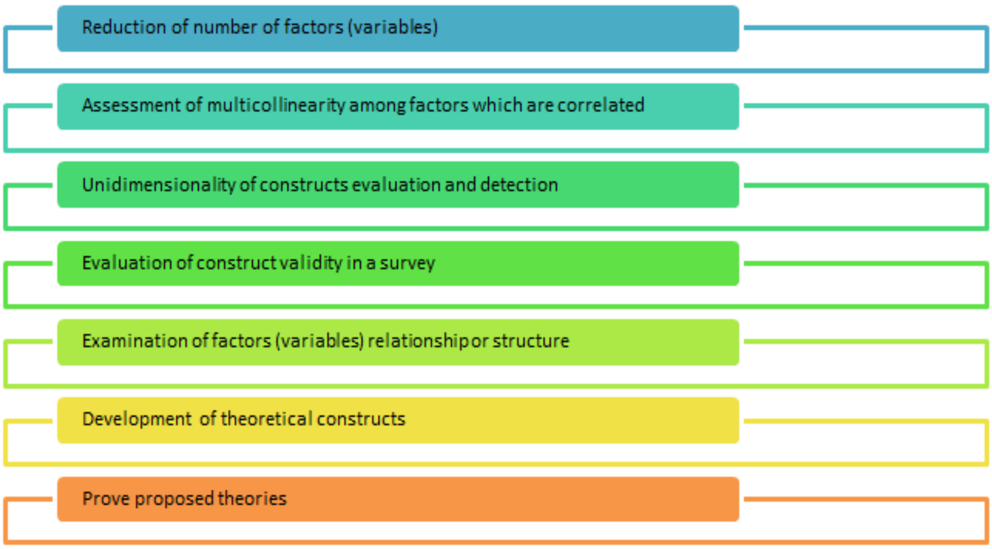
The "aji" are called loadings and are worked out in such a manner that the extracted principal components satisfy two conditions:

Principal components are uncorrelated (orthogonal) and The first principal component (p1) has the maximum variance; the second principal component (p2) has the next maximum variance and so on. This decrease in dimensionality is achieved without loss of variance in the data.

The principal components thus obtained were used instead of original variables for further analysis.

Model Assessment Criteria:
To ensure that the available data is appropriate for Principal component Analysis, tests of reliability and adequacy of the data Kaiser-Meyer-Olkin (KMO) and Bartlett's Tests were used to calculate the correlation among all variables analyzed and the sample for EFA Kaiser-Meyer-Olkin Measure (KMO) of Sampling Adequacy (cut off above .30) and the diagonal element of the Anti-Correlation matrix that has the 'a' superscript (cut-off of above .30) were used

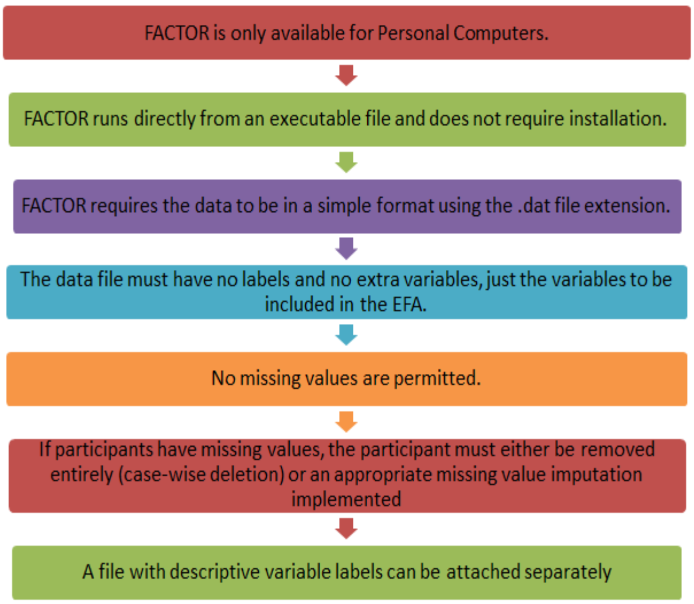
Objectives of Exploratory Factor Analysis (Pett, Lackey et al. 2003, Thompson 2004)[21,13]are:



Smart Art 1: Objectives of Exploratory Factor Analysis

DEMONSTRATINGR FACTOR:

Creation of Data Set:
The data set was prepared in the data/ text file format. A separate text file for the knowledge and the practice scores were used.

