

Structural equations in educational models: Characteristics and phases in their construction

Ecuaciones estructurales en los modelos educativos: características y fases en su construcción

<http://dx.doi.org/10.32870/Ap.v11n1.1402>

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ABSTRACT

Keywords

Structural equations,
maximum likelihood
method, factor analysis,
Learning Management
System, TPACK model

In this article, the characteristics and construction phases of the structural equation models are presented, a useful statistical methodology to study causal relationships through non-experimental information, specifically when the relations are of the linear type. We adopt the strategy of model development through the use of systems of structural equations, in which a model is proposed and the purpose is to improve it through the modification of its structure or its measurements. The maximum likelihood method was used to obtain the common factors. The proposal was made based on the Technological Pedagogical Content Knowledge (TPACK) model. The results obtained from the factorial analysis where user satisfaction was analyzed when they use a Learning Management System to support their face-to-face classes at the Autonomous University of the State of Hidalgo, indicate that there is a strong correlation between the parameters of the TPACK model and the satisfaction of the students, not with the socio-cultural factors. Nor is there a correlation between sociocultural factors and student satisfaction. The importance of this research is the contribution of a model that allows us to determine the satisfaction of students through the model of structural equations with the TPACK model.

RESUMEN

Palabras clave

Ecuaciones estructurales,
método de máxima
verosimilitud, análisis
factorial, Learning
Management System,
modelo TPACK

En este artículo se dan a conocer las características y fases de construcción de los modelos de ecuaciones estructurales, una metodología estadística útil para estudiar las relaciones causales mediante información no experimental, específicamente cuando las relaciones son del tipo lineal. Se adoptó la estrategia de desarrollo de modelo mediante la utilización de sistemas de ecuaciones estructurales, en la que se propone un modelo y el propósito es mejorarlo a través de la modificación de su estructura o en sus medidas. Se utilizó el método de máxima verosimilitud para la obtención de los factores comunes. La propuesta se realizó con base en el modelo Technological Pedagogical Content Knowledge (TPACK). Los resultados del análisis factorial sobre la satisfacción de los usuarios cuando utilizan un Sistema de Gestión del Aprendizaje como apoyo a las clases presenciales en la Universidad Autónoma del Estado de Hidalgo, indican que hay una fuerte correlación entre los parámetros del modelo TPACK y la satisfacción de los alumnos, no así con los factores socioculturales. Tampoco existe correlación entre los factores socioculturales y la satisfacción del alumno. Esta investigación aporta de un modelo que nos permite determinar la satisfacción del alumnado mediante el modelo de ecuaciones estructurales con el modelo TPACK.

Received: April 12, 2018
Accepted: August 14, 2018
Online Published:
March 30, 2019

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INTRODUCTION

Structural equation models (SEM) allow determining the dependence or independence of the relation variables intervening in them through the integration of linear equations. These models allow combining the factorial analysis with the linear regression to determine the adjustment of the information obtained with a model proposed by means of a path analysis (Afifi & Clark, 1990) in which the relation existing between latent and observed variables is represented. Observed variables are those that are not measured directly and can be endogenous (dependent) or exogenous (independent).

By examining in depth the concept of latent variables in structural equation models, we can consider a basic structural equation model. An independent latent variable predicts a dependent latent variable. It is believed that predicting academic achievement (dependent latent variable) could be represented as such:



Any latent variable predicted by other latent variable in a structural equation model known as a dependent variable. If a third latent variable is added to the previous basic structural equation model, the achievement is measured in two points in time.



Intelligence is an independent latent variable; Academic achievement 2 is a dependent variable because there is an arrow pointing toward it from Academic achievement 1. However, there is an arrow pointing to Academic achievement 1 from Intelligence and another arrow from Achievement 1 to Achievement 2. In this basic structural equation model, Achievement 1 is predicted by Intelligence, but afterwards, Achievement 1 predicts Achievement 2. Achievement 1 is first of all a dependent latent variable and afterwards, an independent variable. This type of structural equation model is feasible and it illustrates the indirect effects by using latent variables (Schumacker & Lomax, 2010).

An important aspect of modeling with SEM in comparison with other analysis techniques is that this model takes into account every variable measurement error. This is crucial for the researcher since he/she can evaluate the validity of the variables intervening in the model.

Independent latent variables are measured by independent observed variables through the confirmatory factorial analysis which is generally indicated by an X. Dependent latent variables are measured by dependent observed variables through the confirmatory factorial analysis which is indicated by a Y.

Another important aspect of this analysis is that it allows us to establish the parameter equivalence. This analysis is represented through path diagrams. The rectangles represent the observed variables which are, in general, items; latent variables, both endogenous and exogenous, are represented by ellipses. The relation between an observed variable and a latent variable is unidirectional and is represented by an arrow. The relation between latent variables can be bidirectional and are represented by curved lines with an arrow at each extremity. The errors associated to the endogenous variable are represented without any circles or ovals; however, since it is an unobserved variable, many computer programs do so although at a lesser degree than latent variables (See Figure 1).

