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STRUCTURAL EQUATION MODELING WITH LISREL: AN INITIAL VISION

ABSTRACT

LISREL is considered one of the most robust software packages for Structural Equation Modeling with covariance matrices, while it is also considered complex and difficult to use. In this special issue of the Brazilian Journal of Marketing, we aim to present the main functions of LISREL, its features and, through a didactic example, reduce the perceived difficulty of using it. We also provide helpful guidelines to properly using this technique.

Keywords: LISREL; Covariance Matrix; Structural Equation Modeling; Application of LISREL in Marketing.

MODELAGEM DE EQUAÇÕES ESTRUTURAIS COM LISREL: UMA VISÃO INICIAL

RESUMO

O LISREL é tido como um dos mais robustos softwares para modelagem de equações estruturais com matrizes de covariância, ao mesmo tempo em que é considerado um pacote estatístico complexo de difícil utilização. Neste número especial do Brazilian Journal of Marketing, buscamos apresentar as principais características do LISREL, suas funcionalidades e, por meio de um exemplo didático, reduzir a dificuldade percebida em seu uso.

Palavras-Chave: LISREL; Matriz de Covariância; Modelagem de Equações Estruturais; Aplicação de LISREL no Marketing.

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1 INTRODUCTION

Structural equation modeling (SEM) is a procedure for estimating a series of dependence relationships among a set of concepts or constructs represented by multiple measured variables and incorporated in to an integrated model. SEM is mainly used as a confirmatory, rather than exploratory, technique.

It is very important that a SEM model be based on a theory because all relationships must be specified before the SEM model can be estimated. A construct is an unobservable or latent variable that can be defined in conceptual terms but cannot be measured directly. Rather, a construct is measured approximately and indirectly by examining the consistency among multiple observed or measured variables. It is recommended that each construct be measured by using at least three observed variables.

The LISREL (***Li**near* ***S**tructural* ***Rel**ationships*) was developed in 1970 by Karl Gustav Jöreskog and Dag Sörbom, while they were researchers at the Educational Testing Services and Princeton University. Since LISREL's development, it has been recognized as one of the best solutions for the estimation of structural equation models for covariance matrices.

The creators of LISREL had the intention of developing comprehensive statistical software, which ran on a DOS operating system and provided independence from other statistical programs, and thus it is considered a difficult program to learn and apply. Due to this, several friendlier versions have been developed using the Windows environment and providing more simplified programming languages. However, many users, especially begginers, think that even the friendlier versions are still complex and difficult to use. A basic difficulty is learning the conventions adopted for the representation of variables and associations, due to the use of matrix algebra using Greek letters and symbols. Another difficulty is the understanding of the essential information that is provided by the outputs.

Assuming readers have a basic knowledge of SEM (Structural Equation Modeling), the aim of this work is summarized in a simple and didactic language: to explain the main features of LISREL and, at the same time, illustrate the benefits of its use in marketing research.

The article is structured in four parts, beyond this brief introduction. Section 1 presents a brief history of the conception of LISREL. In section 2, we present the main features of structural equation modeling using LISREL. The following section describes a practical application of LISREL to use the graphical interface of the program - the Path Diagram. The fourth section contains the concluding remarks.

1.1 Brief History of LISREL

In 1970, the Swiss statistician, Karl Gustav Jöreskog, PhD, along with his student Dag Sörbom, today also a teacher and PhD in Quantitative Applied Economics at Uppsala University, developed an algorithm to analyze structural models with latent variables. This algorithm, which is the basis of LISREL, resulted from background studies in which Jöreskog devised a reliable method for calculating maximum likelihood estimates for exploratory factorial analyzes and, in 1969, an algorithm for calculating the confirmatory factor analysis with the use of commands in Fortran programming language.

The first version of LISREL, still in DOS, had no graphical interface to facilitate the operationalization of structural equation modeling. The construction of computational logic was done using commands called LISREL syntax - also available in the current version.

In the versions after 1993, the user can choose the method by which to use the software for analysis of the model. Options include LISREL syntax, the Simplis syntax and the graphic interface Path Diagram.

Table 1 presents the development of the different versions of LISREL.

Table 1 – Versions of LISREL

YEAR	DEVELOPMENT OF LISREL
1970	Release of version I.
1972	Upgrade to version II, incorporating multi-group analysis.
1974	Upgrade to version III. In this year SSI (*Scientific Software International*) begins commercial distribution of LISREL
1978	Upgrade to version IV.
1981	Upgrade to version V.
1984	Upgrade to version VI.
1988	Upgrade to version 7, which is the first for *Windows* environment. Introduction of graphic interface *Path Diagram.*
1993	Upgrade to version 8 and introduction of SIMPLIS language.
1998	Upgrade to version 8.2.
1999	Upgrade to version 8.3.
2001	Upgrade to version 8.5.
2004	Upgrade to version 8.7.
2006	Upgrade to version 8.8.
2008	Upgrade to version 9.
2012	Upgrade to version 9.1, which is the latest version available.