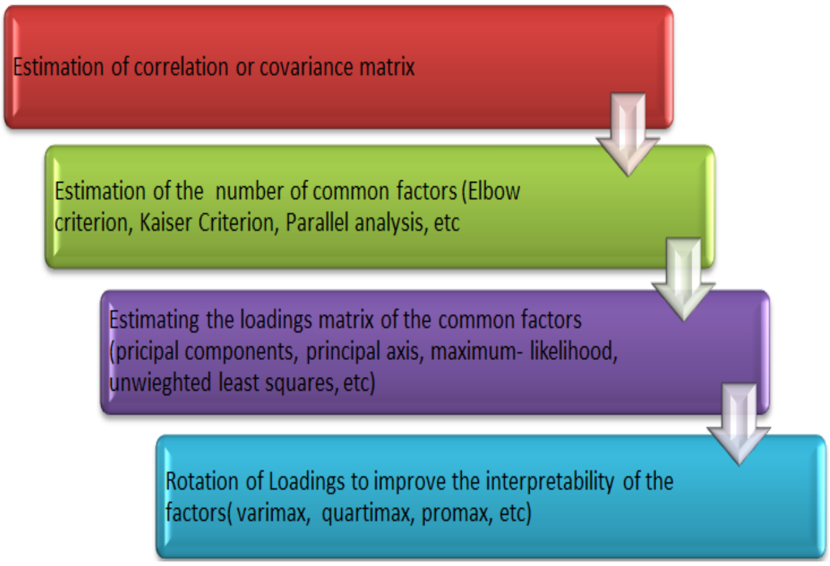


Smart Art 2: Creation of Data Set:

When using the principal axis factoring as the extraction method it should correspond to the principal axis method in R factor analysis and to either "principal axis factoring" or unweighted least squares" in SPSS.(this is according to the R documentation). Since the interpretation is followed according to the "pattern matrix" and the factors are expected to be correlated, Promax oblique rotation method was used.

Simultaneously carrying out the analysis in R and SPSS, sometimes differences are noted.

The two analyses when carried out give a different set of loadings in the pattern matrix. The cumulative variances explained by the R factor and by SPSS factors are slightly different



Factor analysis was used to reduce the dimensionality of the data without losing any scientific information.

RESULTS:
Exploratory factor analysis (EFA)is a common method, widely adopted in social sciences, to explore the underlying pattern of the relationship in the variables.

The researchers intend to decrease the total number of variables in a small number of factors which are composed of highly related variables (Fabrigar, Wegener, MacCallum, & Strahan, 1999, Mamatha. H.K, 2018,) [22, 23], proposed EFA for the above purpose and used appropriate extraction methods and factor rotations.

The result of the knowledge and questions are subjected to analysis using

1. SPSS version 22
2. R factor analysis as proposed by Lorenzo-Seva & Ferrando, 2006).[24]

In the present study, an effort was made to identify the factors that may influence the knowledge and the practices regarding sound management of health care waste among the workers. The number of factors that were with ordinal variable from a set of factors was 32

R – Factor Analysis
The analysis was also performed using Factor – R package for knowledge and practice scores of the questionnaire

The knowledge data collected from 6 cadres in 10 hospitals where the responses were in Likert's scale, was uploaded in the R factor analysis package.

The knowledge component had 12 questions from 2000 subjects, from the different cadres leading to total data points 2000X 12 = 24,000.

The R factor recommends the use of polychoric correlations if the skewness and the kurtosis values are more than 1.

