Predictive relationship of knowledge management and business innovation: A model based on PLS structural equations

Relación predictiva de la gestión del conocimiento y la innovación empresarial: Un modelo basado en ecuaciones estructurales PLS

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Abstract

In this study we describe flexible modeling using structural equations of partial least squares (PLS) based on the analysis of variance, to predict the dependency relationships of a theoretical model supported by internal and external conditions for the development of innovation capabilities that they include the endogenous variables; organizational culture, exploitation innovation, exploration and ambidestreza, innovative performance, competitiveness, University-Business collaboration and business innovation, and its relationship with the exogenous variable; knowledge management practices. In the method, three phases were applied; the consideration of the theory and previous investigations for the construction of the conceptual model, the application of the measurement model related to the attributes of validity and reliability of the constructs, the structural model that evaluates the weight and the magnitude of the relationships between variables. Out of the main results, values higher than the minimum variance value explained were obtained, which is recommended to be Falk $\geq$ 0.10 and a model adjustment value greater than 0.50, thereby inferring the existence of a positive relationship of predictive interdependence and significant variance of the variables, which favor the creation of product, service or process innovations in companies.

Structural equation modeling, Knowledge management, Business innovation

Resumen

En este estudio se describe la modelización flexible mediante ecuaciones estructurales de mínimos cuadrados parciales (PLS) basado en el análisis de la varianza, para predecir las relaciones de dependencia de un modelo teórico sustentado en condiciones internas y externa para el desarrollo de capacidades de innovación que comprenden las variables endógenas; cultura organizacional, innovación de explotación, exploración y ambidestreza, desempeño innovador, competitividad, colaboración Universidad-Empresa e innovación empresarial, y su relación con la variable exógena; prácticas de la gestión del conocimiento. En el método, se aplicaron tres fases; la consideración de la teoría e investigaciones previas para la construcción del modelo conceptual, la aplicación del modelo de medida relacionado con los atributos de validez y fiabilidad de los constructos, el modelo estructural que evalúa el peso y la magnitud de las relaciones entre variables. De los resultados principales, se obtuvieron valores superiores al valor de varianza mínimo explicado, que se recomienda que sea Falk $\geq$ 0,10 y un valor de ajuste del modelo mayor a 0,50, lo que infiere la existencia de una relación positiva de interdependencia predictiva y una varianza significativa de variables que favorecen la creación de innovaciones de productos, servicios o procesos en las empresas.

Modelación de ecuaciones estructurales, Gestión del conocimiento, Innovación empresarial

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Introduction

In recent years, the Models of Structural Equations (MEE) have become a "multivalent analysis tool widely used in the field of economics and social sciences" (Céspedes and Sánchez, 1996).

These models Fornell (1982) calls them as "second generation, since they help link data and theory", allowing to expose a scientific explanation that goes beyond association or description.

The MEEs are intended to make multiple regressions between latent variables and variables. However, not all models of structural equations are based on covariance and factor analysis.

The partial least squares (PLS) analysis technique "aims at the prediction of latent variables and is based on the estimation of ordinary least squares (OLS) and on the analysis of main components, path and regression analysis" (Cepeda y Roldan, 2007). In addition, modeling relationships between multiple predictor variables (independent, exogenous) and criteria variables (dependent or endogenous).

The PLS technique was developed by the Swedish professor Herman Wold, at first it was called NIPALS (Nonlinear Iterative Partial Least Squares in 1973). It is currently known as PLS and its basic design was completed in 1997.

The PLS technique is suitable for predictive purposes (Chin, Marcolin, and Newsted, 2003), oriented "to predictive causal analysis in highly complex situations, but with a poorly developed knowledge or applied in a new context" (exploratory nature) (Wold, 1979; Wong, 2006), so it is "used to develop a nascent theory" (Barclay, Higgins, and Thompson, 1995). Its use has been extended in the areas of knowledge oriented to the organization of companies.

