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Artículos científicos

Análisis factorial confirmatorio: un modelo de gestión del conocimiento en la universidad pública

Confirmatory factor analysis: a knowledge management model in the public university

Análise fatorial confirmatória: um modelo de gestão do conhecimento na universidade pública

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Resumen

El análisis factorial confirmatorio (AFC) es un modelo multivariante de segunda generación en el análisis de estructuras de covarianza (CB-SEM) en la investigación en ciencias sociales. El objetivo de este artículo fue contrastar un modelo de medida a través de datos empíricos provenientes de una muestra que, teóricamente, refleje las características de la población objeto de estudio con el fin de explicar la técnica factorial confirmatoria. La metodología utilizada fue la modelación de ecuaciones estructurales (CB-SEM). Los hallazgos dan evidencia de un modelo factorial confirmatorio con cuatro factores, el cual es sustentado en el modelo SECI de Nonaka y Takeuchi (1995). Esta técnica tiene aplicaciones prácticas en las ciencias sociales y del comportamiento de la investigación científica.

Palabras clave: análisis factorial confirmatorio, análisis factorial exploratorio, modelación CB-SEM.

Abstract

Confirmatory Factor Analysis (CFA) is a multivariate model in the analysis of Covariance Structures (CB-SEM) in Social Science research. The objective of the article is to contrast a measurement model through empirical data from a sample, which theoretically reflects the characteristics of the population under study, in order to explain this confirmatory factorial technique. The methodology used is Structural Equation Modeling (CB-SEM). The research findings provide evidence of a confirmatory factorial model with four factors, supported by the SECI model of Nonaka y Takeuchi (1995). This technique has practical applications in the Social and Behavioral Sciences of scientific research.

Keywords: Confirmatory Factor Analysis, Exploratory Factor Analysis, CB-SEM Modeling.

Resumo

A análise fatorial confirmatória (CFA) é um modelo multivariado de segunda geração na análise de estruturas de covariância (CB-SEM) em pesquisas em ciências sociais. O objetivo deste artigo foi contrastar um modelo de medição por meio de dados empíricos de uma amostra que, teoricamente, reflete as características da população em estudo para explicar a técnica fatorial confirmatória. A metodologia utilizada foi a modelagem de equações estruturais (CB-SEM). Os resultados fornecem evidências de um modelo fatorial confirmatório com quatro fatores, que é apoiado pelo modelo SECI de Nonaka e Takeuchi (1995). Esta técnica tem aplicações práticas nas ciências sociais e comportamentais da investigação científica.

Palavras-chave: análise fatorial confirmatória, análise fatorial exploratória, modelagem CB-SEM.

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Introduction

Structural equation modeling (SEM) is a statistical methodology that takes a confirmatory approach to the analysis of a structural theory related to some phenomenon (Byrne, 2010). In this SEM modeling, there are two techniques in the social sciences: 1) based on covariance (CB-SEM), which stands for covariance-based structural equation modeling, and 2) based on on the partial variance least squares (PLS-SEM). CB-SEM modeling is used primarily to confirm or reject theories. It is a parametric technique in which certain statistical assumptions will have to be met for its application, such as the normality of the data, the sample size, among others. On the other hand, the PLS-SEM is a non-parametric technique, focused in the first instance on prediction, although Henseler (2018) argues that it can be used for all types of research (confirmatory, explanatory, exploratory, descriptive and predictive).

In this context of structural equations, this article is based on the CB-SEM methodology to explain the confirmatory factor analysis. This parametric approach is made up of two types of models: 1) the measurement model and 2) the structural model. Therefore, the confirmatory factor analysis (CFA) is a multivariate model in the analysis of structures of covariance (CB-SEM), which aims to contrast a measurement model through empirical data from a sample, which theoretically reflects the characteristics of the population under study, whose starting point is the construction of a model based on theory and exploratory factor analysis (EFA).

In practice, we can find CFA of the first, second or more levels, depending on the objective of the investigation. The first level CFA shows exogenous variables and the covariance between them, while the second level CFA constitutes an extension of the first level, where a new latent construct is incorporated that is specified by the first level factors, whose objective is to define the variables of the model and the relationship between them. In this way, the difference between the two consists in that the correlations between the factors are replaced by saturations of those same factors in the new exogenous variable of higher order that groups the first-level constructs.

