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Engineering Students' Perception of Financial Mathematics
An empirical study based on the EAPH-MF scale

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Abstract

The EAPH-MF test was administered to a sample of undergraduates, with the purpose of comparing the results with those observed in the original research of García-Santillán, Escalera and Edel (2011), regarding students' perceptions of and attitudes toward financial-mathematics courses. The sample comprised 209 Industrial-Engineering students, who were enrolled in the Mexican university "Instituto Tecnológico Superior de Tierra Blanca", and had finished one or more financial-mathematics courses. This study replicated the method applied in the original research, aiming to assess the relevance of the variables under study and their probable correlation. It was observed that, whenever the teaching-learning process incorporated the variables of the EAPH-MF scale as a didactic strategy, the results validated similar behaviors among students in both samples. These variables—the history of mathematics, spreadsheet programming, design of simulators, a computer platform, and the participation of virtual communities—accounted for 60% of the variance of the phenomenon under study.

Keywords: didactic strategy, engineering student, financial mathematics, student perceptions

1. Introduction

An exhaustive literature review yielded no earlier research work on the use of information and communication technologies (ICT) in contributing to the teaching-learning process (TLP) of financial mathematics. However, worth mentioning that several works related to the use of ICT in the teaching of mathematics at different educational levels in various countries were identified. Those studies have contributed new knowledge in education.

Among those studies are the one of Bazán and Aparicio (2006) on the "… attitudes towards mathematics-statistics within a model of learning", and the one of Álvarez and Ruíz (2010) on "Attitudes towards mathematics among students of Engineering…". ICT have taken a fundamental role in the TLP because they are increasingly linked with the daily life of people through different means such as equipment, systems, protocols, etc.

As various authors have pointed out, the deployment of ICT in educational processes implies not only students' competency, but also the knowledge, skills and attitudes of the teachers, who can favor their level of learning. Riascos, Quintero and Ávila (2009) refer that, in the academic sphere, ICT are tools that have facilitated the access to information and the grasping of knowledge for many students, and this has significantly changed the TLP.

The guiding arguments of the original research by García-Santillán, Escalera and Edel (2011) refer to Mexican authorities from academia, business and government; repeatedly manifesting, in diverse forums, their demands with regard to having students develop competencies related to the "time value of money" concept.

The present research work aims to extend the original one, by replicating the data collection and testing methods against a distinct students' reality. The original work was based on students of administrative sciences from a private university, but this time the sample is taken from a higher-education public school, and the students' field is engineering. This new study was developed as part of the doctoral program in Administrative Sciences at the Universidad Cristóbal Colón, intending to identify the equivalence of results given the contextual difference. So, the primary aim here is defining to what extent the original results are reproduced, using the given variables to explain the students' perceptions of and attitudes toward financial mathematics.

The related preceding studies by Clinard (1993), and Chávez and Salazar (2006), as mentioned by García-Santillán and Edel (2008), are recognized as the foundations or "evidence of an apparent rejection of mathematics..." and its association with TLP, and of an apparent lack of teachers' skill in "selling the idea of learning mathematics..." to students, mainly because its uses or applications are not clearly exposed to them.

The results, got by applying the measuring instruments to a sample of students in the seventh semester of Industrial Engineering, who had already studied the subject of Economic Engineering in the preceding semester (a course equivalent to Financial Mathematics) at the "*Instituto Tecnológico Superior de Tierra Blanca*", contribute to determining if the factors involved and the context change or alter the original results, or strengthen the hypothesis originally proposed by García-Santillán et al. (2011).

2. Design and Method

2.1 Study and Instrument

A cross-sectional descriptive study was carried out because it was required to know the attitude toward statistics of Industrial Engineering undergraduates who have studied Financial Mathematics. For this study, the scale EAPH-MF was applied to students of a higher-education school in Tierra Blanca, Veracruz, Mexico.

The method used by García-Santillán et al. (2011) is replicated. It is a study that seeks to identify the relevance of the variables under study and their probable correlation to explain the students' perceptions of and attitudes toward financial mathematics. The variables, code and items of the scale, are shown in Table 1.

