ASSESSMENT OF SINGLE FACTOR STRUCTURE IN SATS-36 CATEGORIES

by

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ABSTRACT

The attitude of students toward statistics has an impact on students' overall academic performance. For non-science students such as those enrolled in marketing or business, statistics courses are often seen as secondary and/or difficult. The Survey of Attitudes Toward Statistics (SATS) instrument has been developed to measure the attitude towards statistics. The instrument consists of a questionnaire divided into several categories. Statistical analysis performed on the obtained data is based on assumptions that should be valid. Using Factor Analysis method on SATS-36 data collection, we investigate to which extent these assumptions, including normality and dimensionality, are validated. We have found that most items have a score that significantly depart from a normal distribution. The results obtained from exploratory factor analysis indicate that the item score variability within each SATS category is sufficiently accounted for when attributing one single factor.

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Chapter 1: Introduction

Teaching statistics is particularly difficult for students enrolling in psychology, or management programs. Indeed, statistics courses are often seen as secondary to disciplines such as finance or marketing, and students have difficulty perceiving the relevance of such teaching for their future career**.** When registering in a school program, these students do not necessarily expect to receive instruction in relatively detailed statistics. Even if they come from a specialized program, they have very different profiles (scientific, economic, technical and literary) and are not necessarily familiar with quantitative materials. They may feel some apprehension and may develop a priori a negative perspective: some simply do not like the material or think they will have difficulty in understanding it, others consider it useless or will not make the effort to necessary investment in studying. The importance of attitude in the context of an introductory course in statistics is widely established (Leong, 2006). It seems that the attitude developed by the students towards statistics will have an impact on their academic performance, their approach to the course, and finally in their success on the exam (Ramirez et al., 2012). Negative attitudes are a major obstacle to effective learning (Waters et al. 1988). The objective of the Survey of Attitude Toward Statistics (SATS) is to measure the attitude of students toward statistics courses, and to link this attitude to their personal characteristics. The main objective of the present report is to make an assessment of the dimensional structure of SATS-36 study. In practice SATS items are organized into categories that are supposed to be internally consistent. The SATS-36 instrument is built on a 6-dimensional structure. Our purpose is to conduct a study to assess this dimensional structure using new data. Particularly, to investigate on further clarification to what extent one factor can best represent each category of SATS-36. Using factor analysis, we investigate whether the internal consistency of each SATS category is acceptable or not. The data set is collected from fifteen universities in the USA between 2008 and 2010. For the present study, we use the instrument of Schau, the Survey of Attitudes Toward Statistics (or SATS) (1992, 2003), widely used in the literature on the understanding of learning statistics. In the next chapter, we present the

instrument of Schau and its validation. In chapter 3, the methodology is presented and it will be followed by the main results.

Chapter 2: Attitude Scale

The attitude scale is a technique of measuring the intensity of the reactions or feelings of individuals on a given topic. It quantifies the qualitative information to eventually lead to a score, which results from the addition of responses to item statements. Prior to the formulation of items, one should decide about the scale to be used since this affects the nature and the format of the items to be developed. In the *additive scale* type, the same weight is assigned to each item. For a differential scale type, a different weight is assigned to items according to whether they reflect a level of the measured characteristic. In the next section, we present the Likert additive scale which is widely used nowadays especially in psychology and marketing.

2-1. Likert scale

A Likert scale (named after the American psychologist Rensis Likert) is a widespread scale of judgment questionnaires through which the interviewee expresses his or her degree of agreement or disagreement vis-à-vis with a statement [Likert, 1932]. The scale generally contains five or seven answer choices that can quantify the degree of agreement. The development of a Likert-type scale initially assumes the existence of a large set of selected items (specific questions) that are more or less intuitive as to their potential relationship to the object of study. The items of a Likert scale generally consist of positive or negative statements towards the object of study. The degree of agreement or disagreement with the items is however not known exactly. Each item is accompanied by a following type of response: a) strongly disagree; b) somewhat disagree; c) undecided; d) slightly agree; e) strongly agree. For odd scales, the median level expresses no opinion. Respondents select the answer option that best reflects their level of agreement or disagreement with the item. A value of scale (e.g. 1-5 or 1-7) is assigned to each option by: the level of agreement or disagreement expressed by the response option (or equivalently by the favorable or unfavorable position of the item to the object of study). Thus, the answer option reflecting the highest level of agreement with a statement

favorable to the object of study will receive the lowest or the highest scale value. The total score of an individual is the sum (or the mean) of the results obtained in each item.

2-2. Item Analysis

To develop a Likert scale, the initial items set must be assessed in order to eliminate potential ambiguous or undiscerning items. The item discrimination power could be investigated by checking the existence of a statistically significant difference between the means of two groups of subjects: one consisting of subjects who achieved the highest scores (like strongly agree + agree) and the other consisting of subjects with the lowest scores (like disagree + strongly disagree) (Kelly, 1939). A more efficient approach is to calculate the correlation between each item and total. To calculate the correlation, the specific involved item is excluded from the total (of items). An evaluation of the Pearson correlation across the questionnaire Participants is performed. In general, items that are strongly linked with the total are considered good items while items with low correlation and zero correlation with total are usually rejected.

There is a debate between scholars whether Likert variables are categorical (ordinal scale) or continuous (associated with an interval scale) [Norman, 2010]. In the latter case, it is assumed that the intervals between the scale values are equal. While technically the Likert scale item is ordered, under some circumstances Likert scale data can be used in parametric statistical procedures that require interval data (such ANOVA). For example, Lubke & Muthen (2004) found that it is possible to find true parameter values in factor analysis with Likert scale data, if assumptions about skewness, number of categories, etc., were met. In this case, it is strongly recommended that the scale item should at least be five and preferably seven categories.

When analyzing Likert data, it is assumed that it measures a single latent variable (one dimension). Although the Likert approach attempts to locate individuals on an unfavorable-favorable extent, it is not possible to comment on the one-dimensional character of the scale without making further analyses. In addition to item analysis,

authors often carry out exploratory factor analysis or confirmatory factor analysis to assess the dimensional character of the scale. This issue is of concern here in the SATS when a model is assumed to be one-dimensional. In this case, the model can be tested using one single latent factor analysis that accounts for the variability of data. Confirmatory factor analysis could also be used in this context.

Finally, Likert scales may be subject to significant distortions that may result from participants who desire to appear “conventional” in their responses. For example, participants would avoid extreme responses (such as *strongly disagree*) or would provide “fake” responses due to ignorance of the subject [Carifio & Perla, 2008].

Chapter 3: Factor Analysis

3.1 Exploratory factor analysis

Exploratory factor analysis attempts to represent a set of observed variables X_1, X_2, …, X_p in terms of a number of *common* factors. The common factors (sometimes called latent variables or unobservable random variables) are hypothetical variables that can explain why a number of variables are correlated with each other. This is because a subset of variables is related to one or more factors.

Data analysis methods consist of a set of techniques to discover structures, possibly hidden in an array of numbers in several dimensions, and lead to a simpler structure that can be interpreted. Exploratory factor analysis explains the variance and covariance among a set of observed variables in term of a simple structure. To illustrate, the variance and covariance between four observed variables might be explained based on two latent variables. In this case, the dimensionality of the four observed variables is reduced to two factors.

Exploratory factor analysis goes back to the work of Spearman (1904), who introduced for the first time the concept of factor. He looks behind the scores of many topics of numerous tests a hidden exploratory variable he called the general ability factor. Unobservable directly, the latent factors might provide interpretations of scores of the subjects. Burt and Thurstone introduced, later on during the 40s, the several factor problem [Thurstone, 1947; Burt, 1949]. With only a few factors, they found that they could summarize results obtained from an analysis of a multi-dimensional problem.

a. The Orthogonal Factor Model

As indicated above, exploratory factor analysis is a statistical method that can be used to investigate whether a number of observed variables of interest X_1, X_2,…,X_p are linearly related to a smaller number of underlying common factors F_1, F_2, …, F_m. We now

present the factor model following the steps described by Johnson & Wichern [2007]. We consider p observed random variables $\boldsymbol{X} = (X_1, X_2, \ldots, X_p)$ with mean $\mu = (\mu_1, \mu_2, \ldots, \mu_p)$ and variance matrix $\boldsymbol{\Sigma}$. The model assumes that the variability of the observables $\boldsymbol{X}$ around their means are linearly dependent on a small set of unobservable random variables $\boldsymbol{F} = (F_1, F_2, \ldots, F_m)$ called factors. Specifically, in matrix representation, the factor model can be expressed as:

$$\boldsymbol{X} - \boldsymbol{\mu} = \boldsymbol{L}\,\boldsymbol{F} + \boldsymbol{\varepsilon} \qquad [1]$$

where $\boldsymbol{X}$, $\boldsymbol{\mu}$ and $\boldsymbol{\varepsilon}$ are column matrices of rank (p×1), $\boldsymbol{F}$, is a matrix of factors of rank (m×1) and $\boldsymbol{L}$ the factor loadings matrix of rank (p×m). In Equation [1], $\boldsymbol{\varepsilon}$ represents the random errors and only $\boldsymbol{X}$ is known. Therefore, the exact determination of the unknown variables in [1] is not possible since the numbers of unknowns is larger than the numbers of equations of the model. However, by assuming that the unknown variables follow specific properties, it is possible to estimate the potential effect of factors $\boldsymbol{F}$ on the observations. When the following assumptions are added to the model [1], we obtain the Orthogonal Factor Model:

i) $\boldsymbol{F}$ and $\boldsymbol{\varepsilon}$ are independent, which implies that $Cov(\boldsymbol{F},\boldsymbol{\varepsilon}) = \boldsymbol{0}$

ii) The mean and covariance of $\boldsymbol{F}$ are respectively $E(\mathbf{F}) = \boldsymbol{0}$ and $Var(\boldsymbol{F}) = \boldsymbol{1}$ (Identity Matrix)

iii) The errors $\boldsymbol{\varepsilon}$ are random and independent: $E(\boldsymbol{\varepsilon}) = 0$ and $Var(\boldsymbol{\varepsilon}) = \boldsymbol{\Psi}$ is a diagonal matrix.

Based on these orthogonal assumptions, it can be shown that:

- The population covariance matrix $\boldsymbol{\Sigma} = Cov(\boldsymbol{X}) = \boldsymbol{L}\boldsymbol{L}^{\mathrm{T}} + \boldsymbol{\Psi}$
- $Cov(\boldsymbol{X},\boldsymbol{F}) = \boldsymbol{L}$

When the factors are uncorrelated (which is the case if the model is orthogonal), we define the communality h_i^2 for the variable X_i as

$$h_i^2 = \sum_{j=1}^{m} l_{ij}^2$$

where l_{ij} are elements of matrix $\boldsymbol{L}$ (loading of the ith variable on the jth factor). The communality indicates the proportion of the variance of a variable that is accounted for the model. A high numerical value for the communality suggests that the model is a satisfactory solution (the m common factor model would be appropriate if the proportion of the total variance of a variable explained by this m common factor model is large). We can define the specific variance ψ_i for variable X_i, as the proportion of variance that is not accounted for by the factors (unexplained by the m factor model)

$$\psi_i = Var(X_i) - h_i^2$$

Several mathematical procedures can provide estimates for factor loadings. The simplest solution corresponds to $m = 1$, which means that only one factor is sufficient to account for the observations. When $m > 1$, it can be shown that for any arbitrary orthogonal matrix $\boldsymbol{T}$, both $\boldsymbol{L}$ and $\boldsymbol{LT}$ are solutions for the loadings. They have identical statistical properties. The loadings $\boldsymbol{LT}$ have the same ability to reproduce the covariance matrix $\boldsymbol{\Sigma}$ although the loadings $\boldsymbol{LT}$ are different from the loadings $\boldsymbol{L}$.

b. Methods of factor estimations

Two methods of estimating factor loadings are now briefly presented below. These methods can use the sample covariance matrix $\boldsymbol{S}$ or the sample correlation matrix $\boldsymbol{R}$ in order to investigate possible correlations between variables when common factors are considered. In other terms, factor analysis is not useful if the off-diagonal elements of $\boldsymbol{S}$ (or $\boldsymbol{R}$) are too small (or zero). The principal component factor and the maximum likelihood procedures are the most used methods of parameter estimation.

