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Aplicación de la técnica PLS-SEM en la gestión del conocimiento: un enfoque técnico práctico

Application of the PLS-SEM technique in Knowledge Management: a practical technical approach

Aplicação da técnica PLS-SEM na gestão do conhecimento: uma abordagem técnica prática

Minerva Martínez Ávila
Facultad de Contaduría y Administración, Universidad Autónoma del Estado de México, México
mmartineza@uaemex.mx
https://orcid.org/0000-0002-0921-019X

Eréndira Fierro Moreno
Facultad de Contaduría y Administración, Universidad Autónoma del Estado de México, México
efierrom@uaemex.mx
http://orcid.org/0000-0002-4397-1179

Resumen

El objetivo de esta investigación es presentar una revisión documental sobre el método multivariante de segunda generación denominado *modelación de ecuaciones estructurales con mínimos cuadrados parciales* (PLS-SEM, por sus siglas en inglés). Este método está teniendo gran aceptación en la comunidad científica en el área de ciencias sociales por tener un enfoque alternativo, robusto y más flexible al tradicional. En el presente estudio se inicia con aspectos básicos metodológicos de la técnica, a través de datos empíricos, y se evalúa un modelo de investigación con la finalidad de que el lector pueda observar valores de los modelos de medida, del modelo estructural y de la evaluación global del modelo.

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Su originalidad y valor permite conocer el uso de la técnica y las directrices para su aplicación y la interpretación de sus resultados mediante el uso del *software* SmartPLS.

Palabras clave: modelación de ecuaciones estructurales, PLS-SEM, teoría de medición.

Abstract

The objective of this research is to present a documentary review about the multivariate method (second generation) called structural equation modeling with partial least squares that is having a good acceptance in the scientific community in the area of social sciences because it is an alternative approach that is robust and more flexible than the traditional. It begins with basic methodological aspects of the technique and through empirical data and a research model is evaluated with the purpose that the reader can observe values of the measurement models, of the structural model and the evaluation of global model.

The originality and the value allows the use of the technique and the guidelines for the application and the interpretation of their results through the use of SmartPLS.

Keywords: structural equation modeling, PLS-SEM, measurement theory.

Resumo

O objetivo desta pesquisa é apresentar uma revisão documental sobre o método multivariável de segunda geração denominado modelagem de equações estruturais com mínimos quadrados parciais (PLS-SEM, por sua sigla em inglês). Este método está tendo grande aceitação na comunidade científica na área de ciências sociais por ter uma abordagem alternativa, robusta e mais flexível ao tradicional. No presente estudo, começa com aspectos metodológicos básicos da técnica, através de dados empíricos, e um modelo de pesquisa é avaliado para que o leitor possa observar valores de modelos de medição, modelo estrutural e avaliação modelo global.

Sua originalidade e valor permitem conhecer o uso da técnica e as diretrizes para sua aplicação e a interpretação de seus resultados através do uso do software SmartPLS.

Palavras-chave: modelagem de equações estruturais, PLS-SEM, teoria de medição.

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Introduction

One of the fundamental objectives of multivariate statistics techniques is to increase the explanatory capacity of the empirical verification of the theory, or to increase the theoretical knowledge in cases where this is scarce. Structural equation models are a second generation multivariate data analysis technique that gives research a greater level of confidence due to its statistical efficiency through robust and powerful software; Its development has meant a revolution in the field of empirical research, since it allows us to simultaneously examine a series of dependency relations between independent and dependent variables. These models of structural equations can be used by researchers from social sciences, education sciences, behavioral sciences, among others; they are often used in market research, because they allow theoretical testing of causal models (Haenlein and Kaplan, 2004, Statsoft, 2013).

This statistical technique for series of simultaneous equation estimates using multiple regressions is characterized by two basic components: 1) the structural model and 2) the measurement model. The structural model is the guiding model that shows the dependency relationships between independent (exogenous) and dependent (endogenous) variables. The measurement model shows the relationships between constructs (latent variables) and indicators (observable variables); In this model, the researcher can evaluate the contribution of each item (reactive) to the measurement scale, that is, specify which indicators define each construct. In addition, it evaluates the reliability of constructs and indicators.

In the modeling of structural equations (SEM, for its acronym in English) there are two approaches: the first is based on the analysis of structures of covariance (CB, for its acronym in English), which is recommended when contrasting theories, tests of hypothesis or in the design of new theories, based on theory and previous research. The second is the partial least squares approach (PLS) based on the analysis of variance.

In the CB analysis, and in accordance with the recommendations of Levy and Varela (2006), the theory and the previous investigations have to be considered, which should be the starting point of this type of models. In a real situation, the review of the literature on the subject of research will allow obtaining a theoretical model from which the domain of the concepts analyzed and their relationships will be specified. Also, the theory will allow the construction of items referring to the constructs (variables) and dimensions that have been established in theoretical models. In addition, a fundamental characteristic of this approach is compliance with statistical assumptions, such as the normality of the data and the sample size, which is why it is considered a parametric SEM technique. Therefore, Falk and Miller (1992) defined this methodology as a closed system.

The second approach, referring to the PLS method, is based on the analysis of variance, which implies a more flexible modeling methodology by not demanding rigorous parametric assumptions, mainly in the distribution of the data. In this sense, Wolf (1980) states that the modeling of structural equations with partial least squares (PLS-SEM, for its acronym in English) does not require the conditions required by the traditional modeling of structural equations of covariance (CB-SEM, by its abbreviations in English) with respect to the statistical distributions (normality of the data size of the sample in reference to the observed variables); that is, they use nonparametric tests. PLS models are used under prediction and non-confirmatory situations.

Specifically, Hair, Hult, Ringle and Sarstedt (2017, p.2) classify first and second generation multivariate methods as shown in table 1.

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Tabla 1. Organización de los métodos multivariantes.

Técnica	Principalmente exploratorio (predictivas)	Principalmente confirmatoria (probatorias o explicativas)
Técnicas de primera generación	Análisis de conglomerados. Análisis factorial exploratorio. Escalamiento multidimensional.	Análisis de varianza. Regresión logística. Regresión múltiple. Análisis factorial confirmatorio.
Técnicas de segunda generación	PLS-SEM.	CB-SEM.

Fuente: Hair, Hult, Ringle y Sarstedt (2017, p. 2)

Based on the above classification, the objective of this scientific article is to present a documentary review on the second generation multivariate method, SEM-PLS; It starts with basic methodological aspects of the technique and through fictitious data a research model is evaluated in order that the reader can observe values of the measurement models, the structural model and the global evaluation of the model; in this case it was based on a proposal of the theoretical model to be contrasted that had five hypotheses.

Key aspects in the use of the PLS-SEM

The PLS-SEM emerged as a technique to analyze the complex relationships between latent variables that explain the observed data and predictive analysis as a relevant element in scientific research.

The PLS approach was developed to reflect the theoretical and empirical conditions of the social and behavioral sciences. Mathematical and statistical procedures are rigorous and robust; but the mathematical model is flexible, in the sense that it does not establish rigorous premises in the distribution of the data, in the scale of measurement, or in the size of the sample.

To select the use of the PLS-SEM technique, Hair et al. (2017) start from the premise of the research objective. If the key objective is the prediction of constructs, it is advisable to use this technique; On the other hand, if the objective is to prove or confirm a theory, it is best to make use of the CB-SEM. The PLS-SEM presents less restrictive requirements in the measurement of scales of sample size and in the distribution of data. It is an approach that nowadays has acquired great acceptance, mainly in the market studies and, in general, in the social sciences.