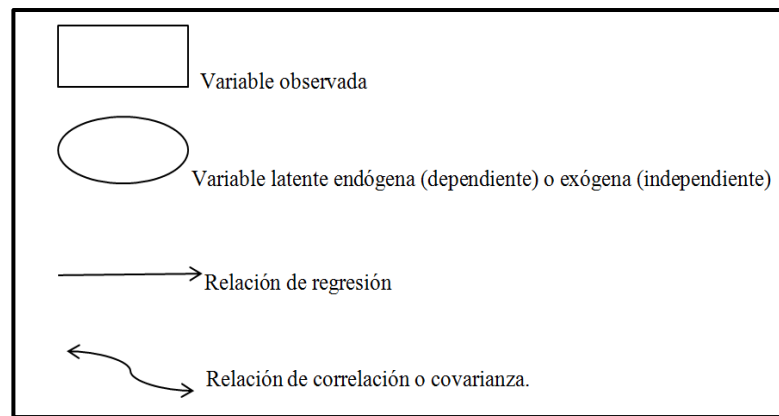


Figure 1. Path diagram representation form.

Figure 2 shows the path diagram of the previous example in which WISC-R, STANFORD, CAL 1, METRO 1, CAL 2 and METRO 2 are the measurement scales for each independent and dependent variables, through independent and dependent observed variables, respectively. e1-e6 shows the errors of every observed variables; e7 and e8 are the errors associated to the Achievement 1 and Achievement 2 latent variables, in said sequence. The Intelligence variable is not associated with any error since it is our independent or exogenous variable.

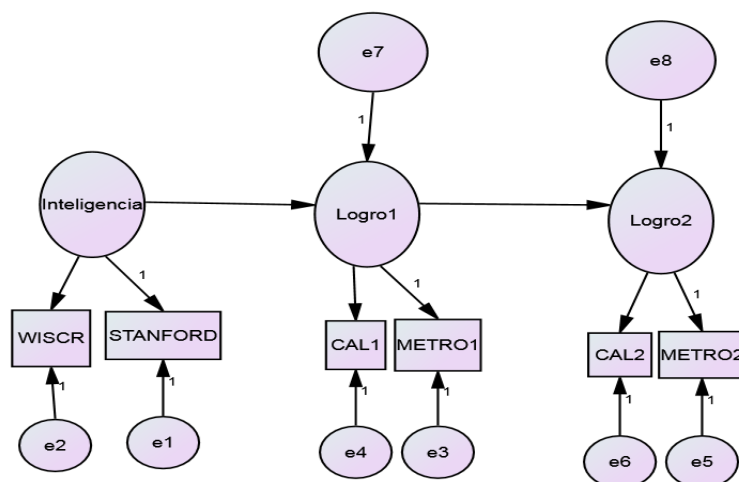


Figure 2. Path diagram of the academic achievement model.
Source: Self development. Adapted from Schumacker y Lomax (2010).

GENERAL STRUCTURE OF THE STRUCTURAL EQUATION MODELS

Structural equation systems emerge out of the need to have alternative tools in regression models (Bollen, 1989). At the beginning of the 20th Century, researchers began making contributions to the creation of these models, and in 1970, Jöreskog presented the covariance structure analysis.

Next, we present several proposed models which indicate the types of intervening variables and the relation between constructs. Figure 3 shows the proposed causal model in which sociocultural factors (SCFs), financial factors (FFs) and academic factors (AFs) that have an impact on school dropout at postgraduate level (PSD). Exogenous variables are SCF (ξ_1), FF (ξ_2) and AF (ξ_3); while the endogenous variables are PSD (η_1). Age (λ_{11}), gender (λ_{12}), last degree of studies (λ_{13}) and civil status (λ_{14}) λ_{32} are observed endogenous variables. The relations that exist between constructs are determined by γ_{11} (SCF- PSD), γ_{12} (FF-PSD), γ_{13} (AF-PSD), γ_{21} (SCF-FF) y γ_{22} (FF-SCF) and they can be indicated as hypotheses based on the needs of researchers and the study.

