

## **Validity Testing with Exploratory Factor Analysis in R: An Evaluation of a Questionnaire on Acceptance of Human Resource Information System in Central Universities**

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### **ABSTRACT :**

*The technique of measuring the accuracy of research instruments (especially questionnaires) known as validity and its importance specially in research have been discussed in several studies. However, their measure is not usually carried out among social science researchers in developing countries. This has been linked to the dearth of knowledge of these tests. This is a review article which explores and describes the construct validity of a research instrument (with special reference to questionnaire). It discusses pre-requisites of validity test and different steps of validity test. The paper further conduct the test on the responses of a questionnaire on user opinion on acceptance of Human Resource information System (HRIS) by Central universities and interprets the result using open source statistical package R.*

**Key words :** Construct, HRIS, Questionnaire, Validity, R

### **1. INTRODUCTION :**

Research in field of social science is complex and mostly based on qualitative data. To avoid socially prefer answers and be able to receive information on the qualitative data, researchers prefers the use of questionnaires asking with evaluative statements. However, the use of such method does not necessarily mean valid indications of someone response can be obtained. It may happen that in the end, some items of the questionnaire can measure a completely different construct. Therefore it is necessary that, a researcher must conduct validity testing of the questionnaire, if any before proceeding with research (Rattray & Jones, 2007). Another major challenge a researcher faces with qualitative data is that the data need to be quantified before conducting any statistical analysis. One of the commonly used technique is Likert scale representation though the distribution of Likert item data fails normality test. This restricts the researcher in using many reliable statistical tools based on normal distribution. In this paper exploratory factor analysis method is used extensively with which validity of a likert scale based questionnaire can be tested (Rattray

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& Jones, 2007). The paper evaluates a questionnaire on user opinion on acceptance of Human Resource information System (HRIS) in Central universities of North East India and discusses different stages of exploratory factor analysis using open source statistical package R.

## 2. COLLECTION OF DATA:

To know user opinion on acceptance of Human Resource information System in central universities, a questionnaire with 11 items have been designed and forth five number of participants have indicated their level of agreement with a 5-point Likert scale (ranging from strongly agree to strongly disagree).

The responses are captured in excel file and then converted into CSV file format. The file is read in R in a data set called “tacntq” and the contents of the dataset is shown in Annexure-A.

## 3. DESCRIBING THE DATA :

It is suggested to look at the data before running any analysis. This will help the researcher to identify and omit any participant who is missing any piece of data. The summary of dataset “tacntq” can be seen with described function in R as shown in Table 1. The table suggests that no items are having missing participants as the number of observations in all cases are 45.

**Table : 1**  
**Summary of the dataset “tacntq”**

| >describe(taccntq) |    |      |      |        |         |      |      |     |       |      |          |       |      |
|--------------------|----|------|------|--------|---------|------|------|-----|-------|------|----------|-------|------|
| vars               | n  | mean | sd   | median | trimmed | mad  | min  | max | range | skew | kurtosis | se    |      |
| q1                 | 1  | 45   | 4.84 | 0.37   | 5       | 4.92 | 0.00 | 4   | 5     | 1    | -1.84    | 1.41  | 0.05 |
| q2                 | 2  | 45   | 4.44 | 0.62   | 4       | 4.49 | 1.48 | 2   | 5     | 3    | -1.17    | 2.68  | 0.09 |
| q3                 | 3  | 45   | 4.51 | 0.73   | 5       | 4.59 | 0.00 | 1   | 5     | 4    | -2.47    | 9.32  | 0.11 |
| q4                 | 4  | 45   | 4.67 | 0.56   | 5       | 4.76 | 0.00 | 3   | 5     | 2    | -1.40    | 0.95  | 0.08 |
| q5                 | 5  | 45   | 4.73 | 0.45   | 5       | 4.78 | 0.00 | 4   | 5     | 1    | -1.02    | -0.98 | 0.07 |
| q6                 | 6  | 45   | 4.40 | 0.58   | 4       | 4.43 | 0.00 | 3   | 5     | 2    | -0.30    | -0.87 | 0.09 |
| q7                 | 7  | 45   | 4.40 | 0.72   | 5       | 4.49 | 0.00 | 3   | 5     | 2    | -0.73    | -0.80 | 0.11 |
| q8                 | 8  | 45   | 4.56 | 0.69   | 5       | 4.68 | 0.00 | 3   | 5     | 2    | -1.20    | 0.03  | 0.10 |
| q9                 | 9  | 45   | 3.60 | 0.89   | 4       | 3.62 | 1.48 | 2   | 5     | 3    | 0.08     | -0.88 | 0.13 |
| q10                | 10 | 45   | 3.71 | 1.08   | 4       | 3.78 | 1.48 | 1   | 5     | 4    | -0.38    | -0.77 | 0.16 |
| q11                | 11 | 45   | 3.58 | 1.31   | 4       | 3.70 | 1.48 | 1   | 5     | 4    | -0.47    | -0.93 | 0.19 |