It should be noted that the PLS technique can be used for both explanatory (confirmatory) and predictive (exploratory) research (Henseler, Hubona y Ray, 2016; Hair *et al.*, 2017).

According to Shmueli and Koppius (2011), an explanatory model is a model constructed with the purpose of checking the causal hypotheses that specify how and why a certain empirical phenomenon occurs. A predictive model refers to the construction and valuation of a model that aims to predict new or future observations or scenarios. The predictive power of a model refers to its capacity to generate accurate predictions of new observations, whether in cross-sectional or longitudinal studies.

Construction of a model based on theory

The SEM starts from the theoretical justification that underpins the dependency relationships. The theory can be defined as a systematic set of relationships that gives a comprehensive explanation of a phenomenon and allows the researcher to distinguish which variables predict each dependent variable. Theory is a priority objective of research. Therefore, the theoretical justification allows the researcher to recognize that the SEM is a confirmatory method, guided more by the theory than by the empirical results; thus, the researcher should examine each proposed relationship from a theoretical perspective to ensure that the results are conceptually valid (Hair, Anderson, Tatham and Black, 2007). Therefore, the SEM can be used to test the theoretical assumptions with empirical data (Haenlein and Kaplan, 2004).

Measurement theory

The measurement theory specifies how variables (constructs) are measured; This methodology of the PLS-SEM presents two measurement approaches. One approach refers to reflective measurement and the other to formative measurement. In a practical way, a research model can contain both (reflective and formative observable variables). The inclusion of one or the other or both will depend on the construct to be measured and the objective of the investigation.

Likewise, the PLS-SEM, like the covariance approach, has several indices that will allow measuring the relevance and validity of the model.

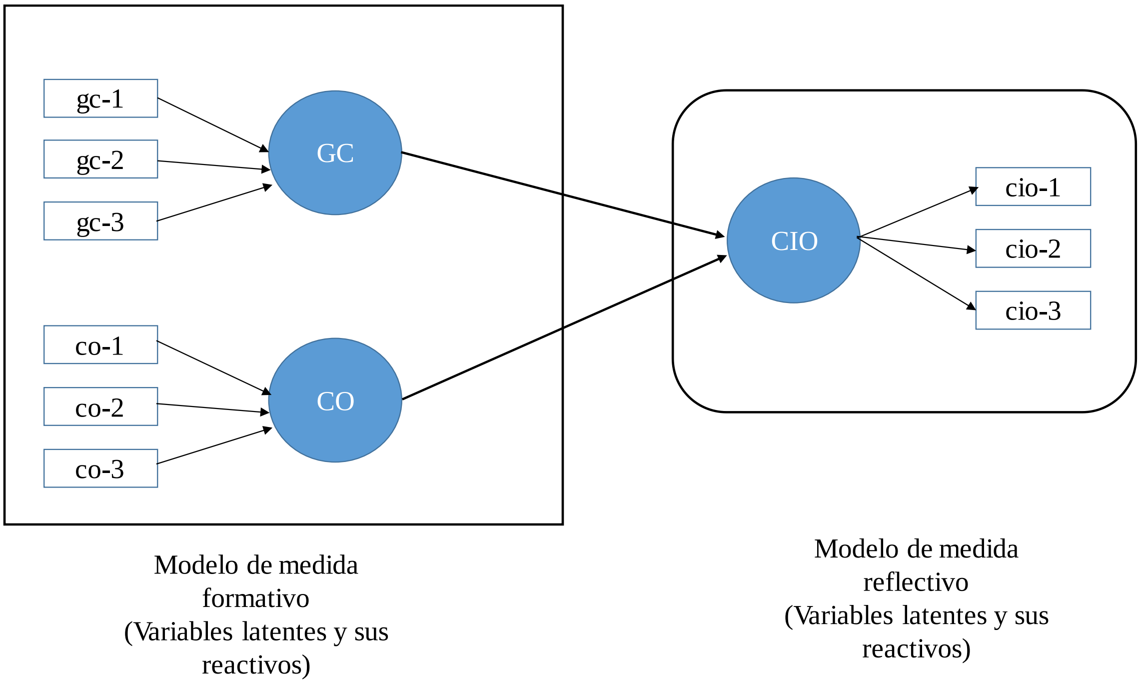
Formative measures versus reflective measures

The formative measures are latent constructs composed of measurement indicators, in which these are the cause or antecedent of the construct (Diamantopoulos and Winklhofer, 2001, Valdivieso, 2013). In the training model, each indicator represents a dimension of the meaning of the latent variable; Eliminating an indicator means that the variable loses part of its meaning, hence the importance of the indicators causing the construct.

Regarding the reflective model, it is considered as a measurement model where the indicators of the latent variable are competitive with each other and represent manifestations of the latent variable. The causal relationship goes from the latent variable to the indicators and a change in that will be reflected in all its indicators. The difference between the two measurement approaches lies in the causal priority between the latent variable and its indicators (Bollen, 1989).

Figure 1 shows the difference between the training measures and the reflective measures. You can talk about a reflective model when the latent variable is the cause of the observed measurements (Simoteo, 2012).

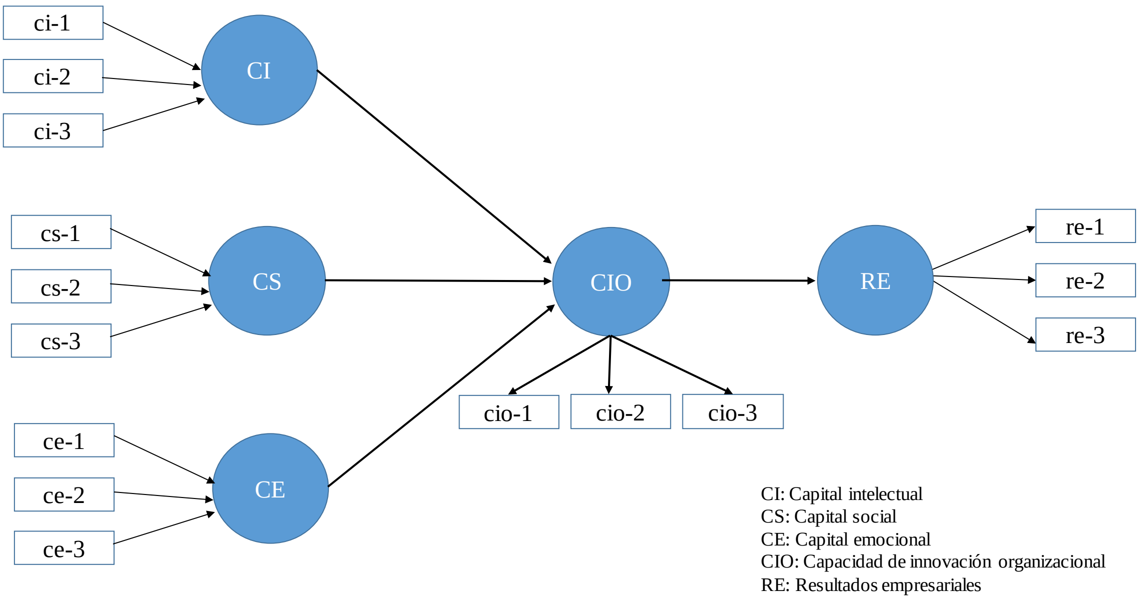
Figura 1. Medidas formativas versus medidas reflectivas.



Fuente: Elaboración propia.