2 USING OF LISREL

LISREL is commonly used for structural equation modeling for covariance matrices. It is, however, a rich statistical package in which it is possible to treat quantitative data using various techniques, such as exploratory and confirmatory factor analysis, linear regression, probit and logistic regressions, handling and processing of data, modeling multilevel structural equations, generalized linear models, multilevel linear models, multilevel generalized linear models, and nonlinear models, among others.

Due to the close relationship made between LISREL and structural equation modeling (SEM, from this point on), several authors have referred to structural models as "LISREL models", regardless of whether this software was used or not in the data analysis. The use of LISREL as a tool for SEM should be grounded on two characteristics of the data analysis strategy: 1) the type of matrix associations in data entry, and 2) desired parameters of the estimation technique.

For data entry, the researcher must decide between a correlation matrix and a covariance matrix. The majority of statistical theory that supported the development of SEM technique assumes that the analysis applies to a covariance matrix, and this is therefore the most natural form of data entry. Bentler *et al*. (2001) argue that the use of a correlation matrix results, in general, in incorrect estimates of standard errors. Moreover, the model covariance structure also has standard solutions and therefore also provides estimates of the correlations and *standard* effect at the end of the analysis. For the correlation analysis, according to Bentler *et al*. (2001), the performance of several consecutive linear regressions would be sufficient, but cannot be applied because the analysis of covariance, in these cases, would give power to the residual error. Even if Chin (1995) recommends the use of correlation matrices for analysis of complex theoretical models and models of formative measurement, Bagozzi and Yi (1988) argue that researchers in the psychology of consumption should choose the covariance matrices for all analyses.

Another key decision in choosing the LISREL is the choice of the estimation technique. The method of maximum likelihood estimation is used in most statistical programs and is more widespread in use (Anderson and Gerbing, 1988). The estimation produced by maximum likelihood is reliable and robust with respect to moderate violations of normality as long as the sample has at least 100 observations (Anderson and Gerbing, 1988). Although there are methods of estimation in LISREL that are not dependent on the assumption of normality of the data, such methods are of limited application because they require very large samples. For example, the weighted least squares method (Weighted Least Squares - WLS) requires a sample sized by the product of the manifest variables or indicators of the same model as this quantity multiplied by another - for example, a model of 50 manifest variables would require 2,550 respondents (n = 50 x 51 = 2,550). For the design of the minimum sample required to use LISREL, we recommend that researchers use the statistical calculator available in http://www.danielsoper.com/statcalc3/calc.aspx?id=89 (accessed March 12, 2014). In general, we recommend that SEM models with five or fewer constructs, each with more than three measured variables, should be estimated with sample sizes of at least 200. For more complex models, the sample size should be larger (Malhotra 2010).

There are several recommendations of steps for construction of structural models with LISREL. Some are slightly more complex (see Byrne, 1998) and others are simple (as in Diamontopoulos and Siguaw, 2000). Our choice for this article is a simplified and pragmatic approach, which facilitates initial learning and can be adapted to more complex situations. We suggest an approach in five phases as shown in Figure 1.