Figures 1, 2, 3 and 4 show measurement models of the first and second order or higher level, as well as models of causal analysis where the CFA can be applied.

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Figure 1. Top-tier AFC

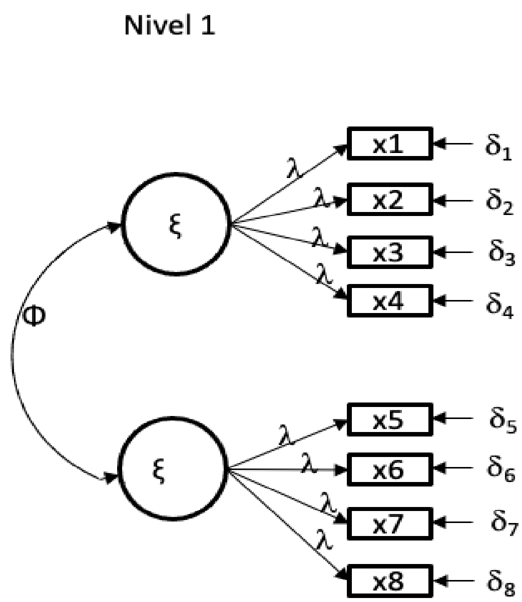

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Figure 2. Second level AFC

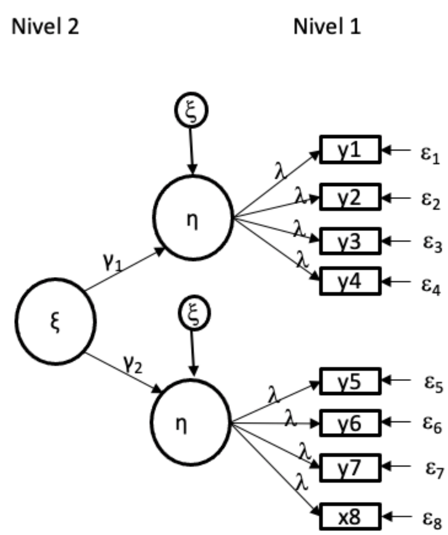

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Figure 3. Causal analysis

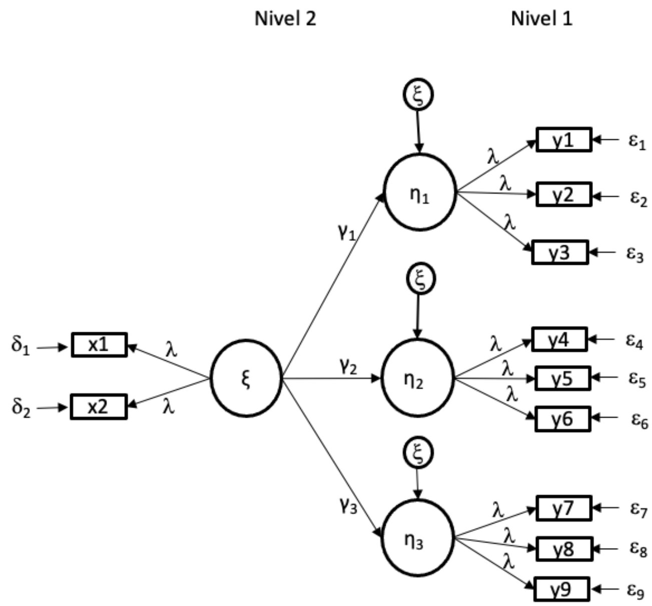

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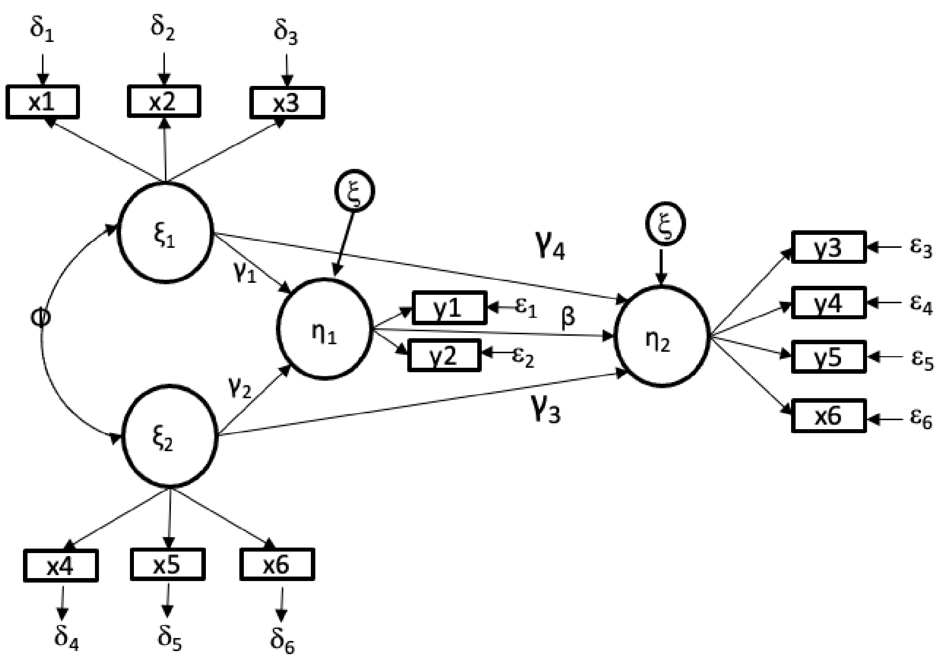
Figure 4. Causal level with two levels of causality



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Therefore, the confirmatory factor analysis estimates the measurement model in order to achieve the reliability and validity of the model to later estimate the structural model, which corresponds to the research model. The CFA is generally made up of six phases: 1) specification of the model, 2) identification, 3) estimation of parameters, 4) model adjustments, 5) interpretation and 6) re-specification, aspects that should be based on the theory and exploratory factor analysis (Lévy and Varela, 2006).

Exploratory factor analysis (EFA) is a statistical technique that allows exploring a set of observable variables (items) through a reduced number of factors that show the correlations between the set of observed variables. In the data set of variables, those that are closely related (or correlated) are searched and they are grouped to form a new dimension. In the first instance, this technique —by analyzing the relationships between the items— makes it possible to determine whether it makes sense to carry out the analysis. If the variables were not linearly associated, the correlations between them would be null and, therefore, it would be an identity matrix that prevents the analysis (Ferrán, 2001). In addition, it is advisable to comply with the principle of parsimony and interpretability, where the phenomena must be explained with the fewest possible elements to be susceptible to substantive interpretation. (Martin, Cabero y De Paz, 2008).