In practice, when you create a trajectory model, like the one shown in Figure 2, you also see that the model contains two elements. The first, a structural model that represents the constructs (ellipses), whose purpose is to display the relationships between them. The second, the measurement model, which shows the relationships between constructs and indicators (rectangles). That is, the constructs (latent variables) are represented by ellipses and indicators (observable variables) by rectangles. The constructs and arrows between them refer to the internal or structural model, and the rectangles and dates that cause the indicator or construct are the measurement model. It is observed that the latent variables, in this case denominated CI, CS and CE, are represented for their measurement in a formative way, while the latent variables CIO and RE are represented for their measurement in a reflective way.

Figura 2. Modelo de investigación.



Fuente: Elaboración propia

Characteristics of PLS-SEM

The PLS-SEM is a multivariate analysis technique whose purpose is to test structural models; Although it was developed for several decades, it is considered an emerging technique. This methodology has as main objective the causal-predictive analysis in which the problems analyzed are complex and the theoretical knowledge may be scarce (Lévy and Varela, 2006).

Hair et al. (2017) argue that the PLS-SEM has several advantages compared to other SEM techniques. Being a more flexible technique, it has the following characteristics: 1) this technique can use small sample sizes, although if it is larger, the accuracy increases, and it is not necessary to assume a normal distribution of the data (since the PLS-SEM a non-parametric method, the scale of average recommended is the ordinal measured in Likert scale[1]); 2) the number of items of each construct measured can be only one or it can be made up of more than one and in the relationships between

[1] Una adecuada escala Likert presentará simetría y será equidistante. La simetría Likert indica que deberá de existir un punto medio (ni de acuerdo ni en desacuerdo) en la escala, definido lingüísticamente, cuya finalidad será calificar a la categoría; y equidistante se refiere a que entre las categorías existe la misma distancia, por lo que también puede considerarse como una escala de intervalo (Hair *et al.*, 2017).

constructs and their indicators, reflective and formative measurement methods can be incorporated; 3) the PLS-SEM aims to maximize the amount of variance explained (maximizes the coefficient of determination [R2]); 4) in the evaluation of the global model (estimation of the measurement model) goodness-of-fit criteria are not established, but reflective and formative measures are evaluated separately; 5) the structural evaluation of the model analyzes the R2, the predictive relevance (Q2), the size and significance of the standardized regression coefficients or path coefficients and the sizes of the effects (f2 and q2), and 6) the basic algorithm of the PLS follows a two-step approach, the first one refers to the iterative estimation of the scores of the latent variables, and the second step refers to the final estimation of the weights, loads and path coefficients by means of the estimation of Ordinary least squares (multiple and simple) and in the analysis of main components (Henseler, Ringle and Sarstedt, 2015).

In general, the PLS-SEM is a nonparametric statistical method. Although it does not require that the data present a normal distribution, it is required to verify that the data are not excessively non-normal, since, in general, this type of data is problematic in the evaluation of the significance of the parameters. It is important to specify that the values of asymmetry and kurtosis[2] greater than one are indicative of highly non-normal values.

One of the characteristics of the PLS-SEM is, precisely, the small sample sizes; however, Marcoulides and Saunders (2006) suggest that the minimum sample size depends on the number of relationships that are specified in the model (among the latent variables). Under this perspective, the suggested sample size for this type of studies is shown in Table 2.

[2] La asimetría valora el grado con el que la distribución de una variable es simétrica; la curtosis mide qué tanto la curva o distribución se encuentra achatada o escarpada.

Tabla 2. Tamaño de muestra sugerido.

Número mínimo de observaciones de la muestra	Número de relaciones en el modelo estructural
52	2
59	3
65	4
70	5
75	6
80	7
84	8
88	9
91	10

Fuente: Marcoulides y Saunders (2006)

Previously, in figure 2, we could observe a model with five latent variables and with four relationships between the latent variables (Intellectual Capital, Social Capital, Affective Capital, Capacity for Organizational Innovation and Business Results); therefore, according to the criteria of Marcoulides and Saunders (Ibid.), the minimum recommended sample size would be 65 observations.

From the point of view of Kwong and Wong (2013), the PLS-SEM is known for its ability to handle small sample sizes; this does not mean that the objective is to meet the minimum sample size requirement. Hoyle (1995) recommends a sample size of 100 to 200 to potentiate the results of the model, since at least 100 observations may be sufficient to reach acceptable levels of statistical power, given a certain quality in the measurement model (Reinartz, Haenlein and Henseler, 2009). Therefore, it is suggested to stick to the minimum sample size of 100, following Hoyle and in order to give robustness to the results (Felipe, Roldan and Leal, 2017, Hernández, 2017, Barba and Atienza, 2017, Hernández et al., 2016).

This methodology estimates the measures of the measurement model and the structural model in the same process. Anderson and Gerbing (1988) suggest that the results be interpreted in two ways: first, evaluating the scales of measures or measurement models (reflective and formative) and, second, evaluating the structural model. This distinction is important because the validation procedures are different (Dimantopoulus, Riefler y Roth, 2008; Kwong y Wong, 2013; Hair *et al.*, 2017).

Systematic process to use the PLS-SEM

Hair *et al.* (2017) They established a methodology consisting of nine stages to make use of the PLS-SEM: 1) specification of the structural model, 2) specification of the measurement model, 3) data collection and examination, 4) estimation of the model, 5) evaluation of formative measures, 6) evaluation of reflective measures, 7) evaluation of the structural model, 8) advanced analysis and 9) interpretation of results.

Based on the foregoing, in the initial stage of a research project (specifically, this research has used the statistical software SmartPLS), it is necessary to first present a diagram that connects the variables (constructs) based on the theory, that is, that shows the logic of the relationship of the hypotheses to be tested. The model is composed of two elements: 1) the structural model (also called internal model in the PLS-SEM) that describes the relationships between the latent variables, and 2) the measurement model, which shows the relationships between the latent variables and its measures (its indicators). The sequence of the constructs in the structural model based on the theory or logic are observed from left to right. The independent constructs (predictors) on the left and the dependent variables (result) on the right side. Therefore, theory and logic should always determine the sequence of the constructs in the conceptual model.

When the structural model is developed, two main aspects are observed: the sequence of the constructs and the relationship between them, which represent the hypotheses and their relationships according to the theory that is being tested. In addition to observing the latent and observable variables, it is also important to mention two aspects that may be immersed in the model in the constructs: mediation and moderation.

Regarding the systematic evaluation of the results of the PLS-SEM, Table 3 shows the statistical tests used both for the evaluation of reflective and formative measurement models and in the overall evaluation of the structural model. It should be considered that each of them has its own restrictions for validity.

Tabla 3. Evaluación de PLS-SEM (pruebas estadísticas).

Evaluación de los modelos de medida	
Modelo de medida reflectivo	**Modelo de medida formativo**
1. Consistencia interna (alfa de *Cronbach*, confiabilidad compuesta). 2. Validez convergente (fiabilidad del indicador y la varianza media extraída [AVE, por sus siglas en inglés]). $\rho_c = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum_i var(\varepsilon_i)}$ $AVE = \frac{\sum_{i=1}^{i} \lambda_i^2}{\sum_{i=1}^{i} \lambda_i^2 + \sum_{i=1}^{i} var(\varepsilon_i)}$ 3. Validez Discriminante	1. Validez convergente 2. Colinealidad entre indicadores 3. Significancia y relevancia de los pesos.
Evaluación del modelo estructural	
1. Coeficientes de determinación (R^2) 2. Relevancia predictiva (Q^2) 3. Tamaño y significancia de los coeficientes *path* 4. Tamaños de efectos (f^2) 5. Tamaños de efectos (q^2)	

Fuente: Hair, et al (2017)

The PLS methodology considers the same statistical tests of the measurement models and the structural model (Hair et al., 2017). However, it is recommended that the results be interpreted in two stages; in the first, the feasibility assessment and the validity of the measurement model must be analyzed; and in the second, the evaluation of the structural model (Ibid, Hulland, 1999, Anderson and Gerbing, 1988). With respect to the evaluation of the measurement model, formative and reflective measures are evaluated separately. It is important to consider these aspects since the validation procedures of models and formative and reflective measures are different.

