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Conceptual and Practical Approach to Structural Equations Modeling

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METHODOLOGICAL ARTICLE

Conceptual and Practical Approach to Structural Equations Modeling

Aproximación conceptual y práctica a los Modelos de Ecuaciones Estructurales
Aproximação conceitual e prática aos modelos de equações estruturais

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ABSTRACT. This methodological article explains a conceptual and practical approach to Structural Equation Models or *Structural Equation Modeling* (SEM). SEMs are considered among the most powerful tools for the study of causal relationships in non-experimental data. They are a combination of factor analysis and multiple regression and are composed of two components: the *measurement model* and the *structural model*. The *measurement model* describes the relationship between a series of observable variables; while in the *structural model* the relationships between variables are hypothesized; i.e., the relationships between latent variables are described with the use of arrows. Performing a SEM involves five stages: 1) A *specification of the Model*; 2) *Identification of the Model;* 3) *Estimation of the Model*; 4) *Evaluation of the Model* and 5) *Re-specification of the Model*. This article provides a series of guidelines on "best practices" for SEM analysis, with examples using the AMOS program.

Key words: Structural Equation Modeling, AMOS, factor analysis, multiple regression

RESUMEN. En el presente trabajo se expone una aproximación conceptual y práctica a los Modelos de Ecuaciones Estructurales o *Structural Equation Modeling* (SEM). Los SEM están considerados entre las herramientas más potentes para el estudio de relaciones causales en datos no experimentales. Son una combinación del análisis

Palabras clave: Modelos de Ecuaciones Estructurales,

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factorial y la regresión múltiple y están compuestos por dos componentes: el *modelo de medida* y el *modelo estructural*. El *modelo de medida* describe la relación existente entre una serie de variables observables; mientras que en el *modelo estructural* se especifican las relaciones hipotetizadas entre las variables, es decir, se describen las relaciones entre las variables latentes mediante el uso de flechas. Llevar a cabo un SEM involucra cinco etapas: 1) *Especificación del Modelo*; 2) *Identificación del Modelo;* 3) *Estimación del Modelo*; 4) *Evaluación del Modelo* y 5) *Re-especificación del Modelo*. El presente artículo provee una serie de guías de "buenas prácticas" para realizar análisis SEM, con ejemplos utilizando el programa AMOS.

AMOS, análisis factorial, regresión múltiple

RESUMO. Neste trabalho expõe-se uma aproximação conceitual e prática aos Modelos de Equações Estruturais ou *Structural Equation Modeling* (SEM). Os SEM estão considerados entre as ferramentas mais potentes para o estudo de relações causais em dados não experimentais. São uma combinação da análise fatorial e a regressão múltipla e têm dois componentes: o *modelo de medida* e o *modelo estrutural*. O *modelo de medida* descreve a relação existente entre uma série de variáveis observáveis; enquanto que no *modelo estrutural* especificam-se as relações hipotéticas entre as variáveis; ou seja, descrevem-se as relações entre as variáveis latentes através do uso de conjuntos. Realizar um SEM envolve cinco etapas: 1) *Especificação do modelo*; 2) *Identificação do modelo;* 3) *Estimativa do modelo*; 4) *Avaliação do Modelo* e 5) *Reespecificação do Modelo*. Este artigo fornece uma série de guias de "boas práticas" para realizar SEM com exemplos utilizando o programa AMOS.

Palavras-chave: Modelos de equações estruturais, AMOS, análise fatorial, regressão múltipla

Inferring the existence of a causal relationship from a correlation supposes a logical error. Covariation between two variables only indicates that changes in one variable (V_1) occur at the same time as changes in another variable (V_2). On the contrary, in a causal relationship it is assumed that every change in one of the variables (cause) necessarily provokes a variation on the other (effect). Thus, to infer that V_1 is the cause of V2, in addition to the *covariation* between them, it is necessary to establish the *direction* (if V_1 precedes a V_2) and the *isolation* of the relationship (discard alternative causes of the changes in V_2).

In experimental research it is possible to evaluate if one variable precedes the other by manipulating the independent variable and controlling the influence of alternative variables by means of experimental control (León & Montero, 2003). In non-experimental research however, it is not possible to guarantee the direction and isolation of a relationship, since neither manipulation nor experimental control exist. In addition to this, it should be considered that in the face of the covariance of two variables, different directions or types of causal relationships can be established.

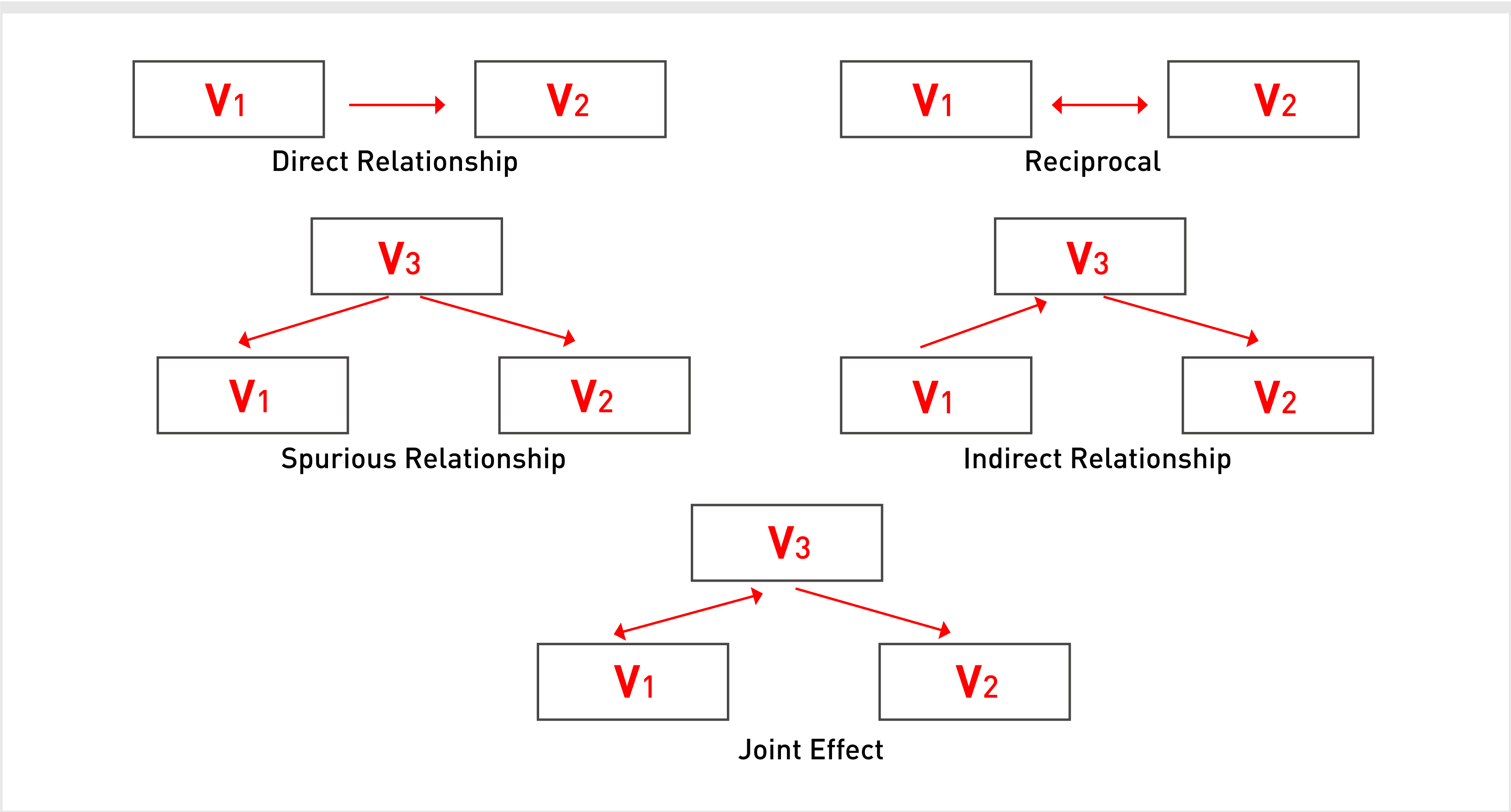


Figure 1. Possible causal relationships that provoke covariance between two variables. Adapted from *Modelos de Ecuaciones Estructurales* [*Structural Equation Modeling*] (p. 26) by J. M. Batista-Foguet & G. Coenders, 2000, Madrid: La Muralla. Copyright 2000 by Editorial La Muralla.