The EFA procedure allows the items to be grouped according to the correlation towards a factor. There are several descriptive statistics that analyze the correlation matrix, among the most common the Bartlett sphericity test, which is used to test the null hypothesis that the correlation matrix is zero; while the Kaiser-Meyer-Oklin KMO index measures the magnitude of the correlation coefficients within the parameter from 0 to 1.

For their part, Garza, Morales and González (2013) consider that KMO values of .90 onwards are excellent, from .80 to .90 good, from .70 to .80 acceptable, .60 to .70 regular, from. 50 to .60 low, and less than .50 unacceptable. It is important to analyze each variable using the diagonal of that matrix. Values must be ≥ .5; if they are less, the variable must be eliminated from the analysis and proceed to a new process (Garza et al., 2013).

Regarding the factor extraction method, there are several, although the most used in statistical software packages are the principal components (PC) and the maximum likelihood component (ML). In this case, the PC was used, which extracts factors based on eigenvalues greater than 1 and determines the explained variance. Likewise, for this to reach a satisfactory level, it is recommended that it be 75% or 80% (Martin et al., 2008). With regard to the factor rotations that indicate the relationship between the factors and the variables, it is advisable to use the Varimax method, which minimizes the number of variables that have high saturations in each factor for an interpretation; here the factor load is analyzed that allows to see the relationship of the variables with each factor (Martin *et al*., 2008).

As far as the measurement scale is concerned, it should mainly contain skewness and equidistance. In addition, it must be supported by the theory underlying the problem, and the sample must meet the parametric requirements regarding size. Figures 5 and 6 show the difference between an exploratory and a confirmatory factorial model.