Table 1. Scale EAPH-MF

Code	Variable	Items
HMCCT	History of mathematics	1, 2, 5-7, 9–15, 17
PHC	Spreadsheet programming	3, 4, 8, 16, 20–23, 26
DSF	Simulation and simulators	18, 24, 25, 27, 28
PI	Computing platforms	19
CV	Virtual learning communities	29–31
Standardized set		

Source: Adapted from García-Santillán et al. (2011)

The justification for this study is supported by the original authors' evidence regarding studies related to the attitudes of students toward mathematics. Among the mentioned works, there is the one on mathematics at the levels of primary and secondary school (Yi Yi, 1989 cited by Bazán & Sotero, 1998). There is also the work of Bazán and Sotero (1998) regarding the attitude of the student toward statistics and the attitude toward mathematics among students just joining the profession. In addition, it is referred as well the validation and reliability of a scale that measures attitudes toward mathematics and mathematics as taught by a computer (Ursini et al., 2004). However, there is no evidence of studies specifically focused on the students' perceptions of financial mathematics.

The methodological design of this research work is defined in four phases:

Prior Phase: The general conceptualization of the work to be undertaken and choosing the school for the application of the evaluation instruments proposed by García-Santillán et al. (2011) are set up during this phase.

This study considers as population the undergraduates of Industrial Engineering, enrolled in the *Instituto Tecnológico de Tierra Blanca*, who have already taken the subject of Financial Mathematics (Economic Engineering), and who are in the seventh semester. There is a total of 209 students from four groups (704-A, 35; 704-B, 35; 704-C, 25; 704-D, 23), two groups in the morning shift and two groups on the evening shift.

Deployment and Development Phase: The collecting of data is carried out using the EAPH-MF instrument (García-Santillán et al., 2011), which in turn takes the EAHM-U scale of Bazán (1997) as a reference. The survey is administered to the 209 students, and SPSS statistical software is used to conduct calculations after capturing and analyzing the collected data.

Evaluation Phase: The evaluation or assessment and interpretation of the results are carried out. The deciding criterion is based on the outcome of the multivariate statistical Factor Analysis procedure to get χ^2 (Chi-squared), KMO, MSA and the correlations between the latent variables, and the components that establish the variance. Using the outcomes of the Sphericity test for a critical level lower than 0.05 the Research Hypothesis (*Hi*) is accepted, and the factor analysis is carried out to undertake the contrasting of results.

The application of the Factor Analysis test is evaluated given that there are five variables of the study. The level of homogeneity of them is identified by the degree of correlation between them. This statistical tool is being used to find the smallest number of dimensions that explain the information associated with it. The statistical software SPSS v20 software is used for this purpose.

By the above exposed, the statistical approach proposed by García-Santillán, Venegas-Martínez and Escalera-Chávez (2013a) is described next.

2.2 Factor Analysis Procedure

In order to measure a set of p observed random variables $(x_1, x_2, \ldots, x_{p-1}, x_p)$ from a population that share m commons (where $m < p$), it is required to find $m + p$ new variables, called common factors $(z_1, z_2, \ldots, z_{m-1}, z_m)$ and unique factors $(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{p-1}, \varepsilon_p)$, for assessing their contribution to the original variables $(x_1, x_2, \ldots, x_{p-1}, x_p)$. According to García-Santillán, Escalera-Chávez and Venegas-Martínez (2013), the model is defined by

$$\begin{bmatrix} x_1 = a_{11}z_1 + a_{12}z_2 + \cdots + a_{1m}z_m + b_1\xi_1 \\ x_2 = a_{21}z_1 + a_{22}z_2 + \cdots + a_{2m}z_m + b_2\xi_2 \\ \cdots \\ x_p = a_{p1}z_1 + a_{p2}z_2 + \cdots + a_{pm}z_m + b_p\xi_p \end{bmatrix} \tag{1}$$

Where:

$z_1, z_2, \ldots, z_{m-1}, z_m$ are common factors

$\xi_1, \xi_2, \ldots, \xi_{p-1}, \xi_p$ are unique factors

Thus, ξ_i influences upon x_i $(i = 1, \ldots, p)$

$$\begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_p \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ & & \cdots & \\ a_{p1} & a_{p2} & \cdots & a_{pm} \end{bmatrix} \cdot \begin{bmatrix} z_1 \\ z_2 \\ \cdots \\ z_m \end{bmatrix} + \begin{bmatrix} b_1\xi_1 \\ b_2\xi_2 \\ \cdots \\ b_p\xi_p \end{bmatrix} \tag{2}$$

In a shorter form, it is:

$$X = AZ + \xi \tag{3}$$

It is assumed that $m < p$, as it is desired to explain the observed variables by a small number of new variables and all of the $(m + p)$ factors are correlated.