Facing this situation, one may ask: is it possible to analyze the existence of causal relationships in non-experimental designs? The answer is not simple and is not free of controversy. However, there is agreement in the scientific community in considering that Structural Equation Modeling (SEM) constitute the most powerful and adequate methodology to analyze the plausibility of a causal relationship, even when non-experimental designs are used. The key to this methodology consists of analyzing the viability of a causal direction and substituting experimental control with statistical control, thus allowing a pseudo-isolation of the variables in the study.

The number of scientific works that appeal to the use of SEM has grown steadily; however, an inadequate use of this methodology has also been observed (Jackson, Gillaspy & Purc-Stephenson, 2009). Different systematic reviews show recurrent problems in works with SEM; for example, not examining normality assumptions, not reporting all parameters involved, considering a single fit index or omitting information about the estimation method utilized (DiStefano & Hess, 2005; MacCallum & Austin's, 2000).

This article's objective is to present a conceptual and practical approach to SEM. While works on this analysis methodology abound in scientific literature (Bagozzi & Yi, 2011; Iacobucci, 2009; Martens & Haase, 2006), there are few articles in Spanish that offer a clear and simplified explanation to allow introducing this topic to non-specialized readers. In this manner, it is the intention to offer an approach to SEM centered more on the explanation of the underlying logic than in its mathematical foundation. Also, it will be attempted to describe in a simple and didactic manner the steps involved with the realization of SEM through the use of the AMOS program. From this we attempt to: (a) explain the conceptual and logical fundamentals of SEM, (b) describe the main steps of the method utilizing the AMOS software, and (c) offer a guide of good practices for reporting information from works utilizing SEM. We expect to offer readers a series of guidelines to direct the decision making process involved with SEM.

UNDERLYING LOGIC OF STRUCTURAL EQUATION MODELING

SEM are considered the most powerful tools for the study of causal relationships on non-experimental data (Aron & Aron, 2001). However, regardless of their sophistication, these models do not prove causality, they only allow to select relevant causal hypothesis and discard those not supported by empirical evidence. In this fashion and following a falsification principle, causal theories are susceptible to be statistically rejected if they contradict observed data.

Structural equation analysis starts from the following premise: covariances can provide information on causal relationships. Although the existence of covariances provide insufficient information since a multitude of possible effects exist that could provoke it (see Figure 1), it is considered possible to elucidate causality by using statistical control and effect selection guided by theoretical criteria. The underlying logic consists of decomposing the covariance among the variables to obtain information about the parameters of the underlying causal process. In this manner, utilizing decomposition rules and selecting possible sources of covariation, the relationship between parameters and covariances is established intuitively. For example, if a covariance is observed between anxiety (A) and social self-efficacy (SS), this relationship could be that anxiety influences social self-efficacy, social self-efficacy influences anxiety or that other variables are affecting the covariance between them (for example, a cognitive bias CB). Since many causal relationships exist that could explain the covariance between A and SS (see Figure 2), by means of theoretical criteria one of the possible causal nexus is elected. For example, a model that proposes that cognitive biases affect social self-efficacy and this increases anxiety.

It is important to emphasize that, while it is attractive to establish a causal relationship, analysis with SEM do not provide enough evidence to "demonstrate" the existence of a causal relationship. Regardless of their sophistication, analysis based on SEM are no other than estimations over cross-sectional data. Only experimental designs with control groups and random assignment provide enough guarantees to corroborate a causal relationship (Ruiz, Pardo, & San Martin, 2010). However, SEM designs do allow to "contrast" causal hypothesis, since if the model fit cannot be corroborated the causal hypothesis proposed can be discarded.

Once the possible causal relationship between the variables is selected, the parameters of the relationship are estimated considering the rules of decomposition of the variance and utilizing estimation methods (e.g., maximum likelihood).

Basically, two rules of decomposition exist: (1) the covariance between two variables is equal to the sum of direct, indirect, spurious and joint effects; and (2) the variance of a dependent variable is

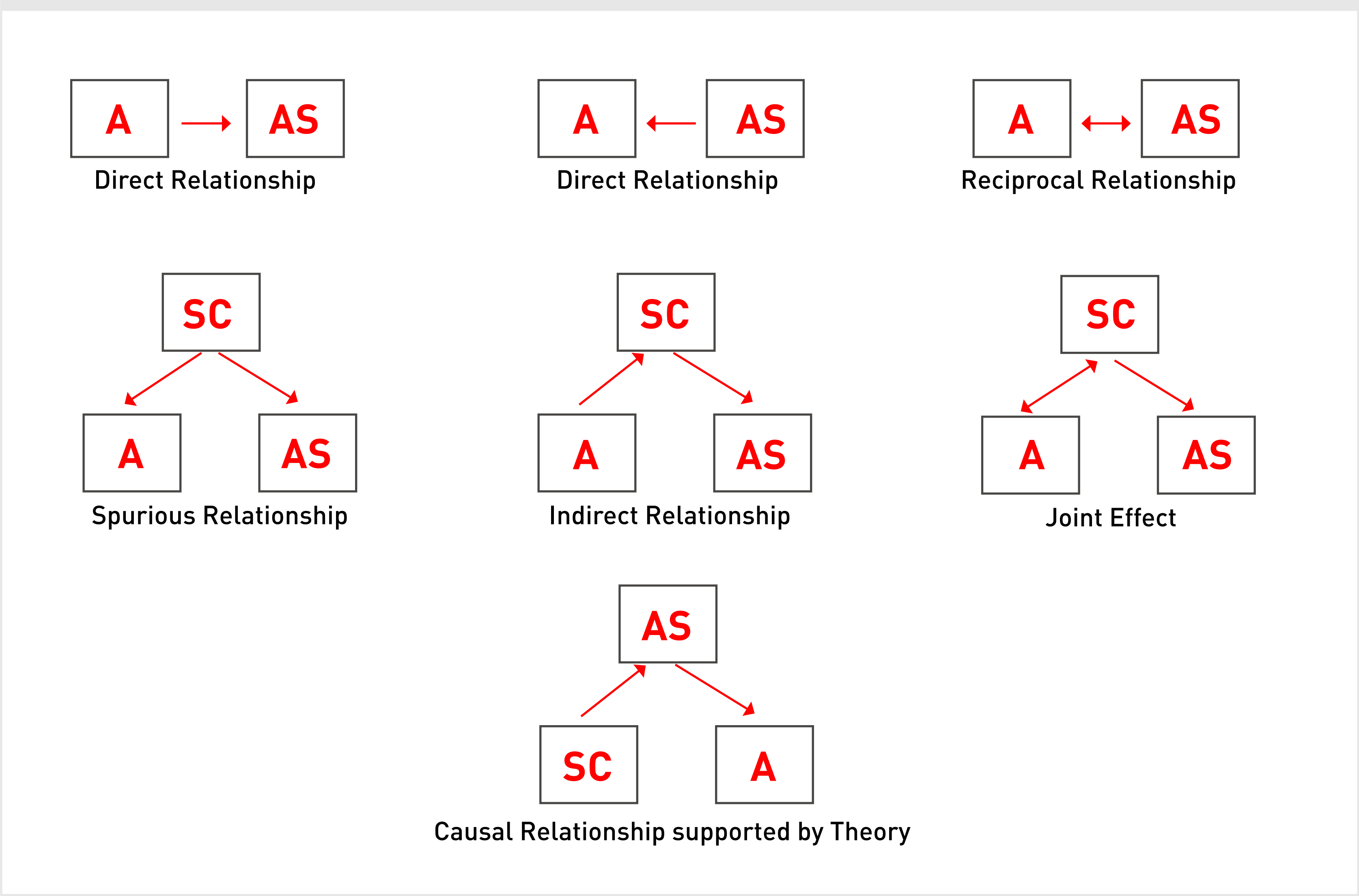


Figure 2. Possible causal relationships that provoke covariance between self-efficacy, anxiety and cognitive biases. Note: S: self-efficacy; SA: social anxiety; CB: cognitive biases

equal to the variance due to the perturbation, plus the variance explained by other variables of the model. By using those rules a structural equation system is constructed that expresses each element of the covariance matrix as a function of the parameters of the model. In other words, said equations impose a particular form or structure on the variance or covariance matrix of the population under study (Batista-Foguet & Coenders, 2000). The logic of SEM would be: *it is possible to derive the values of covariance expected between the variables from the causal effects specified in the model*. This way, if the causal model proposed is correct the expected and observed covariance values should be similar (Ruiz et al., 2010).