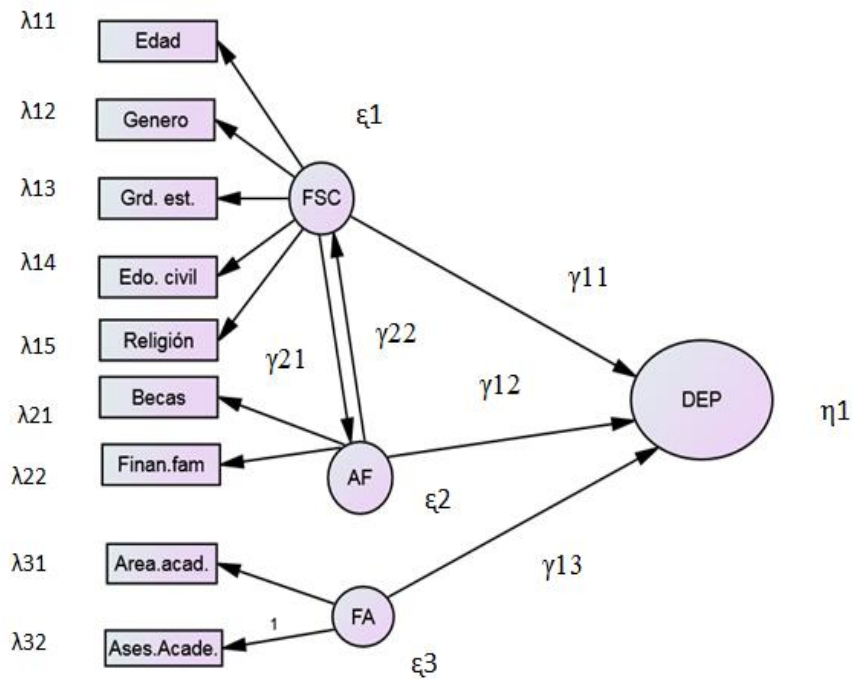


Figure 3. Postgraduate school dropout.
Source: Self development.

Figure 4 shows the proposed causal mode in which sociacultural factors (SCF), equipment structure factors (ES) and organizational context factors (OC) that have an impact on the integration of multidisciplinary teamwork (MDT). The exogenous variables are SCF (ξ_1), FF (ξ_2) and AF (ξ_3); the endogenous are: MDT (η_1). Age (λ_{11}), gender (λ_{12}), last degree of studies (λ_{13}) and civil status (λ_{14}) λ_{33} . The relations that exist between constructs are determined by γ_{11} (SCF–MDT), γ_{12} (ES–TMD), γ_{13} (OC–MDT), γ_{21} (SCF–ES) y γ_{22} (ES–SCF), and they can be indicated as hypotheses based on the needs of researchers and the study.

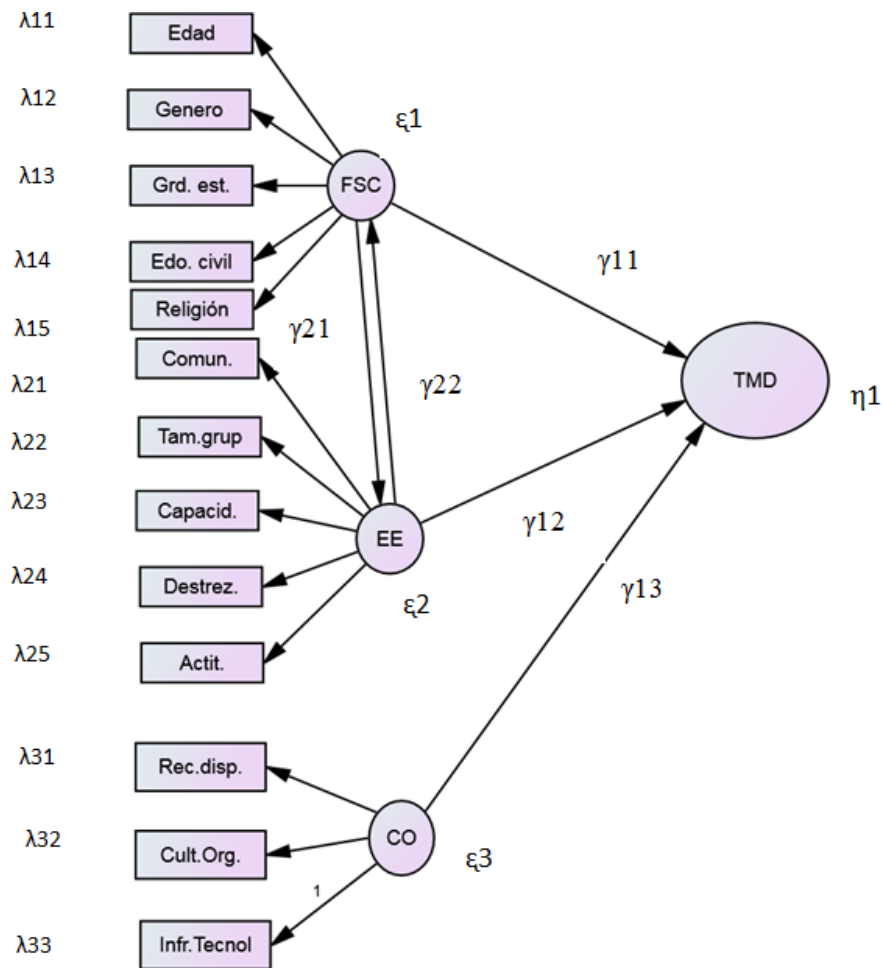


Figure 4. Multidisciplinary Teamwork Integration (MDT).
Source: Self development.

