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Attitude toward Statistic in College Students (An Empirical Study in Public University)

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Abstract

This study aims to measure student's attitude towards statistics through a model that considers the variables proposed by Auzmendi (1992). Was examined whether the constructs: usefulness, motivation, likeness, confidence and anxiety influence the student's attitude towards statistics. Were surveyed face to face 328 students at the *Universidad Politécnica de Aguascalientes* using the questionnaire proposed by Auzmendi. The statistical procedure used was factorial analysis with an extracted principal component. The Statistics Hypothesis: Ho: $\rho = 0$ has no correlation, while Ha: $\rho \neq 0$ does. Statistics test to prove: X^2, Bartlett"s test of sphericity, KMO (Kaiser-Meyer_Olkin) Significance level: $\alpha = 0.05$; $p < 0.01$ The results obtained from the sphericity test of Bartlett KMO (0.592), Chi square X^2 390.552 df 10, Sig. 0.00 < p 0.01, MSA (Usefulness 0.656, Motivation 0.552, Likeness 0.705, Confidence 0.633 and Anxiety 0.507). With all this we obtained significant evidence in order to reject Ho. Finally we obtained two factors that explain attitude toward statistic in college students: One of them is composed by three elements: Confidence (.852), Likeness (.818) and Usefulness (.768) and the other is composed by two elements: Anxiety (.837) and Motivation (.800). Their explanatory power for each factor is expressed by their Eigenvalue: 2.170 and 1.383 (with % variance 43.39 and 27.67 respectively, Total variance explained 71.05%).

Keywords: Components, usefulness, motivation, likeness, confidence and anxiety

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1 Introduction

1.1 Attitude towards Statistic

As refers García-Santillán, Venegas-Martinez and Escalera-Chávez (2013), in the academic institutions, the great majority of the courses offering similar services within the undergraduate and posdegree graduate have been integrated in the curriculums, of mathematics subjects, such as: statistics, calculus, financial engineering and more. As a result, thousands of students in degrees and other specialties not mathematically oriented, continue taken statistics courses worldwide, all this like say Blanco (2008). Also in several studies have been reported: emotional reactions, attitudes and negative beliefs from students towards statistics and with little interest in this subject and a limited quantitative training (Blanco, 2004). It is therefore necessary to continue to explore about this issue, in order to provide empirical evidence that may contributing to the redefinition of the teaching strategies in the teaching-learning process in this regard.

One of the first operative definition and measure about attitude toward statistics is the test of Roberts and Bildderbach (1980) denominated Statistics Attitudes Survey (SAS). It's considered the first measure about construct called "Attitude toward statistics" in fact, was made with the intention of providing a focused test in statistics field in order to measure this subject, from the tradition and professional work of students. In this order of ideas, some arguments exposed in Garcia-Santillán, Venegas-Martinez and Escalera-Chávez (2013) refers that, into the educational research, statistical level has justified the need to pay attention to students' attitude mainly because they have an important influence on the process of teaching and learning and the same way, the immediate academic performance (such as variable input and process).

In the same sense, the argument exposed by Auzmendi (1992), Gal & Ginsburg (1994) and Ginsburg & Schau (1997) about students' attitude toward statistic; they point out that, the attitude is an essential component of the background of student with which, after its university training, may carry out academic and professional activities (cited in Blanco 2008). Other research (Mondejar, Vargas and Bayot, 2008) developed a test based on the methodological principles of Wise (1985) attitude toward statistic (ATS) and scale attitude toward statistics (SATS) of Auzmendi (1992).

About scale ATS, is structured of 29 items grouped in two scales, one that measures the affective relationship with learning and cognitive measures the perception of the student with the use of statistics. Mondéjar et al (2008) refer to that initially validation was based on a sample very small, and was with subsequent studies such as Mondejar et al (2009) or Woehlke (1991) who´s corroborated this structure, and the work of Gil (1999) choose to use an structure with five factors: one of the emotional factor and the remaining four factors related cognitive component. The objectives were to develop a test on students 'attitude statistic and his analyze on influence in the form to study. Mondéjar et al (2008) describe the psychometric properties of this new scale to measuring attitude toward statistics; the result obtained is the creation of a good tool to measuring or quantifying the students´ affective factors. Besides, the result may show the level of nervousness and anxiety and other factors: such a gender and how the course studied may affect the study process. All this could affect students´ attitude like say Phillips (1980), he refers to, that the students' attitude can suppose an obstacle or constituted and advantages for their learning.

Meanwhile, Roberts and Saxe (1982); Beins (1985); Wise (1985); Katz and Tomezik (1988); Vanhoof et al (2006) and Evans (2007) showed the relationship between attitude toward statistic and academic outcomes or the professional use of this tool. They have demonstrated the existence of positive correlation among college students' attitudes and their performance in this matter.