In this context, PLS represents a system of mathematical and statistical data analysis that adapts to the present conditions of the economic-administrative and social sciences "proposing a flexible modeling" (Wold, 1980) "creating optimal linear predictive relationships between variables" (Cepeda and Roldan, 2007).

In this sense of least squares, this means that, "given the data and the model, independent variables become the best possible predictor variables, and dependent variables become the best criteria or predicted variables" (Falk and Miller, 1992).

Flexible modeling can be used, even if one or more of the following conditions and circumstances concur according to Falk and Miller, (1992) in Cepeda and Roldan, (2007):

Conditions that do not limit the use of PLS	
Conditions	**Elements**
Theoretical	The hypothesis is derived from a macro level theory in which not all variables are known. The relationships between theoretical constructs and their manifestations are vague. The relationship between constructs is conjectural.
Measure	Some or all of the manifest variables are categories or present different levels of measurement. The manifest variables have some degree of unreliability. The residuals of latent and manifest variables are correlated (Heterocedasticity).
From Distribution	The data comes from unknown or non-normal distributions.
Practices	It is used in non-experimental research. A large number of latent and manifest variables are modeled. They are available, either too many cases, or a small number.

Table 1 PLS conditions. Source: Falk and Miller, (1992).

For the application of the PLS technique, the exploratory and relational nature of variables should be considered. According to Chin, (1998) the analysis of structural equations responds to two phases: the measurement model and the structural model.

The "measurement model" analyzes whether the theoretical concepts are measured correctly through the observed variables.

This analysis is performed regarding the attributes of validity (it measures what you really want to measure) and reliability (it does so in a stable and consistent way).

On the other hand, the "structural model" evaluates the weight and magnitude of the relationships between variables.

The terms commonly used according to Barroso, (2007) have to do with the "graphic representation of the data, the theoretical constructs, latent or unobservable variable (circle) and the indicators, measures, manifest or observable variables (table)".

The measures for the analysis of the predictive relationship of variables were obtained through the process suggested by Anderson, Rungtusanatham, Schroeder, & Devaraj (1995): descriptive analysis, exploratory analysis (factor analysis of main components and reliability). The measurement model included theoretical modeling through hypotheses, statistical tests and the design of the model according to the recommendations of several authors (Cepeda and Roldan, (2007); Temme (2006), Chin, (1998) and Fornell, (1982), considering that:

The research hypotheses consider a positive relationship between each construct of the variables according to the bivariate analysis.

a) Indicators that were validated under content, criteria and construct are used.
b) There is no evidence of collinearity, since they have reflective-formative indicators, which must be highly correlated and with high levels of internal consistency using Cronbach's Alpha and composite reliability (Chin, 1998).

Method

Due to the nature of the hypothesis (relational) and the exploratory nature of the investigation, the use of PLS is used to perform analyzes between the constructs, which means that the analysis performed is neither causal nor confirmatory.

HE: There is a positive relationship of predictive and significant interdependence of the variances of the endogenous variables that make up the internal conditions (innovative performance, innovation of exploration, exploitation and ambidestreza and organizational culture) and external conditions (Company-University collaboration, competitiveness and indicators of business innovation) and the exogenous variable knowledge management practices in the structural model for the development of innovation capabilities (Figure 1).

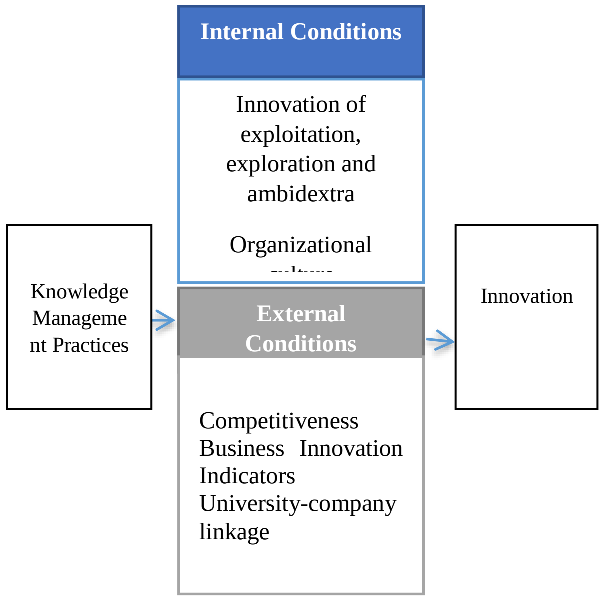

Figure 1 Relation of the general multivariate hypothesis

The study is of a transversal nature, so the results should be treated with caution since "due to the time factor, it is difficult to establish causality, so the data will only be used to investigate relationships between constructs (Im, Pesaran & Shin 2003).