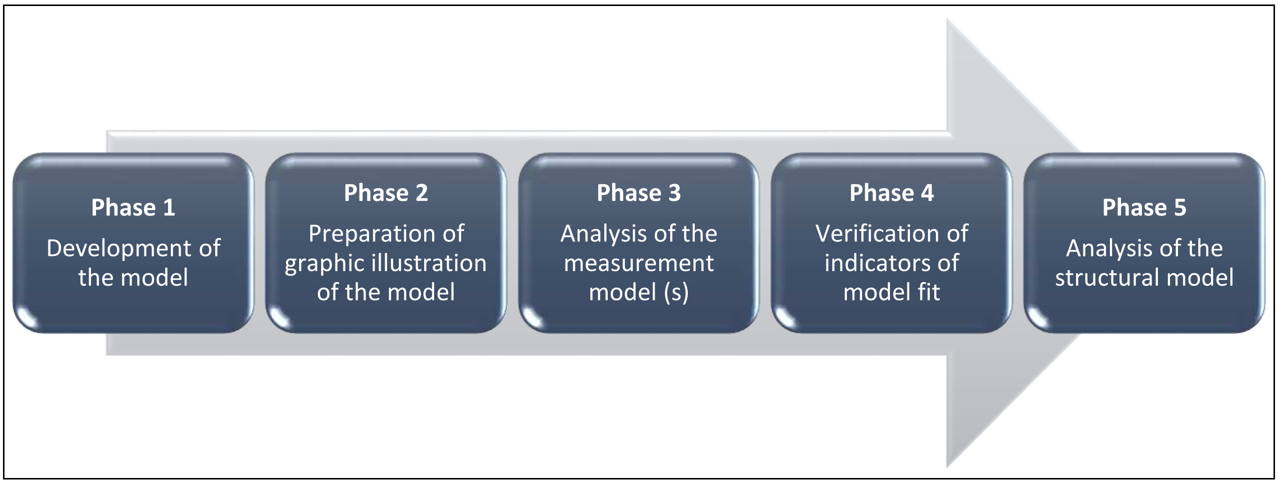

Figure 1 - Phases proposed for SEM with LISREL

Phase 1 (Development of the Model) is the stage in which the researcher elaborates the conceptual model - also called the theoretical model - supporting associations between constructs (or latent variables) and also between the manifest and latent variables. Each relationship between variables (covariance or effect) comes from a pre-existing hypothesis, because the models tested with SEM rely on theories whose consistency to empirical data is verified. For example, the effect of one latent variable on another presupposes the existence of a causal relationship and the test result indicates whether this relationship is plausible.

In Phase 2, the conceptual model is designed as a path diagram in which all relationships are represented. This phase is simple, yet important because it is through the graphical illustration that the researcher will introduce the variables in LISREL. For this phase the symbols presented in section 2.1 will be used.

2.1. Symbols and conventions used in the LISREL

The elements of structural models are symbolized the same way, regardless of the software you use for your analysis. Figure 2 shows how the elements are commonly represented.

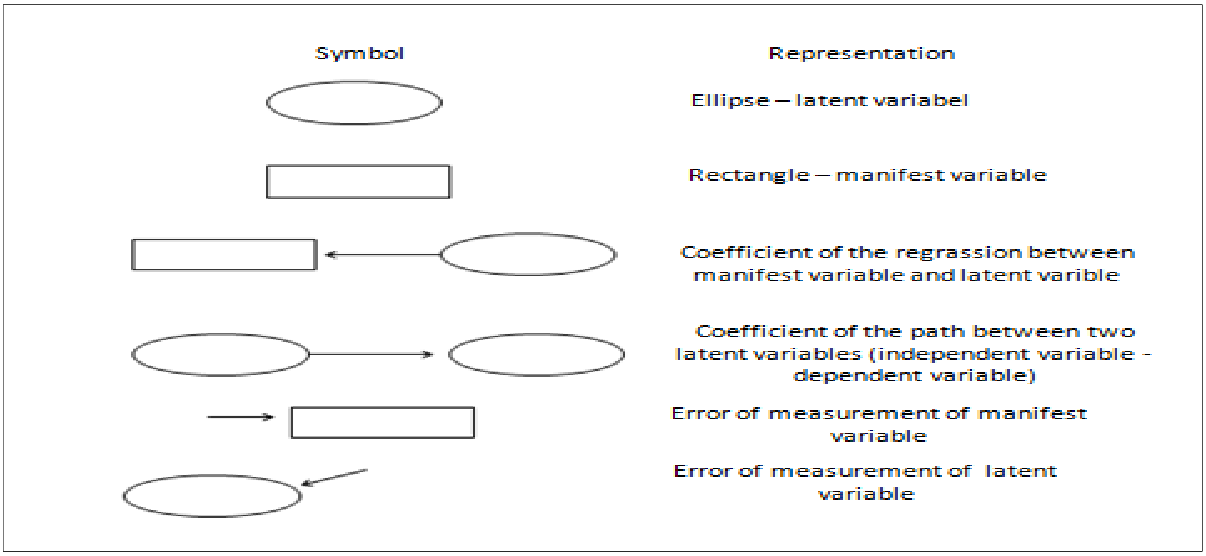

Figure 2 – Symbols of structural models.

Structural models treated in LISREL use a convention about their elements, and these matrices, in general, are represented by Greek letters (see Table 2).