Figure 5. AFE structure

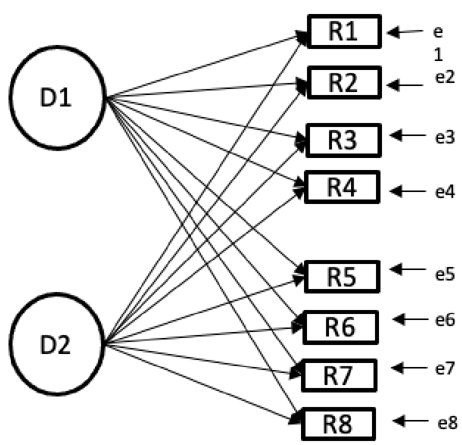

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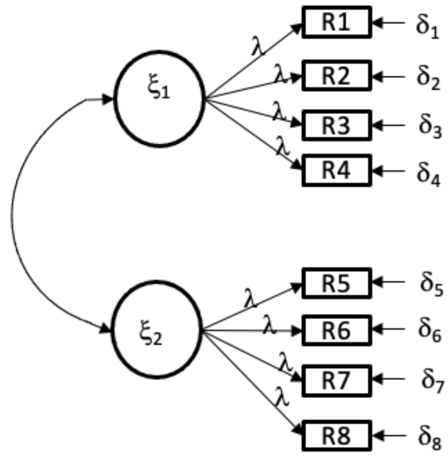
Figure 6. AFC structure



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In these figures it is observed that there are certain differences in their structure; First, the EFA searches for correlation relationships where the scientist has to evaluate which factor or dimension has a greater or lesser factor load to determine which dimension each item corresponds to. This necessarily has to be evaluated with the literature review, which supports the items with their corresponding dimensions so that, if necessary, the researcher makes the respective adjustments, since an item can load on both factors.

On the other hand, Jöreskog (1969) developed the confirmatory procedure where he establishes that the main conceptual difference in both structures is that in CFA the hypothesis about the factorial structure of a series of variables can be verified; in addition, the researcher specifies the number of factors in the theoretical model to contrast the data.

It is important to consider some statistical assumptions for the use of this parametric technique, such as the normality of the data, the number of indicators and the size of the sample. Regarding the size of the sample, around 200 subjects are considered when there are at least three indicators for latent variables. (Anderson y Gerbing, 1984).

Based on this theoretical argument and statistical assumptions, the purpose of this research is to publicize the use of the statistical technique of confirmatory factor analysis (CFA) from empirical data collected in the year 2020 of knowledge management. No statistical relationship or hypothesis test was tested: only the application of the confirmatory factor analysis technique is addressed to estimate the measurement model and achieve reliability and validity.

In summary, this document has the following structure: first, the theoretical perspective is offered to describe the variables under study; second, the method of work; third, the data analysis procedure; fourth, the reliability and validity of the model, and in the last section the discussion of the findings is presented.

Theoretical foundation

The resource-based theory

The present research focuses on resource theory (Barney, 1991; Wernerfelt, 1984) and the knowledge-based view (Grant, 1996). Resource theory is widely recognized as one of the most prominent and powerful for describing, explaining, and predicting relationships in the organization (Barney, 2011 et al ..). It posits that the source of a competitive advantage comes from its internal resources, whether tangible or intangible. One of the most important features of resources is that they must be heterogeneous, rare, inimitable, valuable and non-substitutable (Barney 1991, 2001; Wernerfelt, 1984). Therefore, knowledge is a valuable and strategic intangible resource that makes the most important contribution to organizations. This means that success depends on the organization's ability to create and develop its knowledge-based assets as a key resource for the growth, innovation, performance and sustainable competitive advantage of companies (Nawab, Nazir, Mohsin and Muhammad , 2015; Yusof and Bakar, 2012; Salajarvi, Sveiby and Furu, 2005; Hill, Nancarrow and Wright, 2002; Teece, 2000).

For their part, Krstić and Petrović (2011) argue that knowledge management is a process by which an organization generates value in a contemporary dynamic environment of technological change through the effective and efficient exploitation of knowledge as a key resource of the economy. of knowledge. In a world where technologies, markets, products, competitors and even society change very rapidly, knowledge has become an invaluable asset for organizations to maintain a sustainable competitive advantage (Nonaka, Toyama and Byosiere, 2001) . Therefore, Quinn (1992) emphasizes that the competitive advantage of a company depends more and more on the intangibles based on knowledge.