For the PLS analysis, 7 constructs are included: EEA Innovation (EEAI) with 2 indicators, Organizational Culture (CO) with 3 indicators, Innovative Performance (DI), Competitiveness (Cm), IE Indicators (InI) and EU collaboration (VE-U) and knowledge management practices with 4 indicators each, giving a total of 24. For the PLS analysis the SmartPLS 3.0 software was used.

Results

To determine the predictive relationship of the study, the process of the two phases of the analysis of structural equations was followed: A) the measurement model and B) structural.

A. Measure Model

The analysis of the measurement model according to Cepeda and Roldan, (2007), Barroso, (2007), Chin, (1998) and Fornell, (1982) implies the analysis of individual reliability of the item, internal consistency or reliability of a scale, convergent validity analysis and discriminate validity.

Reliability: Cronbach's Alpha			
Variables	**Component**	**Question Code**	**α item**
Knowledge management practices pc = 0.876 α = 0.779	Available storage systems	PG!	0,735
	Shared knowledge spaces	PG2	0,669
	Collaborative Learning	PG3	0,673
	Knowledge application	PG4	0,902
		DI5	0,932
Terms internal pc = 0.953 α = 0.811	Innovative Performance pc = 0.873 α = 0.831	DI6	0,699
		DI7	0,808
		DI8	0,674
	Exploitation, exploration and ambidestreza innovation pc = 0.638 α = 0.626	IEEA9	0,620
		IEEA10	0,639
	Organization (Culture)p_c=0,953 α=0,944	OC11	0,866
		OC12	0,896
		0C13	0,970
External Conditions pc = 0.940 α = 0.922	Company-University Collaboration pc = 0.737 α = 0.629	CE-U14	0,646
		CE-U15	0,794
		CE-U16	0,622
		CE-U17	0,629
	Competitiveness pc = 0.890 α = 0.878	Cm18	0,831
		Cm19	0,843
		Cm20	0,873
		Cm21	0,825
	Business Innovation Indicators pc = 0.979 α = 0.978	InIE22	0,961
		InIE23	0,983
		InIE23	0,967
		InIE25	0,972

Table 2 Analysis of the PLS average model

Reliability with Cronbach's Alpha presupposes a priori that each indicator of a construct contributes in the same way, the loads are set in the unit (Barclay, Higgins, and Thompson, 1995). The criteria used for the interpretation of the reliability coefficient are: less than 0.6 (low); 0.61 to 0.70 (appropriate); 0.71 to 0.80 (good); greater than 0.80 (high) (Nunnally, 1978). It presents the reliability of the constructs (Table 2).

Considering the results of table 2, in general the constructs are probos, since they have a composite reliability greater than 0.6.1.

Now convergent validity is carried out, which describes "if the different items intended to measure a concept or construct really measure the same, then the items will be significant and highly correlated" (Cepeda and Roldan, 2007). This is obtained through the mean extracted variance (AEV) shown in Tables 3.1 and 3.2.

Convergent validity		
Component		AEV
Latent variable Knowledge Management Practice	Knowledge Management Practice	
	,527	,586

Table 3.1 Convergent validity matrix

Convergent Validity								
Component		Internal conditions			External conditions			AEV
		1	2	3	4	5	6	
Terms internal	1.DI	**0,867**						0,752
	2. EEAI	-0,020	**0,904**					0,817
	3. Or	0,711	-0,261	**0,955**				0,913
Externa Conditio	4.CE-U				**0,685**			0,569
	5. Com				0,835	**0,859**		0,918
	6. IIE				0,739	0,783	**0,970**	0,941

Table 3.2 Convergent validity matrix

In general, the constructs that make up the model, obtained the value of Analysis of Extracted Variance (AEV) greater than 0.50 (Fornell, 1982) complying with the convergent validity condition.