Table 2 – Matrices of LISREL

ELEMENT	MATRIX	ELEMENT OF MATRIX	SOFTWARE CODE	TYPE OF MATRIX	CHARACTERISTICS
Measurement Model					
Lambda-x	Λ_x	λ_x	LX	Regression	Manifest variables to measure the exogenous latent variables
Lambda-y	Λ_y	λ_y	LY	Regression	Manifest variables to measure the endogenous latent variables
Theta delta	Θ_δ	θ_δ	TD	Covariance	Error associated with the exogenous manifest variables
Theta épsilon	Θ_ε	θ_ε	TE	Covariance	Error associated with the endogenous manifest variables
STRUCTURAL MODEL					
Gama	Γ	γ	GA	Regression	Coefficient of the relationship between an independent variable and a dependent variable of the model
Beta	B	β	BE	Regression	Coefficient of relationship between two dependent variables of the model
Phi	Φ	ϕ	PH	Covariance	Covariance between latent variables
Psi	Ψ	ψ	PS	Covariance	Covariance between manifest variables
Ksi	–	ξ	-	Vector	Exogenous latent variables
Eta	–	η	-	Vector	Endogenous latent variables
Zeta	–	ζ	-	Vector	Error associated with the measurement of the dependent variables of the model

To facilitate understanding of the representativeness of letters and matrices in Table 2 and the symbols shown in Figure 2, we show in Figure 3 a complete structural model.

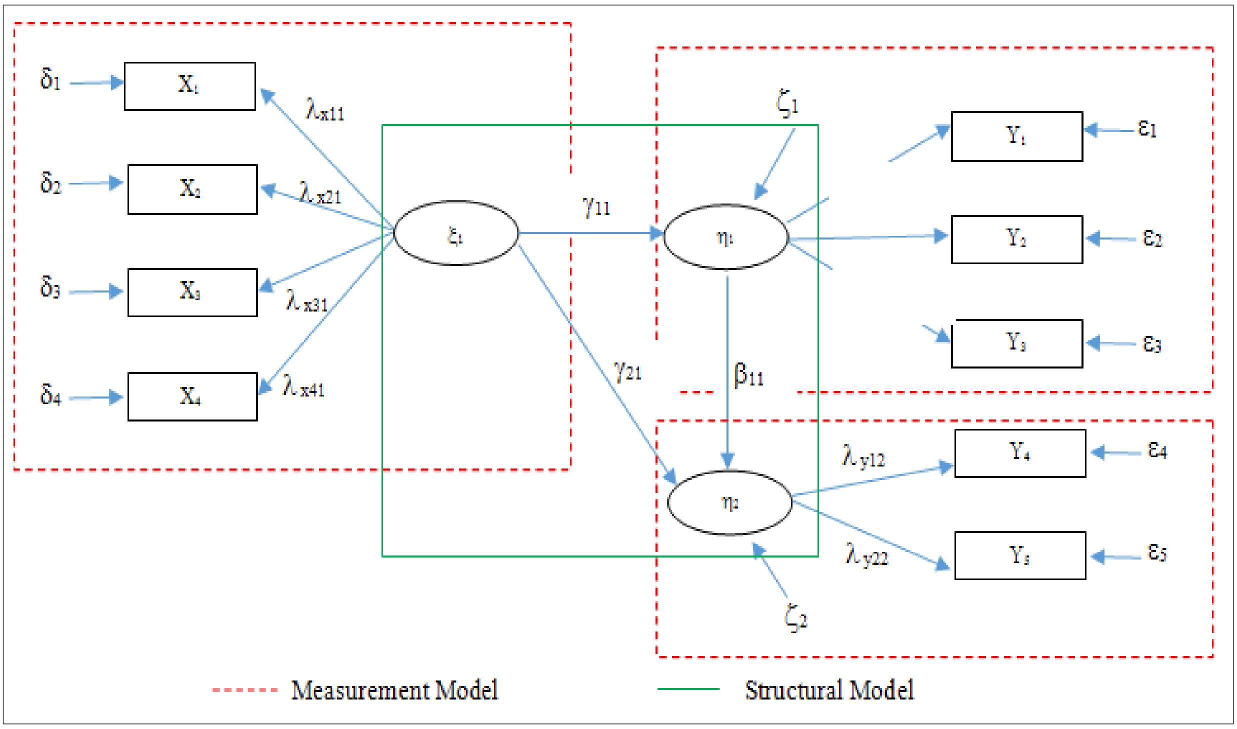

Figure 3 – Structural Model

Even beginners in quantitative data analysis conclude that it is not possible to analyze the data illustrated in Figure 3 by means of linear regression model, as there is more than one dependent variable (η_1 and η_2), plus there is a variable that is dependent and independent at the same time (η_1).

The SEM through LISREL allows simultaneous estimation of a series of separate, but interdependent, equations, incorporating in the calculations both latent variables and manifest variables and measurement error by checking the direct, indirect, and total relations, even though, in the model, there are variables that act as both dependent and independent variables. The model is statistically tested through simultaneous analysis of all matrices of variables, through which we could assess the quality of fit between the theorized model and the data used in the analysis and estimation of variance, and covariance effects between variables.

Phase 3 is the stage in which the researcher analyzes the model of measurement of the structural model. A structural model is composed of two sub-models (often called models for simplicity): (sub) measurement model (or measures) and (sub) structural model (or relationships between constructs).