In general, it is preferable to utilize diagrams to represent theories involving many relationships, since the use of mathematical equations can make difficult the visualization of the causal process involved. To represent appropriately the equations using graphs, certain conventions should be paid attention to:

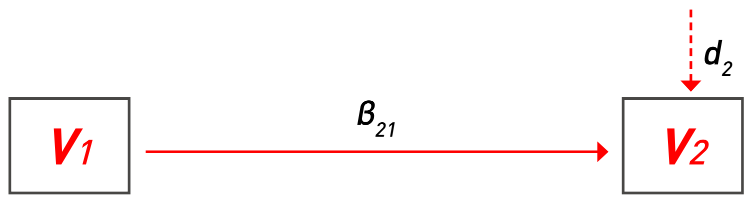
- *The causal relationship* between variables is indicated with an arrow whose direction indicates the direction of the relationship
- *The covariation* between variables, with no directional interpretation, is represented by a bi-directional arrow

- *Each arrow* represents a path coefficient that indicates the magnitude of the effect between both variables
- *Variables influenced* by others are called endogenous and those that are not reached by any arrow exogenous
- *Observable variables* are framed in squares and latent variables in circles.

For example, to represent a causal effect of V_1 on V_2, an equation of the type below can be used:

$$V_2 = \beta_{21} \cdot V_1 + d_2$$

Where d_2 represents a random perturbation (d*isturbance*) or variation of V2 due to causes other than V_1. This same equation can be represented graphically in a path diagram as follows:



Once the set of equations or diagrams is ready, for each path a coefficient similar to the regression coefficient is calculated, which indicate to what extent changes to one variable are related to changes on another variable (Aron & Aron, 2001). Up to here, the process is similar enough to a multiple regression analysis. However, analysis based on SEM have two additional advantages: (1) allows to work with latent variables and includes the specific measurement error of the construct, and (2) allows evaluating the concordance between data estimated by the model and data observed by using fit indices and, in this manner, test the causal model postulated.

COMPONENTS OF SEM: MEASUREMENT MODEL AND STRUCTURAL MODEL

It is possible to think of SEM as a combination of factorial analysis and multiple regression, which leads to differentiating two concepts: measurement model and structural model. In the *structural model* hypothesized relationships between variables are specified, i.e., relationships between latent variables are described with arrows. For example, in the model presented in Figure 3, factors 1 and 2 influence directly on factor 3 and, in turn, factor 2 exerts an indirect effect on factor 3 through factor 1. On the other hand, the *measurement model* describes the relationship existing between a series of observable variables (for example, self-efficacy scales that measure the same construct) and the hypothetically measured construct (Byrne, 2001). Both components are differentiated in Figure 3. The larger box contains the structural model, while the smaller boxes contain the measurement models.

In this manner, the main difference between SEM and multiple regression resides in the measurement model which evaluates how well observable variables (or indicators) combine to identify the hypothesized underlying construct. In this model, the confirmatory factor analysis is utilized to

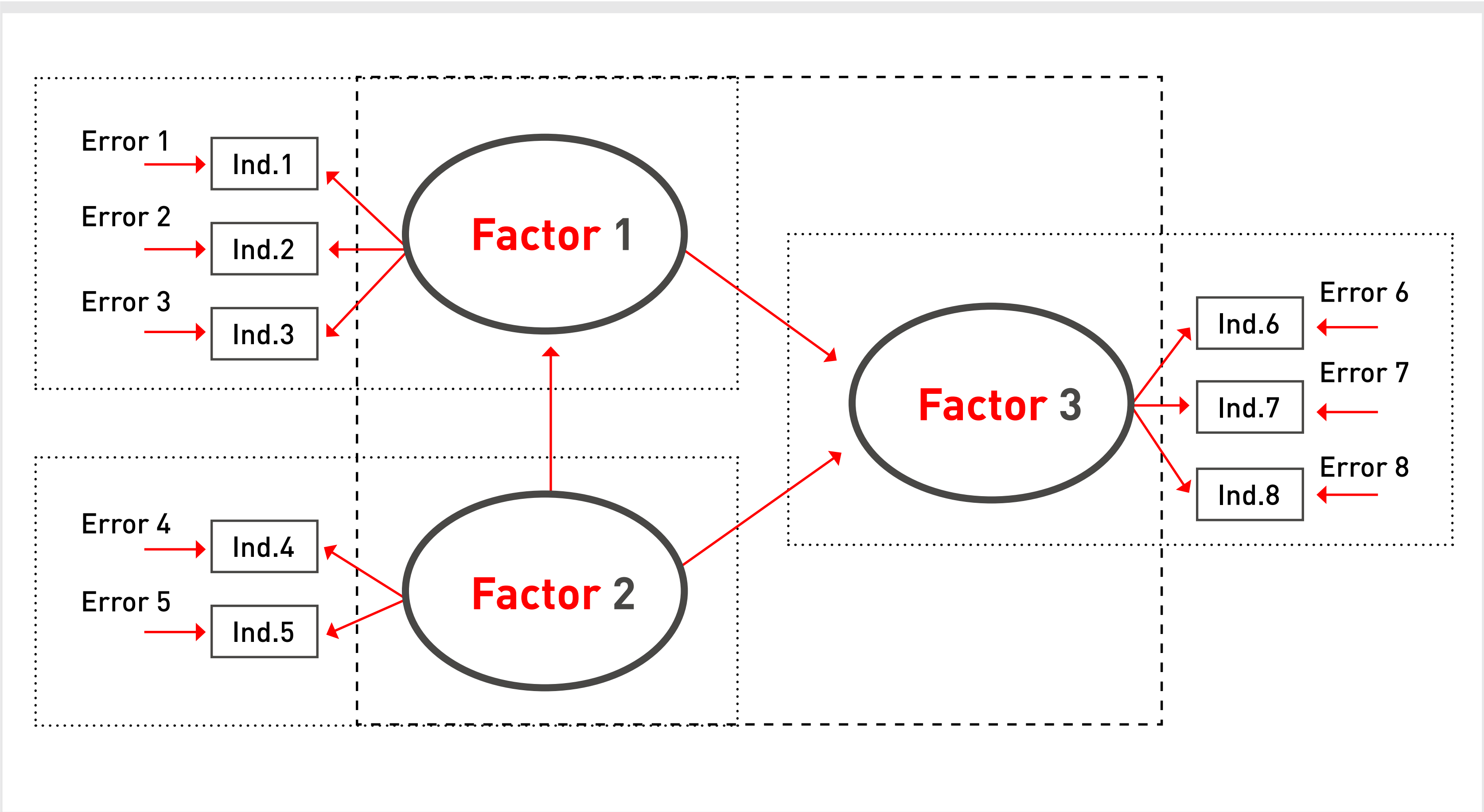


Figure 3. Components of a SEM, measurement model and structural model

verify if the selected indicators represent adequately the latent variable of interest (Weston & Gore, 2006). The literature recommends utilizing three indicators per factor, or else carry out a *path analysis* (Batista-Foguet & Coenders, 2000).

As pointed out before, a second advantage of SEM is the possibility of evaluating concordance of data estimated by the model with the observed data by using fit indices and, in this manner, test the causal model postulated. For this SEM is a very useful technique for developing conceptual models since it allows the testing of hypothetical models and through empirical contrast acquire new theoretical *insights* that refine the model specified initially. In turn, the use of theories well founded and supported by empirical evidence favor a better approach to reality. In this manner SEM could be conceptualized as a technique that intervenes in the back and forth process between the theoretical development and reality facts (Blalock, 1964).