The second refers to discriminant validity (Table 4.1), which is the variance shared between the construct and its measures. This measure should be greater than the variance shared between the construct with the other constructs (square correlation between the two constructs). It will be necessary to demonstrate that each indicator relates better to its own construct than to another.

It is observed in Table 4.1 that the loads of the constructs that make up the internal conditions for the development of innovation capacities are better related to their own construct.

Discriminant validity				
Components	**Innovación EEAI**	**Desempeño Innovador**	**Organización (Cultura hacia la innovación)**	**Prácticas de gestión del conocimiento**
DI5	-0.162	**0.565**	0.942	0.281
DI6	0.040	**0.973**	0.589	0.391
DI7	0.157	**0.874**	0.295	0.286
DI8	-0.087	**0.990**	0.665	0.455
IEEA10	**0.887**	-0.126	-0.260	-0.423
IEEA9	**0.920**	0.074	-0.217	-0.498
OC11	-0.375	0.569	**0.978**	0.434
OC12	-0.162	0.565	**0.942**	0.281
OC13	-0.186	0.856	**0.946**	0.462
PG1	-0.524	0.395	0.421	**0.989**
PG2	-0.274	0.424	0.327	**0.737**
PG3	-0.335	0.402	0.334	**0.778**
PG4	-0.133	0.263	0.310	**0.500**

Table 4.1 Matrix of crossed loads and divergent validity: Internal

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Conditions

*** Calculations made in SmartPLS3.0**.

In table 4.2 it is inferred that the loads of the constructs that make up the external conditions for the development of innovation capacities are better related to their own construct.

For the interpretation of the divergent validity of the level of the charges, "the ranges between 0.50 and 0.60 as acceptable" will be taken (Chin, 1998). It is observed in tables 3.1, 3.2, 4.1 and 4.2 that the loads obtained are greater than 0.50. The results obtained support convergent and divergent validity.

The validity and reliability conditions are met in the measurement model, the second phase corresponding to the structural model will proceed.

Discriminant validity				
Components	**Company Collaboration**	**College Competitiveness**	**Innovation Indicators Business**	**Management Practices knowledge**
CE-U14	0.729	0.481	0.355	0.561
CE-U15	0.516	0.275	0.290	0.263
CE-U16	0.791	0.790	0.509	0.435
CE-U17	0.671	0.698	0.885	0.412
Cm18	0.741	0.791	0.698	0.325
Cm19	0.781	0.922	0.927	0.614
Cm20	0.685	0.889	0.571	0.682
Cm21	0.707	0.830	0.478	0.390
InIE22	0.745	0.780	0.991	0.477
InIE23	0.678	0.714	0.945	0.446
InIE24	0.741	0.786	0.978	0.488
InIE25	0.702	0.754	0.966	0.474
PG1	0.633	0.609	0.434	0.962
PG2	0.477	0.503	0.463	0.815
PG3	0.482	0.508	0.434	0.808
PG4	0.342	0.356	0.274	0.555

Table 4.2 Matrix of crossed loads and divergent validity: External Conditions

Structural model

The objective of the structural model is to confirm "to what extent the relationships specified in the theoretical model are consistent with the data" (Real, Leal and Roldán, 2006). For the evaluation of the model, two basic R^2 indices and standardized path coefficients β will be used.

R^2 It indicates the amount of "variance of the construct that is explained by the model" (Cepeda and Roldán, 2007).

The endogenous variable (R^2) should be greater than or equal to 0.1 (Falk and Miller, 1992). "If the values of R^2 are less than 0.01, even if they are statistically insignificant, changes in the R^2 indicator can be explored to determine if the influence of a particular latent variable on a dependent construct has a substantive impact" (Chin, 1998).