Table 1: Univariate descriptives of the knowledge questions data in the R factor package

Variable	Mean	Confidence Interval (95%)	Variance	Skewness	Kurtosis (Zero centered)
V 1	1.230	(1.20 1.26)	0.334	2.370	4.139
V 2	1.875	(1.84 1.91)	0.377	0.080	-0.424
V 3	1.138	(1.11 1.16)	0.182	3.219	9.76
V 4	1.275	(1.24 1.31)	0.369	2.051	2.778
V 5	1.500	(1.46 1.54)	0.512	1.072	-0.265
V 6	1.614	(1.57 1.66)	0.569	0.770	-0.845

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V 7	1.342	(1.31 1.38)	0.413	1.664	1.387
V 8	1.340	(1.31 1.38)	0.372	1.601	1.376
V 9	1.747	(1.71 1.79)	0.472	0.373	-0.873
V 10	1.568	(1.53 1.61)	0.561	0.895	-0.668
V 11	1.388	(1.35 1.43)	0.486	1.507	0.713
V 12	2.306	(2.26 2.35)	0.678	-0.618	-1.250

The Mardia's (1970) [25], multivariate asymmetry, skewness, and kurtosis result reveals that the skewness is not statistically significant at 1% or at 5% probability level

Table 2: Mardia's multivariate asymmetry, skewness, and kurtosis

	Coefficient	**Statistic**	**df**	**P**
Skewness	39.599	13199.567	364	1.0000
Skewness corrected for small sample	39.599	13222.416	364	1.0000
Kurtosis	235.098	81.852		0.0000**
** Significant at 0.05				

The results that are presented in the tables support the decision of using polychoric correlation instead of Pearson's correlation.

2 tests for the adequacy of the data for further analysis, i.e, Bartlett's statistic test and Kaiser-Meyer-Olkin (KMO) test statistics

Table 3: Bartlett's statistic test and Kaiser-Meyer-Olkin (KMO) test statistics

Determinant of the matrix = 0.059701827766305
Bartlett's statistic=5620.3 (df = 66; P = 0.000010)
Kaiser-Meyer-Olkin (KMO) test = 0.84351 (good)

The results reveal that both tests show satisfaction with a substantial correlation between the items. Bartlett's statistic test shows significance at 66 df and 1% probability level. The Kaiser-Meyer-Olkin (KMO) test statistics value is also more than 0.8. These results reveal the suitability of the data for factor analysis

The explained variance based on the eigenvalues (EV) is presented in the table. The first five factors and their proportion of the variances and the proportion of the cumulative variance too. The first five factors account for the maximum variance. For the remaining factor, i.e., 6 – 12, the cumulative percentage of variance was very less and the cut-off point for the factors was 5 alone. However, the recommendation of the manual states the first 3 factors are more reliable than the rest.

Table 4: Variance based on the eigenvalues (EV)

Variable	**Eigenvalue**	**Proportion of Variance**	**Cumulative Proportion of Variance**
1	3.99331	0.33278	0.33278
2	1.21775	0.10148	0.43425
3	1.11220	0.09268	0.52694
4	0.85913	0.07159	0.59853
5	0.83880	0.06990	0.66843

Communality and the unrotated loading matrix are presented in the table below. We have used varimax orthogonal rotation to rotate the loading variables

Table 5: Unrotated loading matrix and communality for knowledge questions:

Variable	**C 1**	**C 2**	**C 3**	**C 4**	**C 5**	**Communality**
V 1	-0.245	0.009	-0.268	0.298	-0.194	0.771
V 2	-0.258	-0.228	-0.280	-0.014	-0.218	0.649
V 3	-0.249	0.200	0.070	-0.080	-0.118	0.700
V 4	-0.411	0.110	-0.115	-0.165	-0.001	0.601
V 5	-0.502	-0.063	-0.099	0.018	0.334	0.738
V 6	-0.496	-0.113	-0.066	0.107	0.367	0.719
V 7	-0.451	-0.098	-0.023	-0.126	-0.004	0.554