The model used the following hypothetical assumptions:

H_1: The factors are typified random variables and are intercorrelated as follow:

$$\begin{array}{cc} E[z_i] = 0 & E[\xi_i] = 0 \\ E[z_i z_i] = 1 & E[\xi_i \xi_i] = 1 \\ E[z_i z_{i'}] = 0 & E[\xi_i \xi_{i'}] = 0 \\ \multicolumn{2}{c}{E[z_i \xi_i] = 0} \end{array} \tag{4}$$

The factors have a primary goal to study and simplify the correlations between variables, through the correlation matrix. Then:

H_2: The original variables could be typified by transforming them:

$$x_i = \frac{x_i - \bar{x}}{\sigma_x} \tag{5}$$

Considering the variance property:

$$\mathrm{var}(x_i) = a_{i1}^2 \,\mathrm{var}(z_1) + a_{i2}^2 \,\mathrm{var}(z_2) + \cdots + a_{im}^2 \,\mathrm{var}(z_m) + b_i^2 \,\mathrm{var}(\xi_i) \tag{6}$$

Resulting:

$$1 = a_{i1}^2 + a_{i2}^2 + a_{i3}^2 + \cdots + a_{im}^2 + b_i^2 \rightarrow \forall i = 1, \ldots, p \tag{7}$$

2.2.1 Saturations, Communalities and Uniqueness

We denominate *saturations* (coefficient a_{ia}) of the factor z_a in the variable x_i. In order to inform the relationship between the variables and the common factors, the coefficients are required:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1m} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2m} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3m} \\ & & & \cdots & \\ a_{p1} & a_{p2} & a_{p3} & \cdots & a_{pm} \end{bmatrix} \tag{8}$$

$$R = V\Lambda V' = V\Lambda^{1/2}\Lambda^{1/2}V' = AA' \tag{9}$$

$$A = V\Lambda^{1/2} \tag{10}$$

where V is the matrix of eigenvectors and Λ is the matrix of eigenvalues.

The above suggests that a_{ia} matches 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:

$$\text{corr}(i, a) = \frac{a_{ia}}{\sigma_a} = \frac{a_{ia}}{\sqrt{\lambda_a}} \tag{11}$$

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

$$\lambda_a = \sum_{i=1}^{p} a_{ia}^2 \tag{12}$$

Considering that:

$$A'A = (V\Lambda^{1/2})'(V\Lambda^{1/2}) = \Lambda^{1/2}\Lambda' V\Lambda^{1/2} = \Lambda \tag{13}$$

We denominated *communalities* to:

$$h_i^2 = \sum_{a=1}^{m} a_{ia}^2 \tag{14}$$

The communalities show a percentage of variance for each variable i that explains for m factors.

Every coefficient b_i^2 is called variable specificity. Then, the matrix model $X = AZ + \xi$, ξ (unique factor matrix), Z (common factor matrix) will be lower as the greater is the variation explain for every m (common factor).

So, working with typified variables and considering the variance property, there is:

$$1 = a_{i1}^2 + a_{i2}^2 + \cdots + a_{ia}^2 + b_i^2 \tag{15}$$

$$1 = h_i^2 + b_i^2 \tag{16}$$

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 variance of the original variables unexplained and it corresponds to a residue (unique factor).

2.2.2 Reduced Correlation Matrix

Based on the correlation between variables i and i' there is:

$$\text{corr}(x_i x_{i'}) = \frac{\text{cov}(x_i x_{i'})}{\sigma_i \sigma_{i'}} \tag{17}$$

Also:

$$x_i = \sum_{a=1}^{m} a_{ia} z_a + b_i \varepsilon_i \tag{18}$$

$$x_{i'} = \sum_{a=1}^{m} a_{i'a} z_a + b_{i'} \varepsilon_{i'} \tag{19}$$

The starting hypothesis is now:

$$\mathrm{corr}(x_i x_{i'}) = \mathrm{cov}(x_i x_{i'}) = \sigma_{ii'} = E\left[\left(\sum_{a=1}^{m} a_{ia} z_a + b_i \varepsilon_i\right)\left(\sum_{a=1}^{m} a_{i'a} z_a + b_{i'} \varepsilon_{i'}\right)\right] \tag{20}$$

Developing the product:

$$= E\left[\sum_{a=1}^{m} a_{ia} a_{i'a} z_a z_a + \sum_{a=1}^{m} a_{ia} b_{i'} z_a \varepsilon_{i'} + \sum_{a=1}^{m} b_i a_{i'a} \varepsilon_i z_a + \sum_{a=1}^{m} b_i b_{i'} \varepsilon_i \varepsilon_{i'}\right] \tag{21}$$