#### **4. EXPLORATORY FACTOR ANALYSIS :**

Common factor analysis (CFA) also known as principal axis factoring and principal component analysis (PCA) are two widely used multivariate techniques having different goals: PCA is a technique for reducing the dimensionality of one's data, whereas EFA is a technique for identifying and measuring variables that cannot be measured directly (i.e., latent variables or factors) . Thus, in PCA all of the variance in the data – reflected by the full correlation matrix – is used to attain a solution, and the resulting components are a mix of what the variables intended to measure and other sources of variance such as measurement error .By contrast, in EFA not all of the variance in the data comes from the underlying latent variable ( de Winter et.al., 2016).

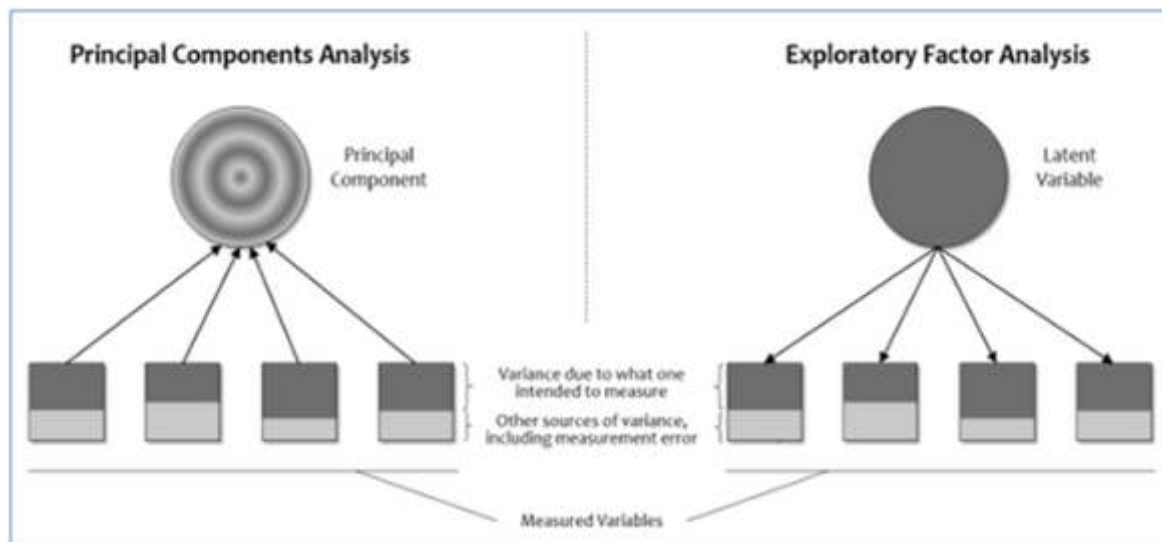


Figure 1 : Graphical comparison of principal components analysis and exploratory factor analysis. (de Winter et.al., 2016).

Figure 1 illustrates that important distinction between PCA and EFA. The arrows in PCA are pointing from the measured variables to the principal component and in EFA it's the other way around. The arrows represent causal relations, such that the variability in measured variables in PCA cause the variance in the principal component. This is in contrast to EFA, where the latent factor is seen as causing the variability and pattern of correlations among measured variables (Marcoulides & Hershberger, 1997).