Gerbin and Anderson (1988) recommended that the SEM is performed in two stages. At first, the researcher must analyze the models for measuring and verifying the convergent validity and discriminant validity of the constructs. Second, the researcher must, analyze the structural model, i.e., referring to the associations between the constructs (latent variables).

Gerbin and Anderson teach that convergent validity is demonstrated when loads of the manifest variables are above 0.60 (matrix Lambda -Λ_x and Λ_y). Discriminant validity is checked by examining the magnitude of the correlations between the latent variables of the model. The existence of discriminant validity is concluded when Phi (ϕ) (correlations between latent variables) matrices are lower (or at most equal) to 0.60. Figure 4 illustrates this analysis. Another measure that is used to assess convergent validity is the average variance extracted (AVE), which is defined as the variance in the indicators or observed variables that is explained by the latent construct. Cross-loadings indicate lack of distinctiveness and present potential problems in establishing discriminant validity. Discriminant validity is established by showing that the average variance extracted is greater than the square of the correlations.

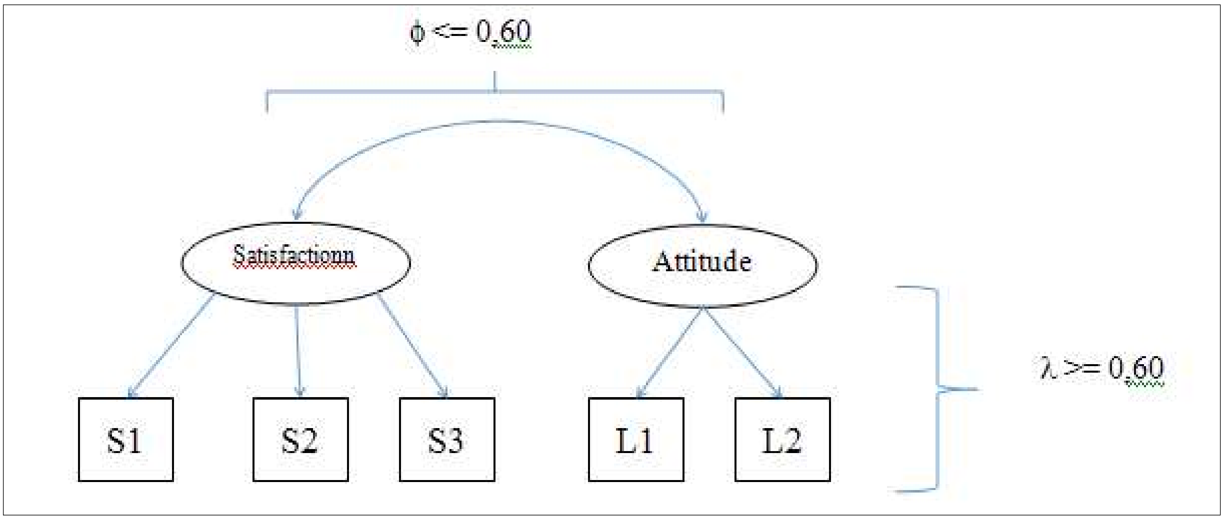

Figure 4 – Verification of discriminant and convergent validities.

We recommend that the manifest variables that do not show minimum loads should be eliminated, thus favoring the convergent validity, and also the parsimony of the model. Similarly, if any Phi matrix exhibits a higher correlation than recommended, this suggests that the correlations between the manifest variables should be measured. The ones with higher correlation with other constructs should be discarded or added to the other constructs. However, the relevance of such changes to the model should be verified with the test data from other samples to ensure the final model is not about mere artifacts.

After the analysis of measurement models, the researcher must examine the fit indices of the model, as indicated in Phase 4, as well as the magnitude of variance, covariance, and effects.

2.2 Indicators of model fit

There are different approaches to estimate the fit of models in SEM. Different measures that capture different aspects of fit should be assessed (Hair *et al.*, 1988). Absolute fit indices estimate the quality of the overall fit of the model, collectively considering the structural and measurement models, regardless of model complexity and the number of estimated parameters. Absolute fit indices are based on the equivalence of the covariance matrix of the data and the matrix implied by the model represented. Incremental fit indices compare the model with a null model (the simplest model that can be theoretically justified, usually composed of a single construct related to all manifest variables without measurement error), rewarding models with higher increments. Parsimonious fit indices measure the overall quality of fit considering the number of estimated coefficients, correcting for any excessive fit.