The path coefficient or standardized regression weights is identified in the monogram by means of the arrows that link the constructs in the internal model (Cepeda and Roldán, 2007). To be considered significant results or path coefficients, they should reach a value of 0.2, and ideally be above 0.3 (Chin, 1998).

It is important to note that the magnitude of the indirect effects on a variable is estimated by multiplying the existing path coefficients along the line of the causal line between two related variables (Arbuckle, 2003).

The monograms were designed using Smart PLS of the Internal Conditions (Figure 2) and External with relation (Figure 3) to the latent variable of knowledge management practices, to identify the variances of the constructs and the strength of relationship.

DI5 Implement innovation projects that respect the environment. DI6 Products developed from the follow-up of customer needs. DI7 Opening of national markets. DI18 Increase in customers. IEEA9 Type of Innovation. IEEA10 Innovation management. OC11 Declared culture towards innovation. OC12 Leadership (senior management support). OC13 Applications and tools (software).

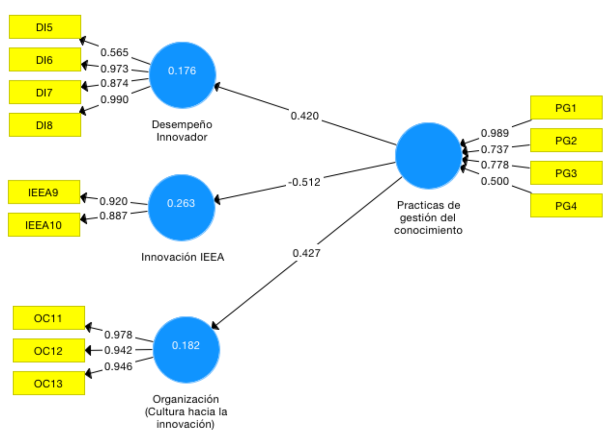

Figure 2 Monogram of the Internal Conditions for the development of innovation capabilities (PLS)

It can be seen in Figure 2, in general, the endogenous variables have a predictive relevance in the three constructs that integrate the internal conditions for the development of business innovation capabilities by obtaining a variance explained in Innovative Performance R^2 = 0.176, EEA Innovation R^2 = 0.263, Organizational (Culture) R^2 = 0.182, exceeding the minimum value of explained variance that is recommended (≥ 0.10 (Falk, 1992: 80).

CE-U14 Reason for collaboration with the University. CE-U15 Collaboration with the University and the government sector for the development of R + D + i projects. CE-U16 The response of the academy to the demands of consulting, research and innovation in the industrial sector. CE-U17 Knowledge transfer. Cm18 Productivity (annual increase according to goals). Cm19 Innovation strategy Expenditure on R + D + i / Sales). Cm20 Registered Patents. Cm21 Design of a financial plan for the development of innovation activities. InIE22 Training oriented towards the creation of innovation. InIE23 Participation of managers in innovation activities. InIE24 Collaboration networks of which the company is a part to identify opportunities for innovation. InIE25 The possibility of implementing an idea arising from the staff of your company, so that it becomes a product or service that is launched to the market.

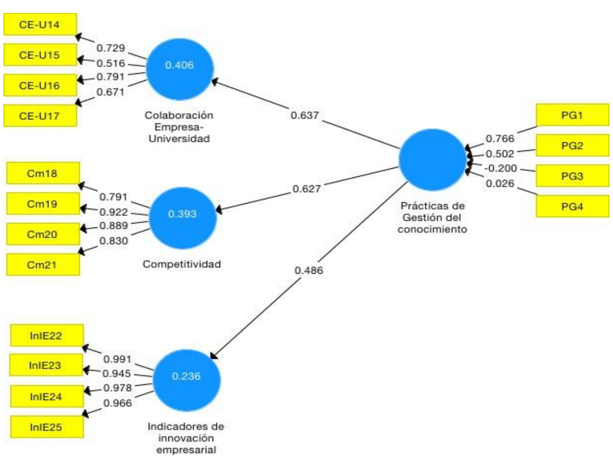

Figure 3 Monogram of the External Conditions for the development of innovation capacities (PLS). Calculations made in SmartPLS3.0

In relation to the external conditions that integrate business innovation capabilities (Figure 3), they obtained the following results; Collaboration E-U R^2 = 0.406, Competitiveness R^2 = 0.393, and Business Innovation Indicators R^2 = 0.296, exceeding the minimum value of explained variance that is recommended (≥ 0.10 (Falk, 1992: 80).