Similar are the studies in Spain performed by Auzmendi (1992), Sánchez-López (1996) and Gil (1999) that also have demonstrated that there are a positive correlation among attitude of college student and their performance. Important background is the work of Wise (1985) and Auzmendi (1992) with the scales ATS y SATS, who have tried to measure the job that underlies this issue. They obtained the most important characteristics of the students regarding their attitude toward statistics, their difficulties with the mathematical component and the prejudice to this issue. To this argument, similarly, there are added the works of Elmore and Lewis (1991) and Schau et al (1995).

Finally we can say that the review of literature about this subject, Blanco (2008) it carried out a critical review on research on students' attitude toward statistics and describe, some inventories test that measure specifically the students' attitude statistic. In his study refer the research of Cherian and Glencross (1997) who cited the most important studies in the Anglo-Saxon context such as: *Statistics Attitudes Survey- SAS* Roberts & Bilderback (1980), Roberts & Reese, (1987), *Attitudes toward Statistics- ATS* Wise (1985), *Statistics Attitude Scale* McCall, Belli & Madjini (1991), *Statistics Attitude Inventory (*Zeidner, 1991), *Students´Attitudes Toward Statistics* Sutarso (1992), *Attitude Toward Statistics* Miller, Behrens, Green and Newman (1993), *Survey of Attitudes Toward Statistics –SATS* Schau, Stevens, Dauphinee and Del Vecchio (1995), *Quantitative Attitudes Questionnaire* Chang (1996) among other.

With the above, and considering that we find answers to the research questions about attitude towards statistic in engineering undergraduate students, we use the scale proposed by Auzmendi. Thus, it set the following:

1.2 Question Research, Objective and Hypothesis

RQ_1. Which the attitude toward statistic in college students?
RQ_2. What factors can help explain the attitude toward statistic in college students?
Objectives

So_1. Determine the level attitude toward statistic in college students.
So_2. Identify which are the factors that explain attitude toward statistic in college students.

The following hypotheses were established from the previously exposed questions:

H_1: Likeness is the factor that most explained the student's attitude towards statistic
H_2: Anxiety is the factor that most explained the student's attitude towards statistic
H_3: Confidence is the factor that most explained the student's attitude towards statistic
H_4: Motivation is the factor that most explained the student's attitude towards statistic
H_5: Usefulness is the factor that most explained the student's attitude towards statistic

2 Materials and Methods

2.1 Design Methodology, Population and Sample

This study is non experimental, transeccional-descriptive, because we need to know the attitude toward statistics in college students at Universidad Politécnica de Aguascalientes. The sample was selected for the trial of non-probability sampling. Were surveyed face to face 328 students at Universidad Politécnica de Aguascalientes from several profiles, as; Engineering in Mechanical, Mecatrónic, Industrial, Strategic System of Information and finally, Business and Management.

The selection criteria were to include students who have completed at least one field of statistics in the degree program they were studying and were available at the institution to implement the survey. The instrument used was a survey of attitudes toward statistics or SATS (Auzmendi, 1992). The scale proposed by Auzmendi indicates the existence of five factors: usefulness, anxiety, confidence, pleasure and motivation. The usefulness factor indicators are: Item 1, 6, 11, 16, 21; anxiety factor indicators are: Item 2, 7, 12, 17, 22; the confidence factor are: items 3, 8, 13, 18, 23; likeness factor indicators are: Item 4, 9, 14, 19, 24. Finally indicators belonging to motivational factor are: items 5, 10, 15, 20, 25. The table 1 described the indicators, definitions and codes/items.

Table 1: Scale factors attitude toward statistics.

Indicators	Definition	Code/items
Likeness	Refers to the liking of working with statistics.	LIK 4,9,14,19 and 24
Anxiety	Can be understood as the fear the students manifests towards statistics.	ANX 2,7,12,17 and 22
Confidence	Can be interpreted as the feeling of confidence of the skill in statistics.	CNF 3,8,13,18 and 23
Motivation	What the student feels towards the studying and usefulness of statistics.	MTV 5,10,15,20 and 25
Usefulness	It is related to the value that a student's gives statistics for its professional future.	USF 1,6,11,16 and 21

Source: take from García *et al* (2012)

2.3 Statistical Procedure

In this study, we used the principal components method to determine the number of indicators that make up each of the factors and select those with a factor loading greater than .70 Table 1 shows the indicators and their corresponding factors.