***i*) Principal component factor method**

The method consists of decomposing the population covariance matrix $\boldsymbol{\Sigma}$ by means of its eigenvectors. The matrix $\boldsymbol{\Sigma}$ is written in terms of the loading matrix $\boldsymbol{L}$. If ($\boldsymbol{e}_1$, $\boldsymbol{e}_2$, …, $\boldsymbol{e}_p$) are the eigenvectors of $\boldsymbol{S}$ corresponding to the eigenvalues ($\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p$), we can write:

$$\boldsymbol{\Sigma} = \lambda_1 \boldsymbol{e}_1 \boldsymbol{e}_1^T + \lambda_2 \boldsymbol{e}_2 \boldsymbol{e}_2^T + \cdots + \lambda_p \boldsymbol{e}_p \boldsymbol{e}_p^T$$

We now fit an *m*-factor model for the sample covariance matrix with $\boldsymbol{\Sigma}$ such that $\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^T + \boldsymbol{\Psi}$, with

$$\mathbf{L} = \left[\quad \left[\sqrt{\lambda_1}\boldsymbol{e}_1\right] \ \left[\sqrt{\lambda_2}\boldsymbol{e}_2\right] \ldots \left[\sqrt{\lambda_m}\boldsymbol{e}_m\right] \quad \right]$$

and

$$\Psi_{ij} = \psi_i \delta_{ij} \quad where\ \delta_{ij} = \begin{bmatrix} 1 & if\ i = j \\ 0 & if\ i \neq j \end{bmatrix}$$

In $\boldsymbol{L}$, the elements $\boldsymbol{e}_i$ (i = [1,…, p]) are column vectors of size p, $\boldsymbol{L}$ is a matrix of rank ($p \times m$) and $\boldsymbol{\Psi}$ is the matrix of residuals of rank ($p \times p$). For clarity, an example is provided below to illustrate the procedure in the principal component factor estimation method. If we consider the following covariance matrix:

$$\mathbf{S} = \begin{pmatrix} 1.014 & 0.640 & 0.696 & 0.697 \\ 0.640 & 1.173 & 0.728 & 0.556 \\ 0.696 & 0.728 & 1.083 & 0.640 \\ 0.697 & 0.556 & 0.640 & 1.315 \end{pmatrix}$$

eigenvalues λ_1 = 3.126, λ_2 = 0.716, λ_3 = 0.406 and λ_4 = 0.337 are associated with the following respective eigenvectors:

$$\boldsymbol{e}_1 = \begin{pmatrix} -.486 \\ -.494 \\ -.503 \\ -.516 \end{pmatrix}, \quad \boldsymbol{e}_2 = \begin{pmatrix} +.031 \\ -.581 \\ -.253 \\ +.773 \end{pmatrix}, \quad \boldsymbol{e}_3 = \begin{pmatrix} -.510 \\ +.631 \\ -.475 \\ +.340 \end{pmatrix}, \quad \boldsymbol{e}_4 = \begin{pmatrix} +.709 \\ +.141 \\ -.676 \\ -.144 \end{pmatrix}$$

We now construct the loading factor matrix as:

$$\mathbf{L} = \left(\sqrt{3.126}\begin{pmatrix} -.486 \\ -.494 \\ -.503 \\ -.516 \end{pmatrix} \quad \sqrt{0.716}\begin{pmatrix} +.031 \\ -.581 \\ -.253 \\ +.773 \end{pmatrix} \quad \sqrt{0.406}\begin{pmatrix} -.510 \\ +.631 \\ -.475 \\ +.340 \end{pmatrix} \quad \sqrt{0.337}\begin{pmatrix} +.709 \\ +.141 \\ -.676 \\ -.144 \end{pmatrix} \right)$$

$$\mathbf{L} = \begin{pmatrix} -0.859 & +0.027 & -0.325 & +0.411 \\ -0.873 & -0.492 & +0.402 & +0.082 \\ -0.890 & -0.214 & -0.303 & -0.392 \\ -0.913 & +0.654 & +0.217 & -0.083 \end{pmatrix}$$

In the case of a model with m = 3 factors, only the first three columns are considered in matrix $\boldsymbol{L}$.

Usually, the number of factors m is not known and its value is chosen arbitrarily. Further analysis may indicate a judicious value of m. When the number of factors is fixed, one can estimate the resulting residual matrix for further analysis purposes

$$\boldsymbol{S} - \boldsymbol{\Sigma} = \boldsymbol{S} - (\boldsymbol{L}\boldsymbol{L}^{\boldsymbol{T}} + \boldsymbol{\Psi})$$

Using the previous example, we can estimate $\mathbf{\Psi}$ from the communality h_i^2. Considering a 2-factor model:

$$\mathbf{\Psi} = \begin{pmatrix} \psi_1 & 0 & 0 & 0 \\ 0 & \psi_2 & 0 & 0 \\ 0 & 0 & \psi_3 & 0 \\ 0 & 0 & 0 & \psi_4 \end{pmatrix} \text{ with } \psi_i = s_{ii} - \sum_{j=1}^{m} l_{ij}^2$$

$$\mathbf{\Psi} = \begin{pmatrix} 0.275 & 0 & 0 & 0 \\ 0 & 0.169 & 0 & 0 \\ 0 & 0 & 0.245 & 0 \\ 0 & 0 & 0 & 0.054 \end{pmatrix}$$

The residual matrix is therefore obtained:

$$\mathbf{S} - \mathbf{\Sigma} = \begin{pmatrix} +0.000 & -0.097 & -0.063 & -0.105 \\ -0.096 & -0.000 & -0.154 & +0.081 \\ -0.063 & -0.154 & +0.000 & -0.033 \\ -0.105 & +0.081 & -0.033 & -0.000 \end{pmatrix}$$

A good model will provide small out-of-diagonal elements of the residual matrix.

In practice, the principal component factor analysis is performed with the use of computers, especially when the number of variables is large. For that purpose, simple routines can be developed and used from various *R*-software packages.

***ii*) Maximum likelihood method**

In statistics, Maximum Likelihood estimation is a method of estimating parameters (mean, variance,…) of a statistical model given data. The method is an optimization procedure widely used in statistics and consists of finding parameters that maximize the likelihood function *L*. It is assumed that the data are independent and identically distributed from a normal distribution whose parameters are unknown. In the present

case, the parameters are the mean vector $\boldsymbol{\mu}$ and the elements of the covariance matrix $\boldsymbol{\Sigma}$. Following [Johnson & Wichern [2007], the likelihood function is given by:

$$L(\boldsymbol{\mu},\boldsymbol{\Sigma}) = (2\pi)^{-\frac{(n-1)p}{2}}|\boldsymbol{\Sigma}|^{-\frac{(n-1)}{2}}exp\left[-\frac{1}{2}Tr\left[\boldsymbol{\Sigma}^{-1}\left(\sum_{j=1}^{n}(x_j-\overline{\boldsymbol{x}})(x_j-\overline{\boldsymbol{x}})^T\right)\right]\right]$$
$$\times(2\pi)^{-\frac{p}{2}}|\boldsymbol{\Sigma}|^{-\frac{1}{2}}exp\left[-\frac{n}{2}(\overline{\boldsymbol{x}}-\boldsymbol{\mu})^T\Sigma^{-1}(\overline{\boldsymbol{x}}-\boldsymbol{\mu})\right]$$

with

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda}\boldsymbol{\Lambda}^{\boldsymbol{T}} + \boldsymbol{\Psi}$$

where n is the total number of observations. In most cases, the maximum likelihood approach requires the use of computer since optimization is done iteratively and the parameter cannot be estimate analytically. With p variables, the degrees of freedom are $df = p(p+1)/2$ [this includes the variances and the covariances of the covariance matrix]. An m-factor model is defined by m factor loadings associated with each variable in addition to p residuals, i.e a total number of parameters to fit is equal to $p(m+1)$. Therefore, the maximum likelihood method can provide estimates only if $df \geq p(m+1)$.

The advantage of the maximum likelihood estimator is that it allows testing to see if there is any evidence that the number of common factors is not sufficient. In this respect, the null hypothesis (H_0: m factors is sufficient) may be rejected according to the obtained p-value. One approach to take is to start with one factor and then increase the number of factors until the null hypothesis is not longer rejected. When the null hypothesis continues to be rejected for increasing m, it could indicate that the MLE fit is not satisfactory.

c. Factor Rotation

We have mentioned above that an orthogonal transformation of factor loadings (a transformation of $\boldsymbol{L}$ into $\boldsymbol{LT}$, where $\boldsymbol{T}$ is an orthogonal matrix) will reproduce a covariance matrix having identical statistical properties with the initial loadings. In matrix algebra, an orthogonal transformation corresponds to a rotation of the system of coordinates. When factor loadings cannot be interpreted, we can perform a factor rotation in an attempt to simplify the structure and make the results interpretable. The main goal is to obtain that all factors are either large (and positive) or close to zero. To illustrate how the factor rotation is useful, we use the case $m = 2$, so it corresponds to a familiar rotation of angle ϕ of the system coordinates in the xy-plane about the z-axis. The transformation matrix $\boldsymbol{T}$ can be expressed as

$$\boldsymbol{T} = \begin{bmatrix} cos\phi & -sin\phi \\ sin\phi & cos\phi \end{bmatrix}$$

The angle ϕ is positive (negative) if the rotation is counterclockwise (clockwise). Pursuing our illustration further, we consider an example a model with $m = 2$ common factors with 6 variables ($p = 6$). We assume that from the analysis described above, it resulted the following loadings for F_1 and F_2 factors: F_1(.15, .22, .25, .28, .35, .42) and F_2(.12, -.24, -.20, .15, -.15, .25). The interpretation of the model factor is not trivial since F_2 is a bipolar factor (contain negative and positive loadings). Using a graph, it is clear that the (F_1, F_2) scatter plot lies into 2 quadrants in the initial system of coordinates (plus symbol in Figure-1). If we now perform a counterclockwise rotation of $\phi = 49^o$ of the factors loadings, we obtain a new estimation F_1^*(.008, .326, .315, .071, .343, .087) and F_2^*(.192, .009, .058, .310, .166, .481). The rotated factor loadings all lie in one single quadrant (circle symbol in Figure-1)

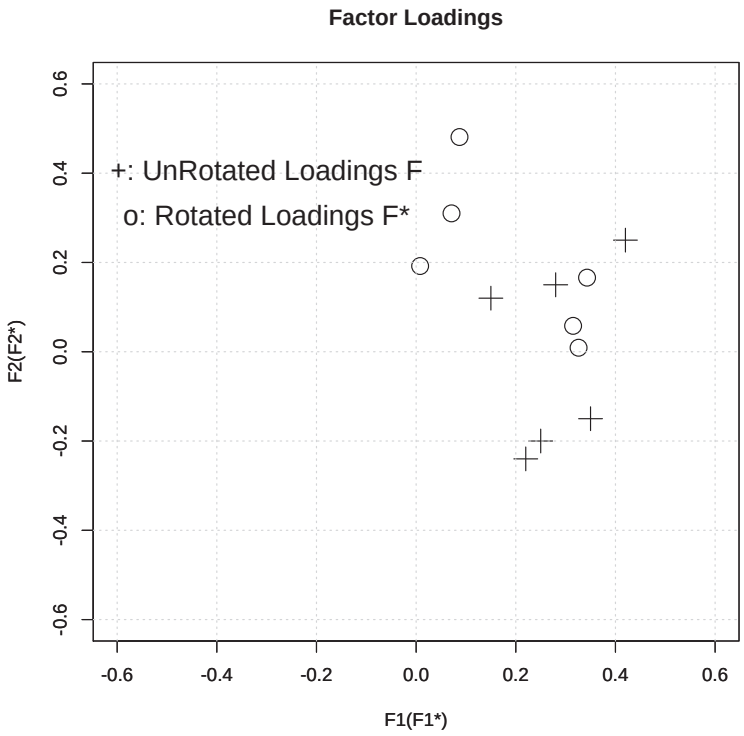

Figure A: Graphics representation of factor rotation

An arbitrary rotation may or may not allow an interpretation of the factors. However, specific rotations can lead to results that are interpretable. *Varimax* rotation is frequently used to try to find useful rotations.

3.2 Confirmatory factor analysis

Exploratory factor analysis (EFA) searches for latent factors that account for observed variation and co-variation in a subset of observed variables. The number of factors is not specified beforehand. Confirmatory factor analysis (CFA) confirms a hypothesized measurement model for the observed variables. This hypothesis is based on theory or previous analytic research (Confirming the EFA) about the number of dimensions that underlie the data and specifying which variables should be associated with which dimension (factor). Then, it allows testing the relationship between the observed variables and their dimensions. Thus, CFA estimates the fit of the model parameters and

the goodness of fit. In a CFA, we propose that the variability of observations is accounted for by the matrix $\mathbf{\Sigma}$:

$$\mathbf{\Sigma} = \mathbf{\Lambda\Phi\Lambda}^T + \mathbf{\Psi}$$

where $\boldsymbol{\Lambda}$ is the matrix of the factor loadings λ_{ij} **,** $\mathbf{\Phi}$ is the covariance matrix of the factors and $\boldsymbol{\Psi}$ the variance matrix of the residuals. In the above equation, the dimension of matrix $\mathbf{\Lambda}$ is $p \times m$, where p is the number of variables and m the number of factors considered and the ranks of matrix $\mathbf{\Phi}$ is $m \times m$.