SEM MODEL STAGE APPLICATION

Several researchers propose six stages of this technique (Schumacker & Lomax, 2010; Haenlein & Kaplan, 2000; Kline, 2005):

- Specification is the first stage in which the relation between variables is hypothetically determined; the analysis will then determine the correct relations.
- Identification is the second stage in which the parameters that integrate the model are determined through variances and sample covariances.
- Parameter estimation is the third stage. At this stage, the value and the error of every one of the unknown parameters are calculated.

Different computer software such as Amos, LISREL, EQS or Sepath, among other, are used to calculate these parameters.

- Adjustment assessment is the fourth stage in which the quality adjustment or goodness of fit is measured to determine if the model serves the researcher's purposes. These measures assess the model fit and compare the proposed model with others indicated by the researchers.
- Model respecification is the fifth stage since, in general, the one proposed initially is not the best fit, hence, the application of methods to add or eliminate parameters that justify these actions. In this case, we recommend reducing the chi-square value to a minimum value of 3.84 (Hair, Anderson, Tatham and Black, 2001).

Table 1 includes the fit criteria to assess SEMs

Table 1. Fit criteria to assess structural equation models

Model fit criterion	Acceptable level	Interpretation
χ^2	The least possible	Recommended to be used mainly in model comparison
CFI (Comparative Fit Index)	0-1	This is the criterion most used since it is not affected by the size of the sample. Values inferior to 0.9 indicate a good model fit
RMSEA (Root Mean Square Error of Approximation)	Less than 0.06	After the CFI criterion, this is the most used to indicate the model fit. However, it is affected when small samples are used.

Source: Self development.

- At the sixth stage, it is recommended to conduct a data analysis in order to establish the correct model to accept or reject the hypotheses.

EXPLORATORY FACTORIAL ANALYSIS

The factorial analysis helps determining which observed variables share variance-covariance characteristics that theoretically define factors or constructs (latent variables). The factorial analysis supposes that some factors, smaller in number than the number of the observed variables, are

responsible for the variance-covariance shared between the observed variables. In practice, data regarding observed variables are collected and analytical techniques are used to confirm that a subset of observed variables defines every construct or factor (Schumacker & Lomax, 2010).

The exploratory factorial analysis (EFA) seeks to find a model that fits the data; hence different alternative models are specified hoping to find one that adapts to the data and that, also has a theoretical support. This is recommended as precursor of the confirmatory factorial analysis when the researcher lacks previous specifications of the model. Schumacker and Lomax (2010) recommend generating a model through EFA in a data sample to find the number and type of latent variables or common factors in the model, in order to explain the responses to the observed variables. In other words, this analysis aims at identifying the number and composition of the common factors (latent variables) necessary to explain the common variance of the items analyzed.

The researcher uses EFA when he does not have enough knowledge of the variable under study; through this analysis, we can identify the latent and manifest variables and the relation between them (Hair *et al.*, 2001).

CONFIRMATORY FACTORIAL ANALYSIS

Model confirmation is, without a doubt, one of the most important structural equation models when evaluating its statistical significance. It should be pointed out that even though this model has an acceptable fit, it is not indicated as being the best, since this can be checked by testing the model; what we can affirm is that it constitutes one of the feasible and viable models.

The confirmatory factorial analysis (CFA) helps corroborate or correct the EFA errors through the covariance matrix besides making a better hypothesis contrast (Bollen, 1989). Correlations between observed variables and factors can be established in CFA through factorial charges. The correlation will be greater when the value is closer to one; the recommendable value is greater than 0.07 (Garson, 2013).

In other words, in the CFA, the researcher seeks to statistically prove the significance of one hypothetical model, i.e., if the data obtained confirm that model; hence, the researcher specifies a certain number of factors which are correlated and the observed variables measure every factor. Through the exploratory factorial analysis, the researcher examines the number of factors, if these factors are correlated and which are the variables that best measure every factor.

In CFA, the researcher has *a priori* a specified model which is not the case in EFA (Schumacker & Lomax, 2010).

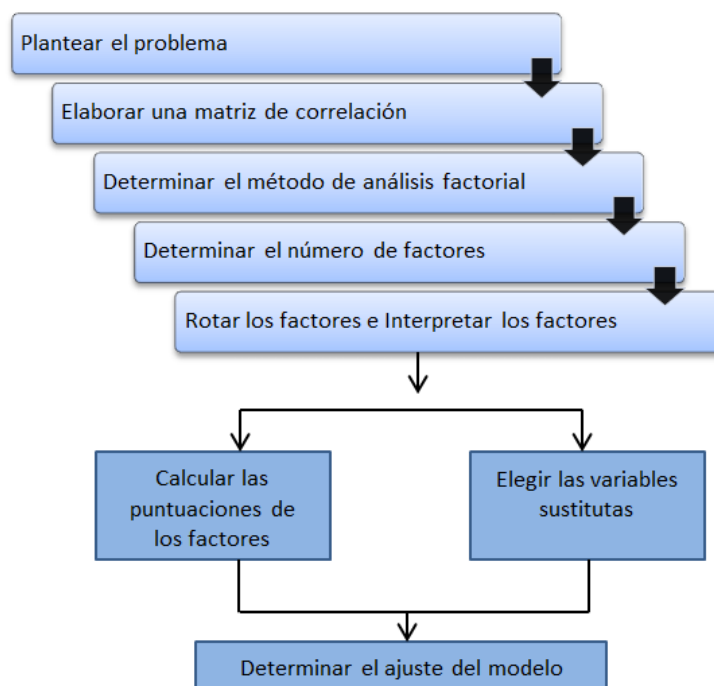


Figure 5. Performance of the Factorial Analysis.
Source: Self development. Adapted from Malhotra (1997).