The magnitude of the relationship effect between the variables that make up this study according to the path coefficient is shown in Table 5:

Constructs	β	Level of Significance
PGC-Innovative Performance	0, 420	<0,3
PGC-EEA Innovation	-0,512	<0,3
PGC-Organization (Culture towards Innovation)	0, 427	>0,3
PGC-Competitiveness	0, 637	<0,3
PGC-E-U Collaboration	0, 627	<0,3
PGC-IE Indicators	0,486	<0,3

Table 5 Path coefficient

With what can be verified that there is a positive relationship at an ideal level when exceeding 0.3 (Chin, 1998) between the prediction of the latent variable that directly and significantly influences the endogenous variables, except in the EEAI construct with influence in a way inverse.

Finally, mention that the PLS technique does not have an index that can calculate the goodness of fit of the model, so Tenenhaus, Vinzi, Chatelin and Lauro (2005: 173) propose a global evaluation criterion, which is calculated by the GoF formula. They are obtained by the root of GoF = AEV * R^2. For this investigation an adjustment index was obtained as follows:

GoF= √,802*,325=,510

Slightly higher than the recommended minimum (0.50). Once the different analyzes of the research model have been carried out, the results obtained from the PLS technique can be considered, the model reaches a predictive relevance in the six endogenous variables with R^2 higher than the minimum value of explained variance that is recommended (≥ to 0.10 (Falk, 1992: 80) and an adjustment value of the upper model 0.50 obtaining a value of 0.510 (Tenenhaus, 2005).

Conclusions

The model based on structural equations denotes that there is a predictive and positive relationship in the deployment of processes that impact knowledge management and business innovation.

For the most part, there are positive and significant statistical relationships at a moderate level, which means that “the greater the relationship between the EEAI, CO and DI variables that make up the internal conditions and knowledge management practices in the organization, the greater the impact on the development of business innovation ”, since individual and organizational knowledge will be mobilized to create innovative processes, services or products that will mark a differentiating advantage for the organization from its competitors.

In general, there is a positive and significant statistical relationship at a high to moderate level, which means that “the greater the relationship between the variables Cm, InIE and VE-U that make up the external conditions with the knowledge management practices in the organization, greater impact on development in business innovation ”, since companies take advantage of the opportunities of the environment through collaboration or linking (competitors, customers, markets, society, government, university, business affiliations) to appropriate information and knowledge, and transform it in products, services or processes that allow them to survive and compete in dynamic and complex contexts.

Companies that wish to achieve greater organizational results must have valuable and inimitable resources and capabilities that can be a source of sustainable competitive advantages (Wernerfelt, 1984; Barney, 1986; Amit and Schoemaker, 1993).

There are several models of knowledge management that can be used by companies in the industrial, commercial and services sector for the generation and use of knowledge, among them, are the Taxonomy of models of knowledge management proposed by Barragan, (2009: 74).

The result of this research proposes a conceptual pattern marked in "scientific and technological models of knowledge management: whose purpose is the management of technological innovation and its purpose is to promote research and development within public or private organizations" (Barragan, 2019: 75).

The knowledge management model to develop innovation capacities in the industrial sector (Villalobos, 2015: 221) is based on knowledge management practices that are developed in three dimensions; organization, R + D + i and the environment, which interact and feed back according to the predictive results shown in the monograms, which were obtained from the application of the ACIEAT survey to IT, Manufacturing, Automotive and Aerospace companies (Alonzo and González , 2015).