V 8	-0.446	0.002	0.081	-0.122	-0.056	0.601
V 9	-0.322	0.091	0.264	0.422	0.013	0.763
V 10	-0.348	-0.111	0.461	0.026	-0.165	0.665
V 11	-0.464	0.109	0.015	-0.044	-0.021	0.473
V 12	-0.079	-0.693	0.195	-0.047	-0.085	0.787

(loadings lower than absolute 0.300 omitted)

Table 6: Rotated Loading Matrix

Variable	C 1	C 2	C 3	C 4	C 5
V 1					0.832
V 2				0.323	0.655
V 3	0.778				
V 4	0.603	0.423			
V 5		0.822			
V 6		0.811			
V 7	0.501	0.456			
V 8	0.645	0.350			
V 9			0.828		
V 10	0.450		0.514	0.430	
V 11	0.536	0.358			

The first component accounted for 6 loadings, i.e, variable 3, 4, 7,8,10, whereas the second component loaded variables 4,5,6,7,8,11. The 3 rd component loaded 9, 1 0, the fourth component loaded 2, 10,12, and the fifth component loaded variables 1 and 2. The exhibit values in the above table are not compactable with the results as there is no reduction in the number of factors.

Therefore it is concluded that Likert's scale ordinal variable, we can use R factor score with proper Parallel Analysis.

SPSS Analysis

The knowledge data were uploaded in the SPSS package and the results are presented. The SPSS package was used to analyze the Likert scale variables collected from 10 hospitals in Mysuru city. The data was collected from 6 cadres in 10 hospitals, except the nonteaching hospitals where some hospitals did not have postgraduates or interns.

The 12 questions from the knowledge component for 2000 subjects, from the different cadres from the hospitals for the analysis. The total data points 2000X 12 = 24,000. All the questions were on a three-point Likert scale as options for answering

Table 7: Correlation Matrix of the knowledge questions score in SPSS

Correlation Matrix													
		V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
Correlation	V1	1.000	.233	.149	.265	.250	.214	.221	.210	.152	.087	.250	-.015
	V2	.233	1.000	.142	.235	.231	.252	.314	.230	.091	.066	.174	.141
	V3	.149	.142	1.000	.407	.238	.249	.334	.399	.281	.266	.378	-.154
	V4	.265	.235	.407	1.000	.466	.335	.328	.451	.162	.190	.461	-.007
	V5	.250	.231	.238	.466	1.000	.536	.450	.420	.255	.235	.354	.049
	V6	.214	.252	.249	.335	.536	1.000	.395	.352	.274	.217	.376	.091
	V7	.221	.314	.334	.328	.450	.395	1.000	.548	.221	.250	.374	.108
	V8	.210	.230	.399	.451	.420	.352	.548	1.000	.302	.331	.380	.075
	V9	.152	.091	.281	.162	.255	.274	.221	.302	1.000	.258	.259	.008
	V10	.087	.066	.266	.190	.235	.217	.250	.331	.258	1.000	.265	.183
	V11	.250	.174	.378	.461	.354	.376	.374	.380	.259	.265	1.000	.022
	V12	-.015	.141	-.154	-.007	.049	.091	.108	.075	.008	.183	.022	1.000
Sig. (1-tailed)	V1		.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.255
	V2	.000		.000	.000	.000	.000	.000	.000	.000	.002	.000	.000
	V3	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000
	V4	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000	.377
	V5	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000	.014

	V6	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000
	V7	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000
	V8	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000
	V9	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000	.353
	V10	.000	.002	.000	.000	.000	.000	.000	.000	.000		.000	.000
	V11	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000		.167
	V12	.255	.000	.000	.377	.014	.000	.000	.000	.353	.000	.167	

Table 8: Covariance Matrix[a] (a. Determinant = 1.99E-006)