In other words, EFA is used to identify the latent variables that are underlying a set of variables i.e. to evaluate a theoretical model with a set of variables while principal components analysis is used to reduce a set of variables to a smaller set of factors (i.e. data reduction). Further, in contrast to commonly used principal component analysis, factor analysis is more reliable for construct validity testing of questionnaire than commonly employed principal component analysis as the latter does not have the presumption that all variance within is shared. (Costell & Osborne, 2005; Field, 2009; Tabachnik & Fidell, 2001) Thus, the paper discusses EFA as tool for construct validity. To represent one's view on acceptance of HRIS in central universities based on his /her total score on the eleven items of the questionnaire of interest, the questionnaire must be construct valid. If a questionnaire is construct valid, then all items together represent the underlying construct well. This construct validity of a questionnaire can be tested with exploratory factor analysis which detects constructs i.e. factors that underlie a dataset based on the correlation between variables/items (Bornstedt, 1977; Rattray & Jones, 2007). In exploratory factor analysis, the factors that explain the highest proportion of variation the variables shared are expected to represent the underlying construct (Costell & Osborne, 2005; Field, 2009; Tabachnik & Fidell, 2001).

## **5. ACCESSING THE FACTORABILITY OF THE DATA :**

Before proceeding with the analysis, factorability of the data must be checked. This can be checked in three stages:

- (a) Kaiser-Meyer-Okin (KMO) measure of sampling adequacy
- (b) Scale input variables
- (c) Bartlett's test of sphericity

### **(a) Kaiser-Meyer-Okin measure of sampling adequacy:**

The sample size must be adequate for conducting reliable factor analysis. In small sample, correlation coefficients between items in one sample may differ to a large extent from the correlation coefficients between items in other sample. However, the size of the sample largely depends on the proportion of variance a factor explains. If a factor explains a lot of variance in a dataset then underlying variable correlates highly with that factor. Usually, a factor with four or more loadings greater than 0.6 is reliable regardless of the sample size (Field, 2009). In order to determine adequacy of the sample size, KMO test can be done to extract the reliable factor. The KMO tests to see if the partial correlations within data are close enough to zero to suggest that there is at least one latent factor underlying variables. The minimum acceptable KMO value is 0.5. However, most authors suggest a value more than 0.5 as a prerequisite for factor analysis (Field, 2009).

Table : 2  
KMO test

|                                                                                     |      |      |      |      |      |      |      |      |      |      |
|-------------------------------------------------------------------------------------|------|------|------|------|------|------|------|------|------|------|
| <pre>&gt;KMO(tacntq) Kaiser-Meyer-Olkin factor adequacy Call: KMO(r = tacntq)</pre> |      |      |      |      |      |      |      |      |      |      |
| Overall MSA = 0.56                                                                  |      |      |      |      |      |      |      |      |      |      |
| MSA for each item =                                                                 |      |      |      |      |      |      |      |      |      |      |
| q1                                                                                  | q2   | q3   | q4   | q5   | q6   | q7   | q8   | q9   | q10  | q11  |
| 0.55                                                                                | 0.54 | 0.53 | 0.60 | 0.42 | 0.54 | 0.53 | 0.65 | 0.57 | 0.65 | 0.50 |

KMO function available in “pysch” package in R evaluates an overall Measure of Sampling Adequacy(MSA) and MSA for each item. The KMO test for dataset “tacntq” is shown in Table 2. The result shows that overall KMO for data is 0.56 which is acceptable for carrying with factor analysis.

#### **(b) Scale (interval or ratio) input variables:**

Another condition for conducting factor analysis is that the variables of the study should be measured at an interval level. But, usually Likert data fails normality tests. Table 3 shows the normality test on the dataset “tacntq” for an item of questionnaire (q1) fails as the test renders p values lower than 0.05. Although many studies has considered Likert scale to an interval scale (Ratray & Jones, 2007) as many authors have shown that Likert scales can indeed be analyzed effectively as interval scales but the scale item should be at least five and preferably seven categories (Baggaley & Hull, 1983; Maurer & Pierce, 1998; and Vickers, 1999; Allen and Seaman, 1997).