The parameters to fit include the factor loadings λ_{ij} elements of $\boldsymbol{\Lambda}$ matrix, the factor covariance ϕ_{ij} and the variances ψ_i of the residual matrix $\boldsymbol{\Psi}$. In practice, the factor loadings matrix $\boldsymbol{\Lambda}$ is expressed in a specific form that reflects structures in the data contents. For an illustration purpose, we consider the case of a data content composed with $p = 6$ items that we like to fit with $m = 2$ factor model. The matrices $\boldsymbol{\Lambda}$, $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$ are expressed as follows:

$$\mathbf{\Lambda} = \begin{pmatrix} \lambda_{11} & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ 0 & \lambda_{24} \\ 0 & \lambda_{25} \\ 0 & \lambda_{26} \end{pmatrix}, \qquad \mathbf{\Phi} = \begin{pmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{pmatrix}$$

and

$$\mathbf{\Psi} = \begin{pmatrix} \psi_1 & 0 & 0 & 0 & 0 & 0 \\ 0 & \psi_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \psi_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & \psi_4 & 0 & 0 \\ 0 & 0 & 0 & 0 & \psi_5 & 0 \\ 0 & 0 & 0 & 0 & 0 & \psi_6 \end{pmatrix}$$

For this model, the number of parameters to fit is q = (p/2)×m + p +(m× (m+1))/2 = 15. The degrees of freedom *df* for the model is equal to the number of elements of the covariance matrix $\boldsymbol{S}$ minus the number of unique free parameters that are estimated from those data:

$$df = \frac{p(p+1)}{2} - q = 21 - 15 = 6$$

In terms of hypothesis, we will be testing

$$H_0: \quad \boldsymbol{\Sigma} = \boldsymbol{\Lambda\Phi\Lambda}^T + \boldsymbol{\Psi}$$

against the general alternative

$$H_A: \quad \boldsymbol{\Sigma} \neq \mathbf{S}$$

where $\boldsymbol{S}$ is the observed covariance matrix (Schermelleh-Engel et al., 2003). The H_0 hypothesis is that the chosen model is acceptable and $\boldsymbol{\Sigma}$ is a good model for the covariance matrix of the population. In the case where H_0 is rejected, the targeted model is not validated.

For the fitting procedure, we minimize the Maximum Log Likelihood function

$$F_{ML} = log|\boldsymbol{\Sigma}| - log|\boldsymbol{S}| + Tr(\boldsymbol{S\Sigma}^{-1}) - p$$

The next step is to examine the goodness of fit. It is necessary to take multiple criteria in consideration given that there is no single test that identifies a good model. In order to judge whether a model is consistent with data, a large number of indices are provided in the literature (Schermelleh-Engel *et al*., 2003). For the present study we use the following indexes:

i)- χ^2 Test Statistics: $\chi^2 = \frac{1}{df}(n-1)\times min(F_{ML})$

The test evaluates whether the fit model accounts for the population covariance matrix $\mathbf{\Sigma}$. One should emphasize that χ^2 test assumes that the data follows a normal distribution and that the sample size is large enough. The null hypothesis is rejected or not is based on the numerical value of χ^2 comparatively to the critical value χ_c^2 or equivalently the obtained *p*-value, which is related to χ_c^2 comparatively to the critical value α_C. = 0.05. A smaller numerical value of χ^2 or bigger numerical value of *p*-value is considered as a good fit.

ii)- RMSEA = Root Mean Square Error Approximation

$$RMSEA = \sqrt{max\left(\frac{\min\,(F_{ML})}{df} - \frac{1}{n-1}, 0\right)}$$

This is another approach to assess if the model fits well the data and the RMSEA is a measure of the goodness of the fit (Steiger, 1990). The approach is concerned with the discrepancy due to approximation. According to Steiger (1990), a RMSEA less than 0.05 is considered as a good fit while a RMSEA value > 0.1 is not acceptable. The approximation is considered as mediocre if 0.05 < RMSEA < 0.1.

Chapter 4: Data Analysis and Statistical Results

4.1 The Survey of Attitudes Toward Statistics Instrument

The objective of statistics courses is to train future professionals who will use statistical thinking. Much of the knowledge in statistics is provided in an introductory course for first year. The teachers must motivate the students in this course, to have the necessary literacy; students may not only acquire certain skills directly in learning, but also need to know the implement of statistical thinking, and be able to make the change if necessary. As noted by Ramirez et al. (2012) in the statistics course, students must:

i) Believe that they are able to understand and use statistics.
ii) Believe that statistics are useful in both their professional and personal life.
iii) Recognize that statistics can be an interesting topic.
iv) Be willing to invest and make efforts to build skills.
v) Be aware of the fact that the statistics are not easy to learn but not too difficult either.

These 5 statements illustrate the attitude towards statistics (Schau, 2003). There is an extensive research on student attitudes toward statistics, but there is no real consensus on how it should be conceptualized. This lack of consensus is illustrated in the significant variations that exist in questionnaires designed to measure this attitude. Ramirez et al. (2012) present a literature review of fifteen measures used between 1980 and 2007 in research specialized papers or presented at conferences. Four of these measures were specifically used in several studies. These are "Statistics Attitude Survey" (SAS) (Roberts and Saxe 1982), "The Attitude Toward Statistics" (ATS) (Wise, 1985), "Survey of Attitudes Toward Statistics-28" (SATS-28) and "Survey of Attitudes Toward Statistics-36" (SATS-36), which is the extension of the (SATS-28) version by two other components. These surveys include one to six components to measure the attitude.

SAS provides a single overall attitude score. Despite its wide use, it received numerous criticisms for including the content and internal structure of its components. The fact that

the score of attitude toward statistics was one-dimensional is a questionable assumption of most theories of attitude (Albarracin et al., 2014). Some questions assess the ability of students to use statistical concepts or solve problems rather than the attitude. To meet the concerns raised by the SAS, Wise (1985) developed the "ATS" [Attitude Toward Statistics] survey that requires no prior knowledge of statistics and can be administered early in the course. This test measures two separate components of attitude: "*Field*", the attitude towards the use of statistics in their field of study, and "*Course*", the attitude in the course they are enrolled. The ATS also provoked some criticisms: the use of its two components is not clearly justified and do not cover the concept of attitude toward statistics (Gal and Ginsburg, 1994).

Schau (1992) and Schau et al (1995) developed the SATS-28 survey (Survey of Attitudes Toward Statistics) followed by the questionnaire SATS-36 (Schau 2003), which improves the previous construct. SATS-28 contained 28 items measuring four components of attitude. The second version of SATS has two additional components. In this last version of SATS, each item is evaluated according to a Likert scale with seven values. The six components retained in the SATS-36 are:

i)- *Affect* (6 items): Feelings towards statistics. The higher the score, the higher is the positive feeling.
ii)- *Cognitive Competence* (6 items): Perception of intellectual competence and capacity to apply statistics. The higher the score, the higher the perception is strong.
iii)- *Value* (9 items): Perceived usefulness, relevance and value of statistics in professional and personal life. The higher the score, the more the perception of statistics is useful.
iv)- *Difficulty* (7 items): Perception of the difficulty of statistics as a subject. The higher the score is, the more the perception of statistics is easy.
v)- *Interest* (4 items): Level of interest in statistics. The higher the score, the more the interest is strong. (SATS-36 only)
vi)- *Effort* (4 items): The amount of work that the student plans to implement in the

statistics course. The higher the score, the more the expected effort is important. (SATS-36 only)

There are two versions of the questionnaire: One administered before the course ("pre-SATS") and another after the course ("post-SATS"). The complete version of SATS-36 is available online: http://evaluationandstatistics.com and pre-questionnaire is also provided in *Appendix* A.

4.2 Item parceling

Following the recommendations of the reference work on the instrument SATS (Schau et al. 1995), a technique of *item parceling* was used to group some items into parcels 3 or 4 items for each dimension. These authors suggested this strategy in order to reduce the problems of non-normality of some items. Some authors, however, pointed out that the parceling procedure might produce biased estimates of model parameters (Bandalos, 2002; Matsunaga, 2008). Optimal parceling techniques have been put forward for creating parcels without distorting the dimensionality of measures (Little et al., 2002). For the present work, we use factor algorithm techniques developed by Lundis et al. (2002). The technique uses one-factor exploratory analysis to create parcels according to loadings numerical values. For a given one dimensional data sample, a one-factor exploratory analysis is carried out and the obtained loadings are ordered from the smallest to the largest magnitude: $\lambda_1 < \lambda_2 < \lambda_3 < \ldots < \lambda_p$, where p is the number of items included in each dimension. If a number of parcels are selected (say 3 for example), item 1 (after ordering) is assigned to parcel 1, item 2 is assigned to parcel 2 and item 3 is assigned to parcel 3 in a first round. Next, item 4 is assigned to parcel 3, item 5 is assigned to parcel 2 and item 6 is assigned to parcel 1. The procedure is iterated until all items are assigned.

4.3 Global results

We now present the statistical results obtained from SATS-36 data. The analysis is carried out using two data samples: Section 67 with a sample size n = 89 and Section 96

with n = 53. The results for the latter section are presented in *Appendix* B. Table 1 shows the mean scores $\hat{\mu}$, variances $\hat{\sigma}^2$ and skewness $\hat{\gamma}$ associated with each item for each category (dimension). The numerical value of the skewness indicates whether the data depart from a normal distribution. The skewness of a normal distribution is equal to 0. The distribution of items according to the dimension (category) is also shown on Table 1.

Table 1a: *Affect*

	$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$		$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$
Item 3	4.76	1.32	-0.164		4.69	2.29	-0.487
Item 4	4.47	2.41	-0.158		4.53	2.30	-0.310
Item 15	4.80	2.73	-0.373		4.69	2.70	-0.572
Item 18	4.09	2.56	-0.030		4.81	1.88	-0.130
Item 19	4.30	1.40	-0.064		4.25	1.80	-0.171
Item 28	4.33	2.99	-0.101		5.11	2.06	-0.268

Table 1b: *Cognitive Comprehension*

	$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$		$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$
Item 5	4.64	2.48	-0.182		4.66	2.32	-0.118
Item 11	5.67	1.63	-0.919		5.84	1.41	-1.050
Item 26	4.37	2.19	-0.190		4.82	1.85	-0.270
Item 31	6.02	1.16	-1.254		5.86	0.80	-0.309
Item 32	5.08	1.44	-0.351		4.90	1.75	-0.642
Item 35	4.24	2.21	-0.306		4.56	1.86	-0.252

Table 1c: *Value*

	$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$		$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$
Item 7	6.03	1.94	-1.758		5.75	1.94	-1.204
Item 9	4.83	2.14	-0.581		4.48	2.98	-0.345
Item 10	5.26	1.74	-0.903		4.87	1.85	-0.657
Item 13	5.69	2.13	-1.343		5.47	1.68	-0.519
Item 16	5.34	2.14	-0.577		5.20	1.71	-0.624
Item 17	4.72	2.80	-0.342		4.10	2.34	-0.056
Item 21	5.25	1.71	-0.403		5.15	1.99	-0.358
Item 25	5.62	2.03	-0.937		5.46	2.00	-0.537
Item 33	5.56	2.11	-0.927		5.34	1.91	-0.777

Table 1d: *Difficulty*

	$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$		$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$
Item 6	4.02	1.39	0.167		4.47	2.07	-0.036
Item 8	3.56	2.07	0.498		3.64	2.53	0.313
Item 22	3.28	1.71	0.389		3.30	1.65	-0.288
Item 24	3.25	1.60	0.036		3.78	1.99	-0.157
Item 30	3.96	1.79	-0.089		4.48	1.91	-0.367
Item 34	3.88	1.81	-0.167		4.15	1.94	-0.237
Item 36	3.74	1.67	0.014		4.08	1.85	0.130

Table 1e: *Effort*

	$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$		$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$
Item 1	6.80	0.87	-5.612		6.72	0.70	-4.772
Item 2	6.61	1.01	-4.122		5.98	1.66	-1.595
Item 14	6.18	1.17	-2.578		5.54	1.86	-0.931
Item 27	6.47	0.91	-3.034		6.12	1.56	-1.287

Table 1f: *Interest*

	$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$		$\hat{\mu}$	$\hat{\sigma}^2$	$\hat{\gamma}$
Item 12	4.54	2.25	-0.442		4.00	2.48	-0.123
Item 20	4.79	1.56	-0.332		4.27	2.02	-0.269
Item 23	4.99	1.58	-0.808		4.29	2.14	-0.450
Item 29	5.16	1.57	-0.650		4.49	2.23	-0.411

Table 1 indicates that the data variability range is quite similar for all SATS-36 items. Overall, all items have a mean numerical value above neutral (4) except *Difficulty* category items. A mean value above neutral means a positive attitude. In this sense, it seems also that there are no significant differences between pre and post data. Moreover, the skewness numerical values are small for only few items (such item 18 or item 24). For most of items, the skewness numerical values are high that indicate a significant departure from a normal distribution. This is particularly obvious for items associated with *Effort* category. Factor analysis assumptions require that the items follow a normal distribution. Item parceling is an attempt to partially remedy to the problem, and its purpose is to obtain a nearly normal distribution of items. Based on the technique of parceling described in section 4.2 and following Schau et al. (1995), we parceled each

dimension according the scheme below given on Table 2. Normal distribution Shapiro-test *p*-Values are also provided for pre- and post- SATS data.