In accordance with the procedure proposed by García-Santillán, Venegas-Martinez and Escalera-Chávez (2013) and in order to measure; $X_1\ X_2 \ldots\ldots X_{328}$ observed random variables, which are defined in the same population that share, m ($m<p$) commons causes to find $m+p$ new variables, which we call common factors (Z_1, Z_2, … Z_m), besides, unique factors ($\varepsilon_1\ \varepsilon_2 \ldots\ldots \varepsilon_p$) in order to determine their contribution in the original variables (X_1 $X_2 \ldots\ldots X_{p-1}\ X_p$), the model is now defined by the following equations:

$$\left|\begin{array}{l} X_1 = a_{11}Z_1 + a_{12}Z_2 + ...a_{1m}Z_m + b_1\xi_1 \\ X_2 = a_{21}Z_1 + a_{22}Z_2 + ...a_{2m}Z_m + b_2\xi_2 \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ X_p = a_{p1}Z_1 + a_{p2}Z_2 + ...a_{pm}Z_m + b_p\xi_p \end{array}\right| \quad (1)$$

Where:
$Z_1, Z_2, \ldots Z_m$ are common factors
$\varepsilon_1\ \varepsilon_2 \ldots\ldots \varepsilon_p$ are unique factors
Thus, $\varepsilon_1\ \varepsilon_2 \ldots\ldots \varepsilon_p$ have influence in all variables X_i (i=1 ………p) ξ_i influence in $X_i (i=1 \ldots\ldots p)$
Model equations can be expressed in matrix form as follow:

$$\begin{vmatrix} X_1 \\ X_2 \\ \cdots \\ X_p \end{vmatrix} = \begin{vmatrix} a_{11}a_{12} \cdots a_{1m} \\ a_{21}a_{22} \cdots a_{2m} \\ \cdots \\ a_{p1}a_{p2} \cdots a_{pm} \end{vmatrix} . \begin{vmatrix} Z_1 \\ Z_2 \\ \cdots \\ Z_1 \end{vmatrix} + \begin{vmatrix} b_1\xi_1 \\ b_2\xi_2 \\ \cdots \\ b_p\xi_p \end{vmatrix} \quad (2)$$

Therefore, the resulting model can be expressed in a condensed form as:

$$X = AZ + \xi_i \quad (3)$$

Where, we assume that $m<p$ because they want to explain the variables through a small number of new random variables and all of the (m + p) factors are correlated variables, that is, that the variability explained by a variable factor, have not relation with the other factors.
We know that the each observed variable of model is a result of lineal combination of each common factor with different weights (a_{ia}), those weights are called saturations, but one of part of x_i is not explained for common factors. As we know, all problems intuitive can be inconsistent when obtaining solutions and therefore, we require the approach of hypothesis; hence, in the factor model we used the following assumptions:

H_1: The factors are typified random variables, and inter correlated, like:

$$E\left[Z_i\right]=0 \qquad E\left[\xi_i\right]=0 \qquad E\left[Z_iZ_i\right]=1$$
$$E\left[\xi_i\xi_i\right]=1 \quad E\left[Z_iZ_{i'}\right]=0 \quad E\left[\xi_i\xi_{i'}\right]=0$$
$$E\left[Z_i\xi_i\right]=0$$

Further, we must consider that the factors have a primary goal to study and simplify the correlations between variables, measures, through the correlation matrix, then, we will understand that:
H_2: The original variables could be typified by transforming these variables of type

$$x_i = \frac{x_i - \bar{x}}{\sigma_x} \quad (4)$$

Therefore, and considering the variance property we have:

$$\mathrm{var}(x_i) = a_{i1}^2 \mathrm{var}(z_1) + a_{i2}^2 \mathrm{var}(z_2) + \ldots\ldots\ldots\ldots a_{im}^2 \mathrm{var}(z_m) + b_i^2 \mathrm{var}(\xi_i) \quad (5)$$

Resulting: $$1 = a_{i1}^2 + a_{i2}^2 + a_{i3}^2 + \ldots.. + \ldots\ldots\ldots a_{im}^2 + b_i^2 \rightarrow \forall_i = 1\ldots\ldots\ldots.p \quad (6)$$

2.3.1 Saturations, Communalities and Uniqueness

We denominated *saturations* of the variable x_i in the factor z_a of coefficient a_{ia}
In order to inform the relationship between the variables and the common factors is necessary determining the coefficient de **A** (assuming the hypotheses $\mathbf{H_1}$ y $\mathbf{H_2}$), where **V** is the matrix of eigenvectors and **Λ** matrix eigenvalues, so we obtained:

$$A = \begin{bmatrix} a_{11}a_{12}a_{13}\ldots\ldots\ldots.a_{1m} \\ a_{21}a_{22}a_{23}\ldots\ldots\ldots.a_{2m} \\ a_{31}a_{32}a_{33}\ldots\ldots\ldots.a_{3m} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ a_{p1}a_{p2}a_{p3}\ldots\ldots\ldots.a_{pm} \end{bmatrix} \quad (7)$$

$$R = V\Lambda V' = V\Lambda^{1/2}\Lambda^{1/2}V' = AA'$$
$$A = V\Lambda^{1/2} \quad (8)$$