In general, the systematic process for the application of PLS must be carried out through two evaluation processes: the pre-evaluation and the evaluation of the PLS models.

In the pre-evaluation stage, the following should be considered: 1) the specification of the structural model, that is, the design of the diagram that illustrates the hypotheses of the investigation and, therefore, evidences the relationships among the variables to be examined; 2) the specification of the measurement models, which is defined by the common factor model and the composite model (reflective and formative); 3) the data collection and analysis of these, and 4) the estimation of the PLS model.

While in the evaluation stage of the PLS models one should consider: 1) the valuation of the global model; 2) the assessment of the measurement model (in this assessment, the evaluation of reflective models and the evaluation of training measurement models must be carried out), and 3) the assessment of the structural model.

PLS-SEM software

Table 4 shows the software used for the development of this technique, based on the proposal of Roldán and Cepeda (2016, p. 61).

Tabla 4. *Software* PLS-SEM.

Software	Desarrollador	Sitio de la web
ADANCO	Composite Modeling	http://www.composite-modeling.com
LVPLS 1.8	Jan-Bernd Lohmöller	http://kiptron.psyc.virginia.edu/disclaimer.html)
matrixpls	Mikko Rönkkö	https://cran.r-project.org/web/packages/matrixpls/matrixpls.pdf
PLS-Graph	Wynne Chin	http://www.plsgraph.com/
plspm	G. Sánchez; L. Trinchera; G. Russolillo	http://cran.r-project.org/web/packages/plspm/plspm.pdf
PLS-GUI	Geoff Hubona	http://pls-gui.com
semPLS	Armin Monecke	http://cran.r-project.org/web/packages/semPLS/index.html
SmartPLS 3.2	SmartPLS GmbH	http://www.smartpls.com/
VisualPLS	Jen-Ruei Fu	http://fs.mis.kuas.edu.tw/~fred/vpls/index.html
WarpPLS 5.0	Ned Kock	http://www.scriptwarp.com/warppls/
XLSTAT-PLSPM	XLSTAT	http://www.xlstat.com/en/products/xlstat-plspm/

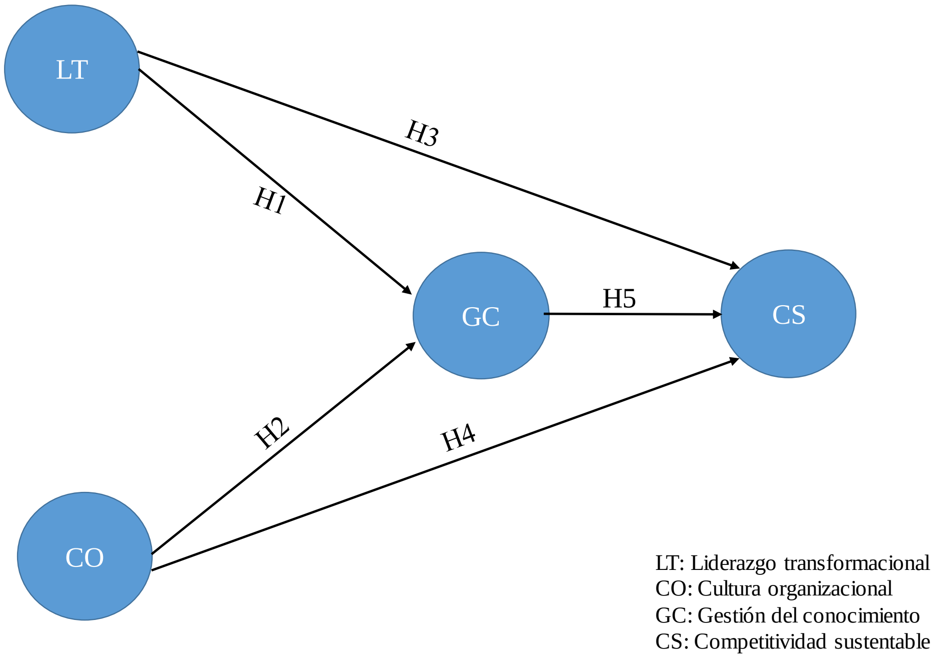
Fuente: Roldan y Cepeda (2016, p. 61).

Application of the PLS-SEM methodology: a practical case

In order to exemplify the PLS-SEM methodology, fictitious information was used.

As a first step, we present a theoretical model that emerges from the literature review; in this case, we assume that figure 3 has that theoretical pillar to propose the model to be tested. As it is observed, it has four constructs or variables (LT, CO, GC and CS), where five hypotheses were established.

Figura 3. Modelo teórico.



Fuente: Elaboración propia

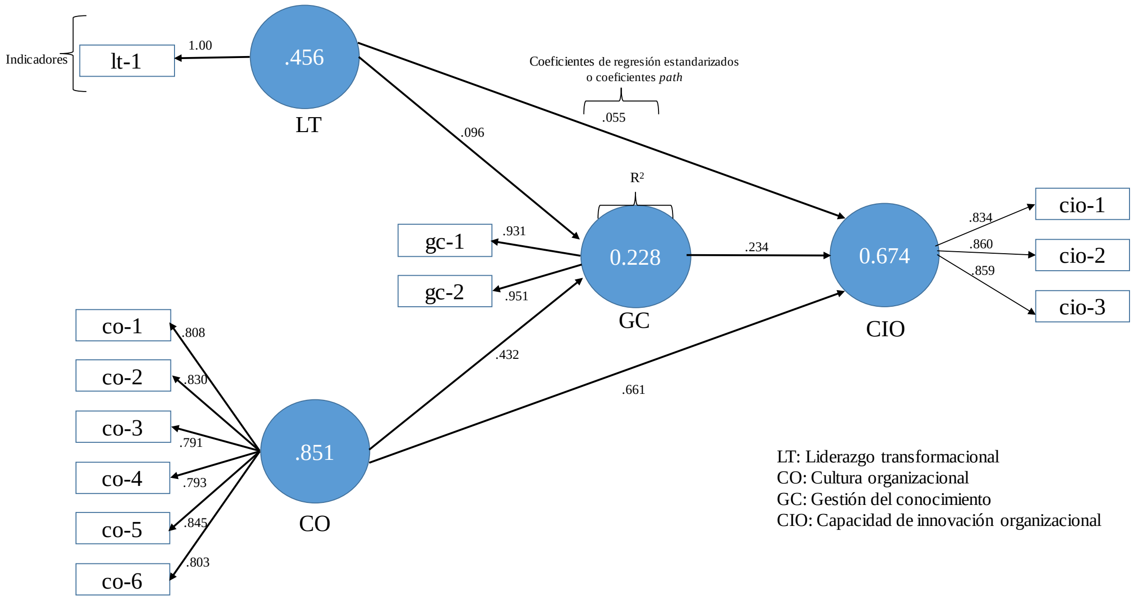
As a second step, it is necessary to generate the observed variables (items or indicators); it is important to consider that they must be formulated with a theoretical support of the latent constructs or variables. In this case, we chose to measure the latent constructs with reflective indicators (Figure 4). The transformational leadership (LT) with one, the organizational culture (CO) with six, the knowledge management (CG) with two and the organizational innovation capacity with three; giving in total 12 reagents in the measuring instrument.

As a third step, it is necessary to generate a database in Excel and export it to SmartPLS, which was elaborated with the information reported by the measurement instrument; in the columns the items or indicators are coded and in the rows the observations. It should be noted that the database must be saved with a CSV extension (limited by commas).