From the linearity of hope and considering that the factors are uncorrelated (starting hypothesis), it is now:

$$\mathrm{cov}(x_i x_{i'}) = \sigma_{ii'} = \sum_{a=1}^{m} a_{ia} a_{i'a} = \mathrm{corr}(x_i x_{i'}) \to \forall i, i' = 1, \ldots, p \tag{22}$$

The variance of the i-th variable is given by:

$$\mathrm{var}(x_i) = \sigma_i^2 = E[x_i x_i] = 1 = E\left[\sum_{a=1}^{m} (a_{ia} z_a + b_i \varepsilon_i)^2\right] = E\left[\sum_{a=1}^{m} (a_{ia}^2 z_a^2 + b_i^2 \varepsilon_i^2 + 2a_{ia} b_i z_a \varepsilon_i)\right] \tag{23}$$

Returning to the starting hypotheses, the following expression can be proved:

$$\sigma_i^2 = 1 = \sum_{a=1}^{m} a_{ia}^2 + b_i^2 = h_i^2 + b_i^2 \tag{24}$$

In this way, it can be evaluated how the variance is divided into two parts: the communality, and the uniqueness which is the residual variance not explained by the model. Therefore, the matrix form is $R = AA' + \xi$, where $R^* = R - \xi^2$.

R^* is a reproduced correlation matrix, obtained from the matrix R:

$$R^* = \begin{bmatrix} h_1^2 & r_{12} & r_{13} & r_{14} & \cdots & r_{1p} \\ r_{21} & h_2^2 & r_{23} & r_{24} & \cdots & r_{2p} \\ r_{31} & r_{32} & h_3^2 & r_{34} & \cdots & r_{3p} \\ & & & & \cdots & \\ r_{p1} & r_{p2} & r_{p3} & r_{p4} & \cdots & h_p^2 \end{bmatrix} \tag{25}$$

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', the reduced correlation matrix has become diagonalizable, whereas a solution of the equation would be: $R - \xi^2 = R^* = AA'$ is the matrix A, whose columns are the standardized eigenvectors of R^*. From this reduced matrix, through a diagonal, as a mathematical instrument, the factor axes are obtained from eigenvalues and vectors.

2.2.3 Feasibility of Factor Analysis

To validate the appropriateness of factor model is necessary to design the sample correlation matrix R, from the obtained data. It should be performed prior to the hypothesis test.

A contrast assessment to be performed is the Bartlett Test of Sphericity. It seeks to determine whether there is a relationship structure 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 only of 1 (ones).

Hence, if the all the h variables are unrelated between them, then all correlation coefficients between each pair of variables would be zero. For this reason, the population correlation matrix matches with the identity matrix and its determinant will be equal to 1.

$$H_0 : |R| = 1 \tag{26}$$

$$H_1 : |R| \neq 1 \tag{27}$$

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

$$-\left[n-1-\frac{(2p+5)}{6}\right]\ln|R| \tag{28}$$

Under the null hypothesis, this statistic is asymptotically distributed through a χ^2 distribution with $p(p-1)/2$ degrees freedom. So, in case of accepting the null hypothesis, it would not be advisable to perform factor analysis. Another indicator is the contrasting test 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 for each variable (MSA)

$$\mathrm{KMO} = \frac{\sum_{j\neq i}\sum_{i\neq j} r_{ij}^2}{\sum_{j\neq i}\sum_{i\neq j} r_{ij}^2 + \sum_{j\neq i}\sum_{i\neq j} r_{ij(p)}^2} \tag{29}$$

$$\mathrm{MSA} = \frac{\sum_{i\neq j} r_{ij}^2}{\sum_{i\neq j} r_{ij}^2 + \sum_{i\neq j} r_{ij(p)}^2}; \quad i = 1,\ldots,p \tag{30}$$

Where: $r_{ij(p)}$ is the partial coefficient of the correlation between variables x_i and x_j in all the cases.

With all the considerations mentioned above, and continuing with the procedure proposed by García-Santillán, Venegas-Martínez and Escalera-Chávez (2013b), the following matrix is obtained, as shown in Table 2.

Table 2. Matrix of Variables

Students	Variables $x_1, x_2, \ldots, x_p$
1	$x_{11}, x_{12}, \ldots, x_{1p}$
2	$x_{21}, x_{22}, \ldots, x_{2p}$
...	...
209	$x_{n1}, x_{n2}, \ldots, x_{np}$

Source: own

In order to measure the data collected from students and to test the hypothesis (Hi) against a set of variables—that form the construct for understanding the students' perceptions of statistics—the following Hypotheses are considered: Ho: $\rho = 0$ have no correlation, and Ha: $\rho \neq 0$ have a correlation.