The above suggests that a_{ia} coincides with the correlation coefficient between the variables and factors. In the other sense, for the case of non-standardized variables, *A* is obtained from the covariance matrix *S*, hence the correlation between x_i and z_a is the ratio:

$$corr(i,a) = \frac{a_{ia}}{\sigma_a} = \frac{a_{ia}}{\sqrt{\lambda_a}} \quad (9)$$

Thus, the variance of the a_i factor is results of the sum of squares of saturations of a_i column of A:

$$\lambda_a = \sum_{i=1}^{\rho} a_{ia}^2 \quad (10)$$

Considering that:

$$A'A = (V\Lambda^{1/2})'(V\Lambda^{1/2}) = \Lambda^{1/2}V'V\Lambda^{1/2} = \Lambda^{1/2}I\Lambda^{1/2} = \Lambda \quad (11)$$

We denominated *communalities* to the next theorem:

$$h_i^2 = \sum_{a=1}^{m} a_{ia}^2 \quad (12)$$

The communalities show a percentage of variance of each variable (i) that explains for *m* factors.
Thus, every coefficient h_i^2 is called variable specificity. Therefore the matrix model **X=AZ+ξ,ξ** (unique factors matrix), **Z** (common factors matrix) will be lower while greater be the variation explain for every *m* (common factor). So, if we work with typified variables and considering the variance property, so, we have:

$$1 = a_{i1}^2 + a_{i2}^2 + \cdots + a_{ia}^2 + b_2^2, \qquad 1 = h_i^2 + b_i^2 \tag{13}$$

Recall that the variance of any variable, is the result of adding their communalities and the uniqueness b_i^2, thus, the number of factors obtained, there is a part of the variability of the original variables unexplained and correspond to a residue (unique factor).

2.3.2 Reduced correlation matrix

Based on correlation between variables i and i' we have now:

$$corr(x_i x_{i'}) = {cov(x_i x_{i'})}/{\sigma_i \sigma_{i'}} \tag{14}$$

Also, we know

$$x_i = \sum_{a=1}^{m} a_{ia} z_a + b_i \varepsilon_i \quad , \quad x_{i'} = \sum_{a=1}^{m} a_{i'a} z_a + b_{i'} \varepsilon_{i'} \tag{15}$$

The hypothesis which we started, now we have:

$$corr(x_i x_{i'}) = cov(x_i x_{i'}) = \sigma_{ii'} = E\left[\left(\sum_{a=1}^{m} a_{ia} z_a + b_i \varepsilon_i\right)\left(\sum_{a=1}^{m} a_{i'a} z_a + b_{i'} \varepsilon_{i'}\right)\right] \tag{16}$$

Developing the product:

$$= E\left[\sum_{a=1}^{m} a_{ia} a_{i'a} z_a z_a + \sum_{a=1}^{m} a_{ia} b_{i'} z_a \varepsilon_{i'} + \sum_{a=1}^{m} b_i a_{i^i} \varepsilon_i z_a + \sum_{a=1}^{m} b_i b_{i'} \varepsilon_i \varepsilon_{i'}\right] \tag{17}$$

From the linearity of hope and considering that the factors are uncorrelated (hypotheses of starting), now we have:

$$\begin{aligned} &cov(x_i x_{i'}) = \sigma_{ii'} = \sum_{a=1}^{m} a_{ia} a_{i'a} = corr(x_i x_{i'}) \\ &\forall i, i' \rightarrow 1 \ldots\ldots\ldots\ldots\ldots\ldots\ldots p \end{aligned} \tag{18}$$

The variance of variable *i*-esim is given for:

$$\begin{aligned} var(x_i) &= \sigma_i^2 = E\left[x_i x_i\right] = 1 = E\left[\sum_{a=1}^{m} (a_{ia} z_a + b_i \varepsilon_i)^2\right] = \\ &= E\left[\sum_{a=1}^{m} (a_{ia}^2 z_a^2 + b_i^2 \varepsilon_i^2 + 2a_{ia} b_i z_a \varepsilon_a)\right] \end{aligned} \tag{19}$$

If we take again the start hypothesis, we can prove the follow expression:

$$\sigma_i^2 = 1 = \sum_{a=1}^{m} a_{ia}^2 + b_i^2 = h_i^2 + b_i^2 \tag{20}$$

In this way, we can test how the variance is divided into two parts: the communality and uniqueness, which is the residual variance not explained by the model
Therefore, we can say that the matrix form is: **R=AA'+ξ** where $\mathbf{R^{*}=R\text{-}\xi^{2}}$.
R^{*} is a reproduced correlation matrix, obtained from the matrix R

$$\mathbf{R}^{*}=\begin{bmatrix} \mathbf{h_1^2 r_{12} r_{13} r_{14} \ldots\ldots r_{1p}} \\ \mathbf{r_{21} h_2^2 r_{23} r_{24} \ldots\ldots r_{2p}} \\ \mathbf{r_{31} r_{32} h_3^2 r_{34} \ldots\ldots r_{3p}} \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \mathbf{r_{p1} r_{p2} r_{p3} r_{p4} \ldots h_p^2} \end{bmatrix} \tag{21}$$