FIVE STEPS TO CARRY OUT A SEM

Developing a SEM involves basically five stages (see Figure 4):

1. ***Specification of the model:*** In this stage the researcher establishes which are the variables to be included in the explanatory model and what is the relationship existing between them. This first stage depends mainly on the theoretical knowledge of the phenomenon to be addressed. A frequent error in this stage is not including in the model relevant variables or of theoretical importance; this is why before specifying a model a comprehensive review of the literature should

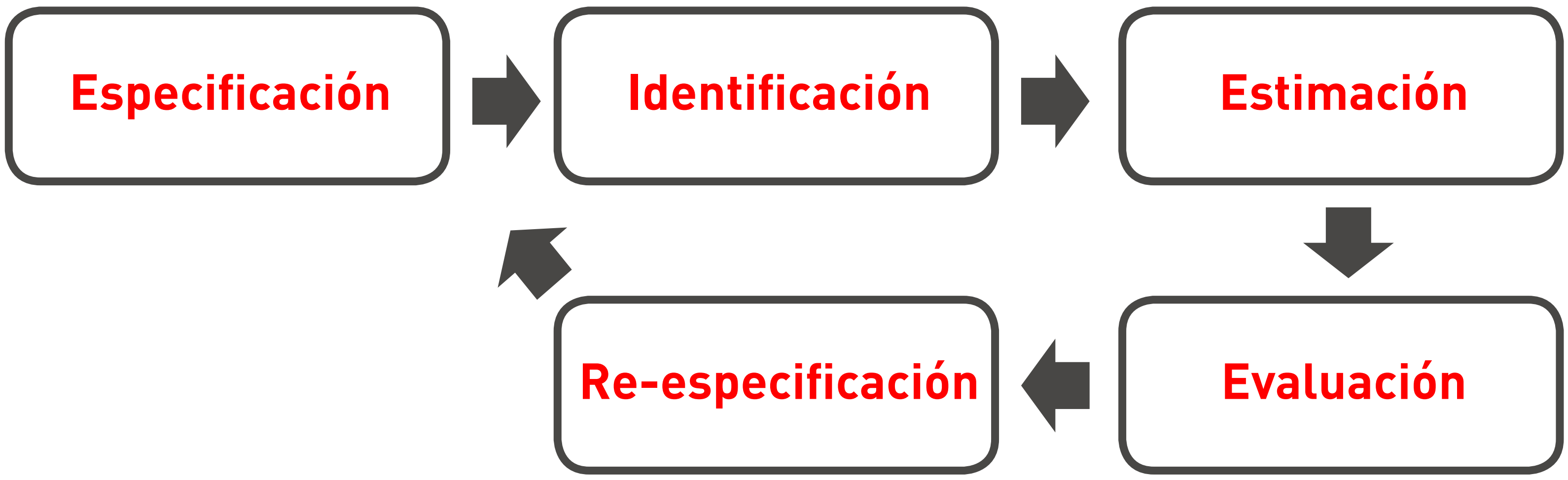


Figure 4. Stages to carry out a SEM

be performed. On the other hand, the mere inclusion of variables with no clear theoretical support also constitutes a specification error, since it could lead to developing less parsimonious models and of a low explanatory value.

2. ***Identification of the model:*** Before collecting data it must be determined if the model is identified correctly. This stage consists of examining if enough information is available to contrast the model. It is worth remembering that SEM is based on the estimation of covariances from the causal relationships specified in the model This implies that each parameter to be estimated should derive from the information contained in the variance-covariance matrix (Ruiz et al., 2010). To determine if the model is identified researchers should calculate the degrees of freedom (df), that are obtained by subtracting the number of parameters to be estimated from the number of known elements from the variance-covariance matrix. This is achieved with the following formula:

df= ½ x (No. of observed variables x (No. of observed variables + 1)) - No. of parameters to estimate

Depending on the values of df obtained, the model can be classified as under-identified ($df < 0$), identified ($df = 0$) or over-identified ($df > 0$). Only those models with a lesser number of parameters than variances and covariances in the observed matrix ($df > 0$) are susceptible to be estimated and contrasted. Additionally, the existence of degrees of freedom imply the simplicity of the model in the sense that it explains reality starting from a smaller number of parameters. This is because models with degrees of freedom impose restrictions in the space of possible covariance matrices. On the contrary, models with no df (under-identified or identified) by not imposing structure on the variance/covariance matrix observed, fit perfectly to any data set and therefore, can never be contrasted.

3. ***Estimation of the model:*** The estimation stage consists of obtaining the values of the parameters specified in the model from the variances and covariances of the sample. As mentioned at the

beginning of this article, with SEM it is possible to estimate a covariation from the decomposition of the covariance, i.e., the covariation could be estimated if the causal effects provoking it are specified correctly. The estimation process would consist of determining which would be the values that the parameters of the model should assume to obtain covariations similar to the covariances observed in the sample. Basically, the different methods of estimation that can be utilized share the same logic: obtain the value of the parameters (regression coefficients or error variance, for example) that maximize the equality between the covariances forecasted by the model and the ones observed in the sample. The differences between the different methods of estimation reside mainly in the "fit function" they utilize, that is, the method they utilize to minimize the differences with the covariances of the sample. The most common method for estimation is the *Maximum Likelihood* (ML) as long as the statistical assumptions are met, such as having a sample of an adequate size, measurements of at least interval level and multivariate normal distribution (Schermelleh-Engel, Moosbrugger, & Muller, 2003). However, this method is robust with slight deviations of the normal distribution (values of up to 70 in the coefficient *Mardia*; Rodríguez Ayán & Ruiz, 2008). In case of working with ordinal data or existing a larger distance from the normal distribution, it is suggested to transform the data, utilize *bootstrapping* methods or apply alternative estimation methods such as the Least Squares Estimation Method or the Asymptotic Distribution-Free (Flora & Curran, 2004), although the latter one requires larger sample sizes (of at least 4,000; Finch, West & MacKinnon, 1997) and have not shown a good performance (Hu, Bentler & Kano, 1992). As a general rule, the recommendation is to utilize ML (Iacobucci, 2010).

4. *Evaluation of the Model:* The objective of the evaluation of the fit is to determine if the relationships between the variables of the estimated model adequately reflect the relationships observed in the data (Weston & Gore, 2006). This clarification is important since in multiple regression the idea of "fit" refers to if the estimated model minimizes the prediction errors committed (least squares method). In SEM instead of evaluating the difference between the forecasted and observed values, the difference between the covariances observed in the sample and the ones forecasted by the specified model are evaluated (Ruiz et al., 2010). There are three types of statistics for goodness of fit: (a) of absolute fit (chi square for instance) that do not utilize an alternative model to contrast but directly analyze the fit between the observed covariance matrix and the one produced by the estimation method; (b) of *relative fit* that compare the fit with respect to another model (CFI, for example); and (c) *of parsimonious* fit (NFI, for example) that value the fit with respect to the number of parameters utilized. None of these fit statistics carry all the information necessary to value the model, for which the recommendation is to utilize several fit indicators. In a review performed by Jackson et al. (2009), it was observed that the most utilized indices in the specialized literature were the Comparative Fit Index (CFI), Non-normed Fit Index (TLI), the root mean square error of approximation (RMSEA) and the goodness of fit index (GFI).

The critical values utilized to evaluate the fit of a model have changed over time. For example, for the CFI index, Bentler and Bonett (1980) recommended a cut off point of .90; later Hu and Bentler (1999) raised that value to .95 and even some authors suggested a cut off point of .97 (Schermelleh-Engel et al., 2003). Probably the most utilized cut off points to evaluate fit indices are the ones proposed by Hu and Bentler (1999), considered by many researchers as the "bible" of cut off points (Barrett, 2007). Those authors recommend values greater than .95 for the CFI, TLI and GFI indices to consider an optimal fit and greater than .90 for an acceptable fit. On the other hand, values under .06 for RMSEA are considered optimal and under .08 acceptable. However, some researchers have criticized the adoption of limits so strict (Barrett, 2007; Marsh, Hau & Wen, 2004; Yuan, 2005) and others have proposed an intermediate position, recognizing the usefulness of those cut off points, but recommending their utilization with caution or contemplating the size of the sample involved (Bentler, 2007; Miles & Shevlin, 2007; Sivo, Fan, Witta & Willse, 2006).