Statistic test to prove: χ^2, ad Bartlett's test of Sphericity, KMO (Kaiser–Meyer–Olkin), MSA (Measure of Sampling Adequacy), significance level: $\alpha = 0.05$; $p < 0.05$, *load factorial of* 0.70, 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 following equation gives the above:

$$\begin{aligned} x_1 &= a_{11}f_1 + a_{12}f_2 + \cdots + a_{1k}f_k + u_1 \\ x_2 &= a_{21}f_1 + a_{22}f_2 + \cdots + a_{2k}f_k + u_2 \\ &\cdots \\ x_p &= a_{p1}f_1 + a_{p2}f_2 + \cdots + a_{pk}f_k + u_p \end{aligned} \tag{31}$$

Where $f_1,\ldots,f_k$ ($k \ll p$) are common factors, $u_1,\ldots,u_p$ 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 $E(f_i) = 0$, $\mathrm{var}(f_i) = 1$, the specific factors have a mean equal to zero and both factors have correlation $\{\mathrm{cov}(f_i,u_j) = 0;\ i = 1,\ldots,k;\ j = 1,\ldots,p\}$ With the following consideration: if the factors are correlated $\{\mathrm{cov}(f_i,f_j) = 0;\ i \neq j;\ j,i = 1,\ldots,k\}$ then it is a model with orthogonal factors, but if it is not correlated then it is a model with oblique factors.

The equation can be expressed as follows:

$$x_1 = a_{11}f_1 + a_{12}f_2 + \cdots + a_{1k}f_k + u_1 \tag{32}$$

Where:

Data matrix	Factorial load matrix	Factorial matrix
$X = \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_p \end{bmatrix}, F = \begin{bmatrix} f_1 \\ f_2 \\ \cdots \\ f_k \end{bmatrix}, U = \begin{bmatrix} u_1 \\ u_2 \\ \cdots \\ u_p \end{bmatrix}$	$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ & & \cdots & \\ a_{p1} & a_{p2} & \cdots & a_{pk} \end{bmatrix},$	$F = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1k} \\ f_{21} & f_{22} & \cdots & f_{2k} \\ & & \cdots & \\ f_{p1} & f_{p2} & \cdots & f_{pk} \end{bmatrix}$

With a variance equal to:

$$\operatorname{var}(x_i) = \sum_{j=1}^{k} a_{ij}^2 + \Psi_i = h_i^2 + \Psi_i; \quad i = 1, \ldots, p \tag{33}$$

Where:

$$\begin{aligned} h_i^2 &= \operatorname{var}\left[\sum_{j=1}^{k} a_{ij} f_j\right] \\ \Psi_i &= \operatorname{var}(u_i) \end{aligned} \tag{34}$$

This equation corresponds to the communalities and the specificity of the variable x_i. Hence, 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 particular variance of each variable. Thus, obtaining:

$$\operatorname{cov}(x_i, x_1) = \operatorname{cov}\left[\sum_{j=1}^{k} a_{ij} f_j, \sum_{j=1}^{k} a_{1j} f_j\right] = \sum_{j=1}^{k} a_{ij} f_{1j} \quad \forall i \neq 1 \tag{35}$$

With the transformation of the correlation matrix determinants, the Bartlett's test of Sphericity is given by:

$$d_R = -\left[n - 1 - \frac{1}{6}(2p+5)\ln|R|\right] = -\left[n - \frac{2p+11}{6}\right]\sum_{j=1}^{p} \log(\lambda_j) \tag{36}$$

Therefore:

$$\left[n - \frac{2p+11}{6}\right] \log \frac{\left[\frac{1}{p-m}\left(\operatorname{traz} R^* - \left(\sum_{a=1}^{m} \lambda_a\right)\right)\right]^{p-m}}{|R^*| / \prod_{a=1}^{m} \lambda_a} \tag{37}$$

3. Data Analysis

After the factor analysis of the data collected by the survey, the following results were computed.

Cronbach's Alpha: It represents a coefficient or a consistency index that is oriented to determining the reliability of the data and the instruments for ensuring stability and coherence of the results. The value of this coefficient ranges from 0 to 1, and the analysis criterion is that the closer the value is to 1 the greater the reliability, where the acceptable level of reliability is beginning at 0.80. The value obtained from the set of variables in this study is displayed in Table 3.