To start the process in SmartPLS, the research model is plotted (based on the theoretical model to be tested) with the latent variable icon and the variables are connected with the date of the connector so that, later, the indicators of each construct are identified or variable. By default, all indicators have a reflective direction; in this case, the software allows the change of address by right clicking on the construct and selecting change between reflective / formative.

As a fourth step, in the main menu of SmartPLS, the PLS algorithm is calculated (model estimation), whose results are shown in figure 4. In this model, the factorial loads of each indicator, the standardized regression coefficients or coefficients are appraised. path and the R2. It should be noted that the keys shown in figure 4 are merely indicative of the following concepts: indicators, standardized regression coefficients or path and R^2.

Figura 4. Estimación del modelo *path.*



Fuente. Elaboración propia

As a fifth step, the research model is evaluated, which requires the evaluation of the reflective measurement model and the formative measurement model.

The evaluation of the reflective measurement model is carried out through: 1) internal consistency (Cronbach's alpha and composite reliability); 2) the convergent validity (reliability of the indicator and the average variance extracted [AVE, for its acronym in English]), 3) the discriminant validity (Fornell-Larcker criterion) and cross-charges between indicators and latent variables and the heterotrait- ratio monotrail (HTMT).

The internal consistency indicates the reliability of the construct. The SmartPLS software provides the composite reliability index (IFC) and the Cronbach alpha. Compound reliability is more appropriate than Cronbach's alpha for PLS, not assuming that all indicators receive the same weighting (Chin, 1998). Nunnally and Bernstein (1994) suggest validating these indicators with a value of at least 0.7, considered as a "modest" level mainly for exploratory research, and values of 0.8 or 0.9 for more advanced stages of research.

Convergent validity indicates that a set of indicators, items or reagents represent a single underlying construct (Henseler, Ringle and Sinkovics, 2009); which is validated with the AVE, which measures that the variance of the construct can be explained through the chosen indicators (Fornell and Larcker, 1981). The AVE must be greater than or equal to 0.50 and provide the amount of variance that a construct obtains from its indicators in relation to the amount of variance due to the measurement error; this means that each construct or variable explains at least 50% of the variance of the indicators.

The reliability of the construct or latent variable allows observing the consistency of its indicators; that is, the simple correlations of the measures or indicators with their respective construct and valued by examining the loads or factorial weights (λ).

Carmines and Zeller (1979) consider factor loads greater than 0.707 adequate; therefore, it is suggested that indicators with loads lower than this range should be eliminated (Hair, Ringle and Sarstedt, 2011). When an indicator has a lower load than indicated, it can be eliminated and the model can be run again to estimate the results (Urbach and Ahlemann, 2010). Table 5 shows fictitious values whose purpose is that the reader can observe the internal consistency, the convergent validity and the reliability of the indicator.

Tabla 5. Fiabilidad del indicador y fiabilidad compuesta.

Variable Latente	Ítem o indicador	Cargas factoriales ➢ 0.70	Validez convergente: Fiabilidad del indicador ➢ 0.50	Validez convergente: AVE > 0.50	Consistencia interna: Fiabilidad compuesta 0.70-0.90	Consistencia interna: Alfa de *Cronbach* 0.70-0.90
LT	lt1	1.00	1.00	1.00	1.00	1.00
CO	co1	0.81	0.65	0.72	0.92	0.90
	co2	0.83	0.68			
	co3	0.79	0.62			
	co4	0.79	0.62			
	co5	0.84	0.70			
	co6	0.80	064			
GC	gc1	0.93	0.86	0.89	0.94	0.87
	gc2	0.95	0.90			
IO	io1	0.83	0.70	0.72	0.89	0.81
	io2	0.86	0.73			
	i03	0.85	0.73			

Fuente: Elaboración propia a partir de Hair *et al.* (2017)

On the other hand, discriminant validity indicates to what extent a given construct is different from other constructs. To assess the discriminant validity it is necessary to evaluate three criteria: 1) Fornell-Larcker criterion, 2) cross-charges between indicators and latent variables and 3) the HTMT matrix.

The Fornell-Larcker criterion considers the amount of variance that a construct captures from its indicators (AVE), which must be greater than the variance that the construct shares with other constructs. Thus, the square root of the AVE of each latent variable must be greater than the correlations it has with the rest of the variables; therefore, to achieve discriminant validity, the square root of the AVE of a construct must be greater than the correlation it has with any other construct, as shown in table 6.

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Tabla 6. Validez discriminante (criterio de Fornell-Larcker).

Constructos latentes	CO	GC	CIO	LT
CO	(0.81)			
GC	0.47	(0.94)		
IO	0.79	0.56	(0.85)	
LT	0.38	0.26	0.37	(1.00)

Fuente: elaboración propia

Nota**:** La raíz cuadrada del valor del AVE es mostrada en la diagonal entre paréntesis, los demás datos son correlaciones de las variables latentes.

On the other hand, it is necessary to compare the cross-factorial loads of the indicators of a latent variable with the loads of the indicators of the other latent variables (Table 7). Factor loads must have greater value with their own variable than with the others that are evaluated in the model (Barclay, Higgins y Thompson, 1995).

Tabla 7. Cargas factoriales cruzadas.

Constructo / Ítems	CO	GC	CIO	LT
co1	0.81	0.44	0.70	
co2	0.83	0.39	0.66	
co3	0.79	0.29	0.63	
co4	0.79	0.35	0.49	
co5	0.84	0.32	0.60	
co6	0.80	0.46	0.72	
gc1	0.39	0.93	0.48	
cg2	0.48	0.95	0.56	
io1	0.68	0.42	0.83	
io2	0.66	0.44	0.86	
io3	0.68	0.55	0.86	
lt1	0.38	0.26	0.37	1.00

Fuente: Elaboración propia.

In addition, Henseler, Ringle and Sartedt (2016), when performing simulation studies, showed that the lack of validity is detected in a better way by means of the HTMT ratio. If the monotrait-heteromethod correlations (correlations between the indicators that measure the same construct) are greater than the heterotrait-heteromethod correlations (correlations between the indicators that measure different constructs) there will be discriminant validity. Thus, the HTMT ratio must be below one (Gold, Malhotra and Segars [2001] consider a value of 0.90). In this sense, a resampling or bootstrapping can also be used to test whether the HTMT ratio is significantly different from one by the confidence interval. According to the established criteria, the confidence intervals for the HTMT must be less than one, which allows validating this criterion (see Table 8).

Tabla 8. La ratio HTMT con SmartPLS algoritmo.

Constructo	CO	GC
CO		0.74
GC	0.63	

Fuente: Elaboración propia

As a sixth step, the formative measurement model is evaluated. The example model only included reflective items. However, it is important to mention that when a research model has a combination of reflective and formative constructs it is necessary to evaluate the different models separately. It is considered functional to mention the statistics and criteria that are used to evaluate formative measurement models.

Although Diamantopoulos and Winkholfer (2001) argue that the traditional evaluation of reliability and validity in the measurement models is not applicable, because the validity must be carried out based on the exhaustive review of the theory and with the opinion of experts, combined because the formative measures do not have to be correlated and are free of error (Bagozzi, 1994), it is important to comment that Chin (2010) proposes that the evaluation of the formative measures models should be carried out in two levels: 1) a level of indicator (multicollinearity and assessment of the factorial loads of the indicators and their significance) and 2) at the construct level (external validity, nomological validity and discriminant validity). Currently, Hair et al. (Op. Cit.) Consider that the evaluations of formative measurement models include three aspects: 1) convergent validity, 2) evaluation of collinearity problems and 3) evaluation of the significance and relevance of the indicators.