Likewise, various authors argue that knowledge management will represent the most significant factor of competitive advantage for organizations (Drucker, 1993; Quinn, 1992; Toffler, 1990). Therefore, the development and practice of knowledge management are continuously increasing in organizations (Halawi, Aronson and McCarthy, 2005). Thus, knowledge management has been applied to activities designed to manage and exchange, create and improve the intellectual assets of the organization (Haggie and Kinston, 2003). In this context, Zaman, Mahtab and Raxa (2014) emphasize that knowledge management is a combination of basic skills and competencies in both information and human resource management, and that it is increasingly recognized as a key asset of the organization, since it generates wealth from its intellectual resources based on knowledge.

For their part, Nonaka and Takeuchi (1995) propose two types of knowledge: explicit and tacit. The former can be written, encoded, filed and processed by the organization's information systems, while tacit knowledge is that which people possess and is stored in their brain, hence it is considered an intangible asset. The CFA of this research is based on the SECI model of Nonaka and Takeuchi (1995), which is described below.

Knowledge creation process

Nonaka (2008) emphasizes that the dynamic theory of organizational knowledge creation considers that knowledge is created through an interaction between tacit and explicit knowledge, which is represented by a two-dimensional spiral: 1) an epistemological one that bases explicit knowledge and tacit knowledge, and 2) an ontological one that contemplates the levels of knowledge (individual, group, organizational and interorganizational) through the four modes of knowledge conversion: 1) socialization; 2) outsourcing; 3) combination, and 4) internalization.

In this sense, Nonaka, Toyama and Byosiere (2001) describe the four modes of conversion or creation of knowledge: socialization is the process of acquiring tacit knowledge through shared experiences, since it is specific to the context and difficult to formalize. The key to acquiring tacit knowledge is commonly through the sharing of activities; For example, people sometimes learn their art not by reading, but by closely observing their teacher's behavior and with practice.

Outsourcing is the process of articulating tacit knowledge as explicit knowledge. This mode of conversion transfers the explicit to the tacit. When tacit knowledge is made explicit, the knowledge has become concrete, at which point it can be shared by others and can become the basis for new knowledge. Outsourcing occurs, for example, when a research and development (R & D) team tries to clarify the concept of a new product.

The combination is the form of connection of explicit knowledge in a set of explicit knowledge that is exchanged by means such as documents, meetings, conversations and computerized communication networks.

Finally, internalization is the process of incorporating explicit as tacit knowledge, hence it is related to learning by doing. Through internalization, the knowledge created is shared throughout the organization, which is why it is used to expand, extend and rethink the two types of knowledge existing in the institution.

Work method

Research approach and design

The research design was non-experimental and cross-sectional. Modeling (SEM-CB) was used, the purpose of which is to evaluate multiple simultaneous relationships to carry out, in this case, the confirmatory factor analysis (Hair, Anderson, Tatham & Black, 2008; Lévy & Varela, 2006). This analysis of covariance structures offers the possibility of examining a set of simultaneous dependency relationships between multiple variables.

This technique is mainly used to test theories (when testing a theoretical model). A complete analysis of the technique implies the evaluation of two models: the measurement one and the structural one. In this case, only the measurement model was analyzed, which reflects the relationships between the observed and latent variables, which specifies which indicators define each construct.

Sample

To meet the objective of explaining the use of confirmatory factor analysis, the data considered were 225 employees and managers who correspond to agencies of the Autonomous University of the State of Mexico, for which a convenience sampling was carried out due to the ease of obtaining the information. The characteristics of the sample were as follows: 55% women and 45% men, the majority with ages ranging between 40 and 49 years.

Measurement of variables

In this research, an instrument was built to measure the knowledge management process from the theoretical basis of various authors (Choi and Heeseok, 2002; Choi and Lee, 2002; Nonaka and Takeuchi, 1995; Nonaka, Toyama and Konno; 2000; Nonaka, Toyama and Byosiere 2001). This made it possible to measure the four modes of knowledge conversion or creation (socialization, externalization, combination and internalization). The measurement was on a Likert scale (1 = totally disagree and 5 totally agree).

Variation of the common method

The common-way method is an important aspect that must be taken into account in the construction of measurement scales. This refers to the extent to which the variance between the correlations derives from the measurement method, and not from the constructs that are measured. In this regard, Podsakoff, MacKenzie, Lee and Podsakoff (2003) suggest several statistical remedies to avoid common method bias, which were reviewed.