The LISREL provides a fairly extensive list of indicators of fit. Although scholars have not reached consensus on what are the most appropriate indicators (Bentler *et al.*, 2001), the vast majority of users of LISREL indicate the RMSEA, GFI, RMSR, and the chi-square divided by degrees of freedom of the model are more robust indicators of absolute fit, while indicating NNFI, and CFI PGFI are the most important indices for incremental fit. Moreover, the AGFI is a widely used parsimonious fit index. Table 3 describes each.

Table 3 - Indicators of structural fit models

INDICATOR	TYPE OF INDICATOR	DESCRIPTION	REFERENCE VALUES
$\chi 2$ (*Chi-square*)	Absolute fit index	Indicates the discrepancy between the proposed model and the model by the researcher suggested by the data sample.	$p > 0.05$
$\chi 2$/d.f. (*Chi-square divided by the degrees of freedom*)	Absolute fit index	As the chi-square is sensitive to sample size, their analysis only makes sense when the degrees of freedom are considered.	Between 1 and 3 good fit To 5 reasonable fit
RMSEA (*Root Mean Square Error of approximation)*	Absolute fit index	Shows the fit of the model to the covariance matrix of the sample, taking into account the degrees of freedom.	< 0.08 reasonable fit < 0.05 good fit
GFI *(Goodness of Fit Index)*	Absolute fit index	Comparison residuals of squares of the model versus the model suggested by the sample.	>= 0.90
AGFI *(Adjusted Goodness of Fit Index)*	Absolute fit index	GFI adjusted by the degrees of freedom.	>= 0.90
NNFI *(Non-normed Fit Index)*	Incremental fit index	Shows whether and to what extent the quality of fit of the model is better than the base model.	>= 0.90
CFI *(Comparative Fit Index)*	Incremental fit index	Shows whether and to what extent the quality of the fit of the proposed model is better than the base model.	>= 0.90
RMSR *(Root Mean Square Residual)*	Incremental fit index	It is the average difference between residuals implicated by the covariance matrix of the theoretical model and the covariance matrix of the sample data.	<=0.05
PGFI *(Parsimony Goodness of Fit Index)*	Incremental fit index	Measure of model complexity.	<= 0.67 acceptable fit <= 0.50 good fit

Finally, the researcher must go to Phase 5, performing the analysis of the coefficients of the structural model through the identification of correlations between latent variables (γ and β), coefficients of determination (R2), and significance of associations and effects (t tests). . In moving from the measurement model to the structural model, the emphasis shifts from the relationships between latent constructs and the observed variables to the nature and magnitude of the relationships between constructs.

In the next section, we present a textbook example of using LISREL through its graphical interface: Path Diagram.

3 A DIDACTIC APPLICATION OF LISREL

Despite being known as complex software, LISREL provides several ways for the researcher to test the collected data. We will use this textbook example of Path Diagram to consider the simplest case for beginners.

In this example, we use for didactic purposes, a model with only three latent variables (Attitude, Behavior, and Intention) and 10 operationalized manifest variables, Atit1 to Atit4 (Attitude), Behav1 to Behav3 (Behavior) and Int1 to Int3 (Intention to). In our theoretical model we hypothetize that the construct Attitude is antecedent of Intention and Behavior (dependent variable in the model). Also, Intention, even as a dependent variable (of the Attitude), is also a variable explaining the behavior of the individual. The variables are presented in Appendix 1.

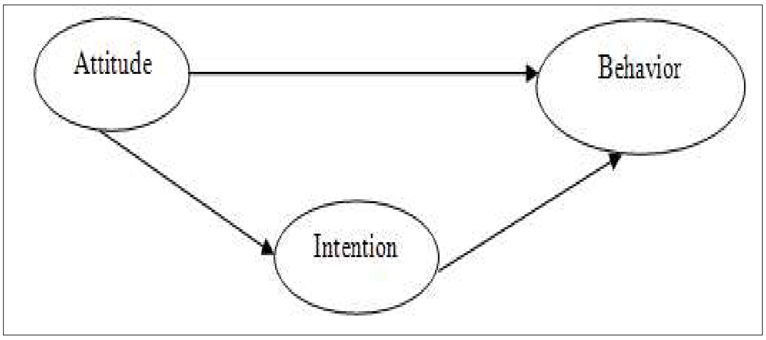

Figure 5 – Theoretical Model

The first step in modeling is to import the data matrix as the basis for testing the theoretical model. The LISREL can import data from files of various software packages (SAS, Minitab, Excel, Stata, SPSS, and others). The import file is quite simple (we use the File => Import External Data in Other Formats command). Once properly read by LISREL, the data file must be saved with the extension .psf.

With the data file already loaded in LISREL, the investigator should indicate the nature of the variables used in the model. In this case study, the variables were measured using a Likert scale of 11 points (anchored at 0 and 10). From a strictly technical standpoint, the scale is ordinal; however, Likert scales are often treated as interval, which we will adopt as a premise. Via Data => Define command variables classify the variables of the study, as indicated in Figure 6.