Table 3. Summary

Cases	N	%	Cronbach's alpha
Valid	209	100%	0.775
Excluded[a]	0	0	Dimensions
Total	209	100%	5

[a] Listwise deletion based on all variables

Source: own.

The resulting Cronbach's Alpha (0.775) presented in Table 3 is statistically interpreted as 0.80. It is enough for guaranteeing the acceptable reliability level of the instrument used for data collection, and the data itself (Hair, 1999).

Table 4 shows the mean and the standard deviation of the variables, which are utilized for computing their coefficients of variation, and then identify the biggest values.

Table 4. Statistics

Variable	N	μ	Σ	CV
HMCTT	209	42.8325	7.03875	16.43%
PHC	209	32.4498	5.33751	16.45%
DSF	209	18.8469	3.34197	17.73%
PI	209	3.8469	0.94843	24.65%
CV	209	10.9474	2.51383	22.96%

Source: own

Based on the results described in Table 4, the variable PI (24.65%) it is showing greater dispersion compared with the rest of the variables that show similar behavior.

With the aim of validating the appropriateness of a factor analysis method for the collected data, it was first conducted a contrasting based on the Bartlett's test of Sphericity, Kaiser–Meyer–Olkin measure (KMO), Chi-squared, and Measure Sample Adequacy (MSA). Table 5 shows the resulting values.

Table 5. Bartlett's Test of Sphericity, KMO, MSA and χ^2

<table>
<tr><th>Variable</th><th>MSA</th><th>KMO</th><th>Bartlett test of Sphericity (χ^2)</th></tr>
<tr><td>HMCTT</td><td>0.791</td><td rowspan="5">0.786</td><td rowspan="5">437.826
df 10</td></tr>
<tr><td>PHC</td><td>0.749</td></tr>
<tr><td>DSF</td><td>0.822</td></tr>
<tr><td>PI</td><td>0.835</td></tr>
<tr><td>CV</td><td>0.755</td></tr>
</table>

Source: own

3.1 Bartlett's Test of Sphericity, Kaiser–Meyer–Olkin, and Measure of Sampling Adequacy

To be sure that the factor analysis procedure, in this case, is appropriate and that it contributes to explaining the phenomenon of study, there were computed Bartlett's test of Sphericity, Kaiser–Meyer–Olkin (KMO), and Measure of Sampling Adequacy (MSA). Those indicators served to identify enough correlation between the variables being studied, and validated the proper use of this method (García-Santillán et al., 2013; García-Santillán et al., 2013b).

The Bartlett test of Sphericity is a statistic used to validate the null hypothesis which states that the correlation matrix is an identity matrix, which presents a variation between 0 and 1, and small values demonstrate that factor analysis would not be appropriate do it, because other variables can not explain the correlations between pairs of variables. In the case there is a lack of strong correlations between the variables, then the factorial model would not be suitable, if the value in KMO is < 0.5, i.e., with that value may not be used factor analysis with the sample data which are analyzed. Where a low KMO index (< 0.5) indicates that the relationship between the variables is not significant, and therefore it would not appropriate to apply a Factor Analysis to try to explain the phenomenon under study.

Table 5 shows the results of the Bartlett test of Sphericity, KMO, MSA, χ^2, with significance ($p < 0.01$). Observed values χ^2 (437.826 with 10 df) shows that are high, the measure of sampling adequacy (overall) KMO (0.786) is located in the rank of acceptance since this value should be greater than 0.5, indicating that the variables are intercorrelated.

Therefore, we can say that the values displayed in the above table are very well suited to perform a factor analysis, therefore, the null hypothesis which refers that the variables are not correlated, it is rejected. It means that the variables included in the model allow us to explain the phenomenon under study, in a way that factor analysis may be performed.

By the above, the developed method included following phases:

1. Selecting the explanatory variables.
2. Testing the correlation matrix.
3. Computing components matrix, communalities, eigenvalue and total variance.

1. - The selection of the explanatory variables was undertaken by means of the application of the EAPH-MF in-

strument: "Scale of Attitudes toward and Perceptions of Financial Mathematics" (García-Santillán et al., 2011), consisting of 31 items. The following methods were used to conduct the analytical testing of the degree of correlation between variables under study.