Data analysis procedure

To assess whether the constructs were correctly evaluated, first, the exploratory factor analysis was carried out and, later, the confirmatory factor analysis.

Exploratory factor analysis

In this type of analysis, the Kaiser-Meyer-Oklin (KMO) sample adequacy index was determined, whose value was KMO = .897. In this regard, it should be noted that its validity parameter is 0 to 1 (the closer to 1, the stronger the correlation). Relative to Bartlett's test of sphericity, it requires that the result be significant. With regard to loads, it is recommended that they be greater than 0.05 (Castañeda, Cabrera, Navarro and DeVries, 2010). In the end, the explained variance of 78.56% was determined.

Scale reliability

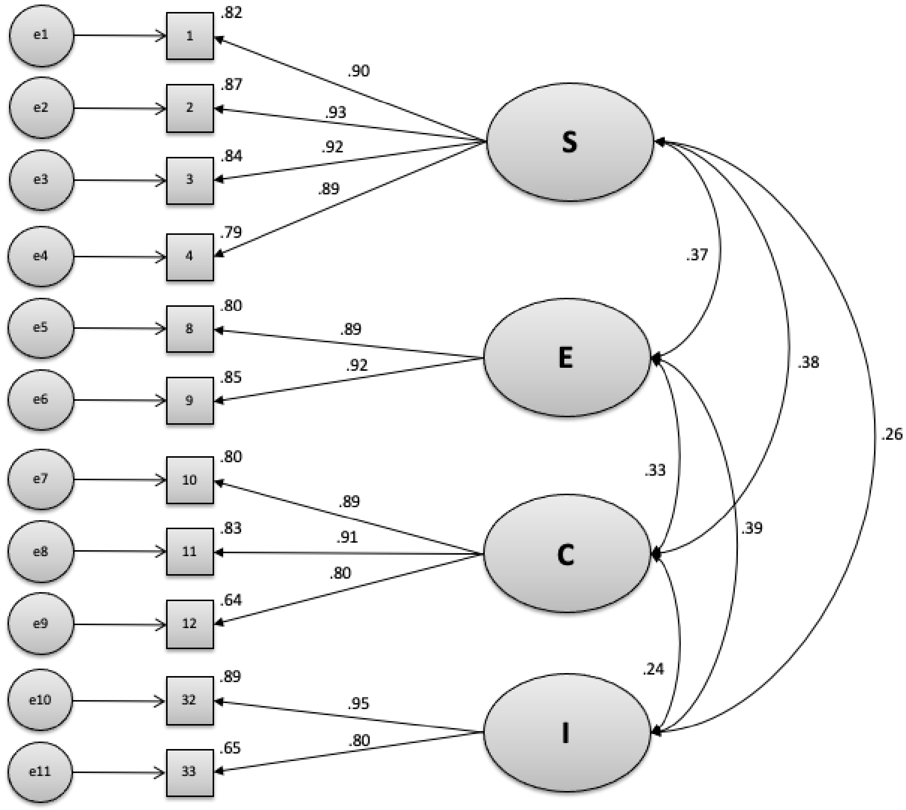
The scale was analyzed by means of a reliability analysis to determine Cronbach's alpha. Socialization was reported to have a reliability of 0.85; outsourcing 0.82; the combination 0.89, and the internalization 0.86. Composite reliability is a measure of the internal consistency of the construct indicators, and must be calculated for each construct. Its recommended threshold must be equal to or greater than 0.70; when the value is lower, it can be accepted if the investigation has an exploratory nature (Hair, Anderson, Tatham y Black, 2007).

Confirmatory factor analysis

Once the exploratory factor analysis presented adequate indices, the confirmatory factor analysis (CFA) was carried out to confirm the reliability and validity of the model of the four modes of conversion or knowledge creation. In this sense, the AFC also made it possible to test whether the measurements were consistent with the theory. Therefore, a structural equation statistical program (AMOS) was used for this analysis. First, the measurement model was estimated, and the standardized coefficients (factorial loads λ) were examined to identify the variance of each indicator that explained the construct. All standardized factor loadings exceeded .70, and the average variance extracted (AVE) exceeded .50. These results show convergent validity and reliability.

Regarding the discriminant validity, Table 1 shows that the AVE is greater than the correlations, which allows us to infer that there is discriminant validity (Fornell y Larcker, 1981; Nunnally, 1978).