The fundamental identity is equivalent to the following expression: R^{*} AA'. Therefore the sample correlation matrix is a matrix estimator AA'. Meanwhile, a_{ia} saturation coefficients of variables in the factors, should verify this condition, which certainly, is not enough to determine them. When the product is estimated AA', we diagonalizable the reduced correlation matrix, whereas a solution of the equation would be: $R\text{-}\xi^{2}=R^{*}=AA'$ is the matrix A, whose columns are the standardized eigenvectors of R^{*}. From this reduced matrix, through a diagonal, as mathematical instrument, we obtain through vectors and eigenvalues, the factor axes.

2.3.3 Factorial analysis viability

To validate the appropriateness of factorial model is necessary to design the sample correlation matrix R, from the data obtained. Also be performed prior hypothesis tests to determine the relevance of the factor model, that is, whether it is appropriate to analyze the data with this model.
A contrast to be performed is the Bartlett Test of Sphericity. It seeks to determine whether there is a relationship structure –relationships-- or not among the original variables. The correlation matrix *R* indicates the relationship between each pair of variables (r_{ij}) and its diagonal will be compose for 1(ones). Hence, if there is not relationship between the variables *h*, then, all correlation coefficients between each pair of variable would be zero.
Therefore, the population correlation matrix coincides with the identity matrix and determinant will be equal to 1.

$$H_o : |R| = 1$$
$$H_1 : |R| \neq 1$$

If the data are a random sample from a multivariate normal distribution, then, under the null hypothesis, the determinant of the matrix is 1 and is shown as follows:

$$-\left[\boldsymbol{n}-\mathbf{1}-\frac{(\mathbf{2}\boldsymbol{p}+\mathbf{5})}{\mathbf{6}}\right]\mathbf{ln}|\boldsymbol{R}| \tag{22}$$

Under the null hypothesis, this statistic is asymptotically distributed through a X^2 distribution with *p(p-1)/2* degrees freedom. So, in case of accepting the null hypothesis would not be advisable to perform factor analysis.

Another index is, the contrast of Kaiser-Meyer-Olkin, which is to compare the correlation coefficients and partial correlation coefficients. This measure is called sampling adequacy (KMO) and can be calculated for the whole or for each variable (MSA)

$$\mathrm{KMO} = \frac{\sum_{j\neq i}\sum_{i\neq j} r_{ij}^2}{\sum_{j\neq i}\sum_{i\neq j} r_{ij}^2 + \sum_{j\neq i}\sum_{i\neq j} r_{ij(p)}^2}, \quad \mathrm{MSA} = \frac{\sum_{i^1 j} r_{ij}^2}{\sum_{i^1 j} r_{ij}^2 + \sum_{i^1 j} r_{ij(p)}^2}; i = 1, \ldots, p \tag{23}$$

Where: $r_{ij\,(p)}$ is the partial coefficient of the correlation between variables X_i and X_j in all the cases.

In order to measure the data obtained as a result of instrument applied, we take a procedure proposed by García-Santillán, Venegas-Martinez and Escalera-Chávez (2013), therefore we have the following matrix:

Students	*Variables X_1 X_2 . . . . . X_p*
1	X_{11} X_{12} .... x_{1p}
2	X_{21} X_{22} .... x_{2p}
.....	………..
328	X_{n1} X_{n2} .... x_{np}

In order to measure the data collected from students and test the hypothesis (H_i) about a set of variables that form the construct for understanding the perception of students towards statistics, we considered the follow Hypothesis: Ho: ρ=0 have no corelation Ha: ρ ≠ 0 have correlation. Statistic test to prove: χ^2, y Bartlett's test of sphericity, KMO (Kaiser-Meyer-Olkin), MSA (Measure of Sampling Adecuacy), significancy level: α =0.05; *p <0.05 load factorial of .70* Critic value: χ^2 calculated > χ^2 tables, then reject *Ho* and the decision rule is: Reject *Ho* if χ^2 calculated > χ^2 tables.