Table 2: Item parcels

	Pre-SATS			**Post-SATS**	
Parcels	**Items**	***P-value***		**Items**	***P-value***
*Affect*_1	3, 28	.0440		15, 19	.0315
*Affect*_2	15, 19	.0045		3, 4	.0048
*Affect*_3	4, 18	.0398		18, 28	.0148
*Cog. Comp*_1	26, 31	.0023		5, 31	.0002
*Cog. Comp*_2	11, 35	.0175		11, 26	.0041
*Cog. Comp*_3	5, 32	.0109		32, 35	.0187
*Value*_1	16, 17, 21	.0136		9, 10, 25	.0427
*Value*_2	7, 33	.0000		13, 33	.0005
*Value*_3	10, 13	.0000		7, 17	.0098
*Value*_4	9, 25	.0005		16, 21	.0054
*Difficulty*_1	6, 8, 34	.0150		8, 22, 24	.0259
*Difficulty*_2	22, 24	.0005		6, 34	.0339
*Difficulty*_3	30, 36	.0003		30, 36	.0675
*Effort*_1	2, 27	.0000		1, 14	.0000
*Effort*_2	1,14	.0000		2, 27	.0000
*Interest*_1	12, 20	.0320		23, 29	.0102
*Interest*_2	23, 29	.0003		12, 20	.0836

There is evidence that all variables obtained from item parceling don't follow normal distribution based on the critical value α_C = .05 except for post *Difficulty*_3 and post *Interest*_2 variables. Figure 1(*a*,*b*) shows the probability plot for each new variables obtained after item parceling for pre SATS-36 data. Figure 2(*a*,*b*) shows the same plot for post SATS-36 data. First and as indicated on Table 2, the obtained test *p-Value*s are all below the critical value (5%) indicating the normality assumption of the data is not validated. The probability plots of Figure 1 and 2 show that the data do not satisfactorily line up along the normality line. This is obvious for *Effort* category. Perhaps parceling SATS data with a reduced total number of variables will result an improvement of *p*-values towards a validation of the normality assumption.

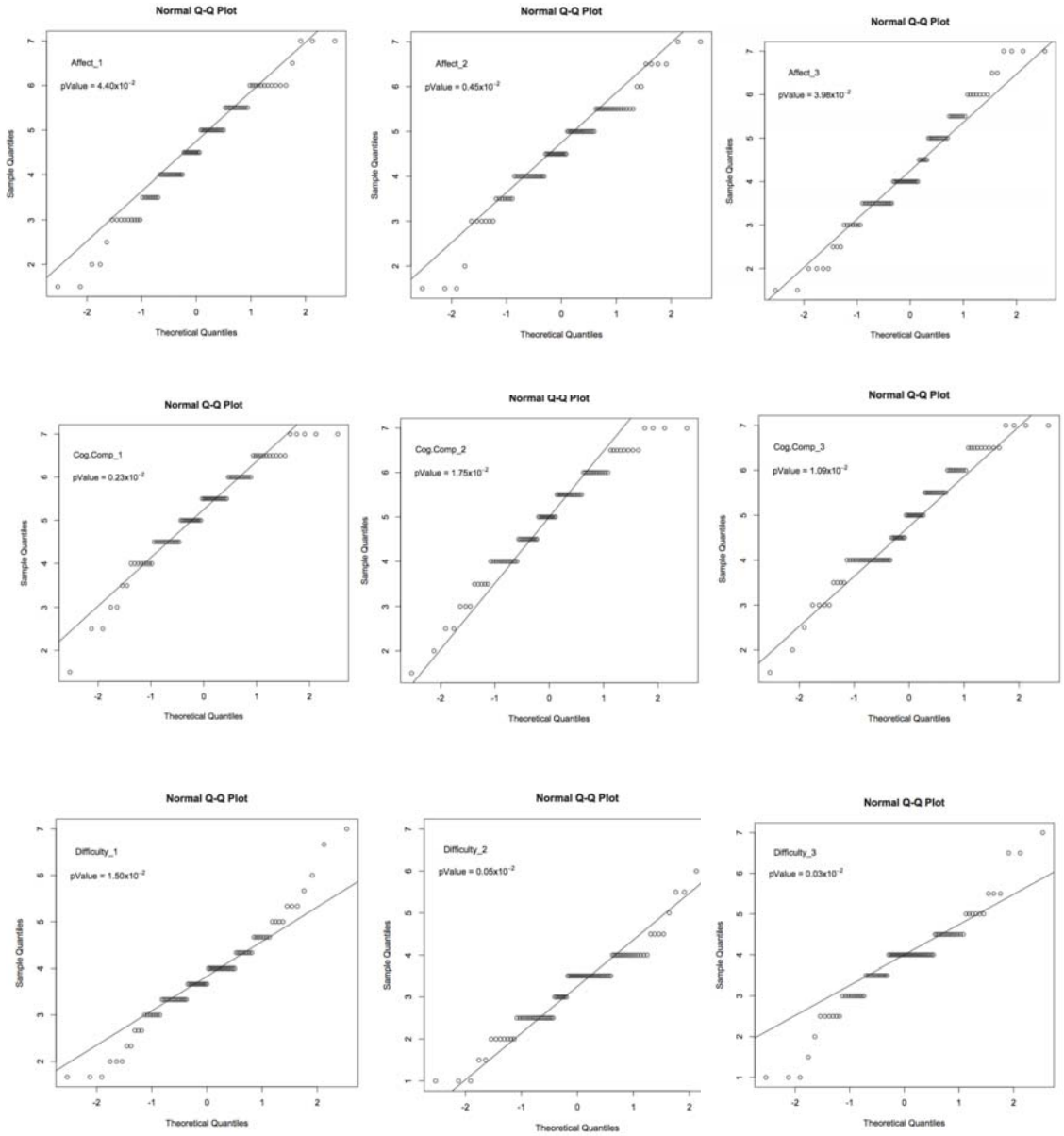

Figure 1(*a*): Probability plots for *Affect* (top panels), *Cognitive Comprehension* (middle panels) and *Difficulty* (Bottom panels) for pre-SATS categories.

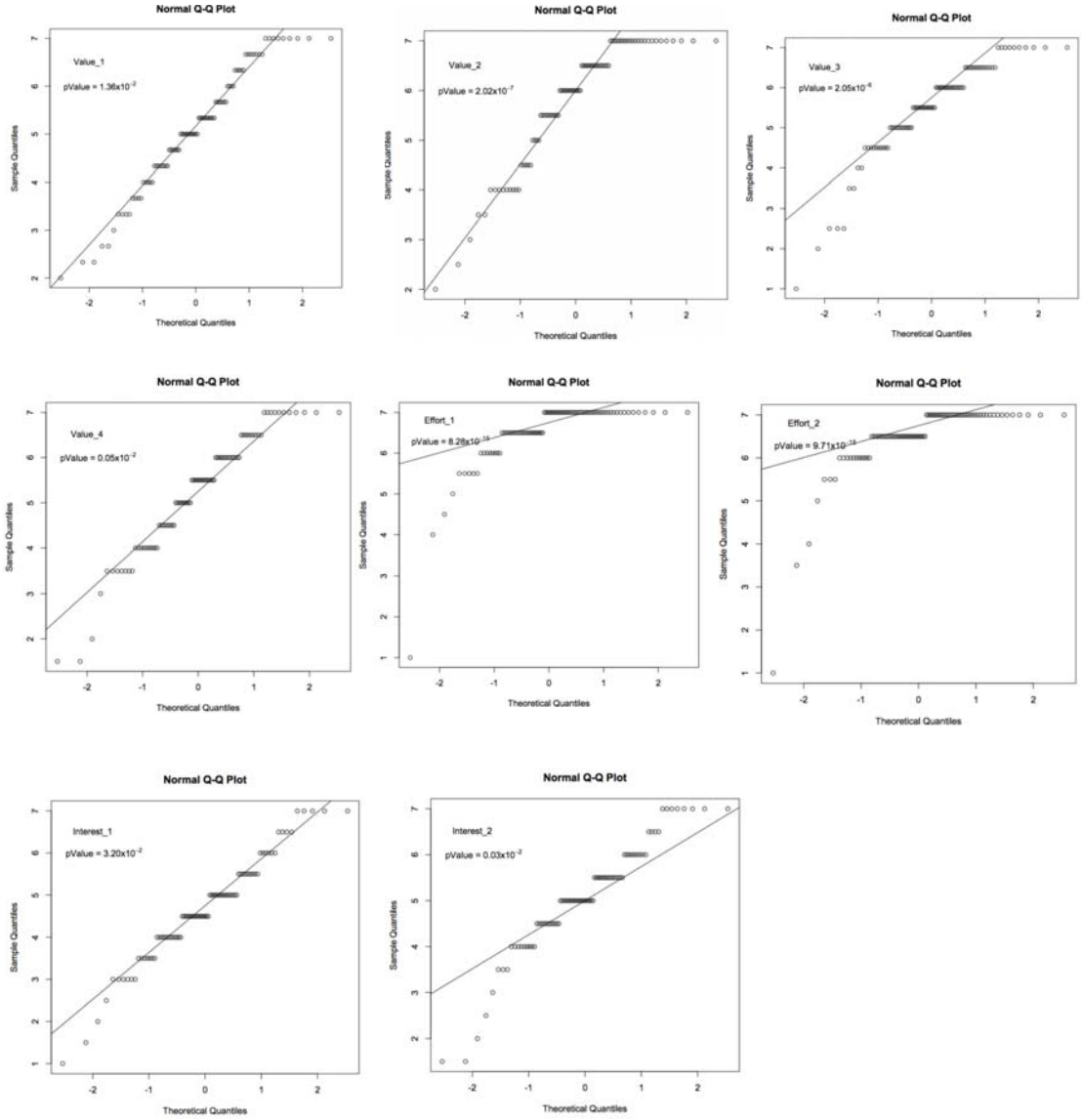

Figure 1(*b*): Probability plots for *Value* (top panels), *Effort* (middle panels) and *Interest* (Bottom panels) for pre-SATS categories.

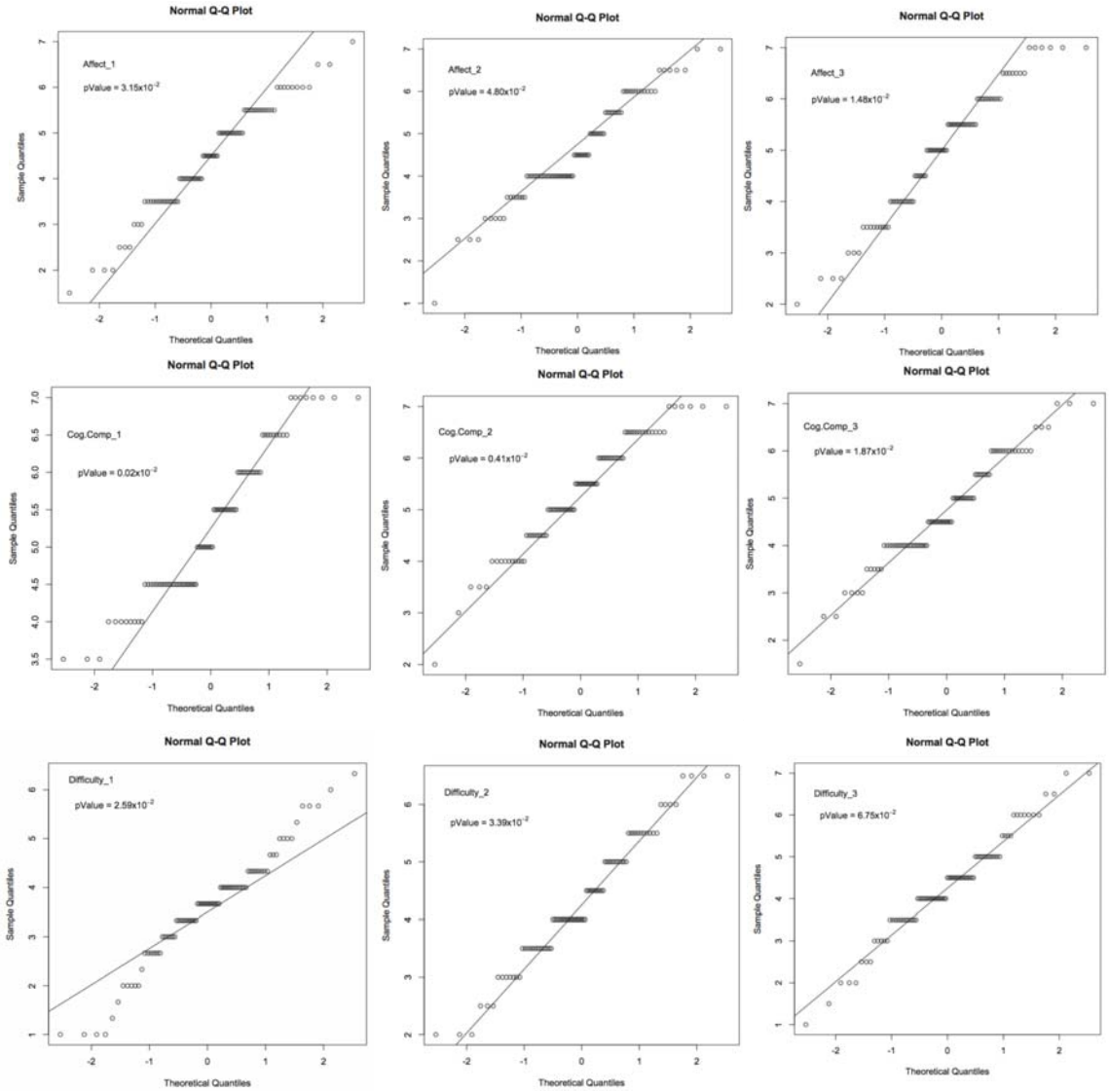

Figure 2(*a*): Probability plots for *Affect* (top panels), *Cognitive Comprehension* (middle panels) and *Difficulty* (Bottom panels) post SATS categories.