COMPUTER PACKAGES FOR SEM

There are several computer packages for SEM, and their function is to calculate and analyze the variables relations. The Amos (Analysis of Moment Structures) program helps assessing and contrasting structural models through a graphic interface; it operates as a basis in the SPSS (Statistical Package for the Social Sciences) platform. AMOS can specify, see and modify the model; subsequently, the fit of the model can be assessed and any modification can be done once more.

The methods implemented in Amos are among the most efficient and reliable methods available. This analysis provides the following methods to assess structural equation models: maximum likelihood, unweighted least squares, generalized least squares, Browne asymptotic distribution criterion, least square scales and Bayesian estimation (Arbuckle, 2012).

The Linear Structural Relations (LISREL), developed by Jöreskog and Sörbom (1996), is another program used to analyze covariance structures. It has a graphic interface and offers a variety of estimation models besides creating automatically a path diagram at the moment of conducting the data statistical analysis.

THEORETICAL MODEL DESCRIPTION

The Technological Pedagogical Content Knowledge (TPACK) was used to specify the proposed model that helps analyzing the users' satisfaction when making use of a learning management system to support face-to face classes at the Univesidad Autonoma del Estado de Hidalgo [Autonomous University of the State of Hidalgo]; this model is explained below in general terms.

TPACK model in LMS

Mishra and Koehler (2006) developed a model centered on educational technology that studies the intersections between technological knowledge (TK), content knowledge (CK) and pedagogical knowledge (PK), and the one called TPACK. According to Tárraga Mínguez, Sanz Cervera, Pastor Cerezuela and Fernández Andrés (2017), this model is used to incorporate jointly the aspects related to the information and communication technologies (ICTs), the curricular content or of content and the pedagogical knowledge.

This model has contributed in identifying the different knowledge teachers in the educational process must possess. Cejas León, Navío Gámez and Barroso Osuna (2016) comment that TPACK presents an interesting way for teachers to integrate technology, pedagogy and content knowledge in their educational activity. This research is based on this model from a competence logic based on the demands of the 21st century. Figure 6 shows the knowledge addressing this model.

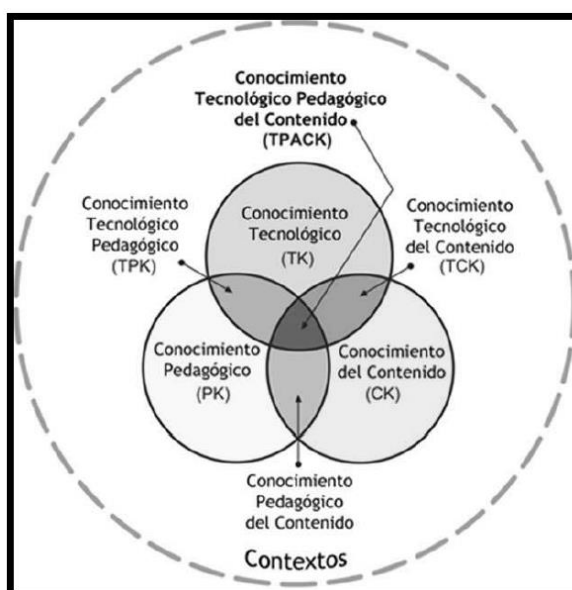


Figure 6. TPACK.

Source: Model. www.tpack.org

According to Cabero (2014), the most important thing this model proposes is the knowledge that the teacher must possess to include ICTs in his/her teaching activity; however, a teacher must not only master the three types of knowledge (CK, PK and CT) but also their intersections.

Roig Villa, Mengual Andrés and Quinto Medrano (2015) point out that the TPACK model synthesizes different knowledge in knowing how to use an efficient methodology to use ICTs, using strategies and pedagogical methods regarding a subject area.

METHODOLOGY

Practical example to obtain the value of the factorial charges

We adopted the model development strategy by using structural equation systems that proposes a model to improve through modifying its structure or its measures. With this strategy, we tried to reformulate a proposed model in order to find a new one (See Table 2).