The above is given by the following equation:

$$\begin{aligned}
X_1 &= a_{11}F_1 + a_{12}F_2 + \ldots\ldots\ldots + a_{1k}F_k + u_1 \\
X_2 &= a_{21}F_1 + a_{22}F_2 + \ldots\ldots\ldots + a_{2k}F_k + u_2 \\
&\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\
X_p &= a_{p1}F_1 + a_{p2}F_2 + \ldots\ldots\ldots + a_{pk}F_k + u_p
\end{aligned} \tag{24}$$

Where F_1,. . . F_k (K << p) are common factors, u_1,.... u_p are specific factors and the coefficients $\{a_{ij}; i = 1, \ldots, p; j = 1, \ldots, k\}$ are the factorial load. It is assumed that the common factors have been standardized or normalized $E(F_i) = 0$, $Var(f_i) = 1$, the specific factors have a mean equal to zero and both factors have correlation $Cov(F_i, u_j) = 0$, $\forall_i = 1, \ldots, k; j = 1, \ldots, p$. With the following consideration: if the factors are correlated

($Cov(F_i, Fj) = 0$, if $i \neq j$; j, i=1,…..,k) then we are dealing with a model with orthogonal factors, if not correlated, it is a model with oblique factors.

Therefore, the equation can be expressed as follows:

$$x = Af + u \;\hat{U}\; X = FA' + U \tag{25}$$

Where:

Data matrix	*Factorial load matrix*	*Factorial matrix*
$x = \begin{pmatrix} x_1 \\ x_2 \\ \dots \\ x_p \end{pmatrix}, f = \begin{pmatrix} F_1 \\ F_2 \\ \dots \\ F_k \end{pmatrix}, u = \begin{pmatrix} u_1 \\ u_2 \\ \dots \\ u_p \end{pmatrix}$	$A = \begin{pmatrix} a_{11}a_{12}\dots a_{ik} \\ a_{21}a_{22}\dots a_{2k} \\ \dots\dots\dots \\ a_{p1}a_{p2}\dots a_{pk} \end{pmatrix}$	$F = \begin{pmatrix} f_{11}f_{12}\dots f_{ik} \\ f_{21}f_{22}\dots f_{2k} \\ \dots\dots\dots \\ f_{p1}f_{p2}\dots f_{pk} \end{pmatrix}$

With a variance equal to:

$$Var(X_i) = \sum_{j=1}^{k} \alpha_{ij}^2 + \Psi_i = h_i^2 + \Psi_\iota,\; i = 1, \dots, p \tag{26}$$

Where:

$$h_i^2 = Var\left(\sum_{j=1}^{k} a_{ij}F_j\right)\dots\text{y}\dots\psi_i = Var(u_i) \tag{27}$$

This equation corresponds to the communalities and the specificity of the variable X_i. Thus the variance of each variable can be divided into two parts: a) in their communalities h_i^2 representing the variance explained by common factors, and b) the specificity Ψ_I that represents the specific variance of each variable. Thus obtaining:

$$Cov(X_i, X_1) = Cov\left(\sum_{j=1}^{k} a_{ij}F_j, \sum_{j=1}^{k} a_{1j}F_j\right) = \sum_{j=1}^{k} a_{ij}a_{1j} \qquad \forall i \neq \ell \tag{28}$$

With the transformation of the correlation matrix's determinants, we obtained Bartlett's test of sphericity, and it is given by the following equation:

$$d_R = -\left[n - 1 - \frac{1}{6}(2p+5)\ln|R|\right] = -\left[n - \frac{2p+11}{6}\right]\sum_{j=1}^{p} \log(\lambda_j) \tag{29}$$

$$\left[n - \frac{2p+11}{6}\right] \log \frac{\left[\frac{1}{p-m}\left(trazR^* - \left(\sum_{a=1}^{m} \lambda_a\right)\right)\right]^{p-m}}{|R^*| \Big/ \prod_{a=1}^{m} \lambda_a} \tag{30}$$

3 Empirical Study

3.1 Finding and Discussions

In order to answer the main question, first the test used in the field research to collect data was validated, obtaining Cronbach's alpha coefficient (table 2 and 3).

Table 2: Case Processing Summary

		N	%
Cases	Valid	328	100.0
	Excluded[a]	0	.0
	Total	328	100.0
a. Listwise deletion based on all variables in the procedure.			

Table 3: Reliability Statistics

Cronbach's Alpha	N of Items
.722	25

We can observed that the reliability of the instrument is 0.722, and based on Cronbach's Alpha criteria >0.6 (Hair, 1999) then we can say that the applied instruments have all the characteristics of consistency and reliability required. It is important to mention that the Cronbach's Alpha is not a statistical test, but rather a reliable coefficient. Therefore, the AC can be written as a function of the same item number (García-Santillán *et al,* 2012).

$$\alpha = \frac{N.\bar{r}}{1 + (N-1).\bar{r}}$$

Where: N = number of items (latent variables), ř = correlation between items.

Within this order of ideas, we can now describe table 4, its mean and its standard deviation in order to determine the coefficient's variance and make it possible to identify the variables with the most variance with respect to others.