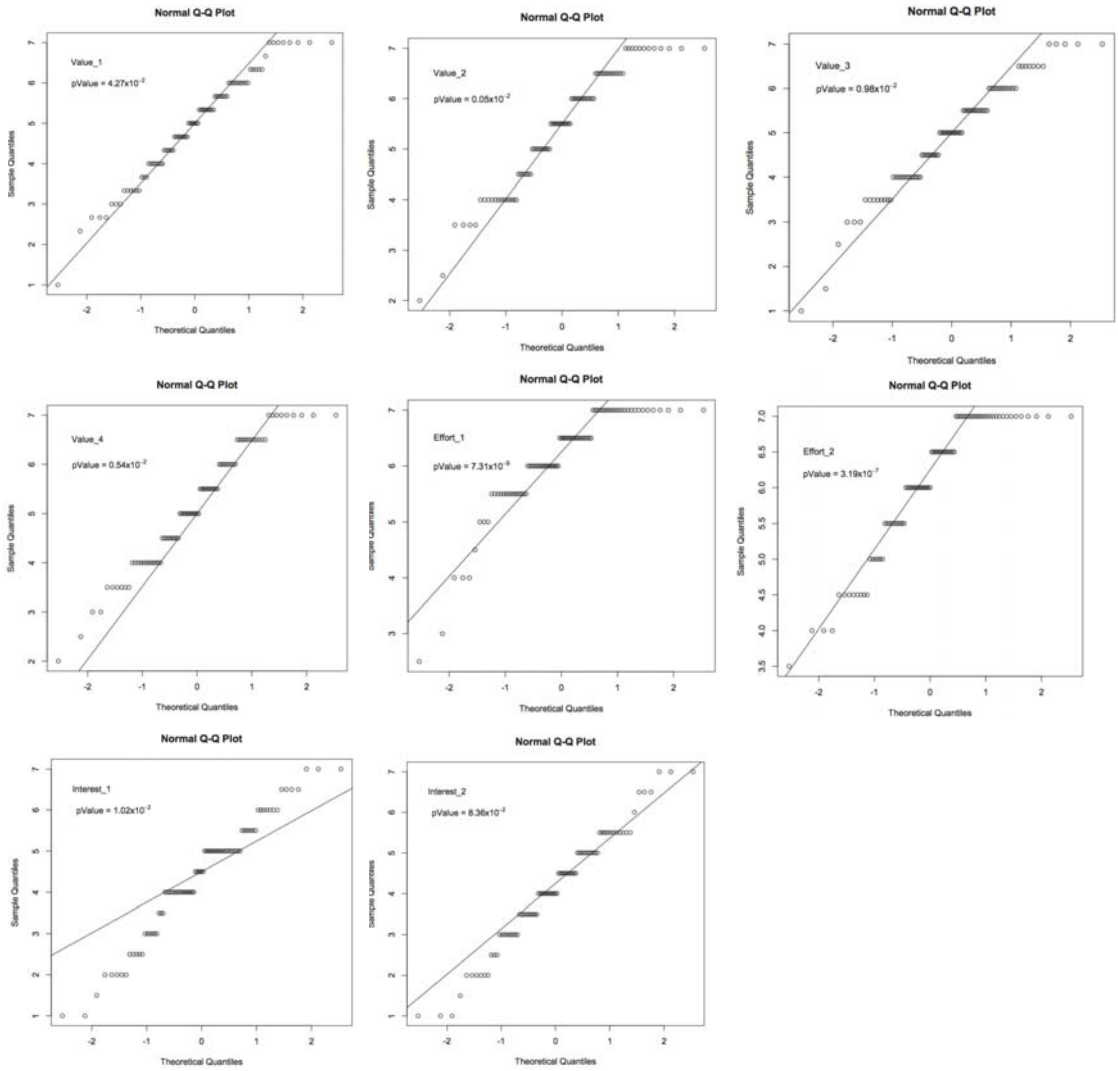

Figure 2(*b*): Probability plots for *Value* (top panels), *Effort* (middle panels) and *Interest* (Bottom panels) for post-SATS categories.

Moreover, in order to see if there is a significant relationship between participant responses to SATS-36 items, the coefficient of correlation (Spearman) between the six dimensions is calculated. The post SATS numerical values are given in bold character.

Table 3: Correlation coefficients between categories

	Affect	**Cog.Comp.**	**Value**	**Difficulty**	**Effort**	**Interest**
Affect	1.000	0.750	0.501	0.675	0.435	0.005
Cog.Comp.	**0.729**	1.000	0.412	0.629	0.310	0.084
Value	**0.504**	**0.490**	1.000	0.170	0.681	0.315
Difficulty	**0.582**	**0.558**	**0.255**	1.000	0.186	0.198
Effort	**0.465**	**0.306**	**0.665**	**0.142**	1.000	0.102
Interest	**0.010**	**0.159**	**0.247**	**0.072**	**0.202**	1.000

The obtained determination for the correlation coefficients above seem to indicate a possible dependence between categories *Affect – Cog.Comp*, *Affect – Value*, *Affect – Difficulty*, *Cog.Comp – Difficulty* and *Value – Effort*. For each previous two catergories, the correlations coefficient is larger than 0.5. It seems that this result is valid for both pre and post SATS-36 data. The correlation between SATS-36 categories may point to item overlap that could exist between the considered factor structures.

4.4 Dimensional analysis of SATS-36 categories

In the present section, we aim to investigate the dimensionality of SATS-36 categories using both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) on the data items. Particularly, a 1-factor model is of prime interest since each category is supposed to represent a single aspect of the attitudes towards statistics. Before proceeding to the dimensional analysis, we first examine whether each category (*Affect* ,…) is internally consistent, i.e the extent to which to all items positively contribute to measure the same category (*Interest* for example). The quality of a score is related to a consistency

within its category. While *Pearson*'s (or *Spearman*) coefficient looks at the correlation between interval data, *Cronbach*'s α examine how well a set of a survey items measure a single characteristic. The latter coefficient is widely used to measure the internal consistency of a data set. If k is the number of items, σ_i^2 and σ_T^2 are the variance associated with item i and the variance of the total of k item scores respectively, the Cronbach coefficient is defined as:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{1}{\sigma_T^2}\sum_{i=1}^{i=k}\sigma_i^2\right)$$

There is no widely accepted threshold for α that indicates whether or not a set of items is internally consistent. However, a numerical value exceeding 0.7 is advocated in the literature [Nunnally, 1978]. The internal consistency is considered as poor if *Cronbach* α is less than 0.7.

Table-4: *Cronbach* coefficient α

Category	**PRE**	**POST**
Affect	0.78	0.77
Cognitive Comprehension	0.85	0.77
Value	0.88	0.90
Difficulty	0.76	0.80
Effort	0.82	0.67
Interest	0.87	0.90

The calculated *Cronbach* coefficients as listed on Table-4 above provide a strong indication that each of the 6 categories used in SATS-36 are internally consistent. For post-SATS-36 data, *Value* and *Interest* categories provide the highest magnitude (α =

.90) while *Value* has the highest (α = .88) among the 6 categories in the case of pre-SATS data. Overall, all coefficient numerical values are higher than 0.76 except post-SATS *Effort* category.

a) Exploratory factor analysis

We pursue our analysis in using the exploratory factor analysis procedure on SATS-36 categories. The purpose is to probe features indicating whether each SATS-36 category has more than factor, i.e. depart from one-dimensional structure. As seen above, *Affect*, *Cog.Comp* and *Difficulty* categories are parceled into 3 groups, *Value* category into 4 groups and *Effort* and *Interest* categories into 2 groups. Based on the number of obtained variables (groups) of each category, we run one–factor analysis model for *Effort* and *Interest*, 1– and 2–factor model for *Affect*, *Cog.Comp* and *Difficulty* and 1–, 2– and 3–factor model for *Value*. In each case, the cumulative proportion variance is determined. Table 5 summarizes the exploratory factor analysis obtained results for each category. Clearly, 1-factor model is quite satisfactory for both *Effort* and *Interest* categories since it accounts for ~90% of the variance. For the remaining categories, 1-factor model explain most of the variability of the data content (above ~ 70%) for both pre- and post data.

Table 5: Cumulative Proportion Variance

	PRE				**POST**		
	1-Factor	2-Factor	3-Factor		1-Factor	2-Factor	3-Factor
Affect	0.732	0.904			0.730	0.898	
Cog.Comp	0.750	0.892			0.694	0.878	
Value	0.694	0.813	0.910		0.758	0.873	0.947
Difficulty	0.657	0.871			0.726	0.880	
Effort	0.910				0.862		
Interest	0.899				0.906		

Finally, the numerical values for the factor loadings λ_{ij} in the 1-factor model are given on Table 6 below. Overall, the Table shows that the loadings associated with each category have nearly the same weight as it is expected since parceling is not supposed to have an impact on the category structure.

Table 6: One-Factor loadings

	PRE					POST			
	λ_1	λ_2	λ_3	λ_4		λ_1	λ_2	λ_3	λ_4
Affect	-1.051	-0.960	-1.096			-1.004	-0.995	-1.004	
Cog.Comp	+1.133	+1.018	+1.018			-1.030	-0.862	-0.889	
Value	-1.042	-1.016	-0.994	-1.053		-1.092	-1.028	-1.074	-1.032
Difficulty	+0.839	+0.845	+0.825			+0.939	+0.910	+1.001	
Effort	+0.797	+0.812				+0.832	+0.877		
Interest	-1.149	-1.088				-1.315	-1.306		

b) Confirmatory factor analysis

We pursue our analysis further using confirmatory analysis to evaluate the dimension of SATS-36 categories. The construction of item categories assumes that each category contains proper items. If selected items fit two or more categories, it is reflected in the dimension of SATS-36. We explore the possible dependence between SATS-36 categories with a 2-factor model CFA. Precisely, two categories are selected and we use a 2-factor model to examine whether the hypothesis of independence is rejected or not. Explicitly and as explained above in Section 3.3, the null hypothesis assumes that the population covariance $\mathbf{\Sigma}$ is given by:

$$H_0: \quad \boldsymbol{\Sigma} = \boldsymbol{\Lambda}\boldsymbol{\Phi}\boldsymbol{\Lambda}^T + \boldsymbol{\Psi}$$

where $\boldsymbol{\Lambda}$ is a 2-factor loading matrix which elements are to be determined. The null hypothesis is afterward tested using indicators (such χ^2). For instance, to explore a possible dependence through items between *Affect* and *Value* categories, we use a 2-factor model with the following structure for the loading and residual matrices given by:

$$\boldsymbol{\Lambda} = \begin{pmatrix} \lambda_1 & 0 \\ \lambda_2 & 0 \\ \lambda_3 & 0 \\ 0 & \lambda_4 \\ 0 & \lambda_5 \\ 0 & \lambda_6 \\ 0 & \lambda_7 \end{pmatrix} \qquad and \qquad \Psi = \begin{pmatrix} \psi_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \psi_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \psi_3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \psi_4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \psi_5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \psi_6 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \psi_7 \end{pmatrix}$$

To perform CFA, the c*fa* routine from *lavaan* package in R is used. It provides resources for users dealing with latent variable modeling. Two SATS-36 categories, for which the parceling have been performed, are provided as input data variables to *lavaan-cfa* routine along with 2-factor model assignment.

The routine provides a detailed diagnosis, which allows us to test the interdependence between categories taken two-by-two. Test indicators as such χ^2, *p-Values*, RMSEA are calculated by the routine and provided as output. The null hypothesis is rejected or not based on the *p-Values* provided by *lavaan*. Both *p-Values* and RMSEA are reported on Table 7 and Table 8 below; coefficients written in bold correspond to post-SATS data.

Table 7: ***Lavaan p*-values**

	Affect	Cog.Comp.	Value	Difficulty	Effort	Interest
Affect		.040	.007	.372	.214	.267
Cog.Comp.	**.765**		.177	.306	.285	.486
Value	**.025**	**.006**		.077	.438	.137
Difficulty	**.126**	**.001**	**.177**		.109	.117
Effort	**.352**	**.386**	**.004**	**.709**		.484
Interest	**.001**	**.274**	**.012**	**.218**	**.652**	

Table 8: ***Lavaan RMSEA***

	Affect	Cog.Comp.	Value	Difficulty	Effort	Interest
Affect		.107	.116	.030	.071	.058
Cog.Comp.	**.000**		.062	.045	.054	.000
Value	**.101**	**.119**		.082	.000	.078
Difficulty	**.080**	**.164**	**.062**		.100	.097
Effort	**.034**	**.020**	**.143**	**.000**		.000
Interest	**.205**	**.057**	**.127**	**.070**	**.000**	

In order to see whether there is a possible interdependence between two categories, the obtained *p-Value* from *lavaan* package are compared to the critical α_c = 0.05; RMSEA index is also used to illustrate the approximation power of the fit. Table 7 indicates that there are 8 cases for which *p-Value* is less than α_c: the pre *Affect-Cog.Comp*, the pre *Affect-Value*, the post *Affect-Value*, the post *Affect-Interest* the post *Cog.Comp-Value*, the

post *Cog.Comp*-Difficulty, the post *Value-Effort* and the post *Value-Interest*. For these cases, item independence assumption can be rejected. Therefore, there is evidence for an overlap between each of two categories listed above. This result agrees with the RMSEA index values, which indicate that there is evidence that the fit is not acceptable (RMSEA > 0.1). However, taking account of *Bonferroni* correction because we performed all possible pairs of comparison with the same data, the critical *p-Value* is $\alpha_{cc} = \alpha_c/p$ for each individual test, where p is a number of comparisons which is 15 in our study, α_c is the original critical p-Value and α_{cc} is the corrected critical alpha. Taking into account *Benferroni* correction, *lavaan* results provide *p-Values* higher then α_{cc} for all cases except the post *Affect-interest and* the post *Cog.Comp-Difficulty*. To illustrate the correction, the post *Affect-Interest* has p-value= 0.001 which is less then = 0.05/15 = 0.003. Therefore, for all cases except the two cases the post *Affect-interest* and the post *Cog.Comp-Difficulty* and based on *p-Values*, there is no evidence that the items overlap. We notice that although a p-Value greater than α_c does not always correspond to a good approximation case (RMSEA < 0.05). Most of RMSEA index values correspond to a mediocre approximation (.05 < RMSEA < 0.1).