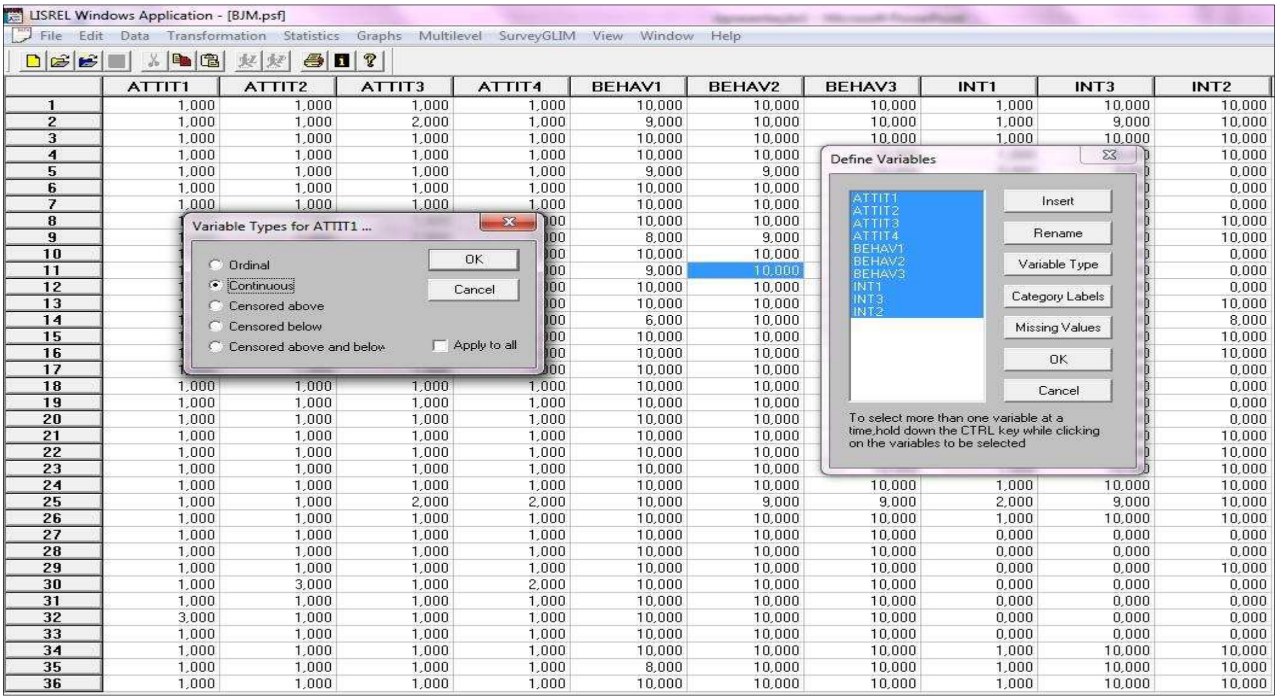

Figure 6 – Classification of variables

With the File => New => Path Diagram command we started a new project of SEM, as shown in Figure 7.