The convergent validity of formative measurement models is evaluated by determining to what degree a measure correlates positively with another reflective measure of the same construct. That is, a formative construct is created as a predictor variable (exogenous variable) with a latent endogenous variable with one or more reflective indicators. In order to evaluate this type of validity, it is necessary that in the measurement instrument an item or reagent has been defined that encompasses all the measurements of the construct (this is called the global item). The purpose of this global item is to contain the essence of the latent formative variable so that it occupies the place of an exogenous variable. With this information, a new model is constructed for each training construct and the PLS algorithm is executed. It should be specified that the path coefficient between the variables must have a minimum recommended value of 0.70 (Ibid.).

To evaluate the level of colinearity there are various statistical tests. The most usual is the inflation factor of variance (IVF), whose value ideally must be greater than five (Ibid.). Another statistic is tolerance, which represents the amount of variance of a formative indicator not explained by the other indicator in the same block, both statistics carry the same information. In the context of the PLS-SEM, a tolerance value below 0.20 and a VIF above five of the predictor constructs imply critical levels of collinearity. On the other hand, Belsley (1991) proposes to use jointly the condition index (CI) and the proportion of decomposition of variance, made through an advanced diagnosis of collinearity within a multiple regression analysis that can be calculated by means of software SPSS. If a variable has a CI greater than 30 and two or more variables have a high variance proportion greater than 0.5, then they are considered collinear. On the other hand, Diamantopoulos and Siguaw (2006) consider that high multicollinearity exists when the VIF is greater than 3.3.

For the valuation of the factorial weights of the indicators and their significance, a resampling or bootstraping process must be executed, where if the indicators have a significance greater than 0.05, they must be eliminated. However, when eliminating a formative indicator, it is necessary to verify that the meaning of the construct is not lost. Thus, Roberts and Thatcher (2009) recommend including the indicator in the model. In this same sense, Hair et al. (Op. Cit.) Suggest a flexible posture if the factorial weights are greater than 0.05 so as not to lose the meaning of the construct being measured.

As a seventh step, considering that the reflective model has contained validity and reliability, we proceed to evaluate the structural model, where five aspects are considered: 1) evaluation of collinearity; 2) evaluation of the algebraic sign, magnitude and statistical significance of the path coefficients; 3) assessment of R2; 4) evaluation of the sizes of the effects (f2), and 5) assessment of the Q2 and the sizes of the effects (q2) (Ibid.).

Regarding the evaluation of collinearity, Hair et al. (Ibid.) Consider indications of multicollinearity when the IVF is greater than five and the tolerance level is below 0.20. With the fictitious data, SmartPLS reported that the IVF values are between 1.17 to 1.41. However, for the results to be strengthened, a diagnosis of collinearity was made through SPSS in the linear regression section. First verified with the dependent variable IO and the other variables served as independent, later another process was executed in which the variable GC was placed as a dependent variable and the variables LT and CO as independent or predictors. The results of the IVF when evaluating the variables of this study were found below the ideal value, that is, 1.49, 1.56 and 1.80, respectively; however, tolerance values were adequate with values above 0.20.

For the evaluation of the algebraic sign, magnitude and statistical significance of the standardized regression coefficients (path coefficients), it is important to comment that these (standardized regression coefficients) show the relationships of the hypothesis of the research model. First, we must analyze the algebraic sign that was postulated in the hypothesis: if this is contrary to that established in the hypothesis, it will not be supported. Second, the magnitude and statistical significance are analyzed. The magnitude of the path coefficients are observed as standardized values in a range +1 to -1; The higher the value, the greater the relation (prediction) between constructs and the closer to 0, the lower the convergence to the construct. If the result of a path value is contrary to the sign postulated in the hypothesis, it indicates that the hypothesis will not be supported. The level of significance is determined from the Student t value derived from the re-sampling or bootstrapping process, which is a non-parametric technique (there are no initial parameters, it is tested if the paths between variables are feasible), which evaluates the precision of the PLS estimates. When in a model the hypotheses indicate the relation of the direction (+ or -), it is necessary to use a distribution t of a tail with n-degrees of freedom, where n is number of sub samples (bootstraping = 5000 sub samples; 0.05, 4999 = 1645, t = 0.01, 4999 = 2327, t = 0.001, 4999 = 3092); for two-tailed distributions with n-1 (t = 0.1, 4999 = 1645, t = 0.05, 4999 = 1960, t = 0.01, 4999 = 2577, t = 0.001, 4999 = 3292). Therefore, if the empirical value of t is greater than the critical value of t, then the coefficient is significantly different from zero; that is, if the empirical result of t is below a certain threshold value, it means that it is not possible to have confidence in the distribution and thus the hypotheses are not verified.

As can be seen in Table 9, the relationship between the constructs CO → IO is strong (0.743), the relationship between the constructs CO → GC is moderate (0.460) and the relationship between LT → GC is weak (0.149), while that the relationship between the LT → IO constructs is not significant.

Tabla 9. Coeficientes *path* (coeficientes de regresión estandarizados).

Relaciones hipotéticas	**Coeficientes *path* (Estandarizados β)**	**Estadístico t *Student* (Boostrapping)**	**Valor P**
LT → GC	0.149	2.045	0.000
CO → GC	0.460	5.615	0.000
LT → IO	0.072	0.679	0.060
CO → IO	0.743	11.023	0.000

Fuente: Elaboración propia

It should be considered that the PLS-SEM technique, when used to maximize the predictive capacity of dependent variables, requires the evaluation of R2, which represents a measure of predictive value. This indicates the amount of variance of a construct that is explained by the predictor variables of the endogenous construct, whose values oscillate between zero and one. The higher the value of R2, the more predictive it is presented. Falk and Miller (1992) consider that an R2 must have a minimum value of 0.10; Chin (1998) considers 0.67, 0.33 and 0.10 (substantial, moderate and weak); while Hair et al. (2017) recommend 0.75, 0.50, 0.25 (substantial, moderate and weak). In the model under study (Figure 4) an R2 was obtained = 0.674 (substantial value) and R2 = 0.228 (moderate value); which implies that organizational culture and transformational leadership, through its effect on knowledge management, explain 67.4% of organizational innovation capacity and 22.8% of knowledge management is explained by transformational leadership and culture. organizational In this model should also be considered the probable case of mediation of knowledge management between transformational leadership and organizational culture with organizational innovation capacity.

In addition to evaluating the R2 value of all endogenous constructs, it is necessary to know the change in R2 when a certain exogenous construct is omitted from the model; that is, f2 can be used to evaluate whether the omitted construct has a substantive impact on endogenous constructs. For this, Cohen (1998) specifies the following values to evaluate the f2: 0.02 is a small effect, 0.15 is an average effect, and 0.35 is a large effect. As can be seen in table 10, the organizational culture has a large effect with the capacity for organizational innovation and knowledge management; However, transformational leadership has almost no effect on organizational culture and knowledge management.

Tabla 10. Tamaños de efectos f^2.

	Constructos endógenos			
	Capacidad de innovación organizacional (CIO)		Gestión del conocimiento (GC)	
Constructos Exógenos	Coeficientes *Path*	Efectos (f^2)	Coeficientes *Path*	Efectos (f^2)
Liderazgo transformacional (LT)	0.055	0.01	Liderazgo transformacional (LT)	0.01
Cultura organizacional (CO)	0.661	0.95	Cultura organizacional (CO)	0.35
Gestión del conocimiento (GC)	0.234	0.13		Sin valor

Fuente: Elaboración propia.