Chi square (x^2) is a fundamental measurement to value the global fit of the model and is the only index that has an associated statistical significance test. In the case of not obtaining statistically significant results (p values greater than .05) the null hypothesis of equality between the observed and estimated covariance matrices is accepted. However, this index presents some difficulties. Firstly, the values of x^2 tend to decrease as parameters are added to the model. The values of x^2 tend to be lower in more complex models than in simpler models due to the reduction of degrees of freedom (Hooper, Coagulant & Mullen, 2008). Secondly, when the size of the sample is larger and maintaining constant the degrees of freedom, the values of x^2 tend to increase. This means that the larger the size of the sample the worst the fit. That is, even slight differences between matrices will generate statistically significant values ($p < .05$). For this the utilization of x^2 as a statistical test is not recommended but simply as a descriptive measure of fitness. An alternative version that allows to weigh the sample size is the division of the x^2 coefficient by the degrees of freedom (x^2/df). According to the literature, values under 3 indicate a good fit (Iacobucci, 2010; Kline, 2005).

On the other hand, the x^2 coefficient results particularly useful when rival models must be compared. In this way, if we are in the presence of two theoretical models that present an acceptable fit, we must lean towards the one with the lowest x^2 values. In addition to x^2, it is usual to resort to alternative indices or criteria such as the Aikake Information Criterion (AIC). This index fits the statistic chi-square to the number of degrees of freedom of the model. Lower AIC values for a model indicate a relative better fit with respect to alternative models.

Finally, remains pointing out that the evaluation of a model is not restricted to the examination of the fitting indices but should be analyzed also the magnitude of the estimated parameters and the variance explained by the variables.

5. ***Re-specification of the model:*** The analysis of the model fit does not end with the examination of the fit indices. A detailed analysis of residuals allows to detect unnoticed problems in the global diagnosis and suggest possible modifications to the model to improve it. In this manner, high residuals between pairs of variables imply the need to introduce additional parameters susceptible to explain the relationship between the variables in question. From the inspection of said residuals it is possible to do re-specifications in the model to improve its fit. It is important that decisions to add or eliminate parameters are coherent with the underlying theory of the model.

An inspection of the modification indices usually results very useful in this stage. The value of the modification value corresponds approximately to the reduction in x^2 obtained if the coefficient were estimated. A value > 3.84 suggests that a statistically significant reduction is obtained in ^{2} when the coefficient is estimated. It is important not to do re-specifications that cannot be supported at a theoretical level. Otherwise, a model fitted to the sample of the study will be derived but of poor theoretical foundation.

Although analysis through SEM can be synthesized roughly in these five stages, it is convenient to consider some additional aspects. One important aspect is the size of the sample. According to Barrett (2007) the size of the sample cannot be less than 200 and other authors even suggest values greater than 400 when utilizing maximum likelihood as an estimation method (Boomsma & Hoogland, 2001; Schermelleh-Engel et al., 2003). However, it is also proposed the possibility of reaching a good fit despite having a sample size smaller than 200 (Hayduk et al., 2007; Markland, 2007). Although a large sample size is desirable because increases the power of the tests, it should be recognized that there are other factors that could affect the power, for example, to have small measurement errors or to work with observable variables with small single variances and a larger shared variance (Browne, MacCallum, Kim, Andersen & Glaser, 2002). As a general rule it can be said that having large samples is always better, but if the model is simple, has clean measurements (items with high factorial loads and reliable factors) and has strong effects, smaller samples can be used (Bollen, 1990; Iacobucci, 2010).

Another aspect to consider is working with variables that do not present a normal distribution. As mentioned before, in the context of SEM is usual the assumption of a multivariate normality. It is important to remember that the sample distribution of a statistic is key each time a statistical inference process is carried out. For example, to estimate a confidence interval we should know the parameter (it can be obtained from sample data) and have an estimation of the typical error (which depends of the sample distribution in question). Some statistical procedures perform inferences assuming that the data is distributed normally. For example, Sobel's test, used to evaluate the statistical significance of indirect effects, assumes normality. This means that the non-fulfilment of that assumption can lessen control of error type 1 (Preacher & Hayes, 2008).

In this scenario, have become popular data re-sampling methods, among which are the *Jackknife* and the *bootstrap*. The underlying logic of these methods is to extract a large number of repeated samples with replacement from the observed data (Ledesma, 2008). The advantage of these procedures is that they allow to estimate these properties, approaching empirically the sample distribution of the statistic in question, that is, without the usual normality assumptions (Enders, 2005). In simple terms, *bootstrap* consists of creating a large number of sub-samples with replacement from the same data (one thousand samples for example) and, subsequently, calculate for each resulting sample the value of the statistic in question. It is thus obtained an approximation to the sample distribution of the statistic, from which we can perform inferences (for example, build a confidence interval). In this manner it is possible to dispense with assumptions relative to distributions, since instead to assuming a priori a specific theoretical distribution, *bootstrap* generates an empirical distribution from re-sampling. In this manner the stability of the parameters estimated can be examined and these values reported with a higher level of precision (Byrne, 2001). This methodology has demonstrated being efficient in a large variety of situations (for example, correlation and regression analysis) and, in particular, in analysis based on SEM (Fan, 2003). In the following section the five stages described to carry out SEM will be presented as well as the utilization of *bootstrap* with the AMOS program.

THE FIVE STEPS OF SEM USING THE AMOS PROGRAM.

Analysis based on SEM can be carried out with different programs. In 1973, Jöreskog developed the program LISREL (Linear Structural Relations), being this the first software that would allow to perform SEM (Ruiz et al., 2010). Another program used traditionally is EQS (abbreviation for Equations) developed by Bentler (1985). Both programs are highly utilized but require the use of syntax which may be problematic for new users. As an alternative, Arbuckle (1997) developed AMOS (Analysis of Moment Structures) which has a graphical environment which is friendlier, although it also allows specifying models using syntax. Next, the use of SEM in five steps in shown using the graphical interface of AMOS.

To illustrate the use of AMOS an example of an investigation will be used, in which it was evaluated if the stress perceived and the cognitive processes of rumination and catastrophizing predicted the levels of anxiety of one person. In this model it is proposed that when facing a stressful situation, automatically the cognitive processes of rumination (a tendency to dwell on negative thoughts and excessive worries) and catastrophizing (tendency to exaggerate or amplify the negative consequences of an event) are triggered, which increases anxiety levels and perpetuate them (Medrano, Muñoz & Cano-Vindel, 2016). After administering a series of instruments to a sample of 386 participants, analysis with SEM will be performed using AMOS 20.

1. ***Estimation of the model with AMOS:*** The specification of models with the program AMOS is simpler than with other programs (for example, LISREL). This is because AMOS allows the use of a graphical interface to specify the hypothesized relationships between the variables in question. For this, the model should be represented using the tools that appear in the program dashboard. It is important to represent appropriately the equations, keeping in mind conventions about the use of graphs, which were presented at the beginning of this article (see Figure 5).

2. ***Identification of the model with AMOS:*** To verify if the model has enough degrees of freedom to be estimated and contrasted, it is enough to click on the menu *Analyze/Degrees of freedom*. Immediately a window is displayed that informs the number of degrees of freedom of the model. In this case, the model has 31 degrees of freedom (see Figure 6).

3. ***Estimation of the model with AMOS:*** The AMOS program presents by default the maximum likelihood method; however, in case we wish to use another method, this can be selected by clicking on the icon *Analysis properties* and subsequently choosing the estimation method considered most appropriate. Once the method is selected, the program should be requested

to perform the estimation of the model by clicking on *Analyze/Calculates* Estimates (see Figure 7). In this example, the maximum likelihood estimation method was used. In the same dialogue box, the information one desires to obtain can be selected in *Output*. In the case of the example (see Figure 7), it was requested from the program the standardized regression coefficients, the coefficients of determination (R^2), the indirect, direct and total effects, the modification indices and information relative to multivariate normality and atypical cases.

4. ***Evaluation of the model with AMOS:*** To evaluate the fit of the model, one should click on "*Model Fit*" and inspect the values obtained for the fit indices (see Figure 8). Some of the fit indices obtained for this model were: CFI=.88; GFI=.95; RMSEA=.06. The standardized regression coefficients should also be examined to corroborate the hypothesized relationships in the model.

5. ***Re-specification of the model with AMOS:*** In this stage it is useful to inspect the indices of modification. This information should be requested since AMOS does not include it by default. For this, the icon *Analysis Properties* should be selected and click on the tab "*Output*". There the user can select the displaying of additional information. In this case, one should select: "*Modification indices*". As explained this information is helpful for generating modifications in the model. However, it is very important to be cautious and not to include parameters without a clear theoretical support. Otherwise the model starts losing theoretical value.