Figure 7. Estimation of measurement model parameters



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In the first instance, multicollinearity was reviewed according to the data in figure 7. As can be seen, the variables socialization and combination present the highest covariance of .39, which is not a representative multicollinearity problem. However, a collinearity analysis was also carried out to assess multicollinearity, where the variance inflation factor (VIF), tolerance and condition index were analyzed. The following were reported: IVF = 2.9, tolerance 0.84 and CI = 11.23, which indicates that there are no collinearity problems, since an IVF> 3.3, tolerance below 0.20 and CI> 30 present collinearity problems (Belsley, 1991; Diamantopoulos and Siguaw, 2006).

Reliability through the CFA was calculated based on the loads and AVE of the construct indicators, shown in figure 7. An example of the calculation of a construct is presented below, where 1 is subtracted from each variance (1-.80 = 0.20; 1-.83 = 0.17; 1-.64 = 0.36).

$$C = \left(\frac{(0.89+0.91+0.80)^2}{(0.89+0.91+0.80)^2 + 0.20+0.17+0.36}\right) = 0.90$$

Likewise, an example of the determination of the AVE is offered. The total amount of variance of the indicators taken into account by each of the latent constructs. One way is to use an established formula or determine the average per construct. For a sample, the following example is illustrated C = 0.80 + 0.83 + 0. 64/3 = 0.75

As can be seen in Table 1, the reliability of all the constructs exceeds the established threshold of 0.75, while the mean variance extracted must always be greater than 50% (Lévi and Varela, 2006). Therefore, these results show the suitability of the indicators for the empirical explanation of the latent constructs.

Table 1. Construct reliability and convergent validity

Constructo	Fiabilidad	AVE
S	0.95	0.83
E	0.90	0.82
C	0.90	0.75
I	0.86	0.77

Source: self made

Table 2. Reliability and validity (convergent and discriminant)

Variable	Fiabilidad	Socialización	Externalización	Combinación	Internalización
Socialización	0.812	*(0.83)*			
Externalización	0.901	0.285	*(0.82)*		
Combinación	0.876	0.377	0.555	*(0.75)*	
Internalización	0.921	0.395	0.379	0.356	(0.77)

Note: The values shown in parentheses are the mean variance extracted (AVE), which implies convergent validity.

Source: self made

Evaluation of the fit of the mean model

To verify if the data fit the model, the goodness of fit indices were analyzed through three types of global fit. (Bollen, 1989; Hair, Anderson, Tatham y Black, 2007; Lévy y Varela, 2006; Marsh y Hocevar, 1985; Mohamad y Wan, 2013; Tanaka y Huba 1989):

- Absolute fit indices. They establish to what extent the model predicts the observed covariance matrix from the estimated parameters; where the chi-square index (Chi Squared, $\chi 2$) that analyzes the null hypothesis that a model is not significant is evaluated; that is, it indicates the significance of the differences of the covariance or correlation matrices, whose recommended value is $\chi 2$ / df <5 (Ghorbanhosseini, 2013). However, there are criticisms against this statistic in relation to the sample size (Bagozzi, 1994. To solve this problem of chi-square to the sample size, other adjustment measures are proposed, such as the index of the mean square root of the error of the approximation (Root Mean Squaree Error of Approximation, RMSEA), which considers a value less than 0.05 as a good fit (Kline, 2011; Levy and Varela, 2006); although other authors consider values ≤ 0.08, which represent an acceptable error of population approximation (Ghorbanhosseini, 2013), and the goodness of fit index (GFI), whose value is between 0 and 1, the latter indicating a perfect model fit; however, an acceptable fit is 0.90 (Jöreskog and Sörbom, 1984).
- Incremental adjustment rates. They compare the global fit of the analyzed model with another null (model specified with no relationship between the variables). The most commonly used incremental fit measures are the normalized fit index (NFI), which measures the proportional reduction in the proper fit function when we go from the null model to the proposed one; the Comparative Fit Index (CFI), which measures the improvement in the measurement of the non-centrality of a model, whose values are between 0 and 1. The value must be greater than 0.9 (Levy y Varela, 2006; Ghorbanhosseini, 2013).
- Parsimony adjustment indices. Here we have the following indices: Akaiké information criterion (Akaike Information Criterion, AIC), which is a comparison between models, whose value close to zero indicates a good fit (Levi and Varela, 2006); the normalized parsimonious fit index (Parsimonious Normed Fit, PNFI); the

Parsimonious Goodness of Fit Index (PGFI), whose threshold ranges from 0 to 1 (values close to 1 indicate a better fit).