We emphasize that above results are obtained from the course section 67 data collected during Spring 2009. Conclusive results require a comprehensive study that includes several course sections. The study of additional sections allows comparisons and affords to make a reliable assessment on the dimensional structure of SATS-36 categories. In addition to course section 67, we analyzed SATS-36 data of section 96 collected during Fall 2009. The same analyses including a normality test and factor analyses have been performed on the data. For section 96, the data sample size (n = 53) is slightly less than for section 67 (n = 89). The obtained results are shown in Appendix B. Overall, the results obtained from the analysis of section 96 are in a very good agreement with those obtained from section 67. First, the internal consistency indicator *Cronbach* α coefficient numerical values are very similar with those found in section 67. The lowest obtained numerical value is associated with post SATS *Difficulty* category data, α = 0.68 quite

close to the threshold of 0.70 is required for the internal consistency. Like results from section 67, *Interest* category *Cronbach* α is the highest (.91). Also, for section 67, there is evidence that most of item values after parceling fail the normality test at 5% level of significance. The results of the exploratory factor analysis and confirmatory factor analysis are very similar to those of section 67.

Chapter 5: Conclusion

The dimensional structure of the six categories of STAS-36 is examined using factor analysis. The study is based on data collected in year 2009 from two course sections. Each section is considered separately in our data analysis. First, the normality test performed on the item values fail at 5% level of significance for most of the items (36 total). Exploratory factor analysis results strongly indicate that the variability of data related to each category can be accounted for with one single factor. Confirmatory factor analysis provides results that suggest that the specific items composing each category are exclusive in most of the cases. This means that item overlap between the categories remain weak although not negligible. The internal consistency of each category is also examined through *Cronbach* coefficient α. The obtained values of α show evidence of a quite strong internal consistency for data of both sections 67and 96. These results confirm that the 6-factor structure is suited to the inherent structure reflected in SATS-36 data. This is still valid on data collected recently. This may suggest that SATS-36 structure seems to be linked with students' attitude rather than educators. We should however mention that our main result is based on the use of combinations of items (parcels) rather than individual items. Therefore, our study only provides a limited insight into the underlying structure of the SATS. In summary and based on new data, our study shows that the item score variability within each SATS category is sufficiently accounted for by attributing one single factor. These results are in agreement with the initial dimensional structure introduced by Schau in 2003.

Bibliography

Albarracin, D., B. T. Johnson, and M. P. Zanna, The handbook of attitudes, *Psychology Press*, New York, 2014.

Bentler, P. M., Comparative fit indexes in structural models, *Psychological Bulletin*, **107**, 238-246, 1990.

Burt, C. L., Alternative Methods of Factor Analysis and their Relations to Pearson's Method of Principal Axes, *British Journal of Psychology*, **2**: 98–121, 1949.

Carifio, J. & R. Perla, Resolving the 50-years debate around using and misusing Likert scales, *Medical Education*, **42**, 1150-1152, 2008.

Gal I., and L. Ginsburg, The role of beliefs and attitudes in learning statistics: Towards an assessment framework, *Journal of Statistics Education*, **2**(2): 1994. (http://www.amstat.org/publications/jse/v2n2/gal.html)

Johnson, R. A. and D. W. Wichern, Applied Multivariate Statistical Analysis, 6th Edition, *Pearson Education Inc.*, New Jersey, 2007.

Kelley, T. L., The selection of upper and lower groups for the validation of test items, *Journal of Educational Psychology*, **30**(1) 7-24, 1939.

Leong, J. L., High school students' attitudes and beliefs regarding statistics in a service-learning based statistics course, *Georgia State University*, Georgia, 2006.

Likert, R., A technique for the measurement of attitudes, *Archives of Psychology*, **140**, 5-53, 1932.

Little, T. D., W. A. Cunningham, G. Shahar, and K. F. Widaman, To parcel or not to

parcel: Exploring the question, weighing the merits, *Structural Equation Modeling*, ***9***, 151-173, 2002.

Lubke, G. H. and Muthén, B. O., Applying Multigroup Confirmatory Factor Models for Continuous Outcomes to Likert Scale Data Complicates Meaningful Group Comparisons, *Structural Equation Modeling*, **11**(4), 514–534, 2004.

Lundis, R. S., D. J. Beal, and P. E. Tesluk, A comparison of approaches to forming composite measures in structural equation models, *Organizational Behavioral Research*, ***3***, 186-207, 2002.

Norman, G., Likert scales, levels of measurement and the "laws" of statistics, *Adv. In Health Sci. Educa.*, **15**, 625-632, 2010.

Nunnaly, J. C., Psychometric theory, *Mc-Graw-Hill*, New York, 1978.

Ramirez C., Schau C., and E. Esma, The importance of attitudes in statistics education, *Statistics Education Research Journal*, **11**(2), 57-71, 2012.

Roberts, D. M., and J. E. Saxe, Validity of a statistics attitude survey: A follow up study, *Educational and Psychological Measurement*, **42**(3): 907-912, 1982.

Schau, C., J. Stevens, T. L. Dauphinee, and A. D. Vecchio, The Development and Validation of the Survey of Attitudes toward Statistics, *Educational and Psychological Measurement* **55**(5), 868-875, 1995.

Schau, C. (1992), Survey of Attitudes Toward Statistics (SATS-28).
(http://evaluationandstatistics.com)

Schau, C. (2003), Survey of Attitudes Toward Statistics (SATS-36).
(http://evaluationandstatistics.com)

Schermelleh-Engel, K., H. Moosbrugger, and H. Müller, Evaluating the Fit of Structural Equation Models: Tests of Significance and Descriptive Goodness-of-Fit Measures, *Methods of Psychological Research*, **8**, (2), 23-74, 2003

Spearman, C., General intelligence: Objectively determined and measured, *American Journal of Psychology* **15**, pp201-293, 1904.

Steiger, J. H., Structural model evaluation and modification: An interval estimation approach, *Multivariate Behavioral Research*, **25**, 173−180, 1990.

Thurstone, L. L., Multiple-Factor analysis, *University of Chicago Press*, Chicago, 1947.

Waters, L. K., T. A. Martelli, T. Zakrajsek, and P. M. Popovitch, Attitudes toward statistics: an evaluation of multiples measures, *Educational and Psychological Measurement*, **48**(2): 513-516, 1988.

Wise, S. L., The development and validation of a scale measuring attitudes toward statistics, *Educational and Psychological Measurement*, **45**(2): 401-405, 1985.

Appendix A: Pre SATS-36 Questionnaire

Pre SATS - Spring 2009

SATS Pretest Spring 2009 - © Schau, 1996, 2003

Welcome!

This is the website to take the Survey of Attitudes Toward Statistics© (SATS©). The survey consists of an identification page, a page in which you give your consent for participation, and then the SATS© survey.

Thank you for your participation.

Identification Page

Since this study includes responses to the SATS© Pretest and Posttest and course grades, we need your name and birthdate so that we can match all three sets of information. Your name will be removed once we have completed this matching.

Some instructors may give credit or extra credit for project participation. You will receive this credit even if you choose NOT to take the SATS© survey. However, you will need to fill in the following identifying information in order to receive this credit. Thus, we need to ensure that we have identifying information for everyone.

***Name (please give your first and last names as they appear on grade lists, with the first letter of each capitalized - thanks):**

First Name

Last Name

***Birthdate**

Enter your birth date MM / DD / YYYY

Informed Consent Page

Description of the Study: We are conducting an educational research study about students' attitudes toward statistics. We are interested in (1) what these attitudes are, (2) how attitudes relate to student and instructor characteristics, (3) how attitudes relate to course grades, and (4) how attitudes change across the course. The long-term goal of this kind of research is to improve instruction in statistics courses.

Conditions of Participation: Participation is voluntary. You may discontinue participation at any time. Declining to participate or discontinuing participation will NOT result in any penalty.

Confidentiality: You have been asked to give us your name. The sole purpose is to link your Pretest responses with your Posttest responses, as well as with your grade in the course. Once we have completed this matching, your name will be removed. To ensure your confidentiality, all of our findings will be presented in summary form with no names. Your instructor will never see your name with your responses.

Study Procedures: The entire survey should take no more than 10 - 15 minutes to complete. It is important to our research that you complete every item, but you are not required to do so.

Page 1

Pre SATS - Spring 2009

Potential Benefits and Risks to You: This study is educational research and does not have any known associated risks. By filling out the survey, you may be better able to identify your feelings toward statistics.

If you have any questions about the survey or if you decide that you no longer wish to participate in the study after you have given your consent, please contact Marjorie Bond at mebond@monm.edu or (309) 457 - 2338.

***I have read and understand the terms and conditions of this research study and hereby agree to participate. I understand my participation is voluntary and that I may withdraw at any time without penalty. By clicking "yes" I am indicating my permission to participate in the study.**

- ◯ YES
- ◯ NO

SATS Pretest Page 1

The statements below are designed to identify your attitudes about statistics. Each item has 7 possible responses. The responses range from "Strongly disagree" through "Neither disagree nor agree" to "Strongly agree". If you have no opinion, choose "Neither disagree nor agree." Please read each statement. Mark the ONE response that most clearly represents your degree of agreement or disagreement with that statement. Try not to think too deeply about each response. Record your answer and move quickly to the next item. Please respond to all of the statements.

	Strongly disagree			Neither disagree nor agree			Strongly agree
I plan to complete all of my statistics assignments.	◯	◯	◯	◯	◯	◯	◯
I plan to work hard in my statistics course.	◯	◯	◯	◯	◯	◯	◯
I will like statistics.	◯	◯	◯	◯	◯	◯	◯
I will feel insecure when I have to do statistics problems.	◯	◯	◯	◯	◯	◯	◯
I will have trouble understanding statistics because of how I think.	◯	◯	◯	◯	◯	◯	◯
Statistics formulas are easy to understand.	◯	◯	◯	◯	◯	◯	◯
Statistics is worthless.	◯	◯	◯	◯	◯	◯	◯

Please check that you have answered every question on this page (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pretest Page 2

Pre SATS - Spring 2009

	Strongly disagree			Neither disagree nor agree			Strongly agree
Statistics is a complicated subject.	◯	◯	◯	◯	◯	◯	◯
Statistics should be a required part of my professional training.	◯	◯	◯	◯	◯	◯	◯
Statistical skills will make me more employable.	◯	◯	◯	◯	◯	◯	◯
I will have no idea of what's going on in this statistics course.	◯	◯	◯	◯	◯	◯	◯
I am interested in being able to communicate statistical information to others.	◯	◯	◯	◯	◯	◯	◯
Statistics is not useful to the typical professional.	◯	◯	◯	◯	◯	◯	◯
I plan to study hard for every statistics test.	◯	◯	◯	◯	◯	◯	◯

Please check that you have answered every question on this page (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pretest Page 3

	Strongly disagree			Neither disagree nor agree			Strongly agree
I will get frustrated going over statistics tests in class.	◯	◯	◯	◯	◯	◯	◯
Statistical thinking is not applicable in my life outside my job.	◯	◯	◯	◯	◯	◯	◯
I use statistics in my everyday life.	◯	◯	◯	◯	◯	◯	◯
I will be under stress during statistics class.	◯	◯	◯	◯	◯	◯	◯
I will enjoy taking statistics courses.	◯	◯	◯	◯	◯	◯	◯
I am interested in using statistics.	◯	◯	◯	◯	◯	◯	◯
Statistics conclusions are rarely presented in everyday life.	◯	◯	◯	◯	◯	◯	◯

Please check that you have answered every question on this page (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pretest Page 4

	Strongly disagree			Neither disagree nor agree			Strongly agree
Statistics is a subject quickly learned by most people.	◯	◯	◯	◯	◯	◯	◯
I am interested in understanding statistical information.	◯	◯	◯	◯	◯	◯	◯
Learning statistics requires a great deal of discipline.	◯	◯	◯	◯	◯	◯	◯
I will have no application for statistics in my profession.	◯	◯	◯	◯	◯	◯	◯
I will make a lot of math errors in statistics.	◯	◯	◯	◯	◯	◯	◯
I plan to attend every statistics class session.	◯	◯	◯	◯	◯	◯	◯
I am scared by statistics.	◯	◯	◯	◯	◯	◯	◯

Pre SATS - Spring 2009

Please check that you have answered every question on this page (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pretest Page 5

	Strongly disagree			Neither disagree nor agree			Strongly agree
I am interested in learning statistics.	◯	◯	◯	◯	◯	◯	◯
Statistics involves massive computations.	◯	◯	◯	◯	◯	◯	◯
I can learn statistics.	◯	◯	◯	◯	◯	◯	◯
I will understand statistics equations.	◯	◯	◯	◯	◯	◯	◯
Statistics is irrelevant in my life.	◯	◯	◯	◯	◯	◯	◯
Statistics is highly technical.	◯	◯	◯	◯	◯	◯	◯
I will find it difficult to understand statistical concepts.	◯	◯	◯	◯	◯	◯	◯
Most people have to learn a new way of thinking to do statistics.	◯	◯	◯	◯	◯	◯	◯

Please check that you have answered every question on this page (unless you intentionally left the question blank). If you have no opinion, choose "Neither disagree nor agree."