Table 4: Descriptive Statistics

	Mean	Std. Deviation	Analysis N	Variation coefficient VC=sd/mean
Likeness	14.3049	3.40242	328	0.23785
Confidence	17.0244	3.45518	328	0.20295
Usefulness	17.9207	2.61491	328	0.14592
Anxiety	11.9695	4.23676	328	**0.35396**
Motivation	13.6037	2.79278	328	0.20530

Source: self made

Based on the results described in Table 4, it can be seen that the variable ANXIETY (35.39%) is the largest compared to the rest of the variables that show similar behavior (among 14.59% to 23.78%). After collecting the data, and in order to validate whether the statistical technique of factor analysis can explain the phenomena studied, we first conducted a contrast from Bartlett's test of sphericity with Kaiser (KMO) and Measure Sample Adequacy (MSA) to determine whether there is a correlation between the variables studied and whether the factor analysis technique should be used in this case. Table 5 shows the results.

Table 5: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.592
Bartlett's Test of Sphericity	Approx. Chi-Square	390.552
	df	10
	Sig.	0.000

Source: self made

As we already know, Bartlett’s test of sphericity allows the null hypothesis that the correlation matrix is an identity matrix, whose acceptance involves rethinking the use of principal component analysis as the KMO is > 0.5, in which case the factor analysis procedure should not be used. Now, observing the results in the table above; the KMO statistic has a value of 0.592 which is more than >0.5 and Bartlett sphericity test with X^2 =390.552 with 10 df and sig. 0.000, indicating that the data is adequate to perform a factor analysis. Therefore a factor analysis can be made that allows answering the research question.

The results obtained from the correlation matrix are shown in Table 6; we observe the behavior of each variable with respect to others. The criteria for determining low correlation is the higher number, lower versus higher determining the correlation, then one can predict the degree of intercorrelation between the variables.

Table 6: Correlation Matrix[a]

		Likeness	Anxiety	Confidence	Motivation	Usefulness
Correlation	Likeness	1.000				
	Anxiety	-.153	1.000			
	Confidence	**.540**	-.321	1.000		
	Motivation	.304	.354	.154	1.000	
	Usefulness	.463	-.053	**.542**	.131	1.000

a. Determinant = .300

Source: self made

In the above table we see that the determinant is high (0.300) indicating a low degree of intercorrelation between the variables (<0.5) however, it shows a positive correlation (except: anxiety vs. likeness -.153; anxiety vs. confidence -.321 and anxiety vs. usefulness -0.053), this should be taken with caution when wording the conclusions. Just to mention some examples of significant correlations (the highest) should be correlated: Confidence

vs. Likeness (0,540), Confidence vs. Usefulness (0,542) and the rest of the variables are presented in the order of 0.13 to 0.46 their respective correlations between the variables involved in this study.
Following, in the Table 7 shows the results obtained from the anti-image matrix, which shows the covariance matrix and the anti-image correlation matrix. The covariance matrix of anti-image contains the negatives of the partial covariance; and correlation anti-image matrix contains the partial correlation coefficients with inverted signs (the correlations between two variables is biased, regarding the other variables included in the analysis).

The diagonal line of correlation matrix anti-image is the measure of sampling adequacy for each variable (MSA). If the chosen factor model is appropriate to explain the data, the diagonal elements of anti-image matrix correlations should have a value close to *1* and the other elements should be small.

Table 7: Anti-image Matrices

		Likeness	Anxiety	Confidence	Motivation	Usefulness
Anti-image Covariance	Likeness	.610	.092	-.170	-.195	-.158
	Anxiety	.092	.701	.213	-.319	-.115
	Confidence	-.170	.213	.527	-.092	-.246
	Motivation	-.195	-.319	-.092	.727	.056
	Usefulness	-.158	-.115	-.246	.056	.646
Anti-image Correlation	Likeness	**.705**[a]	.141	-.301	-.293	-.252
	Anxiety	.141	**.507**[a]	.350	-.447	-.171
	Confidence	-.301	.350	**.633**[a]	-.148	-.421
	Motivation	-.293	-.447	-.148	**.552**[a]	.082
	Usefulness	-.252	-.171	-.421	.082	**.656**[a]

a. Measures of Sampling
Adequacy(MSA)

In the above table shows the results obtained from the coefficients anti-image correlation (diagonally) ranging from 0.507 to 0.705 (Likeness .705; Confidence .633; Usefulness .656, Anxiety .507 and Motivation .552) these are significantly higher. So it is confirmed that the factor analysis is appropriate to identify the structure of the latent variables that can explain the student's attitude towards statistic and thus answer the research question.
The percentage of variance that explains the case studied was obtained from the extraction of the principal components. Primarily, the communalities were obtained, which are the proportion of variance of the extracted component (Table 8), and later analyzed under the criteria of eigenvalues more than one, according to the latent root criteria (> 1).
The number of components obtained from the analysis is two, as shown in graph 1. Moreover, the sum of the square root of the loads, of the initial extraction the eigenvalues of each component is shown in table 9; where we can see that the component removed (two) explain 71.062% of the variance of the studied phenomena.
Thus, now it shows the following tables and sedimentation graphs:

Table 8: Communalities

	Initial	Extraction
Likeness	1.000	.681
Anxiety	1.000	.777
Confidence	1.000	.757
Motivation	1.000	.748
Usefulness	1.000	.591
Total variance		3.553=71.062%

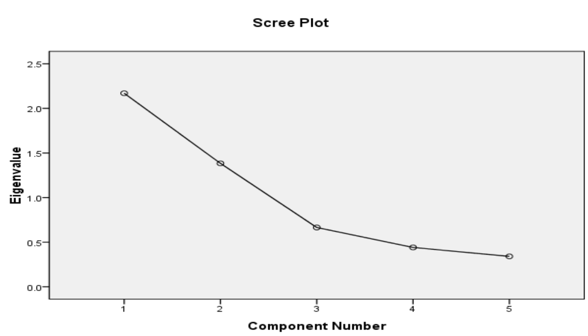
Extraction Method: Principal Component Analysis.

Table 9 shows that the first component may explain the phenomenon in a 43.39% and the second component 27.67%. Thus Eigenvalues for each component are in the "Total" column and the next column shows the total percentage of variance explained by the extraction method (71.06%), however to apply the rotation of the axis look like the percentage of particular explanation varies, but the accumulated remains are the same, this is because at the time of the rotation, component variables change, but the goal remains the same, which is to minimize the distances between each group losing as little information as possible while increasing the ratio of the remaining variables in each factor.

Table 9: Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.170	43.393	43.393	2.170	43.393	43.39%
2	1.383	27.669	71.062	1.383	27.669	71.06%
3	.665	13.294	84.356			
4	.441	8.828	93.184			
5	.341	6.816	100.000			

Extraction Method: Principal Component Analysis.



In the table 10 shows the obtained factors and their order of importance (2.170 and 1.383, respectively), which represents 71.05% of the total variance of the object of study, addition to being represented by the information contained in the factor matrix of the solution of these two factors.

Table 10: Component Matrix[a]

	Component	
	1	2
Likeness	**.818**	.105
Anxiety	-.277	**.837**
Confidence	**.852**	-.173
Motivation	.327	**.800**
Usefulness	**.768**	.041
	2.170	1.383
% variance	43.393	27.669
	Total variance	71.05%

a. 2 components extracted.

Therefore, the rate of this solution is adequate; the variables are in fact highly correlated. The factors that compose this structure and their variables have a statistical and practical significance, i.e. educational institutions may consider developing strategies for improving the attitudes of the students towards statistics and thus reduce the rate of failure of the students. In this regard, the studies of García-Santillán, Moreno, Carlos, Zamudio and Garduño (2012) whose results are consistent with those obtained in the present study.

4 Conclusions

The aim of study was to determine the level attitude toward statistic in college students and identify which are the factors that explain attitude toward statistic in college students, for this, we used the scale proposed by Auzmendi (1992) which integrates the dimensions: likeness, usefulness, confidence, motivation and anxiety as factors that influence the student's attitudes towards statistics. The empirical results allow us to say that there are two factors that explain the phenomenon of study, and these are: Favorable attitude towards statistics composed by three factors (Confidence (.852), Likeness (.818) and Usefulness (.768)) and other Unfavorable attitude toward statistics composed by two factors (Anxiety (.837) and Motivation (.800)). Their explanatory power for each factor is expressed by their Eigenvalue: 2.170 and 1.383 (with % variance 43.39 and 27.67 respectively, Total variance explained 71.05%).

Similar outcomes are the obtained by García-Santillán, Venegas-Martinez and Escalera-Chávez (2013), in a study carry out in a private University, they surveyed 298 students at Cristóbal Colón University from several profiles, as; economy, management, accounting, marketing and tourism business management. They obtained two factors: first one composed of three elements: usefulness, confidence, liking and other incorporates two elements: anxiety and motivation. The values of this last factor indicate if the student anxiety increased, decreased motivation and their explanatory power for each factor are expressed by their Eigenvalue 2.351 and 1.198 (with % variance 47.016 and 23.964 respectively, Total variance 71.08%)

These results are consistent with those presented by Auzmendi (1992) who notes that the factors that have the greatest influence are those related to motivation, liking and the utility.

Finally, the factor the most explained the student attitude toward statistic is: Confidence, following of Likeness and Usefulness that integrate the first component that explain 43.39% of variance and Anxiety and Motivation that integrate the second component that explain 27.67% of total variance.

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