Table 2. Methodological procedure sheet

Ficha de procedimiento metodológico	
Técnica e instrumento de recogida de información	Encuesta de satisfacción. El instrumento es un cuestionario que consiste en 19 ítems iniciales respecto a la satisfacción del alumnado cuando el profesor hace uso del LMS como apoyo a su actividad docente
Universo	Alumnos de la licenciatura en Administración
Ámbito	Escuela Superior de Tlahuelilpan, Universidad Autónoma del Estado de Hidalgo
Unidades de análisis	Cuarto y octavo semestres de la Licenciatura en Administración
Forma de contacto	Autorización de la coordinación de la Licenciatura en Administración
Muestra definida	32 alumnos
Fecha	Octubre 2017

Source: Self development.

Model proposed

Figure 7 shows the proposed causal model that evaluates the impact of SCF, pedagogical technological knowledge and content (TPACK) when the teacher uses a LMS as support in his/her teaching activity (SA). We indicated the latent and endogenous variables (η_1), such as SA, and exogenous such as SCF (ξ_1) and TPACK (ξ_2). Among the observed endogenous variables, there are λ_{11} (age), λ_{12} (gender), λ_{13} (last degree of studies) and λ_{14} (civil status), λ_{21} (technological knowledge), λ_{22} (pedagogical knowledge) and λ_{23} (curricular content knowledge). The relations between the constructs are determined by γ_{11} (SCF-SA), γ_{12} (TPACK-SA), γ_{21} (SCF-TPACK), as well as γ_{22} (TPACK-SCF).

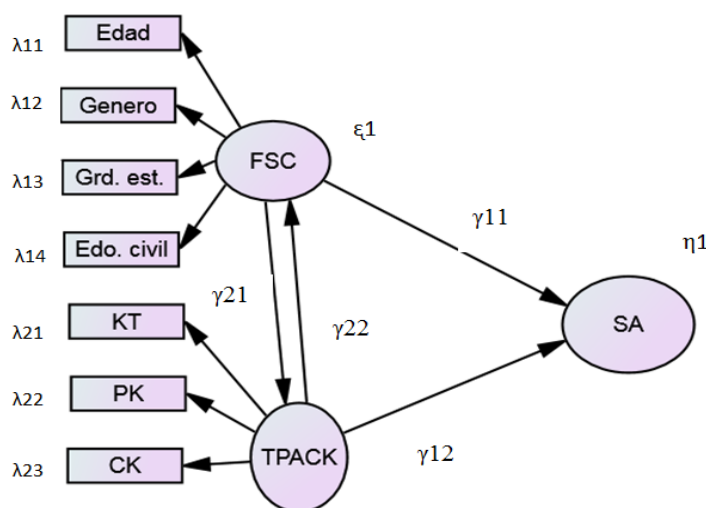


Figure 7. Students' satisfaction when the teacher uses LMS as his/her teaching activity support.
Source: Self development.

The parameters of the structural model that explain the students' satisfaction were estimated by means of the IBM-SPSS Amos 22.0.0 software. In this document, we analyzed the factorial charges only, a method necessary to apply the structural equation model. There are different methods to obtain common factors such as the main component method, major axis method and the maximum likelihood method. In this example, we used the maximum likelihood method, which advantage is that the estimated values do not depend on the variable measure scale. It also allows selecting the number of factors based on the hypothesis contrast.

The maximum likelihood method can be used in CFA, in which the researcher proposes assumptions – for example, that some factorial charges are null or that some variables are correlated with some factors,

etc. – and, by applying statistical tests, he/she can determine if they are true or false. This method has an inconvenient; if the variables are not normal, convergence problems may arise.

Mathematical model and value obtainment of parameters through the IBM-SPSS Amos 22.0.0 software

Being X_j a series of observed variables, where $j= 1,2,3,\dots,p$; is the response to j -ith question or item of the survey; in this case under study, the value is 19. The model supposes the existence of a set of factors F_1, F_2, \dots, F_m of latent variables (TPACK, SCF) such as:

$$X_1 = \mu_1 + V_{11} F_1 + V_{12} F_2 + \dots + V_{1m} F_m + e_1$$

$$X_2 = \mu_2 + V_{21} F_1 + V_{22} F_2 + \dots + V_{2m} F_m + e_2$$

.

.

$$X_j = \mu_j + V_{j1} F_1 + V_{j2} F_2 + \dots + V_{jm} F_m + e_j$$

Where:

μ_j = is defined as the measures of variables X_j . To simplify the notation, variables are standardized so $\mu_j=0$

F_k = are the latent variables or common factors where $k=1,2,\dots,m$

V_{jm} = are defined as the factorial charges and indicate the weight of each one of the variables.

e_j = Specific factors

Moreover, the number of m factors is supposedly much lesser than the number of p variables, in the case at hand, $m=3$, $p=19$.