According to these established parameters, the confirmatory factor analysis model under study is adjusted satisfactorily, since it complies with the main goodness-of-fit indices that are commonly reported from the model. (Hu y Bentler, 1999): $\chi 2$ = 738.03, gl = 263, p < .001; $\chi 2$/gl = 2.685. Índice de Tucker-Lewis (TLI) = .924; comparative fit index (CFI) = .930; Incremental fit index (IFI) = .931; mean square residual of the standardized root (SRMR) = 0.052; mean square error of approximation (RMSEA) = 0.062.

Discussion

The purpose of this research was to present the use of the statistical technique of confirmatory factor analysis (CFA) from empirical data collected on the SECI model. In this sense, the measurement model was valid and reliable, due to its internal consistency results (Cronbach's alpha) and those referring to exploratory factor analysis (KMO, Bartlett's test of sphericity and explained variance). Regarding the results of the confirmatory factor analysis (the factor loadings and the global goodness of fit indices of the model of the three typologies [absolute fit indices, incremental fit indices and parsimony indices], as well as the convergent and discriminant validity, and the reliability and validity of the model through the reliability of the construct and the mean variance extracted) were in accordance with the established parameters (Bagozzi, 1994; Bollen, 1989; Ghorbanhosseini, 2013; Hair, Anderson, Tatham and Black, 2007, 2008 ; Jöreskog and Sörbom, 1990; Kline, 2011; Lévy and Varela, 2006; Marsh and Hocevar, 1985; Mohamad and Wan, 2013; Tanaka and Huba 1989).

These results are consistent with Stock, Tsai Jiang and Klein (2021), who approach a shared knowledge model, although it should be noted that their CFA is very limited in terms of the indices they report, since it only takes the reliability of Cronbach's alpha and some indexes of the evaluation of the fit of the measurement model. Along the same lines, Zhang, Dawson and Kline (2020) evaluate a research model with the use of modeling (CB-SEM), where the CFA is applied, which, in turn, also limits the reporting of reliability statistics, validity and fit of the mean model.

Limitations and practical implications of the research

This research was carried out in academic bodies of the Autonomous University of the State of Mexico, for which data from 235 subjects were collected. Therefore, the results cannot be generalized, since the object of the investigation did not support any hypothetical argumentation, but only the explanation of the use of the CFA technique.

However, it is suggested that HEIs incorporate knowledge management practices through the four conversion modes explained, which could give greater value to the intangible assets of knowledge. In this regard, it should be emphasized that knowledge has become the engine of today's economy, hence its management and exploitation will allow the development of intellectual capital that is essential to generate competitive advantage. (Chou y Ta, 2005; Quinn, 1992).

Conclusions

Validating a scale of measurement by means of confirmatory factor analysis (CFA) made it possible to explain the entire statistical technique and show how the reliability and validity of the model is achieved. In the social and behavioral sciences, this type of technique is recommended, provided that the parametric assumptions required by the technique are met (mainly, the normality of the data and the size of the sample), which would be one of the parametric requirements. .

In this sense, this technique has the following benefits: 1) it allows to evaluate measurement models of large samples, 2) it is a robust technique in its mathematical algorithm, 3) it allows to test a measurement scale supported by theory, and 4) there are various statistical software to apply it, such as Amos, EQS, Lisrel, among others. Regarding weaknesses, it is not recommended for small samples or for non-parametric statistics.

In summary, the confirmatory factorial model shows the validation of the four dimensions supported by the literature review, specifically through the goodness-of-fit indices of three global fit typologies with the established parameters, which indicates that the factorial model it presents reliability, validity and is correctly adjusted to its factors.

Future lines of research

The model proposed by Nonaka, Toyama and Byosiere (2001) describes the four modes of conversion or creation of knowledge that can be applied in any organization. For this reason, researchers are encouraged to expand this work through empirical tests that use this model, albeit with other constructs, whether they are of the first order or of a higher order. Furthermore, the model can be studied as an independent or dependent variable, or act as a mediator or moderator construct.

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