The inverse of the Covariance Matrix of the knowledge questions score in SPSS

Inverse of Covariance Matrix												
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1	3.462	-.491	.136	-.382	-.216	-.081	-.139	-.052	-.176	.036	-.312	.128
V2	-.491	3.171	-.130	-.317	-.025	-.275	-.600	-.063	.038	.175	.070	-.303
V3	.136	-.130	8.185	-1.325	.492	-.149	-.664	-.810	-.634	-.613	-.671	.872
V4	-.382	-.317	-1.325	4.559	-1.059	-.008	.351	-.965	.332	.111	-.925	.013
V5	-.216	-.025	.492	-1.059	3.449	-1.089	-.712	-.289	-.221	-.165	-.007	.084
V6	-.081	-.275	-.149	-.008	-1.089	2.758	-.305	-.058	-.280	-.039	-.419	-.123
V7	-.139	-.600	-.664	.351	-.712	-.305	4.145	-1.534	.090	-.045	-.410	-.183
V8	-.052	-.063	-.810	-.965	-.289	-.058	-1.534	4.821	-.430	-.464	-.105	-.103
V9	-.176	.038	-.634	.332	-.221	-.280	.090	-.430	2.584	-.301	-.223	.031
V10	.036	.175	-.613	.111	-.165	-.039	-.045	-.464	-.301	2.234	-.241	-.393
V11	-.312	.070	-.671	-.925	-.007	-.419	-.410	-.105	-.223	-.241	3.110	-.008
V12	.128	-.303	.872	.013	.084	-.123	-.183	-.103	.031	-.393	-.008	1.670

To measure the appropriateness of the data for factor analysis, Kaiser-Meyer-Olkin (KMO) is used as a measure of sampling adequacy, the value of which can vary from 0-1.

To test if the original correlation matrix was an identity matrix Bartlett's test of sphericity was used.

Table 9: KMO and Bartlett's Test

KMO and Bartlett's Test[a]		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.844
Bartlett's Test of Sphericity	Approx. Chi-Square	5620.345
	df	66
	Sig.	.000
a. Based on correlations		

Table 10: Extracting the factors:

Several methods are available to extract the factors in SPSS. We have used the Principal Component Analysis(PCA). PCA is a multivariate analysis technique used to reduce the dimensionality of the data set.

Communalities:

Communalities is the proportion of each observed variable from all the factors associated with it. The initial and the extracted communalities are presented

Table 11: Communalities of the components initially and after extraction

Communalities				
	Raw		Rescaled	
	Initial	Extraction	Initial	Extraction
V1	.335	.334	1.000	.999
V2	.378	.378	1.000	1.000
V3	.182	.093	1.000	.511
V4	.369	.359	1.000	.972
V5	.512	.509	1.000	.994
V6	.569	.569	1.000	1.000

V7	.413	.411	1.000	.994
V8	.372	.372	1.000	1.000
V9	.472	.471	1.000	.998
V10	.562	.561	1.000	.999
V11	.487	.486	1.000	1.000
V12	.679	.677	1.000	.998
Extraction Method: Principal Component Analysis.				

Extraction:
Several extraction methods are available for factor analysis. PCA is the default extraction method in SPSS. The PCA extracts the uncorrelated variables in a linear combination and provides a maximum variance.

The variance accumulated by 12 PCA components is 100%, out of which component 1 accumulated 32.53% of the variance. The cumulative percentage of variance for PC1 to PC5 is 69.75%. The components PC6 to PC12 accounted for fewer number variances and are not considered in the study.

Normally more than 75% of the variance is considered for any study but in social sciences, 60% of the variance is enough to carry out the study. (Joseph F et al, pg 107) [26]

Table 12: Total Variance Explained among the components using Initial Eigenvalues

		Initial Eigenvalues [a]		
	Component	Total	% of Variance	Cumulative %
Raw	1	1.733	32.526	32.526
	2	.719	13.486	46.011
	3	.514	9.648	55.659
	4	.392	7.362	63.021
	5	.359	6.730	69.751
	6	.331	6.205	75.956
	7	.300	5.628	81.584
	8	.275	5.163	86.748
	9	.243	4.556	91.303
	10	.207	3.886	95.189
	11	.147	2.763	97.952
	12	.109	2.048	100.000