Table : 3  
Shapiro Test (Normality Test)

|                                                                                                                        |  |  |  |  |  |  |  |  |  |  |
|------------------------------------------------------------------------------------------------------------------------|--|--|--|--|--|--|--|--|--|--|
| <pre>&gt; shapiro.test(tacntq\$q1) Shapiro-Wilk normality test data: tacntq\$q1 W = 0.43539, p-value = 6.231e-12</pre> |  |  |  |  |  |  |  |  |  |  |
|------------------------------------------------------------------------------------------------------------------------|--|--|--|--|--|--|--|--|--|--|

#### **(c) Bartlett's Test of Sphericity :**

The final step before conducting factor analysis is to check whether or not the variables inter correlate at all. This test is done by evaluating the observed correlation

matrix against an identity matrix. If result of the test is not significant then only a factor analysis should be employed. This test can be conducted with Bartlett's Test of Sphericity (Field, 2009). The result of the Bartlett's test for the dataset "tacntq" is shown in Table 4.

Table : 4  
Bartlett's test

---

```
>cortest.bartlett(tacntq)
R was not square, finding R from
data
$'chisq'
[1] 136.2896
$p.value
[1] 7.577007e-09
$df [1] 55
```

---

Bartlett's test shows that p value is less than 0.5 (Table 4) and hence the test is statistically significant (Table -4) inferring that correlation matrix among the items is not an identity matrix and suggesting that at least some of the variables are correlated with each other.

## **6. DETERMINING THE NUMBER OF FACTORS TO EXTRACT:**

The next decision that needs to be considered for factor analysis is the number of factors to be extracted. In order to achieve most appropriate number of factors, there are number of techniques and most commonly used techniques are screen plot and parallel analysis. The simplest technique is screen plot (Costell & Osborne, 2005).

### **6.1. Screen plot :**

The scree plot is based on the concept of eigen values and eigen values are a measure of the amount of variance accounted by a factor. They are useful in determining the number of factors to be extracted. Usually statistical packages retain factors with eigen values greater than 1.0 were. However, it has been observed that in this technique too many factors are retained.

The more easy method is to look into screen plot and observe the factors with values above the point at which curve flattens out and only those factors should be retained and the factors with values at the break point or below should be eliminated ( Costell & Osborne,2005). The screen plot with screen function in R for the dataset "tacntq"

in R is shown in Figure 2. The involves drawing a straight line through the plotted eigen values with highest value. The last point to fall on this line represents the last factor that to be extracted. If a straight line is drawn at the first

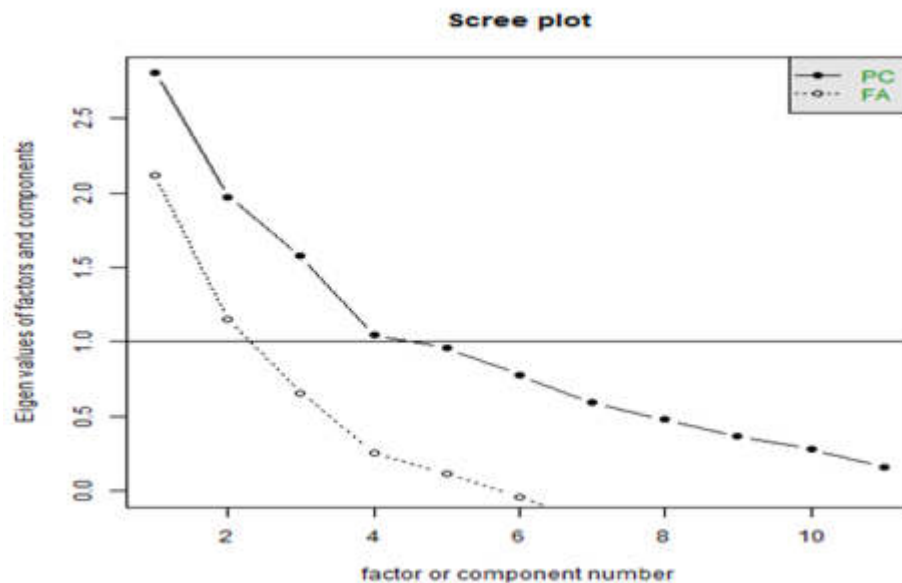


Figure 2 : Screen plot for dataset " tacntq"

factor, probably it may be concluded that there are four factors in the dataset with both of these methods. However regarding number of factors to be extracted a closer look into both of these factor solutions is required.