Based on the above, next we define vectors and matrixes:

$$\underline{x} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix} \quad \underline{f} = \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_m \end{bmatrix} \quad \underline{e} = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_p \end{bmatrix} \quad v = \begin{bmatrix} V_{11} & V_{12} & \dots & \dots & V_{1m} \\ V_{21} & V_{22} & \dots & \dots & V_{2m} \\ & & \ddots & & \\ & & & \ddots & \\ V_{p1} & V_{p2} & \dots & \dots & V_{pm} \end{bmatrix}$$

The factorial model can be expressed as follows:

$$\underline{x} = v \underline{f} + \underline{e}$$

The v matrix contains the values of the factorial charges. With the data obtained in the surveys, and according to the previous model, we obtained the values of the factorial charges and the covariances.

Figure 8 shows the diagram with the latent variables (TPACK, SCF and SA) with their respective covariances and the observed variables or items with their respective errors, and the factorial charges of the observed variables regarding the latent variables. In the following tables, we analyze the values obtained, as pointed out, in this case, we are only interested in the value of the factorial charges to determine the number of items belonging to every latent variable and that will make up the correct instrument. The value of the factorial charges in this diagram does not have standardized values (when $\mu_j \neq 0$) with the purpose of comparing the diagram with standardized values (when $\mu_j = 0$).

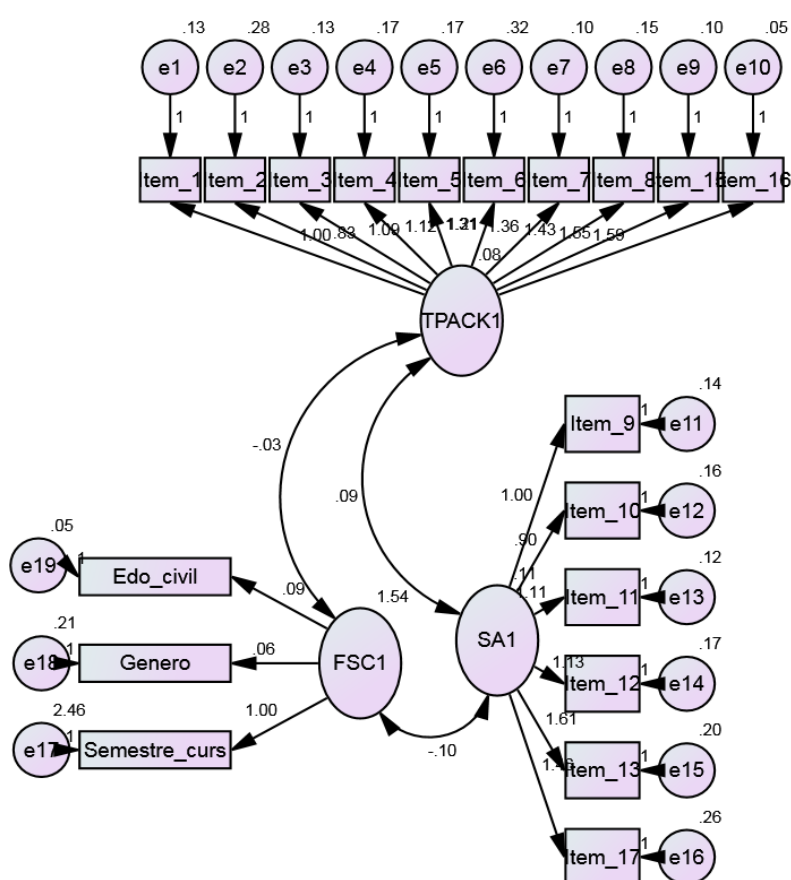


Figure 8. Diagram with non-standardized values.
Source: Self development.

Figure 9 shows the diagram with standardized values of the factorial charges; in the case of the value of the factorial charge of item 1 and the TPACK1 variable is 0.57, item 3 is 0.62, and so on. Further on, we will

analyze the values obtained to determine the items belonging to each one of the latent variables. Let's keep in mind that these values were obtained with the AMOS software, although it is also possible to obtain them with the SPSS program; this will depend of the researcher. By standardizing the covariance values, they convert into the correlations that exist between latent variables.