In addition to R^2 as a predictive criterion, Hair et al. (2017) recommend that researchers examine Q^2 to assess the predictive relevance of the structural model. Chin (1998) mentions that the predictive relevance of constructs must be positive and with values greater than zero; so also Hair et al. (Op. Cit.) Establish values of 0.02 as small values, values of 0.15 as mean values and values 0.35 as large values to consider predictive validity of the model.

Geisser (1974) and Stone (1974) recommend evaluating the Stone-Geisser test as a criterion for Q^2. To determine this in SmartPLS it is necessary to generate the blindfolding procedure. The endogenous constructs of the fictitious case had a strong and medium prediction, because Q^2 had a value of 0.46 for IO and Q^2 had a value of 0. 15 for GC.

The size of the q^2 effect allows to evaluate how an exogenous construct contributes to an endogenous latent construct Q2 as a measure of predictive relevance; which can be small (0.02), medium (0.15) or large (0.35). It is observed that the values are the same as the f^2 (Cohen, 1998); and its calculation derives from the expression q^2 = (Q^2included and Q^2excluded) / (1 - Q^2included). This calculation is done manually because the SmartPLS software does not provide it (Hair et al., 2017). In a very similar way (Table 11), the greater effect q^2 in the construct of the organizational culture with capacity for organizational innovation had a value of 0.661 and the organizational culture with the knowledge management had a value of 0.15 (small effect).

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Tabla 11. Tamaños de efectos q^2.

	Constructos endógenos			
	Capacidad de Innovación organizacional (CIO)		Gestión del conocimiento (GC)	
Constructos Exógenos	Coeficientes *Path*	Efectos (q^2)	Coeficientes *Path*	Efectos (f^2)
Liderazgo transformacional (LT)	0.055	0.01	Liderazgo transformacional (LT)	0.00
Cultura organizacional (CO)	0.661	0.23	Cultura organizacional (CO)	0.15
Gestión del conocimiento (GC)	0.234	0.05		Sin valor

Fuente: Elaboración propia

Henser, Hubona and Ray (2016) consider that the results of the PLS model can be evaluated globally (general model) and locally (measurement models and structural model). At present, the only adjustment criterion of the global model is the normalization of residual mean square root (SRMR) (Hu and Bentler, 1998, 1999). It is considered a model with an adequate adjustment when the values are less than 0.08. Therefore, a value of 0 for SRMR would indicate a perfect fit and, in general, an SRMR value less than 0.05 indicates an acceptable fit (Byrne, 2008). A recent simulation study shows that a correct specified model implies SRMR values greater than 0.06 (Henseler et al., 2017).

Recently, Albort-Morant, Henseler, Cepeda-Carrión and Leal-Rodríguez (2018, p.1) consider that in the PLS-SEM technique, the evaluation of the adjustment of the global model must first be done by means of: "(i) the standardized root mean residual squared (SRMR); (ii) the unweighted least squares discrepancy (dULS); and (iii) the geodesic discrepancy (fG) ". Subsequently, perform the evaluation of the measurement model, and the structural model.

Conclusions

The purpose of this scientific article was to show how to use the PLS-SEM methodology with the use of SmartPLS software through fictitious data that allowed to evaluate a research model (media model, structural model and global evaluation of the model); in this case, everything started from the proposal of the theoretical model to be contrasted that contained five hypotheses.

The results of the measurement model showed the necessary information to evaluate the validity of a reflective model through the internal consistency (Cronbach's alpha and composite reliability), the convergent validity (reliability of the indicator and the AVE), the discriminant validity (Fornell-Larcker criterion, and cross-loading), and the Heterotrait-Monotrail ratio (HTMT) according to established parameters (Carmin and Zeller, 1979, Fornell and Larcker, 1981, Chin, 1998, Nunnally and Bernstein, 1994 Herseler, Ringle and Sinkovics, 2009, Hair, Ringle and Sarsted, 2011, Urban and Ahlemann, 2010, Barclay, Higgins and Thompson, 1995, Henseler, Ringle and Sartedt, 2016, Gold, Malhotra and Segars, 2001). As regards the training model, indicators of that type were not included. However, it was considered important to mention the statistics that are necessary in their evaluation and the criteria established for the validation (Bagozzi, 1994, Diamantopoulos and Winkholfer, 2001, Chin, 2010, Hair, Hult, Ringle and Sarstedt, 2017; Hair, Sarstedt , Ringle and Mena 2012, Belsley, 1991, Roberts and Thatcher, 2009, Hair, Hult, Ringle and Sarstedt, 2017).

Regarding the evaluation of the structural model, Hair et al. (2017) recommend validating the model by checking the coefficients of collinearity, the evaluation of the algebraic sign, magnitude and statistical significance of the path coefficients, the assessment of R2, the evaluation of Q2 and the effect sizes f2 and q2, which were considered to exemplify the validation of the structural model. Likewise, the analysis of the values R2 and Q2 was made as predictive criteria of the PLS-SEM model and methodology; the values proposed for the evaluation of the structural model were commented (Hair et al., 2017, Falk Miller, 1992, Chin, 1998, Geisser, 1974, Stone, 1974, Cohen, 1998). In the same way, for the overall evaluation of the model the SRMR was commented, considered as an adjustment indicator of the most recent PLS-SEM model (Hu & Bentler, 1998, Henseler, Hubona & Ray 2016, Byrne, 2008).

It is concluded that the statistical technique PLS-SEM is a technique that has gained great interest among researchers of the social sciences for being an alternative approach to the modeling of structural equations. There are several publications in first quartile journals (top journals) that validate their use. Therefore, the scientific community is encouraged to use this statistical technique.

Bibliography

Albort-Morant, G. Henseler,J., Cepeda-Carrión, G. y Leal-Rodríguez, A.L. (2018). Potential and Realized Absorptive Capacity as Complementary Drivers of Green Product and Process Innovation Performance, sustainability, 10, 381, 1-20.

Albort-Mont, G., Leal-Rodriguez, A.L. y Cepeda-Carrión, G. (2016). The antecedents of green innovation performance: A model of learning and capabilities. *Journal of Business Research*, *69*(11), 4912-4917.

Anderson, J. y Gerbing, D. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411-423.

Bagozzi, R. (1994). Structural equation models in marketing research: Basic principles. En R. Bagozzi (Ed), *Principles of marketing research* (pp. 317-385). Oxford, Reino Unido: Blackwell.

Barba, V. y Stienza, C. (2017). Environmental Proactivity and Environmental and Economic Performance: Evidence form the Winery Sector. *Sustainability*, *8(*10), 1-15.

Barclay, D., Higgins, C. y Thompson, R. (1995). The partial least squares (PLS) approach modelling: Personal computer adoption and use as illustration. *Technology Studies*, *2*(2), 285-309.

Belsley, D. (1991). *Conditioning diagnostics: Collinearity and weak data in regression*. Nueva York, Estados Unidos: John Wiley & Sons.

Bentler, P. y Bonett, D. (1980). Significance tests and goodness of fit in the analysid of covarianza structures. *Psychological Bulletin, 88*(3), 588-606.

Bollen, K. (1989). *Structural Equation with latent variables*. Estados Unidos, North Carolina: John Wilet & Sons.

Byrne, B. (2008). *Structural Equation Modeling with EQS: Basic Concepts, Applications, and Programming.* Nueva York, Estados Unidos: Psychology Press.

Carmines, E. y Zeller, R. (1979). *Reliability and validity assessment. N. 07-017, Sage University Paper Series on Quantitative Applications the Social Sciences.* Beverly, Estados Unidos: Sage.