## 6.2. Parallel Analysis :

Parallel analysis is a better method for evaluating the scree plot. In this analysis not only eigen values are plotted but also random correlation matrices and random eigen values are generated. This is done to see that the observed eigen values that are higher than their corresponding random eigen values are likely to form meaningful factors (Cokluk & Kocak, 2016). The parallel analysis for the dataset "tacntq" is shown in Figure 3.

The figure 3 represents parallel analysis scree plot of the dataset "tacntq" with fa.parallel function in R. The plot shows that 3 factors in the factor analysis lie above the simulated data line and 3 components in the principal components parallel analysis lie above the corresponding simulated data line

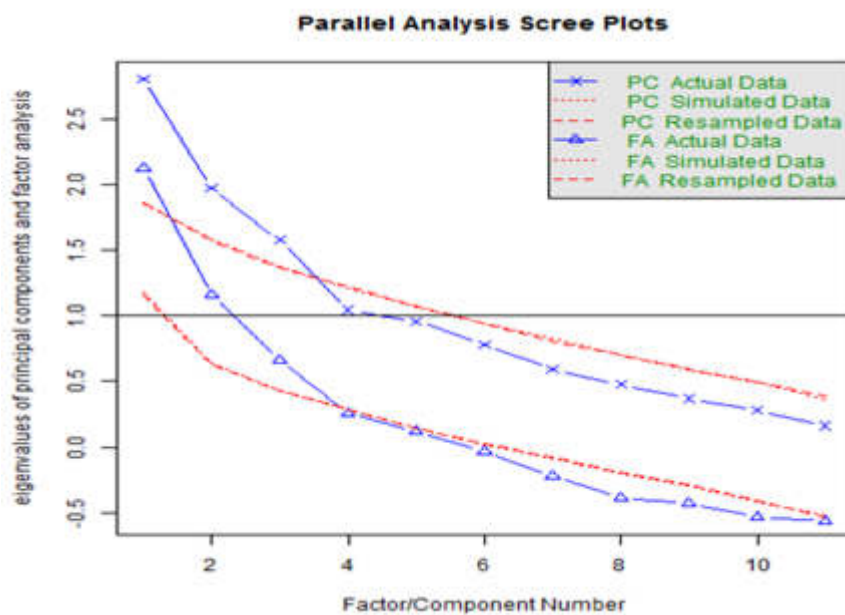


Figure 3 : Parallel Analysis Scree plot for dataset “ tacntq”

## 7. ESTIMATION METHODS IN EXPLORATORY FACTOR ANALYSIS:

There are two most popular estimation methods in exploratory factor analysis a) Principal axis factoring (PAF) and b) maximum likelihood factor analysis (MLFA). Fabrigar, Wegener, MacCallum and Strahan (1999) argued that if data are relatively normally distributed, maximum likelihood is the best choice as it permits statistical significance testing of factor loadings and correlations among factors and the computation of confidence intervals. However, if the assumption of multivariate normality is “severely violated” then “principal axis factors” method is recommended. (Fabrigar et al., 1999).

### 7.1. Principal Axis Factoring (Common Factor Analysis):

In the previous section it is concluded that number of factors to be extracted are three. The principal axis factoring can be conducted with ‘fa’ function for the dataset “tacntq” as follows:

- `pa3.out=fa(taccntq, nfactors=3, fm="pa", max.iter=100, rotate="oblimin")`  
where "taccntq" = dataset  
nfactors = no of factors to be extracted  
fm = type of factor analysis (pa stands for Principal Axis Factoring)  
max.iter = maximum number of iteration to use for underlying the best solution  
rotate = type of rotation to be used (oblimin). The use of rotate function is discussed in section 7.2 .