SATS Pretest Additional Items -1

Please notice that the labels for each scale on this page change from item to item.

	Very poorly						Very well
How well did you do in mathematics courses you have taken in the past?	◯	◯	◯	◯	◯	◯	◯
	Very poor						Very good
How good at mathematics are you?	◯	◯	◯	◯	◯	◯	◯
	Not at all						Great deal
In the field in which you hope to be employed when you finish school, how much will you use statistics?	◯	◯	◯	◯	◯	◯	◯
	Not at all confident						Very confident
How confident are you that you can master introductory statistics material?	◯	◯	◯	◯	◯	◯	◯

Please check that you have answered every question on this page (unless you intentionally left the question blank).

SATS Pretest Additional Items - 2

Please notice that the labels for each scale on this page change from item to item.

Pre SATS - Spring 2009

Are you required to take this statistics course (or one like it) to complete your degree program?

- ◯ Yes
- ◯ No
- ◯ Don't know

	Not at all likely						Very likely
If the choice had been yours, how likely is it that you would have chosen to take any course in statistics?	◯	◯	◯	◯	◯	◯	◯

Please check that you have answered every question on this page (unless you intentionally left the question blank).

SATS Pretest Demographic Items - 1

What is your major? If you have a double major, pick the one that best represents your interests.

- ◯ Arts/Humanities
- ◯ Biology
- ◯ Business
- ◯ Chemistry
- ◯ Economics
- ◯ Education
- ◯ Engineering
- ◯ Mathematics
- ◯ Medicine/Pre-Medicine
- ◯ Psychology
- ◯ Sociology/Social Work
- ◯ Statistics
- ◯ Other

Current grade point average (please estimate if you don't know; give only one single numeric response: e.g. 3.52). If you do not yet have a grade point average, please enter 99:

For each of these three items, give one single numeric response (e.g., 26). Please estimate if you don't know exactly.

Number of credit hours earned toward the degree you are currently seeking (don't count this semester)	
Number of high school mathematics and/or statistics courses completed	
Number of college mathematics and/or statistics courses completed (don't count this semester)	

Please check that you have answered every question on this page (unless you intentionally left the question blank).

SATS Pretest Demographic Items - 2

Thank you for your answers so far. You are almost done.

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Degree you are currently seeking:

- ◯ Associate
- ◯ Bachelors
- ◯ Masters
- ◯ Doctorate
- ◯ Certification
- ◯ Post-Bachelor's Licensure
- ◯ Specialist
- ◯ Other

What grade do you expect to receive in this course?

- ◯ A+
- ◯ A
- ◯ A-
- ◯ B+
- ◯ B
- ◯ B-
- ◯ C+
- ◯ C
- ◯ C-
- ◯ D+
- ◯ D
- ◯ D-
- ◯ F

Please check that you have answered every question on this page (unless you intentionally left the question blank).

SATS Pretest Final Demographics

In order to describe the characteristics of your class as a whole, we need your responses to the following two items.

Your sex:

- ◯ Male
- ◯ Female

Your citizenship:

- ◯ US citizen
- ◯ Foreign student
- ◯ Other

Please check that you have answered every question on this page (unless you intentionally left the question blank).

Thanks page

You have reached our "Thank You" page in one of two ways.

The first is that you have completed the SATS. If so, thanks for your help!

The second is that you chose to NOT participate by clicking the "no" button on the Informed Consent page. If you have changed your mind and decided that you do want to participate, click the "Prev" button below and then click the "yes"

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Pre SATS - Spring 2009

button on the Informed Consent page. You then will be able to take the SATS. We thank you for considering our request to assist us.

If you have time and are willing, we would appreciate your responses to two further questions. We will use this feedback to improve our website. Thanks so much.

1. What did you like about taking the SATS on the web?

2. What did you dislike about taking the SATS on the web?

Appendix B: Results for section 67

Affect

	μ	σ^2	$\hat{\gamma}$		μ	σ^2	$\hat{\gamma}$
Item 3	4.85	1.21			4.79	1.74	
Item 4	4.21	2.17			4.49	3.02	
Item 15	4.40	1.47			4.32	2.34	
Item 18	3.43	1.71			4.17	2.49	
Item 19	4.57	0.98			4.15	1.71	
Item 28	3.96	2.96			4.53	3.41	

Cognitive Comprehension

	μ	σ^2	$\hat{\gamma}$		μ	σ^2	$\hat{\gamma}$
Item 5	4.66	1.69			4.55	2.29	
Item 11	5.04	1.34			5.08	2.61	
Item 26	4.60	1.71			5.15	1.98	
Item 31	5.62	1.24			5.83	0.95	
Item 32	5.17	1.22			5.43	0.83	
Item 35	4.00	1.54			3.96	1.77	

Value

	μ	σ^2	$\hat{\gamma}$		μ	σ^2	$\hat{\gamma}$
Item 7	6.13	1.23			5.85	1.75	
Item 9	5.62	1.28			5.06	2.25	
Item 10	5.38	1.55			4.92	1.96	
Item 13	5.57	1.52			5.19	2.12	
Item 16	5.40	1.44			4.83	2.03	
Item 17	4.64	1.81			3.55	2.91	
Item 21	5.17	1.72			5.13	1.50	
Item 25	5.62	1.51			5.72	1.28	
Item 33	5.62	1.20			5.34	1.57	

Difficulty

	μ	σ^2	γ		μ	σ^2	γ
Item 6	3.92	0.54			4.52	1.94	
Item 8	3.28	1.55			2.55	1.37	
Item 22	3.23	1.79			2.32	1.26	
Item 24	3.00	0.81			2.68	1.26	

Item 30	3.85	0.94			4.34	2.31	
Item 34	3.62	1.05			3.49	1.25	
Item 36	3.74	0.98			3.85	2.02	

Effort

	μ	σ^2	$\hat{\gamma}$		μ	σ^2	$\hat{\gamma}$
Item 1	6.57	0.90			6.68	0.38	
Item 2	6.49	0.99			6.19	0.77	
Item 14	6.26	1.9			6.15	0.82	
Item 27	5.98	1.37			6.00	2.69	

Interest

	μ	σ^2	$\hat{\gamma}$		μ	σ^2	$\hat{\gamma}$
Item 12	5.23	1.87			4.09	2.09	
Item 20	5.08	1.07			4.49	1.91	
Item 23	5.17	1.22			4.85	2.09	
Item 29	5.42	1.21			4.87	1.81	

Item parceling and *p*-Values

	Pre-SATS			**Post-SATS**	
Parcels	**Items**	***p*-Value**		**Items**	***p*-Value**
*Affect*_1	19, 28	.0158		3, 28	.0070
*Affect*_2	3, 4	.0148		18, 19	.0140
*Affect*_3	15, 18	.0196		4, 15	.1335
*Cog. Comp*_1	11, 26	.1104		11, 32	.0022
*Cog. Comp*_2	5, 32	.0118		5, 26	.0073
*Cog. Comp*_3	31, 35	.0309		31, 35	.0047
*Value*_1	7, 25, 33	.0002		10, 17, 21	.5892
*Value*_2	10, 13	.0109		7, 13	.0008
*Value*_3	9, 21	.0119		9, 25	.0161
*Value*_4	16, 17	.0198		16, 33	.0418
*Difficulty*_1	6, 8, 34	.0078		6, 30, 36	.0562
*Difficulty*_2	22, 30	.0309		22, 24	.0044
*Difficulty*_3	24, 36	.0054		8, 34	.0359
*Effort*_1	1, 2	.0000		14, 27	.0000
*Effort*_2	14, 27	.0000		1, 2	.0000

*Interest*_1	12, 20	.0644		23, 29	.0006
*Interest*_2	23, 29	.0010		12, 20	.0062

Correlation coefficients between SATS categories (post data are in bold character)

	Affect	**Cog.Comp.**	**Value**	**Difficulty**	**Effort**	**Interest**
Affect	1.000	0.548	0.138	0.634	0.047	0.491
Cog.Comp.	**0.766**	1.000	0.431	0.340	0.286	0.535
Value	**0.288**	**0.304**	1.000	0.044	0.531	0.660
Difficulty	**0.409**	**0.560**	**0.328**	1.000	0.179	0.504
Effort	**0.141**	**0.125**	**0.107**	**0.135**	1.000	0.642
Interest	**0.523**	**0.526**	**0.625**	**0.666**	**0.389**	1.000

***Cronbach* coefficient α**

Category	**PRE**	**POST**
Affect	0.83	0.84
Cognitive Comprehension	0.74	0.75
Value	0.89	0.82
Difficulty	0.79	0.68

Effort	0.85	0.70
Interest	0.90	0.91

Cumulative Proportion Variance

	PRE				POST		
	1-Factor	2-Factor	3-Factor		1-Factor	2-Factor	3-Factor
Affect	0.774	0.898			0.743	0.913	
Cog.Comp	0.616	0.921			0.745	0.891	
Value	0.694	0.854	0.941		0.682	0.838	0.927
Difficulty	0.726	0.891			0.627	0.831	
Effort	0.869				0.900		
Interest	0.885				0.919		

One-Factor loadings

	PRE					POST			
	λ_1	λ_2	λ_3	λ_4		λ_1	λ_2	λ_3	λ_4
Affect	-1.019	-0.912	-0.973			1.149	1.161	1.187	
Cog.Comp	-0.864	-0.743	-0.677			+1.313	+0.890	0.751	

Value	-0.853	-0.905	-0.889	-0.916		-0.859	-0.873	-0.890	-0.913
Difficulty	-0.716	-0.614	-0.651			+0.816	+0.657	+0.734	
Effort	+0.863	+0.874				-1.025	-0.528		
Interest	-1.043	-0.994				+1.236	+1.253		

Lavaan p-Values

	Affect	Cog.Comp.	Value	Difficulty	Effort	Interest
Affect		.013	.213	0.971	.326	.107
Cog.Comp.	**.021**		.133	.214	.176	.105
Value	**.228**	**.290**		.001	.007	.001
Difficulty	**.263**	**.125**	**.190**		.350	.032
Effort	**.203**	**.004**	**.168**	**.315**		.823
Interest	**.068**	**.088**	**.877**	**.069**	**.639**	

Lavaan RMSEA

	Affect	Cog.Comp.	Value	Difficulty	Effort	Interest
Affect		.163	.073	.000	.055	.131
Cog.Comp.	**.154**		.091	.081	.105	.131
Value	**.070**	**.057**		.181	.177	.206
Difficulty	**.069**	**.105**	**.078**		.046	.176
Effort	**.096**	**.232**	**.093**	**.059**		.000
Interest	**.149**	**.139**	**.000**	**.149**	**.000**	