Chin, W. (1998). The partial least square approach to structural equation modelling. En G. Marcoulides (Ed.), *Modern Methods for Business Research* (pp. 295-369). Mahawah, Estados Unidos: Lawrence Erlbaum.

Chin, W. (1998a). Issues and opinion on structural equation modeling. *MIS Quarterly 22*(1), 7–16.

Chin, W. (2010). How to write up and report PLS analyses. En E Vinzi, W. Chin, J. Henseler y H. Wang (Eds.), *Handbook of partial least squares: Coceots, methods and applications* (pp. 655-690). Berlín, Alemania: Springer-Verlag.

Cohen, J. (1998). *Statically power analysis for the behavioral sciences*. Estados Unidos, New York: Laurence Erlbaum Associates.

Diamantopoulos, A. y Siguaw, J. (2006). Formative versus Reflective Indicators in Organizational Measure Development: A Comparison and Empirical Illustration. *British Journal of Management*, *17*(4), 263-282.

Diamantopoulos, A. y Winklhofer, H. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of marketing research, 38*(2), 269-277.

Diamantopoulos, A., Riefler, P. y Roth, K. (2008). Advancing formative measurement models. *Journal of Business Research, 61*(12), 1203-1218.

Falk, R. y Miller, N. (1992). *A Primer for Soft Modeling*. Akron, Estados Unidos: University of Akron Press.

Felipe, C., Roldan, J. y Leal, A. (2017). Impact of Organizational Culture Values on Organizational Agility. *Sustatainability*, *9*(12), 2-23.

Fornell, C. y Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*, 39–50.

Geisser, S. (1974). A predictive approach to the random effects model. *Biometrika, 61*, 101-107.

Gefen, D. y Straub, D. (2005). A practical guide to factorial validity using PLS-graph: Tutorial and annotated example. *Communications of the Association Systems, 16*, 91-109.

Gold, A., Malhotra, A. y Segars, A. (2001). Knowledge management: an organizational capabilities perspective. *Journal of Management Information Systems, 18*(1), 185-214.

Götz, O., Liehr, K. y Krafft, M. (2010). Evaluation of structural equation models using the partial least squares (PLS) approach. En V. Esposito y W Chin (Eds.), *Handbook of partial least squares*, (pp. 691-711). Berlín, Alemania: Springer.

Green, S. (1991). How many subjects does it take to do a regression analysis? *Multivariate Behavioral Research, 26*, 499–510.

Haenlein, M. y Kaplan, A. (2004). A Beginner´s Guide to Partial Least Squares Analysis. *Understanding Statistics, 3*(4), 283-297.

Hair, J., Anderson, R., Tatham, R. y Black, W. (2007). *Análisis multivariante*. España, Madrid: Pearson.

Hair, J., Hult, G., Ringle, M. y Sarstedt, M. (2011). PLS-SEM: Indeed, a Silver Bullet. *Journal of Marketing Theory and Practice, 2*(19), 139–151.

Hair, J., Hult, G., Ringle, C. y Sarstedt, M. (2017). *A Primer on Partial Least Square Structural Equation Modeling (PLS-SEM).* Estados Unidos, California: Sage.

Hair, J., Ringle, C. y Sarstedt, M. (2011). PLS-SEM: Indeed, a silver bullet. *Journal of Marketing Theory and Practice, 19*(2), 137-149.

Hair, J., Sarstedt, M., Ringle, C. y Mena, J. (2012). PLS-SEM. An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*, 414-433.

Henseler, J., Ringle, C. y Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115-135

Henseler, J., Hubona, G. y Ray, P. (2016). Using PLS path modeling new technology research: updated guidelines. *Industrial Management & Data* Systems, *116*(1), 2-20.

Henseler, J., Ringle, C.M, y Sinkovics, R.R (2009). The use de partial least squares path modeling in international marketing. Advances in International marketing, 20, 277-320.

Henseler, J., Ringle, C. y Sarstedt, M. (2016). Testing measurement invariance of composites using partial least squares. I*nternational Marketing Review*, *33*(3), 405-431.

Hernández, F. (2017). Influencia de la responsabilidad social en el desempeño de las empresas familiares. *Journal Globalization, Competitiviness & Gobernability*, *11*(3), 58-73.

Hernández, F., Moreno-García, J., Yáñez, B. (2016). The mediating role of competitive in international entrepreneurial orientation. *Journal of Business Research*, *69*(11), 5383-5389 .

Hoyle, R. (1995). *Structural Equation Modeling.* Thousand Oaks, Estados Unidos: Sage

Hu, L. y Bentler, P. (1998). Fit indices in covariance structure modeling: sensitivity to underparameterized model misspecification. *Psychological Methods*, *3*(4), 424-453.

Hu, L. y Bentler, P. (1999). Cutoff criteria for fitindexes in covariance structure analysis: conventional criteria versus new alternative. *Structural Equation Modeling*, *6*(1), 1-55.

Hulland, J. (1999). Use of Partial Least Squares (PLS) in strategic management research: a review of four recent studies. *Strategic Management Journal*, *20*(2), 195-204.

Kwong, K. y Wong, K. (2013). Partial Least Square Structural Equation Modeling (PLS-SEM). Techniques Using SmartPLS. *Marketing Bulletin*, *24*, 1-32.

Lévy, J. y Varela, J. (2006). *Modelación con Estructuras de Covarianzas en Ciencias Sociales*. España, Madrid: Editores Netbiblo.

Marcoulides, G., Chin, W. y Saunders, C. (2009). A critical look at Modeling. *MIS Quarterly*, *1*(33), 171-175.

Marcoulides, G. y Saunders, C. (2006). PLS: A silver bullet*? Management Information Systems Quarterly*, *30*(2), 3-9.

Nunnally, J. y Bernstein, I. (1994). *Psychometric theory* (3a ed.). Nueva York, Estados Unidos: McGraw-Hill.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society*, *36*, 111-147.

Reinartz, W., Haenlein, M. y Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM, *International Journal of Research in Marketing*, *26*(4), 332-344.

Roberts, N. y Thatcher, J. (2009). Conceptualizing and testing formative constructs: Tutorial and a noted example. *The data Base for Advances in Information Systems*, *40*(3), 9-39.

Roldan, J. y Cepeda, G. (2016). Modelos de Ecuaciones basados en la Varianza: Partial Least Squares (PLS) para Investigadores en Ciencias Sociales (3a ed.). Apuntes del curso en la Universidad de Sevilla, España.

Shmueli, G. y Kopplus, O. (2011). Predictive analytics in information systems research. *MIS Quarterly*, *35*(3), 553-572.

Simoteo, A. (2012). Formative and reflective models: state of the art. *Electronic Journal of Applied Statistical Analysis*, *5*(3), 452-457

Teo, T., Srivastava, S. y Jiang, L. (2008). Trust and electronic government success: an empirical study. *Journal of Management Information Systems*, *25*(3), 99-132.

Urbach, N. y Ahlemann, F. (2010). Structural equation modeling in information systems research using partial least squares. *Journal of Information Technology Theory and Application*, *11*(2), 5-40.

Valdivieso, C. (2013). Comparación de los modelos formativo, reflexivo y de antecedentes de evaluación estudiantil del servicio de la docencia. *Revista de Métodos Cuantitativos para la Economía y la Empresa*, *16*, 95-120.

Rol de Contribución	Autor(es)
Conceptualización	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Metodología	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Software	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Validación	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Análisis Formal	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Investigación	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Recursos	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Curación de datos	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Escritura - Preparación del borrador original	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Escritura - Revisión y edición	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Visualización	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Supervisión	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Administración de Proyectos	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno
Adquisición de fondos	Igual: Dra. Minerva Martínez Ávila Dra. Eréndira Fierro Moreno