Table 13: Total Variance Explained among the components after Rotation Sums of Squared Loadings

		Rotation Sums of Squared Loadings		
	Component	Total	% of Variance	Cumulative %
Raw	1	.455	8.539	8.539
	2	.484	9.075	17.615
	3	.682	12.793	30.407
	4	.563	10.573	40.980
	5	.416	7.797	48.778
	6	.347	6.521	55.299
	7	.388	7.285	62.584
	8	.504	9.452	72.035
	9	.550	10.329	82.365
	10	.469	8.803	91.167
	11	.362	6.784	97.952

SCREE PLOT
Cattell's (1966)[27], screen test, is an alternative to the Kaiser's value. The eigenvalues are plotted on the ordinate (Y axis) with the order or variables presented on the X-axis. The visual inspection of the scree plot provides the number of factors that are to be retained for the analysis. This is taken as the point that the inflection occurs signifying the flattening of the line as the best fit. The scree plot(SP)in the figure also confirms that the first five components are sufficient for this study. The remaining components are (PC6- PC-12) are in a straight line parallel to the X-axis.

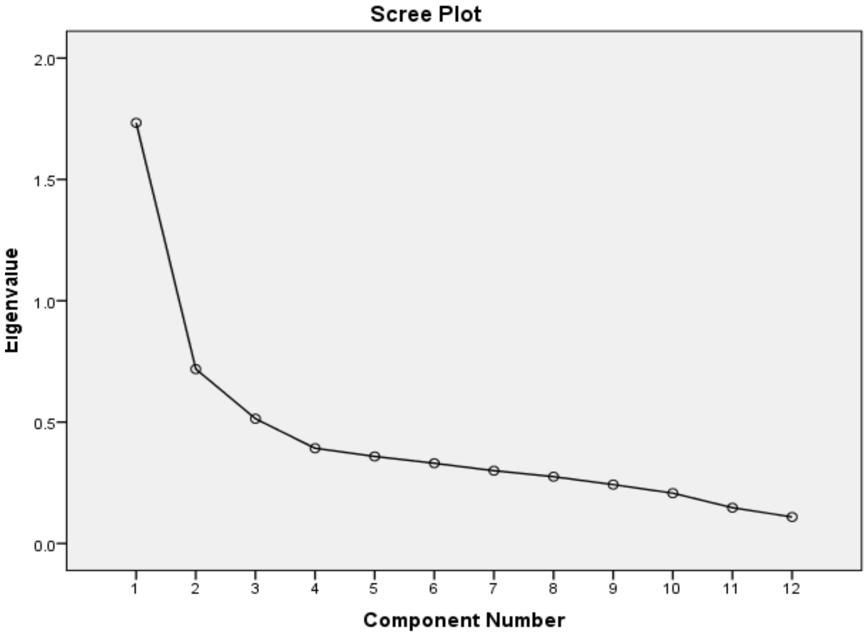

Figure 1: Scree Plot fro extraction of factors

Both the cumulative percentage and the scree plot, support the extraction to nearly 70% of the variance

COMPONENT MATRIX

The component matrix that is extracted using SPSS is presented in the table. From the table, it is observed that eight variables show values greater than 0.3, which indicates that the maximum variance is retained by these variables i.e, the PCA-1, whereas PCA 2, PCA 3, PCA 4,and PCA 5 shows one variable in each.

Table 14: Component Matrix

Component Matrix[a]					
	Raw Component				
	1	2	3	4	5
V1	.227	-.078	-.104	.090	.184
V2	.248	.065	-.247	.112	.234
V3	.212	-.112	.090	.076	.035
V4	**.387**	-.115	-.075	.196	-.033
V5	**.526**	-.072	-.159	-.137	-.197
V6	**.537**	-.025	-.188	-.337	-.198
V7	**.443**	.010	-.078	.104	.044
V8	**.427**	-.017	.054	.123	.050
V9	**.329**	-.051	.286	**.346**	**.378**
V10	**.376**	.219	**.509**	.098	-.194
V11	**.463**	-.099	.048	.200	.034
V12	.133	**.785**	-.124	-.007	.059
Extraction Method: Principal Component Analysis.					
a. 11 components extracted.					