Table 6. Matrix of correlations[a]

		HMCTT	PHC	DSF	PI	CV
	HMCTT	1.000				
	PHC	0.638	1.000			
Correlations	DSF	0.634	0.617	1.000		
	PI	0.386	0.462	0.384	1.000	
	CV	0.627	0.415	0.601	0.420	1.000
	HMCTT					
	PHC	0.000				
Sig. (Unilateral)	DSF	0.000	0.000			
	PI	0.000	0.000	0.000		
	CV	0.000	0.000	0.000	0.000	

[a] Determinant = 0.119

Source: own

2. - Table 6 shows the values of correlations obtained from the studied variables. They are all intercorrelated and the correlations among the variables present high values (> 0.05) in almost all of the cases shown, which leads to thinking that there is a concordance among the set of variables in the model, practice as well as statistics, which means that factor analysis is appropriate.

Table 6 allows to observe significant correlations (> 0.5), $p < 0.01$, $p < 0.05$, within the variables studied. An example of this is: HMCTT versus PHC (0.638), HMCTT vs. DSF (0.634), HMCTT vs. CV (0.627), PHC vs DSF (0.617), DSF vs CV (0.601) and the rest of correlations have values < 0.5, however all of them are positive.

With regard to the value of the determinant is suggested that theoretically it should be below 0.05 which would mean that there is evidence of high correlations, i.e., if it is closer to zero, there is further evidence of good correlation between the variables. Thus, while the value of the determinant obtained in this study is 0.119 (greater than recommended 0.05 value), it was possible to get a set of variables which correlate with them, in a positive way and, in the majority of cases, with values higher than 0.5.

With the transformation of the correlation matrix determinants, Bartlett's test of Sphericity is computed as shown in Table 5, and is given by:

$$d_R = -\left[n - 1 - \frac{1}{6}(2p+5)\ln|R|\right] = -\left[n - \frac{2p+11}{6}\right]\sum_{j=1}^{p}\log(\lambda_j) \tag{38}$$

3.2 Components Matrix, Communalities, Eigenvalue, and Total Variance

Tables 6 and 7 show the component matrix and the communalities, as well as the eigenvalue whose explanatory power embraces the total variance.

The percentage variance required to explain the phenomenon under study was computed and principal component extraction procedure was performed.

The percentage variance of the extracted component (communalities) was obtained (Table 7), and later analyzed by the criteria of eigenvalues greater than 1 (the latent root criteria). The number of components derived from the analysis is one, as shown in Figure 1. Moreover, the sum of the square root of the loads of the initial extraction—the eigenvalue of each component—is presented in Table 8; where it can be seen that the removed component (one) explains 61.906% of the variance of the studied phenomenon.

Table 7. Components Matrix, Communalities, Eigenvalue and Total Variance

	Component 1	Communalities
HMCTT	0.851	0.724
PHC	0.803	0.644
DSF	0.836	0.700
PI	0.644	0.415
CV	0.783	0.613
Eigenvalue	3.095	
Total Variance	61.906%	

Source: own

Table 8. Total variance explained

Component	Initial eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of the variance	% cumulative	Total	% of the variance	% cumulative
1	3.095	61.906	61.906	3.095	61.906	61.906
2	0.698	13.967	75.873			
3	0.581	11.623	87.496			
4	0.369	7.379	94.875			
5	0.256	5.125	100.000			

Extraction Method: Principal Component Analysis.
Source: own

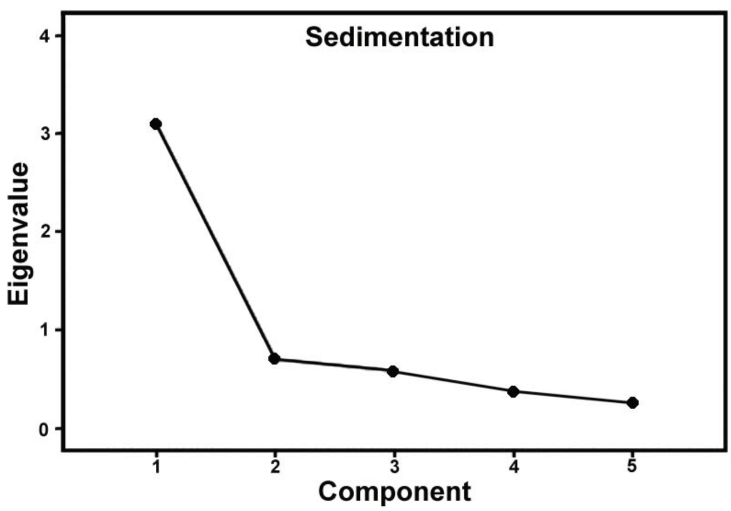

Figure 1. Scree plot

In addition, in the same Table 7, factorial weights obtained by the principal component extraction method are shown. The above corresponding to each factor that integrate component 1, where it may be noticed that all have a factorial weight > 0.50, being HMCTT (0.851) the largest weight (history of mathematics), followed by DSF (0.836) (simulation and simulator design) and smaller factorial weight, but always observing behavior > 0.5 is PI (computing platforms) (0.644). Moreover, at the side of the proportion of variance explained through the communalities HMCTT (0.724) is the highest value, and at the opposite extreme or smallest value is PI (0.415).