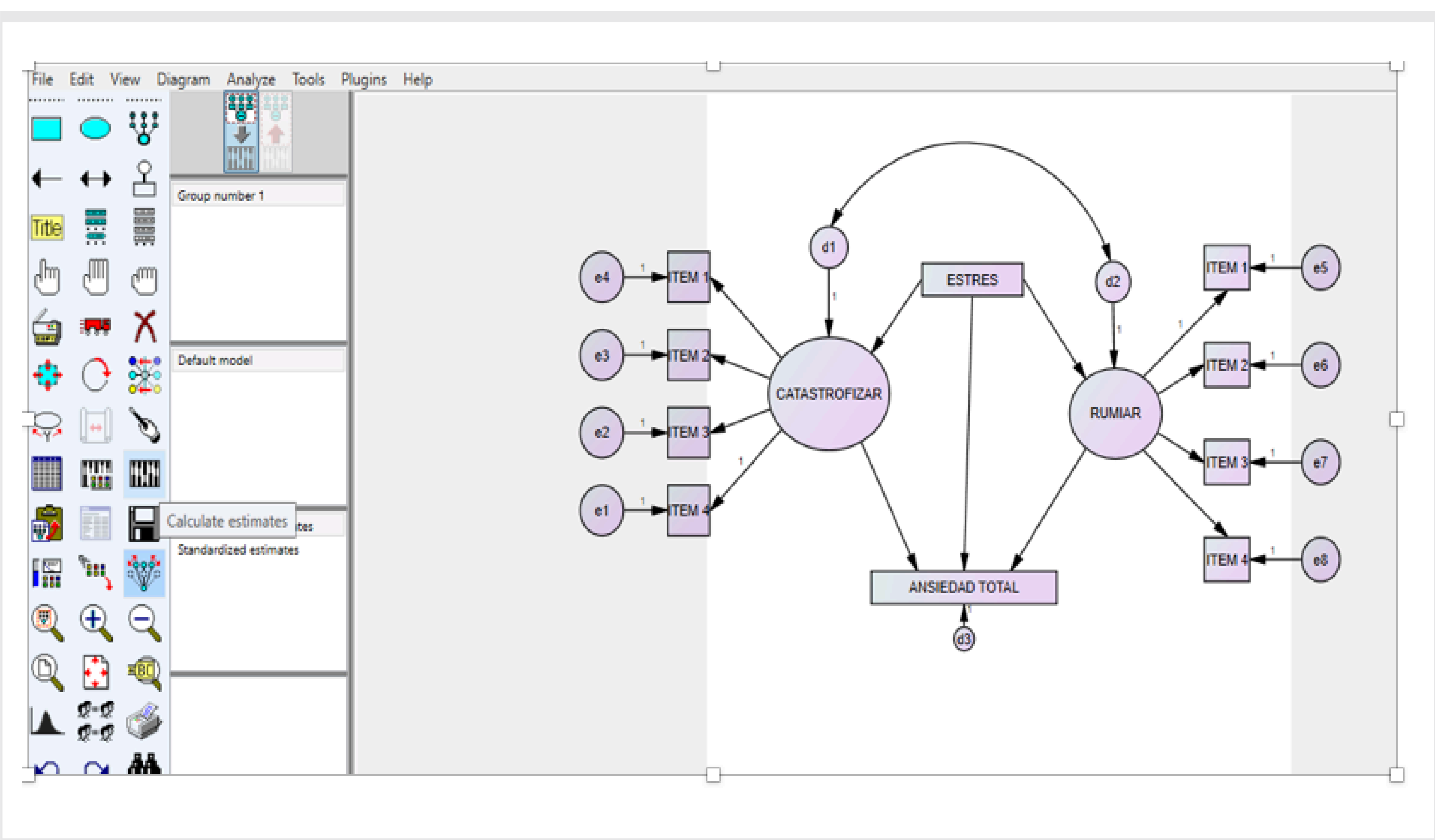


Figure 5. Screen capture of the AMOS program

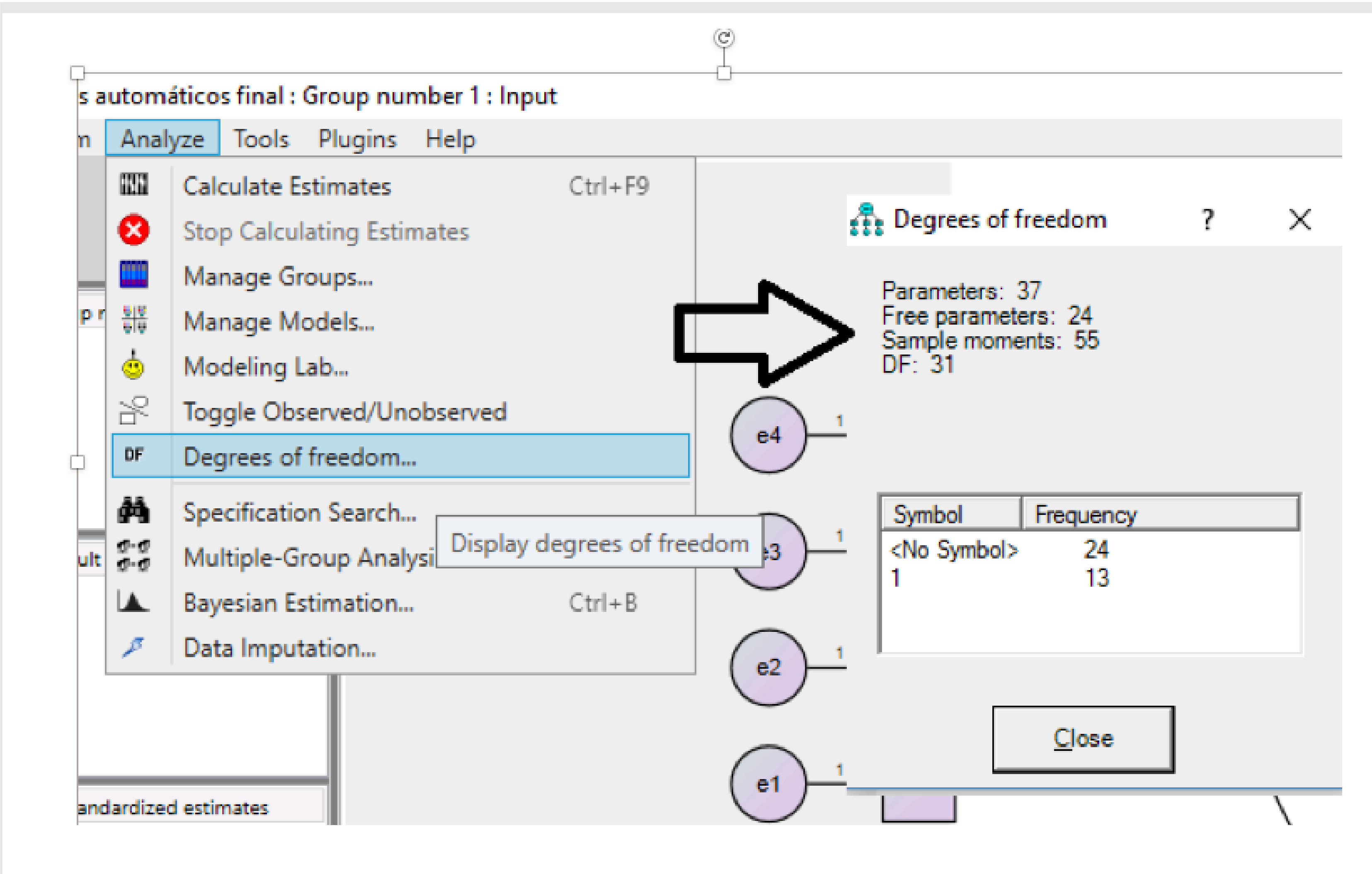


Figure 6. Illustration of the step Identification of the Model.