### **FACTOR ROTATION :**

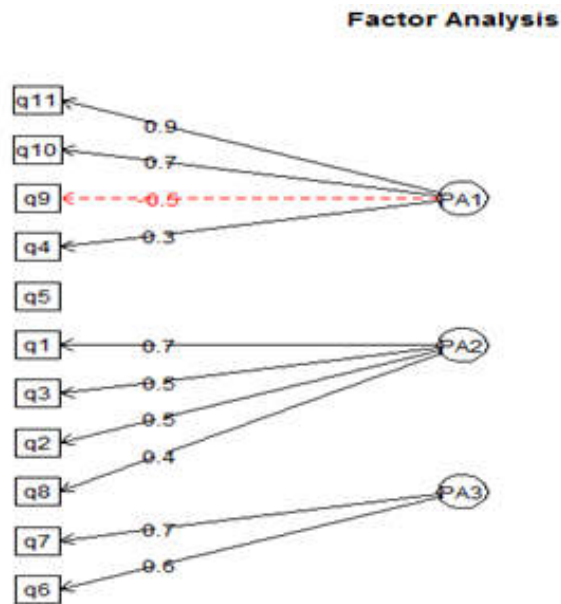
Factors are extracted from the factor analysis and the interpretations are based on the items which are loaded on these factors (Field, 2009). However, it becomes difficult to determine the construct they represent when many variables load on several factors. In such cases, factors are rotated towards some variables and away from some variables. There are two types of rotation. One type of rotation is 'orthogonal rotation'. This type of rotation is used if the factors are assumed to be independent of each other. (Field, 2009, Tabachnik & Fidell, 2001) The other type of rotation is 'oblique rotation' and this type of rotation is used if the factors are assumed to correlate each other.

In this paper, it is assumed that all the 11 items in this questionnaire measured the same underlying construct and therefore an oblique rotation is appropriate. While conducting principal axis factoring with "fa" function, oblimin rotation is opted. However, even if factors are independent, it is suggested to perform with factor analysis with oblique rotation first (Costell & Osborne, 2005).

The result of the parallel axis factoring with rotated factor solution can be visualized with `fa.diagram` function in R as shown in Figure 4. The three factor solution seems to replicate the expected factor structure nicely except q5 which is not loaded to any factor only.

Figure 4 : Factor Analysis

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The figure 4 shows the largest loadings for each item for each factor. However each item will

Table : 5  
Factor Loading Matrix

|                | PA1    | PA2    | PA3    |
|----------------|--------|--------|--------|
| q1             | 0.290  | 0.752  | 0.303  |
| q2             | -0.217 | 0.396  | -0.179 |
| q3             | 0.195  | 0.553  | 0.022  |
| q4             | 0.387  | 0.373  | 0.376  |
| q5             | 0.230  | 0.061  | 0.219  |
| q6             | -0.085 | 0.368  | 0.675  |
| q7             | -0.060 | -0.025 | 0.692  |
| q8             | 0.203  | 0.465  | 0.192  |
| q9             | -0.496 | 0.338  | -0.082 |
| q10            | 0.731  | 0.279  | 0.014  |
| q11            | 0.917  | 0.136  | -0.054 |
|                | PA1    | PA2    | PA3    |
| SS loadings    | 2.045  | 1.733  | 1.295  |
| Proportion Var | 0.186  | 0.158  | 0.118  |
| Cumulative Var | 0.186  | 0.343  | 0.461  |

however load on each of the factors to a greater or lesser degree and which may be seen at the full factor loading matrix (with function `print(pa3.out$Structure)`) as shown in Table 5. The factor loading matrix shows us the factor loadings for each variable after they have been rotated to simple structure.

#### **FACTOR INTERPRETATION :**

Usually Variables which loaded less than 0.3 on a factor are omitted and therefore item q5 may be omitted as loading of this item for each factor is very low (Field,2009,Tabachnik & Fidell,2001). Therefore, analysis shows that except q5 variables(item) can be eliminated and all other variables (items) are loaded more than 0.3 towards three extracted factors. Further all the factors seems important as they explain considerable amount of variance in the data set (Table 5 shows 18%, 15% and 11% variance).

#### **7.2. Maximum likelihood factor analysis (MLFA) :**

This measure tests how well a model of particular amount of factors accounts for the variance within a dataset (Fabrigar et al., 1999).

Hypothesis for the dataset "tacntq" can be written as

HO = 3 no of factors fits well the dataset.

H1= A Model with larger amount of factors should be considered.

Maximum likelihood factor analysis (MLFA) in R can be conducted with "factanal" function and the result of the test is shown in Table 6 .