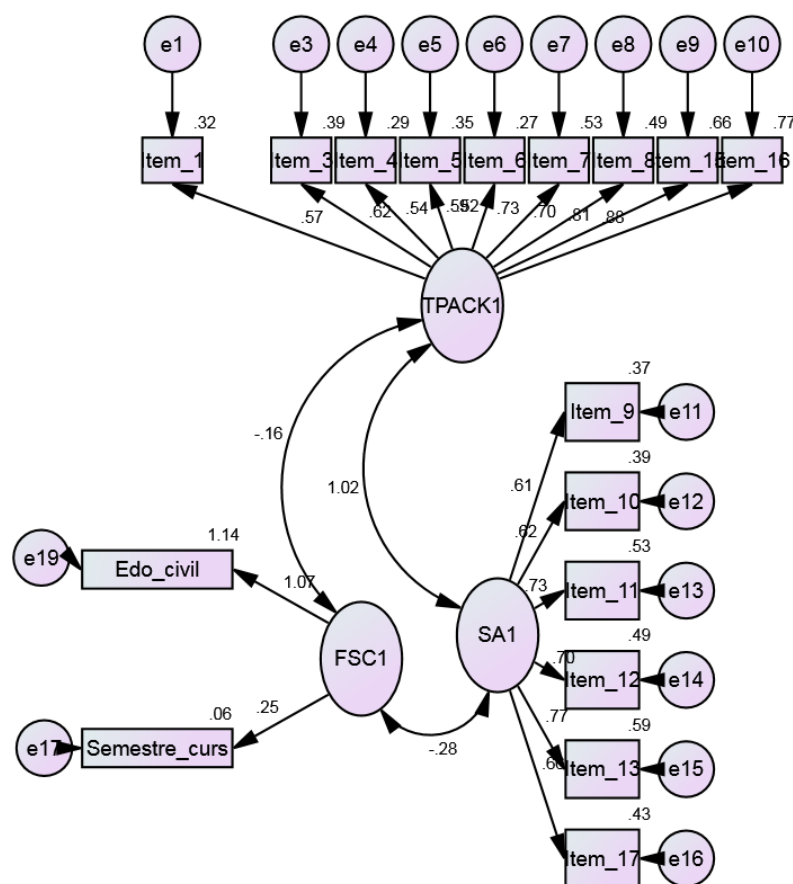


Figure 9. Diagram with non-standardized values.
Source: Self development.

ANALYSIS OF VALUES OBTAINED

In order to determine the items that belong to each latent variable, we examined the standardized values of the factorial charges regarding each one of the variables shown in Table 3; we adopted the criterion of accepting those that have a minimum value of 0.4. regarding the factorial charges of the items of the TPACK latent variable, all have a value higher than 0.5; hence, they show an acceptable factorial charge and all the items are accepted; the same occurs for the SA1 variable; however, the completed

Semester item has a charge of 0.254, which is unacceptable, hence, we decided to remove it. In the original model, the Campus where you study variable appeared, but since we carried out this test in one institute only, the statistical test considered it as a constant; hence, we eliminated it and the number of items or observed variables was reduced from 19 to 17.

Table 3. Standardized values of each one of the factorial charges

		Estimate
Item_1	<--- TPACK1	.568
Item_3	<--- TPACK1	.621
Item_4	<--- TPACK1	.541
Item_5	<--- TPACK1	.593
Item_6	<--- TPACK1	.518
Item_7	<--- TPACK1	.731
Item_8	<--- TPACK1	.697
Item_15	<--- TPACK1	.813
Item_16	<--- TPACK1	.880
Item_9	<--- SA1	.610
Item_10	<--- SA1	.625
Item_11	<--- SA1	.729
Item_12	<--- SA1	.703
Item_13	<--- SA1	.771
Item_17	<--- SA1	.658
Semestre_curs	<--- FSC1	.254
Edo_civil	<--- FSC1	1.070

Source: Self development.

In regard to the relation between the latent variable, we conducted the analysis based on the covariance and the correlation. In regard to the covariance, Table 4 shows the non-standardized values between latent variables. Let's keep in mind that when the values are not standardized, the estimated values between latent variables are covariances; in this case, the value between SCF1 and TPACK1 is negative (-0.021) and the same occurs between SCF1 and SA1 (-0.043); in contrast, the value between TPACK1 and SA1 is positive (0.080); hence, the relation exists only between these two variables.

Table 4. Covariance estimated values

		Estimate	S.E.	C.R.	P	Label
TPACK1	<--> SA1	.080	.036	2.229	.026	par_15
FSC1	<--> TPACK1	-.021	.063	-.333	.739	par_16
FSC1	<--> SA1	-.043	.116	-.371	.711	par_17

Source: Self development.

In regard to the analysis based on correlation, in Table 5, we show the standardized values, thus, the values between latent variables are correlations. The correlation between SCF1 variable and TPACK1 is negative; the same occurs with SCF1 and SA1, however, it is not the same between TPACK1 and SA1. This indicates that there is only a relation between latent variables TPACK1 and SA1. This statement is obtained with both covariance and correlation values.

Table 5. Correlation estimated values

			Estimate
TPACK1	<-->	SA1	1.019
FSC1	<-->	TPACK1	-.161
FSC1	<-->	SA1	-.279

Source: Self development.

CONCLUSIONS

Our study allows establishing a contribution for the combination of the structural equation model with the TPACK model to determine the correlation of the factors that intervene in the students' satisfaction when using a Learning Management System as learning technological tool, main object of this research. Therefore, we can infer that there is a strong correlation between technological, pedagogical and content factors and the students' satisfaction; however, the satisfaction shows a low correlation with the students' sociocultural factors. Likewise, sociocultural factors have little correlation with technological, pedagogical and content factors.

In accordance with the above, we can conclude that a learning management system in an educational institution must take into account the technological, pedagogical and content factors on which the TPACK is based in order to achieve learning satisfaction of the students that use it. It is important to mention that this study is the result of part of the research conducted at the Univesidad Autónoma del Estado de Hidalgo [Autonomous University of the State of Hidalgo].

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