ROTATION

Varimax rotation was applied to maximize the sum of the variances of the squared loadings. The squared loadings of the component without rotation are more or less similar to the un-rotated matrix. The first PCA after rotation, instead of eight variables loaded in un-rotated condition, has one loaded after varimax rotation. Out of the 12 variables applied in the study, 12 loadings were higher in the un-rotated components .i.e., above 0.3, whereas in rotated components, instead of 12, 5 variables accompanied the same variances.

Table 15: Rotated Component Matrix[a]

Rotated Component Matrix[a]							
	Raw Component						
	1	2	3	4	5	6	7
V1	.057	.032	-.008	.013	.039	**.564**	.058
V2	.057	.014	.043	.005	.070	.062	**.597**
V3	.213	.087	-.086	.080	.105	.006	.022
V4	**.553**	.004	.017	.018	.029	.074	.055
V5	.131	.070	.010	.062	.122	.071	.060
V6	.102	.085	.032	.057	.104	.059	.077
V7	.094	.046	.035	.057	**.579**	.053	.090
V8	.147	.078	.020	.087	.146	.045	.051
V9	.056	**.665**	-.002	.074	.043	.039	.016
V10	.074	.082	.072	.723	.059	.017	.005
V11	.169	.070	.003	.073	.091	.072	.037
V12	-.043	-.002	**.815**	.074	.032	-.011	.056
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.[a]							
a. Rotation converged in 6 iterations.							

Variable 4, i.e. question no 4 “Does your health care setting have a waste management plan”, with the options of Yes/No/ Not sure, on a three-point Likert scale, which accounted for 32.53% of the variance. Therefore it was concluded that the question” Does your health care setting have a waste management plan” is the primary question and the remaining 11 questions are the supporting questions to this question. It can be explained that if the healthcare institutions have a waste management plan, then only it is possible to carry out the waste management activities. Therefore question no 4 is substantial in explaining the waste management irrespective of the cadres and the type of hospitals. Hence we can PC1 as the hospital waste management plan component.

The 2[nd] component that explains the variance which is greater than the rest is a question no 9 “Is the waste generated at the source, stored in the same area itself”, which accounts for 13.49% of the variance of the total variance proposed in the study. Question no 9 talks about the waste generation storage at the source of generation itself. Both these components accommodate around nearly 50 % i.e., 46.02%. If these two questions are properly addressed in the health care institutes (hospitals), and among the different cadres, the need to ask the other questions regarding waste management may not be required.

So it is concluded that the primary aspects in waste management, as well as the related issues, are concentrated in

a. The waste management plan of the hospital
b. Storage facilities at the point of generation of the waste.

If both these questions are properly addressed in any hospital, the awareness of hospital waste management will increase in the cadres.

The conclusion drawn from the study was supported by the component plot in the figure, where PCA 1 and PCA2 are away from the rest of the PCAs in the study.