Appendix C: R-routine used for Data Analysis

```
SATS_Analysis <- function(y,n1,n2,flag)
# flag = 0[pre, Sec. 67], = 1[pos, Sec. 67], = 2[pre, Sec.96], 3[pos,
Sec. 96]

{
      n <- n2 - n1 + 1                        # Sample size
i <- c0                                       # Select item parceling
if (flag == 1) {
i <- c1
} else if (flag == 2) {
i <- c2
} else if (flag == 3) {
i <- c3
}
Z <- y[n1:n2,]
X1  <- rowMeans(Z[,i[1:2]])                   # Parcel 1 Affect
X2  <- rowMeans(Z[,i[3:4]])                   # Parcel 2 Affect
X3  <- rowMeans(Z[,i[5:6]])                   # Parcel 3 Affect
X4  <- rowMeans(Z[,i[7:8]])                   # Parcel 1 Cog. Comp.
X5  <- rowMeans(Z[,i[9:10]])                  # Parcel 2 Cog. Comp.
X6  <- rowMeans(Z[,i[11:12]])                 # Parcel 3 Cog. Comp.
```

```
X7  <- rowMeans(Z[,i[13:15]])                # Parcel 1 Value
X8  <- rowMeans(Z[,i[16:17]])                # Parcel 2 Value
X9  <- rowMeans(Z[,i[18:19]])                # Parcel 3 Value
X10 <- rowMeans(Z[,i[20:21]])                # Parcel 4 Value
X11 <- rowMeans(Z[,i[22:24]])                # Parcel 1 Difficulty
X12 <- rowMeans(Z[,i[25:26]])                # Parcel 2 Difficulty
X13 <- rowMeans(Z[,i[27:28]])                # Parcel 3 Difficulty
X14 <- rowMeans(Z[,i[29:30]])                # Parcel 1 Effort
X15 <- rowMeans(Z[,i[31:32]])                # Parcel 2 Effort
X16 <- rowMeans(Z[,i[33:34]])                # Parcel 1 Interest
X17 <- rowMeans(Z[,i[35:36]])                # Parcel 2 Interest

#
# Making Category matrices
A <- matrix(c(X1,X2,X3),nrow=n,ncol=3,byrow=FALSE)
C <- matrix(c(X4,X5,X6),nrow=n,ncol=3,byrow=FALSE)
V <- matrix(c(X7,X8,X9,X10),nrow=n,ncol=4,byrow=FALSE)
D <- matrix(c(X11,X12,X13),nrow=n,ncol=3,byrow=FALSE)
E <- matrix(c(X14,X15),nrow=n,ncol=2,byrow=FALSE)
I <- matrix(c(X16,X17),nrow=n,ncol=2,byrow=FALSE)

#
AA <- Z[,i[1:6]]                             # Affect Matrix
```

```
CC <- Z[,i[7:12]]                          # Cog. Comp. Matrix
VV <- Z[,i[13:21]]                         # Value Matrix
DD <- Z[,i[22:28]]                         # Difficulty Matrix
EE <- Z[,i[29:32]]                         # Effort Matrix
II <- Z[,i[33:36]]                         # Interest Matrix

#
# Cronbach alpha coefficient
alphaA <- ( 1 - sum( diag(cov(AA) ))/var( rowSums(AA) ) )*6/5
alphaC <- ( 1 - sum( diag(cov(CC) ))/var( rowSums(CC) ) )*6/5
alphaV <- ( 1 - sum( diag(cov(VV) ))/var( rowSums(VV) ) )*9/8
alphaD <- ( 1 - sum( diag(cov(DD) ))/var( rowSums(DD) ) )*7/6
alphaE <- ( 1 - sum( diag(cov(EE) ))/var( rowSums(EE) ) )*4/3
alphaI <- ( 1 - sum( diag(cov(II) ))/var( rowSums(II) ) )*4/3
alpha <- c(alphaA,alphaC,alphaV,alphaD,alphaE,alphaI)

#
# Normality Test
nTestA1 <- shapiro.test(X1)
nTestA2 <- shapiro.test(X2)
nTestA3 <- shapiro.test(X3)
nTestC1 <- shapiro.test(X4)
nTestC2 <- shapiro.test(X5)
```

```
nTestC3 <- shapiro.test(X6)
nTestV1 <- shapiro.test(X7)
nTestV2 <- shapiro.test(X8)
nTestV3 <- shapiro.test(X9)
nTestV4 <- shapiro.test(X10)
nTestD1 <- shapiro.test(X11)
nTestD2 <- shapiro.test(X12)
nTestD3 <- shapiro.test(X13)
nTestE1 <- shapiro.test(X14)
nTestE2 <- shapiro.test(X15)
nTestI1 <- shapiro.test(X16)
nTestI2 <- shapiro.test(X17)
pVal <- c(nTestA1$p.value,nTestA2$p.value,nTestA3$p.value,
              nTestC1$p.value,nTestC2$p.value,nTestC3$p.value,
              nTestV1$p.value,nTestV2$p.value,nTestV3$p.value,
              nTestV4$p.value,
              nTestD1$p.value,nTestD2$p.value,TestD3$p.value,
              nTestE1$p.value,nTestE2$p.value,
              nTestI1$p.value,nTestI2$p.value)



#
# One Factor Analysis components
```

```
eA <- eigen(cov(A))        # Eigen modes for Affect Matrix

pvar1_A = eA$values[1]/sum(diag(cov(A)))    # 1-Factor
                                            proportion variance

# eC <- eigen(cov(C))
pvar1_C = eC$values[1]/sum(diag(cov(C)))

# eV <- eigen(cov(V))
pvar1_V = eV$values[1]/sum(diag(cov(C)))

# eD <- eigen(cov(D))
pvar1_D = eD$values[1]/sum(diag(cov(C)))

# eE <- eigen(cov(E))
pvar1_E = eE$values[1]/sum(diag(cov(E)))

# eI <- eigen(cov(I))
pvar1_I = eI$values[1]/sum(diag(cov(I)))

# Making Matrix with parcels
X <- matrix(c(X1,X2,X3,X4,X5,X6,X7,X8,X9,X10,X11,X12,X13,X14,X15,
                  X16,X17),nrow=n,ncol=17,byrow=FALSE)
```

```
    ##-----------------B E G I N  L A V A A N -------------------#

#
U <- as.data.frame(X)
#
# item overlap between Affect & Cog. Comp.
AffCog.model <- ' Affect  =~ V1 + V2 + V3
CogComp =~ V4 + V5 + V6 '
fitAC <- cfa(AffCog.model, data = U,std.lv=TRUE)
sAC <- fitMeasures(fitAC)
sAC <- fitMeasures(fitAC, c("pvalue", "rmsea"))
sAC <- list(pval.AC = sAC[1],rmsea.AC = sAC[2])

#
AffValue.model <- ' Affect  =~ V1 + V2 + V3
Value =~ V7 + V8 + V9 + V10 '
fitAV <- cfa(AffValue.model, data = U,std.lv=TRUE)
sAV <- fitMeasures(fitAV)
sAV <- fitMeasures(fitAV, c("pvalue", "rmsea"))
sAV <- list(pval.AV = sAV[1],rmsea.AV = sAV[2])
```

```
#
AffDifficulty.model <- ' Affect  =~ V1 + V2 + V3
Difficulty =~ V11 + V12 + V13 '
fitAD <- cfa(AffDifficulty.model, data = U,std.lv=TRUE)
sAD <- fitMeasures(fitAD)
sAD <- fitMeasures(fitAD, c("pvalue", "rmsea"))
sAD <- list(pval.AD = sAD[1],rmsea.AD = sAD[2])

#
AffEffort.model <- ' Affect  =~ V1 + V2 + V3
Effort =~ V14 + V15 '
fitAE <- cfa(AffEffort.model, data = U,std.lv=TRUE)
sAE <- fitMeasures(fitAE)
sAE <- fitMeasures(fitAE, c("pvalue", "rmsea"))
sAE <- list(pval.AE = sAE[1],rmsea.AE = sAE[2])

#
AffInterest.model <- ' Affect  =~ V1 + V2 + V3
Interest =~ V16 + V17 '
fitAI <- cfa(AffInterest.model, data = U,std.lv=TRUE)
sAI <- fitMeasures(fitAI)
sAI <- fitMeasures(fitAI, c("pvalue", "rmsea"))
```

```
sAI <- list(pval.AI = sAI[1],rmsea.AI = sAI[2])

#
CogValue.model <- ' CogCom  =~ V4 + V5 + V6
Value =~ V7 + V8 + V9 + V10 '
fitCV <- cfa(CogValue.model, data = U,std.lv=TRUE)
sCV <- fitMeasures(fitCV)
sCV <- fitMeasures(fitCV, c("pvalue", "rmsea"))
sCV <- list(pval.CV = sCV[1],rmsea.CV = sCV[2])



#
CogDifficulty.model <- ' CogCom  =~ V4 + V5 + V6
Difficulty =~ V11 + V12 + V13 '
fitCD <- cfa(CogDifficulty.model, data = U,std.lv=TRUE)
sCD <- fitMeasures(fitCD)
sCD <- fitMeasures(fitCD, c("pvalue", "rmsea"))
sCD <- list(pval.CD = sCD[1],rmsea.CD = sCD[2])

#
CogEffort.model <- ' CogCom  =~ V4 + V5 + V6
Effort =~ V14 + V15 '
fitCE <- cfa(CogEffort.model, data = U,std.lv=TRUE)
```

```
sCE <- fitMeasures(fitCE)
sCE <- fitMeasures(fitCE, c("pvalue", "rmsea"))
sCE <- list(pval.CE = sCE[1],rmsea.CE = sCE[2])

#
CogInterest.model <- ' CogCom  =~ V4 + V5 + V6
Interest =~ V16 + V17 '
fitCI <- cfa(CogInterest.model, data = U,std.lv=TRUE)
sCI <- fitMeasures(fitCI)
sCI <- fitMeasures(fitCI, c("pvalue", "rmsea"))
sCI <- list(pval.CI = sCI[1],rmsea.CI = sCI[2])

#
ValueDifficulty.model <- ' Value  =~ V7 + V8 + V9 + V10
Difficulty =~ V11 + V12 + V13 '
fitVD <- cfa(ValueDifficulty.model, data = U,std.lv=TRUE)
sVD <- fitMeasures(fitVD)
sVD <- fitMeasures(fitVD, c("pvalue", "rmsea"))
sVD <- list(pval.VD = sVD[1],rmsea.VD = sVD[2])

#
ValueEffort.model <- ' Value  =~ V7 + V8 + V9 + V10
Effort =~ V14 + V15 '
```

```
fitVE <- cfa(ValueEffort.model, data = U,std.lv=TRUE)
sVE <- fitMeasures(fitVE)
sVE <- fitMeasures(fitVE, c("pvalue", "rmsea"))
sVE <- list(pval.VE = sVE[1],rmsea.VE = sVE[2])

#
ValueInterest.model <- ' Value  =~ V7 + V8 + V9 + V10
Interest =~ V16 + V17 '
fitVI <- cfa(ValueInterest.model, data = U,std.lv=TRUE)
sVI <- fitMeasures(fitVI)
sVI <- fitMeasures(fitVI, c("pvalue", "rmsea"))
sVI <- list(pval.VI = sVI[1],rmsea.VI = sVI[2])

#
DifficultyEffort.model <- ' Difficulty  =~ V11 + V12 + V13
Effort =~ V14 + V15 '
fitDE <- cfa(DifficultyEffort.model, data = U,std.lv=TRUE)
sDE <- fitMeasures(fitDE)
sDE <- fitMeasures(fitDE, c("pvalue", "rmsea"))
sDE <- list(pval.DE = sDE[1],rmsea.DE = sDE[2])

#
DifficultyInterest.model <- ' Difficulty  =~ V11 + V12 + V13
```

```
Interest =~ V16 + V17 '
fitDI <- cfa(DifficultyInterest.model, data = U,std.lv=TRUE)
sDI <- fitMeasures(fitDI)
sDI <- fitMeasures(fitDI, c("pvalue", "rmsea"))
sDI <- list(pval.DI = sDI[1],rmsea.DI = sDI[2])

#
EffortInterest.model <- ' Effort  =~ V14 + V15
Interest =~ V16 + V17 '
fitEI <- cfa(EffortInterest.model, data = U,std.lv=TRUE)
sEI <- fitMeasures(fitEI)
sEI <- fitMeasures(fitEI, c("pvalue", "rmsea"))
sEI <- list(pval.EI = sEI[1],rmsea.EI = sEI[2])


      ##----------------E N D  L A A V A N---------------##


#
PVALUES <- list(pAf_1=pVal[1],pAf_2=pVal[2],pAf_3=pVal[3],
                  pCC_1=pVal[4],pCC_2=pVal[5],pCC_3=pVal[6],
                  pVa_1=pVal[7],pVa_2=pVal[8],pVa_3=pVal[9],
                  pVa_4=pVal[10],
```

```
                    pDf_1=pVal[11],pDf_2=pVal[12], pDf_3=pVal[13],
                    pEf_1=pVal[14],pEf_2=pVal[15],
                    pIn_1=pVal[16],pIn_2=pVal[17])

#
CRONBACH <- list(alphaA=alpha[1],alphaC=alpha[2],
                      alphaV=alpha[3],alphaD=alpha[4],
                      alphaE=alpha[5],alphaI=alpha[6])

#
PVAR_1FACTOR <-
list(PVAR_Aff=pvar1_A,PVAR_CG=pvar1_C,PVAR_Val=pvar1_V,PVAR_Diff=
pvar1_D,PVAR_Eff=pvar1_E,PVAR_Int=pvar1_I)

#
    print( unlist(PVALUES) )
    cat("\n")
    print( unlist(CRONBACH) )
    cat("\n")
    print( unlist(PVAR_1FACTOR) )
    cat("\n")
    print ( unlist(sAC) )
    cat("\n")
```

```
print ( unlist(sAV) )
cat("\n")
print ( unlist(sAD) )
cat("\n")
print ( unlist(sAE) )
cat("\n")
print ( unlist(sAI) )
cat("\n")
print ( unlist(sCV) )
cat("\n")
print ( unlist(sCD) )
cat("\n")
print ( unlist(sCE) )
cat("\n")
print ( unlist(sCI) )
cat("\n")
print ( unlist(sVD) )
cat("\n")
print ( unlist(sVE) )
cat("\n")
print ( unlist(sVI) )
cat("\n")
print ( unlist(sDE) )
```

```
    cat("\n")
    print ( unlist(sDI) )
    cat("\n")
    print ( unlist(sEI) )
    cat("\n")
    #
    res <- 0
    return(res)
}
```

Curriculum Vitae

Candidate's full name: Jameelah Safar Al Shahrani

Universities attended:

King Khalid University, 2004, Bachelor of Science in Mathematics

University of New Brunswick, 2016, Masters of Science in Statistics