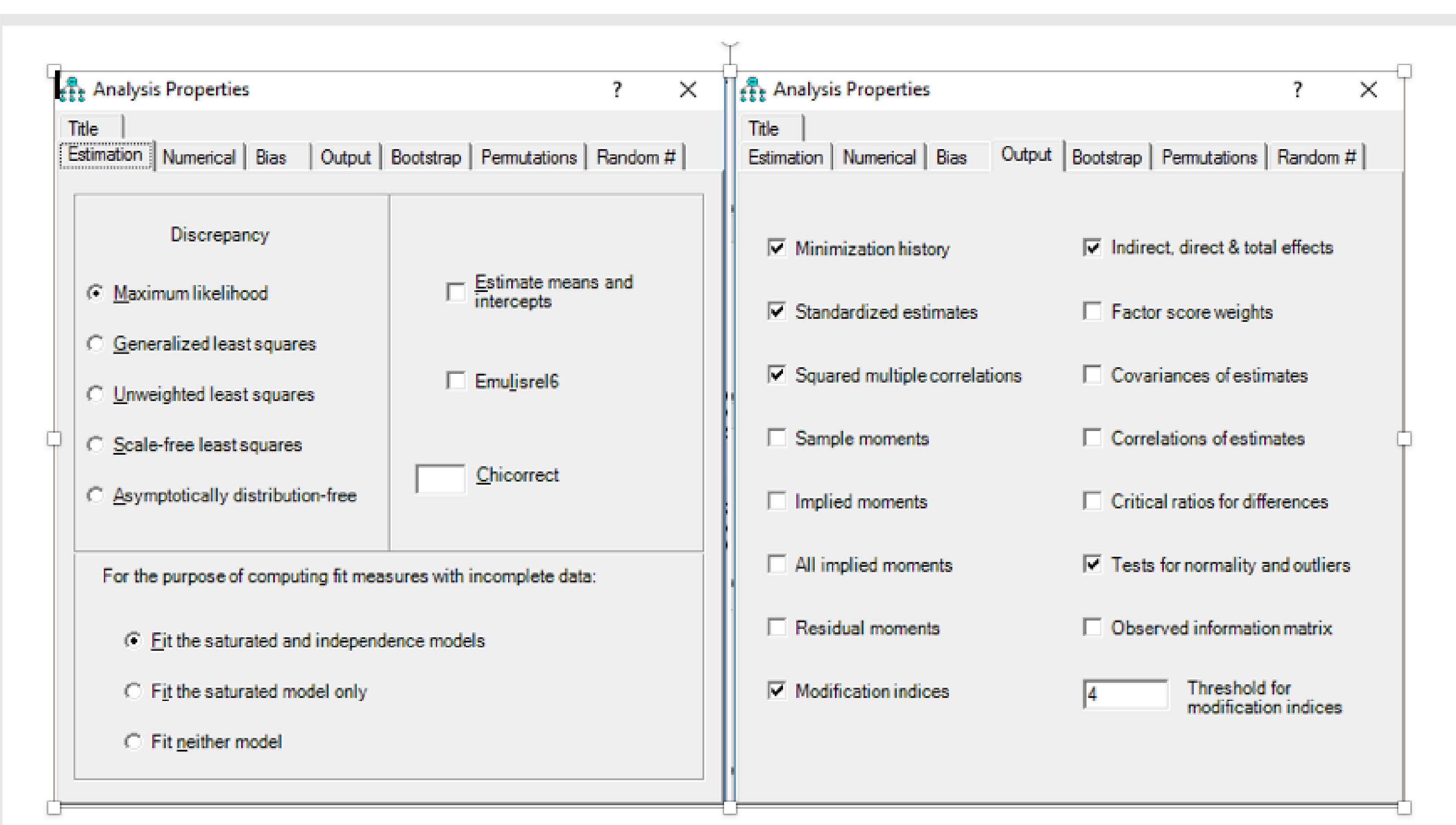
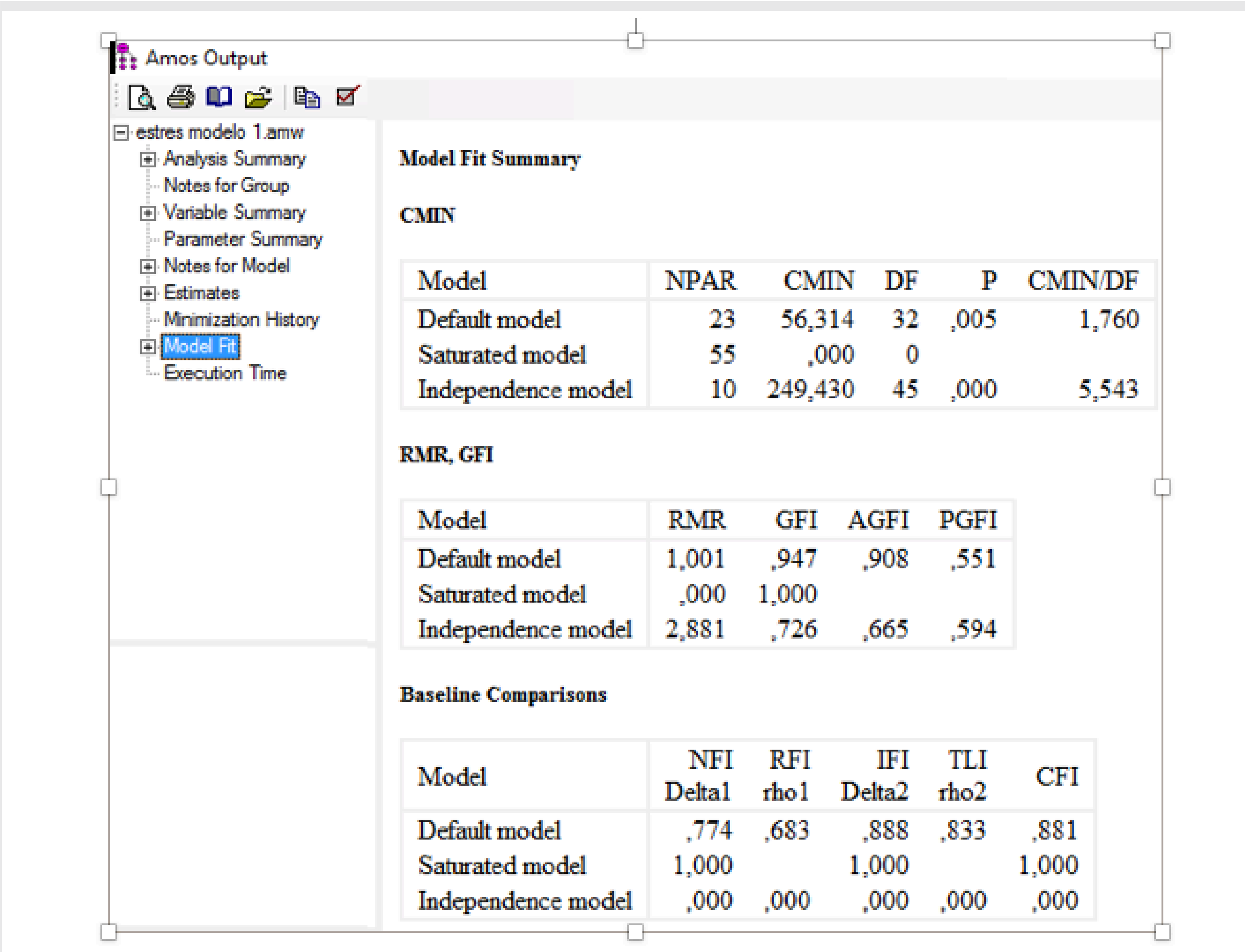


Figure 7. Illustration of the Estimation stage



Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	23	56,314	32	,005	1,760
Saturated model	55	,000	0		
Independence model	10	249,430	45	,000	5,543

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	1,001	,947	,908	,551
Saturated model	,000	1,000		
Independence model	2,881	,726	,665	,594

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,774	,683	,888	,833	,881
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Figure 8. Illustration of the fit evaluation stage

As previously mentioned, working with non-normal distributions may affect markedly the analysis with SEM, above all when maximum likelihood is used, because this estimation method is based on the assumption of a multivariate normality. Although this method is robust at non-fulfilment of normality (works adequately even with Mardia values of 70, Rodríguez Ayán & Ruiz, 2008),the recommendation is to complement the analysis with *Bootstrap* when the distance from normality is greater. For this, in the dialogue box in figure 7 the option *Bootstrap*, should be selected; subsequently, the number of samples to be used for re-sampling and the desired confidence interval should be specified. The literature recommends utilizing between 500 and 1000 replications of *bootstrap* (Cheung & Lau, 2008) and confidence intervals corrected at 90% (Bias-corrected confidence intervals). Another option available is to use the Bollen-Stine approximation to evaluate the absolute fit of the model. This approximation serves as an alternative to the traditional x^2 and its interpretation is simple since it considers that the model has an acceptable fit if the p values obtained are greater than .05. However, although it is an interesting complement, the Bollen-Stine option is highly sensitive for which significant p values will be obtained even when facing slight differences between the matrices (Byrne, 2001). This is why multiple fit indices should also be analyzed when the *bootstrap* methodology is used.