4. Discussion of Findings and Recommendations

With the obtained results, *Ho* is rejected, so *Hi* is accepted, which refers that a set of latent variables allows for understanding of the undergraduates' perceptions of Financial Mathematics. This result is consistent with the initial works of García-Santillán et al. (2008), and García-Santillán et al. (2011). The results of this study constitute empirical evidence that allows inferring that the latent variables of the EAPH-MF scale can offer valuable information for understanding the undergraduates' perceptions of Financial Mathematics.

This evidence adds to the research of Roblyer and Edwards (2000), Gómez (2002), Hodgins (2000), Macías (2007) and Cocconi (2008) in which it is contended that the current technological environment has made itself present at practically all levels of the educational process, meaning that ICT is being used as an educational resource of unprecedented importance (Dávila, 2007, Domínguez, 2003).

The ICT empowers interactivity and consequently the social-cognitive development of students and a more positive attitude toward mathematics (Gómez, 2002). ICT is seen as a powerful tool having useful functionalities for the teaching and learning of mathematics. This research reinforces the action of including four variables that consider ICT (PHF, DSF, PI, CV) in the EAPH-MF instrument and when applying factor analysis, the communalities show values > .5 (except for PI) which points to the fact that these are statistically significant latent variables for explaining the object under study, which is the attitude toward financial mathematics.

The teaching of mathematics implies promoting, designing and validating of learning environments that favor social interaction within the framework of ICT, which is of great value for improving the learning of mathematics and, in consequence, decrease failure in school (Murillo, Martin & Fortuny, 2000). The alternatives to traditional teaching are forcing us to re-frame it radically, emphasizing its essential role as guide, motivation, support, encouragement, interaction, humanity and affection (Alsina, 1998; Petriz, Barona, López & Quiroz, 2010). This research sustains that the variable, "design simulators" (DSF) it is an important subject, because it is intended to promote in students building upon their theoretical-practical knowledge and with the help of ICT, they may create simulators upon which to test various scenarios depending on the topic under study.

Workshop-style class is focused on getting students to work by being free to invent, rehearse, make mistakes, create and recreate knowledge, as stated by Araya (1997). By using this form of teaching the possibility will exist of generating evidence that reinforces the underpinning of significant learning, in which the teacher propitiates challenges to draw the interest of the students and to achieve an interaction between the new information and pre-existing ideas in the cognitive structure of the student (Ausubel, Novak & Hanesian, 1998).

Based on the results got from the empirical evidence, it is interesting to ask: Why must the teaching-learning process concerning financial mathematics evolve? The epistemological model consistent with tendencies in the philosophy of mathematics points to the adoption of assumptions about mathematics, firstly as a human activity that implies the solving of problems and in the search of these solutions, the techniques, rules and their respective justification emerge and evolve progressively and are shared socially; likewise this supposes that knowledge of and familiarity with the types of problems and the available resources for their solution is required. To follow such evolution, the history of these techniques and/or rules that have collaborated in the solving of the problems must be known, and they must be taken as the starting point for generating new methods of solving problems, motivating students to use ICT in solving problems, favoring significative learning.

The importance of gaining an understanding of the attitudes by students toward financial mathematics obeys to the fact that this is a very interesting discipline as, depending on the use it is given, there will be the corresponding capitalizing on monetary resources. The research of Bazán, Espinosa and Farro (2001), Aliaga and Pecho (2000), Cueto, Ramírez, León and Pain (2003), has made clear the relationship between yield and attitude toward mathematics in the school system, just as García-Santillán et al. (2008), García-Santillán et al. (2011), have proven that the attitudes were negative and related to low yield. The first work has shown that, as the years of schooling advance, the students' attitudes toward mathematics become less favorable.

It is, therefore, indispensable to empirically support these attitudes so as later to take the right decisions for helping achieve an improved profit. Such attitudes are considered to be a good predictor of the assimilation of contents, of motivation, of memory and of the future use of the subject. All of it leads to posting the hypothesis that they (the attitudes) can impede or ease learning (Eagly & Chaiken, 1992; Álvaro & Garrido, 2003).

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