#### **FACTOR INTERPRETATION :**

If alpa level set at 0.05 which is a common practice in social science research (Field, 2009) then a model with three factor should be considered as p-value is more than 0.05. Also all the factors seems important as they explain considerable amount of variance in the data set (Table 6 shows variance are 17%,15% and 10% ) However , item q5 to be eliminated as the variables with loading less than 0.3 are considered to be non significant impact on a factor (Field,2009).

---

```
factanal(tacntq,factors=3,rotation="oblimin")
```

Call :

```
Factanal (x = tacntq, factors = 3, rotation = "oblimin")
```

Uniquenesses :

| q1    | q2    | q3    | q4    | q5    | q6    | q7    | q8    | q9    | q10   | q11   |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| 0.238 | 0.681 | 0.756 | 0.773 | 0.940 | 0.467 | 0.447 | 0.729 | 0.576 | 0.502 | 0.005 |

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**Loadings :**

|                      | <b>Factor1</b> | <b>Factor2</b> | <b>Factor3</b> |
|----------------------|----------------|----------------|----------------|
| q1                   | 0.221          | 0.780          | 0.154          |
| q2                   | -0.288         | 0.485          | -0.266         |
| q3                   |                | 0.500          |                |
| q4                   | 0.212          | 0.251          | 0.286          |
| q5                   | 0.157          |                | 0.172          |
| q6                   | -0.151         | 0.329          | 0.602          |
| q7                   |                | 0.747          |                |
| q8                   | 0.161          | 0.458          |                |
| q9                   | -0.550         | 0.410          | -0.171         |
| q10                  | 0.666          | 0.164          |                |
| q11                  | 0.985          |                |                |
| <hr/>                |                |                |                |
| SS loadings          | Factor1        | Factor2        | Factor3        |
|                      | 1.972          | 1.679          | 1.175          |
| Proportion Var       | 0.179          | 0.153          | 0.107          |
| Cumulative Var       | 0.179          | 0.332          | 0.439          |
| <hr/>                |                |                |                |
| Factor Correlations: |                |                |                |
|                      | Factor1        | Factor2        | Factor3        |
| Factor1              | 1.0000         | -0.133         | 0.0206         |
| Factor2              | -0.1329        | 1.000          | - 0.1418       |
| Factor3              | 0.0206         | -0.142         | 1.0000         |

Test of the hypothesis that 3 factors are sufficient.  
The chi square statistic is 32.56 on 25 degrees of freedom.  
The p-value is 0.143

**Table 6: Maximum likelihood factor Analysis**

## **8. CONCLUSION :**

All the items except question no 5(q5) in the questionnaire seems construct valid and therefore these items together seem to measure the underlying construct. The extraction of the three factors seems to be consequences of the wording of the questionnaire items. Output of the both methods of factor analysis is same and hence results confirm the construct.

Factor analysis is an excellent method for evaluating and validating underlying constructs. It is a highly subjective tool and researcher have to decide regarding type of extraction method, number of factors to extract, factor rotation method and eventually

interpretation of the factors. The outcome of the factor analysis will be highly dependent upon the variables that are selected for analysis. Further if too many variables that are highly correlated then researcher may group them to form a factor.

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**Annexure -A**  
**Dataset : tacntq**

| Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Q11 |
|----|----|----|----|----|----|----|----|----|-----|-----|
| 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 2   | 1   |
| 5  | 5  | 4  | 5  | 5  | 5  | 5  | 4  | 3  | 3   | 3   |
| 5  | 4  | 5  | 5  | 5  | 5  | 4  | 4  | 4  | 3   | 3   |
| 5  | 5  | 5  | 4  | 4  | 4  | 4  | 4  | 5  | 4   | 3   |
| 5  | 5  | 4  | 5  | 5  | 5  | 4  | 5  | 5  | 4   | 2   |
| 5  | 5  | 5  | 5  | 5  | 4  | 5  | 5  | 5  | 3   | 3   |
| 5  | 4  | 4  | 4  | 4  | 5  | 5  | 5  | 3  | 2   | 1   |
| 5  | 4  | 5  | 4  | 5  | 5  | 5  | 5  | 4  | 1   | 2   |
| 4  | 5  | 4  | 5  | 4  | 4  | 5  | 4  | 4  | 3   | 1   |
| 4  | 4  | 4  | 4  | 4  | 5  | 3  | 5  | 5  | 3   | 2   |
| 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 2   | 1   |
| 5  | 5  | 4  | 5  | 5  | 5  | 5  | 4  | 3  | 3   | 3   |
| 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 3   | 2   |
| 5  | 4  | 4  | 5  | 5  | 5  | 5  | 3  | 4  | 4   | 3   |
| 4  | 5  | 5  | 3  | 5  | 3  | 3  | 3  | 3  | 3   | 2   |
| 4  | 4  | 1  | 3  | 5  | 3  | 4  | 3  | 3  | 2   | 3   |
| 5  | 4  | 4  | 5  | 5  | 5  | 5  | 5  | 3  | 3   | 5   |
| 4  | 4  | 4  | 5  | 5  | 4  | 5  | 3  | 3  | 2   | 3   |
| 5  | 4  | 4  | 4  | 5  | 4  | 5  | 5  | 4  | 3   | 4   |
| 5  | 5  | 5  | 4  | 4  | 4  | 3  | 5  | 4  | 3   | 4   |
| 5  | 5  | 5  | 5  | 4  | 4  | 3  | 4  | 5  | 4   | 3   |
| 5  | 5  | 5  | 4  | 4  | 4  | 5  | 5  | 4  | 4   | 3   |
| 5  | 4  | 4  | 4  | 5  | 4  | 5  | 5  | 4  | 3   | 4   |
| 5  | 5  | 5  | 4  | 4  | 4  | 3  | 5  | 4  | 3   | 4   |
| 5  | 5  | 5  | 5  | 5  | 5  | 5  | 5  | 3  | 5   | 4   |
| 5  | 5  | 5  | 5  | 5  | 4  | 4  | 5  | 4  | 5   | 5   |
| 4  | 2  | 4  | 5  | 5  | 4  | 4  | 5  | 2  | 4   | 3   |
| 5  | 5  | 5  | 5  | 5  | 4  | 3  | 4  | 3  | 4   | 4   |
| 5  | 4  | 5  | 5  | 5  | 4  | 5  | 5  | 3  | 5   | 3   |
| 4  | 4  | 5  | 5  | 4  | 4  | 5  | 4  | 3  | 4   | 4   |
| 5  | 4  | 5  | 5  | 5  | 4  | 4  | 5  | 3  | 5   | 5   |
| 5  | 4  | 5  | 5  | 5  | 5  | 5  | 5  | 3  | 5   | 5   |
| 5  | 4  | 4  | 5  | 5  | 4  | 4  | 5  | 4  | 4   | 5   |

*Validity Testing with Exploratory Factor Analysis in R : An Evaluation of a Questionnaire on Acceptance of Human Resource Information System in Central Universities*

|   |   |   |   |   |   |   |   |   |   |   |
|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 5 | 5 | 5 | 5 | 4 | 4 | 5 | 2 | 4 | 5 |
| 5 | 4 | 5 | 5 | 5 | 4 | 4 | 5 | 4 | 5 | 5 |
| 5 | 5 | 4 | 5 | 5 | 5 | 4 | 5 | 3 | 5 | 5 |
| 5 | 4 | 5 | 5 | 5 | 5 | 5 | 4 | 3 | 5 | 4 |
| 5 | 4 | 5 | 5 | 4 | 4 | 5 | 3 | 2 | 5 | 5 |
| 5 | 5 | 4 | 4 | 4 | 5 | 5 | 4 | 4 | 5 | 4 |
| 5 | 4 | 4 | 4 | 4 | 5 | 5 | 5 | 3 | 4 | 5 |
| 5 | 4 | 5 | 5 | 5 | 5 | 5 | 5 | 3 | 5 | 5 |
| 5 | 4 | 4 | 5 | 5 | 4 | 4 | 5 | 4 | 4 | 5 |
| 5 | 5 | 5 | 5 | 5 | 4 | 4 | 5 | 2 | 4 | 5 |
| 5 | 4 | 5 | 5 | 5 | 4 | 4 | 5 | 4 | 5 | 5 |
| 5 | 5 | 4 | 5 | 5 | 5 | 4 | 5 | 3 | 5 | 5 |

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