GOOD PRACTICES IN THE SEM REPORT.

One important aspect of good practices when using SEM refers to the information that should be reported when works that use this methodology are published. Good practices in information reporting are key to science progress. In fact, all the necessary information should be provided for the reader to understand the decisions made by researchers and analyze the robustness of the results. To report adequately is even more important when two studies reach different conclusions about the same topic. In these cases is of particular importance to evaluate whether the differences observed are not attributable to methodological aspects.

Although there are no universal criteria as to how to report the information in a SEM study, a widespread agreement exists with regards to the following items (Jackson et al., 2009):

1- *Theoretical foundation and data collection:* authors should justify clearly all the parameters specified in the model. Before reporting results, solid theoretical arguments should be presented that explain the model formulated and, if possible, present also rival models that may prove interesting. Also, the selection of tools used should be justified as well as the adequacy of the sample size.

2- *Data preparation:* the examination of statistical assumptions should be reported, for example the multivariate normality. Another aspect to point out is the treatment of lost values, for example, explaining if a data imputation method was utilized or if the option was a *listwise* deletion strategy, which is usually the most used (McKnight, McKnight, Sidani, & Figueredo, 2007). It is also recommended to specify criteria for the detection and treatment of atypical cases, indicate if a transformation method was used in the case of non-fulfilment of normality and the criteria for item parcelling in case that methodology is used (for a deeper discussion of this point see Little, Cunningham, Shahar & Widaman, 2002)

3- *Decisions regarding the analysis:* once the data are prepared, researchers face two important decisions: which data matrix and which estimation method to use? Most investigations utilize the variance-covariance matrix and the maximum likelihood estimation method, but, even so, it is always important to make both aspects explicit. On the other hand, in some cases it may be advantageous to use an alternative option. For example, use least square method in case of non-fulfilment or an approach based in the re-sampling of data, especially if working with small samples or the normality assumption is not fulfilled. It is also important to indicate which is the software used to carry out the analysis.

4- *Evaluation and modification of the model:* criteria should be made explicit to determine the cut off points and the selection of fit indices. In addition to reporting fit indices it is suggested to analyze standardized residuals to evaluate with greater precision the functioning of the specified parameters. Re-specifications in the model should not be done only in consideration of the modification indices. It should be made explicit the theoretical reasons that justify the inclusion of new parameters or modifications with respect to the original model.

5- *Reporting of findings:* analysis based on SEM generate a great volume of information, for which it is recommended to discern carefully when deciding which information to communicate. It should be avoided the inclusion of unnecessary statistical results or that contribute little to the understanding of the work. More concretely, it is recommended to report the estimation parameters (factor saturation and standardized path coefficients), the variance of exogenous variables and proportion of the variance explained by endogenous variables, In case of contrasting rival models, it should be clearly communicated which is the model chosen by the author and support the decision not only by the fit of the model but also by its theoretical implications.

CONCLUSIONS

Analysis based on SEM are currently the analysis strategy preferred by researchers for non-experimental data. However, there are few works in Spanish that offer an approach to them centered in conceptual and logical aspects, allowing the introduction of SEM analysis to the non-specialized reader.

In this methodological article the conceptual and logical foundation of structural equation modelling were examined and its use was illustrated with the AMOS program. It is important to point out this article is of an introductory nature and does not replace more profound literature on the topic. However, it is expected it to be an interesting and relevant work for the non-specialized reader. It offers an adequate framework to orient the decision making process involved with SEM. In this manner, it is expected to contribute to the development of research that utilizes this methodology in the Latin American region.

SEM is a very useful technique for developing conceptual models since it allows the testing of hypothetical models and through empirical contrast acquire new theoretical *insights* that refine the model specified initially. In this manner SEM could be conceptualized as a technique that intervenes in the back and forth process between the theoretical development and reality facts (Blalock, 1964).

For many SEM constitutes the most powerful methodology when working with non-experimental data (Aron & Aron, 2001); however, it should highlighted that the power and usefulness of this methodology depends mainly on having an adequate theoretical baseline model. Regretfully, it is frequently observed an inadequate use of this procedure, by including or removing parameters in order to improve the fitting of the model. This work modality with SEM is strongly under discussion, since the soundness of the model will not come only from its statistical fit but also from its theoretical coherence.

In this respect it is worth pointing out some of the suggestions that will allow for a sensible examination of models obtained through SEM. In this regard, it is worth considering the criteria communicated by Hawking and Mlodino (2010) to analyze if a model is satisfactory:

1) it is elegant,
2) contains few arbitrary or adjustable elements.
3) concurs with existing observations and provides an explanation for them,
4) realizes detailed predictions that will allow to refute or falsify the model.

The elegance of a model is not something that can be easily evaluated but is quite appreciated among scientists since it implies the absence of adjustable elements or post facto explanations. An example of lack of elegance would be to include new correlations or remove items or correlate errors only to improve the fitting of the model. This type of "corrections" force the model to fit to a specific set of observations, thus generating a "tailored" model and not a useful theory.

In general, the absence of elegance comes from the obstinate attempts to rescue a model that does not present a good fit. It is worth mentioning that is valid to introduce changes to improve the fitting or predictive value of the model, but only if these are technically grounded. On the contrary, generating cunning and poorly discussed alterations lead to an unintelligible model. These "over-manipulated" models are usually unstable and lose their good fit when replicated on another sample. This happens because the modification indices only indicate that new parameters can improve the fitting of the model to the covariance matrix of the sample of the study, but logically those parameters can result of little benefit in another sample. This is why it is recommended to re-specify parameters only when theoretical support exists and not follow only modification indices. Otherwise models with much fitting will be obtained for particular samples and little generalization power.

Related to this topic, it is worth mentioning the criticism of Hayduk et al. (2007) to the emphasis that some authors put of the fitting of SEM (Barrett, 2007). The objective of SEM is not to obtain model that fit well but to contrast theories. It should be recognized that in scientific literature many works can be found focused more on the *fit* than in the *theoretical model* that provides that fit. Regretfully, it is common practice among researchers to focus on the superficial analysis of statistical values and lose sight of substantial theoretical questions. As pointed out by Hayduk et al. (2007) *"to abandon the theoretical reasoning is to abandon the very essence of science"* (p. 842).

In addition to elegance, the existence of few arbitrary elements and the fitting of the model to the data, it is important to consider the predictive power of the model. Having true predictions implies that the model is formulated corrected, increasing its soundness. Another remarkable aspect is proposed by Barrett (2007), who suggests that many SEM models do not present observable variables anchored "in the real world". The absence of an external criterion may lead to many SEM models simply being a statistical model that explains the covariation between different theoretical constructs. In fact, many researchers build "blind" or "mechanical" models where one or more latent variables are "created" to explain the causal variations, without an external criterion to allow contrasting said model.

It is also important to highlight that even when a model presents a good fit, this does not discard that other models may exist that also have the same characteristic; it simply indicates that it is one of the models that potentially may present a good fit to the data. For this it is recommended to contrast different models that could also be endorsed by theory or even supported by a rival theory (Hayduk et al., 2007). Therefore, it is recommended to evaluate the fit of different models with the purpose of analyzing if others are equally plausible.

Another controversial aspect comes form Barnett's (2007, p. 820) statement "if the model fits, the researchers will proceed to inform and discuss the characteristics of the model". Facing this, the following question arises: Shouldn't researchers also publish and discuss models that do not present a good fit? In this sense, Hayduk et al. (2007) argues that the discussion about models that do not fit adequately is crucial to the scientific development of a discipline, since not recognizing openly the deficiencies of theoretical models in use may obstruct the passing to more adequate theories.

In contemporary psychological science many SEM models are observed that fulfil the aforementioned requirements. This allows scientists and professionals to have solid theoretical models that offer greater guarantees and support in the decision making process.

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