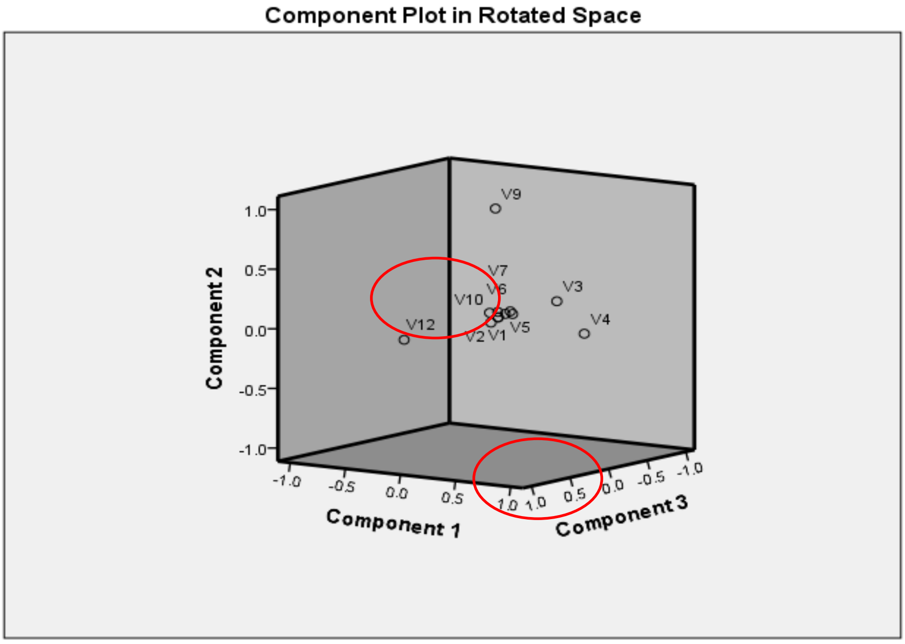

Figure 2: Extraction of factors from the components

In SPSS, only limited factors were loaded which could be used for dimensionality reduction. From the foregoing study, we have understood that for any practical related solution we have to use both IBM-SPSS and Likert's ordinal scale in R package analysis and compare the results for the definite conclusion, instead of using one package for a practical solution with a definite conclusion.

DISCUSSION

Many studies were carried out previously on managerial and operational aspects of healthcare waste management which focuses on knowledge, attitude and the practice components of the staff working at the hospitals. These were related to different aspects of rules and regulations of waste management and the standard operating procedures followed at the individual organizations. **Studies identifying the factors that are responsible for these are rare in the literature**. Hence it is important to identify these factors as they can be useful to the managers and the policy makers to bring about a behavioral change in the staff. This change could be by using motivational factors or monetary incentives. The exact policy may vary between the organizations; it becomes very important to identify the factors that can bring about an influential change in behavior. **This study was an attempt to identify the factors that can bring about the change in the knowledge and the practices of health care workers to adopt sound health care waste management practices.** The variable correlation matrix was used to check the multi-collinearity of the data. Sample adequacy was checked using Kaiser-Meyer-Olkin (KMO) test. The KMO value was .844 for knowledge in SPSS and 0. 843 in R-factor. The KMO values for practice scores were 0.835 in SPSS and 0.835 in R factor, which is greater than the minimum requirement of 0.5. The P value for the Bartlett's test was <0.001; hence, the null hypothesis regarding the correlation matrix being an identity matrix was rejected. A total of five factors, were extracted based on principal component analysis (PCA). The extracted factors represented 69.75% for knowledge questions and 68.82 % for practice questions, which explained the variance in the model. The factors were rotated using varimax to have a simple structure (Pritchard, 1984) [28] with minimum cross-loadings. We retained only those variables that had factor loadings above 0.3. For cross-loading items, a cut off value of around 0.3 (Anderson et al., 2015) [29] was used.

In the Knowledge Component:

The variable 4, i.e.the question no 4 "Does your health care setting have a waste management plan" and the 2nd component explains the variance which is greater than the rest is question no 9 "Is the waste generated at the source, stored in the same area itself" were the Principal Components that were extracted .

CONCLUSION

The rise in demand for healthcare services and the growth of healthcare institutions has resulted in an exponential increase in biomedical waste production. It is suggested that the proper handling of biological waste at the source is the most acceptable method of disposal. The involvement of doctors, postgraduates, interns, nurses, technicians, and housekeeping staff in the assessment of their knowledge becomes highly significant because healthcare workers from all strata of the healthcare system are directly or indirectly involved in its development. Factor analysis aids in the measurement of latent characteristics that are difficult to assess directly. This offers the additional benefit of condensing the data set into a smaller number of characteristics without sacrificing critical information. Behavioral studies are performed to better understand the cognitive rationale underlying a certain behavioral trend. The goal of this study was to figure out what elements are crucial in changing current knowledge among healthcare workers.

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