The efforts of the research academy are glimpsing new theoretical and practical approaches to the development and use of knowledge in companies, since it is evident that in an economy where the only certainty is uncertainty, the only source of lasting competitive advantage and Sure is knowledge (Nonaka, Takeuchi and Konno, 2000).

In this context, companies must generate their own source of knowledge and use it to produce innovations of process, product and service, flexible collaboration between the Academy-Government-Society-Industry, is and will be the key to the success of a nation with a vision for innovation.

References

Alonzo, M. D. L. Á. V., & González, A. E. R. (2015). Diseño y validación de cuestionario para la exploración de capacidades de innovación para empresas de alta tecnología de México. Revista QUID, (25).

Anderson, J. C., Rungtusanatham, M., Schroeder, R. G & Devaraj, s. (1995). “A Path analytic Model of Theory of Quality Management Method: Preliminary empirical Findings”. Decision Sciences. Vol 26, núm. 5, pp.637-638.

Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. Strategic management journal, 14(1), 33-46.

Barclay, D., Higgins, C. y Thompson, R. (1995): “The Partial Least Squares (PLS) Approach to Causal Modelling: Personal Computer Adoption and Use as an Illustration”, Technology Studies, Special Issue on Research Methodology, 2(2): 285-309.

Barney, J. B. (1986). Strategic factor markets: Expectations, luck, and business strategy. Management science, 32(10), 1231-1241.

Barragán Ocaña, A. (2009). Aproximación a una taxonomía de modelos de gestión del conocimiento.

Barroso-Tanoira-Tanoira, F. G. (2013). Gestión del conocimiento en empresas y organizaicones sociales productivas exitosas. Un estudio en el Sureste de México. Hitos de Ciencias Económico Administrativas, 19 (55): 103-114.

Cepeda, G. y Roldan, J. L. (2007). Aplicando en la práctica la técnica PLS en la administración de empresas. Departamento de Administración de Empresas y Comercialización e Investigación de Mercados, Facultad de Ciencias Económicas y Empresariales Universidad de Sevilla España.

Céspedes, L. J. J. y Sánchez, P. M. (1996). Tendencias y desarrollos recientes en métodos de investigación y análisis de datos en dirección de empresas. Revista Europea de Dirección y Economía de la Empresa, 5(3,): 23-40.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. Modern methods for business research, 295(2), 295-336.

Chin, W.W., Marcolin, B.L. y Newsted, P.R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: results from a Monte Carlo simulation study and an electronic mail emotion/ adoption study. Information Systems Research, 14(2): 189-217.

Falk, R.F. y Miller; N.B. (1992). A Primer for Soft Modeling. Akron, Ohio: The University of Akron.

Atistical methods for rates and proportions. New York: John Wiley and Sons

Fornell, C. (1982). A Second Generation of Multivariate Analysis: An Overview. New York: Praeger Publishers.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of econometrics, 115(1), 53-74

Nonaka, I. y Toyama, R. y Konno, N. (2000). SECI, Ba and leadership: A uni!ed model of dynamic knowledge creation. Long Range Planning, 33, 5-34.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y. M., y Lauro, C. (2005). PLS path modeling. Computational statistics & data analysis, 48(1), 159-205.

Villalobos, A. M. A. Modelo de gestión del conocimiento para el desarrollo de Capacidades de Innovación en el sector indusctrial de alta tecnología en México. (2015). Tesis Doctoral. Universidad Popular Autónoma del Estado de Puebla. UPAEP. México

Von Krogh, G., Roos, J. y Slocum, K. (1994). An essay on corporate epistemology. Strategic Management Journal, vol. 15, pp. 53-71.

Wernerfelt, B. (1984). A resource-based view of the firm. Strategic management journal, 5(2), 171-180.

Wold, H. (1979). Model Construction and Evaluation when Theoretical Knowledge Is Scarce: An Example of the Use of Partial Least Squares. Cahiers du Département D´Économétrie. Genève: Facultédes Sciences Économiques et Sociales, Université de Genève.

Wong, Y. K. (2006). Modern Software Review: Techniques and Technologies. Hershey, PA, USA:IRM Press.

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