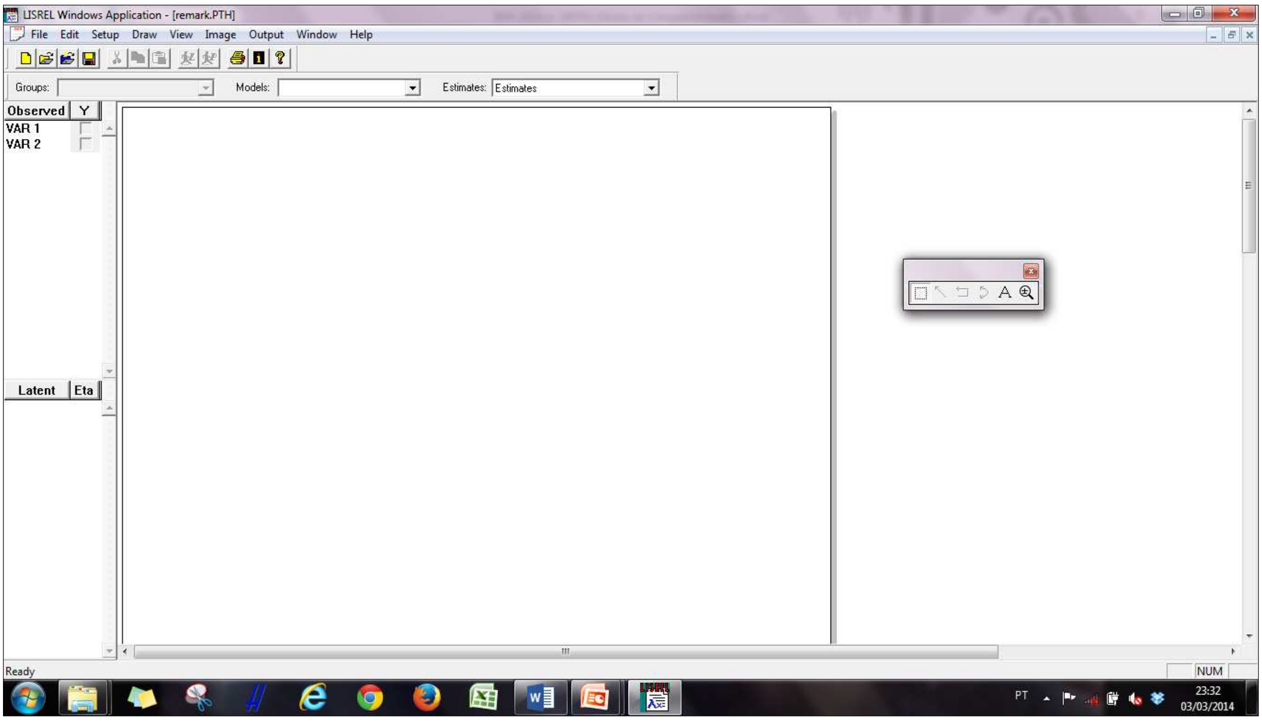

Figure 7 - Start of new project of SEM by path diagram

The manifest variables of the model are imported into the new SEM project when the .psf file type is loaded to the new project. As the latent variables are not measured and therefore not included in the file, this should be stated in the program as indicated in Figure 8.

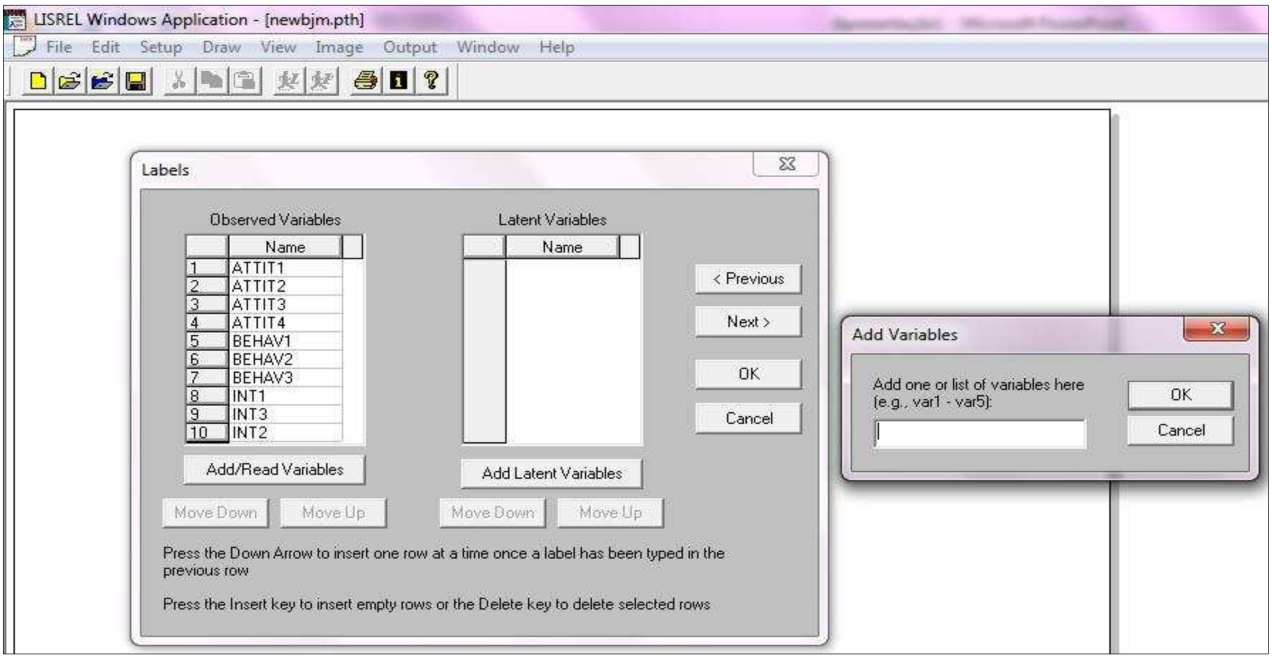

Figure 8 - Inclusion of the latent variables of the model

Then the researcher must assemble the measurement model on the LISREL screen. For this, you drag the manifest variables and the latent variables, indicating the relationship between them.

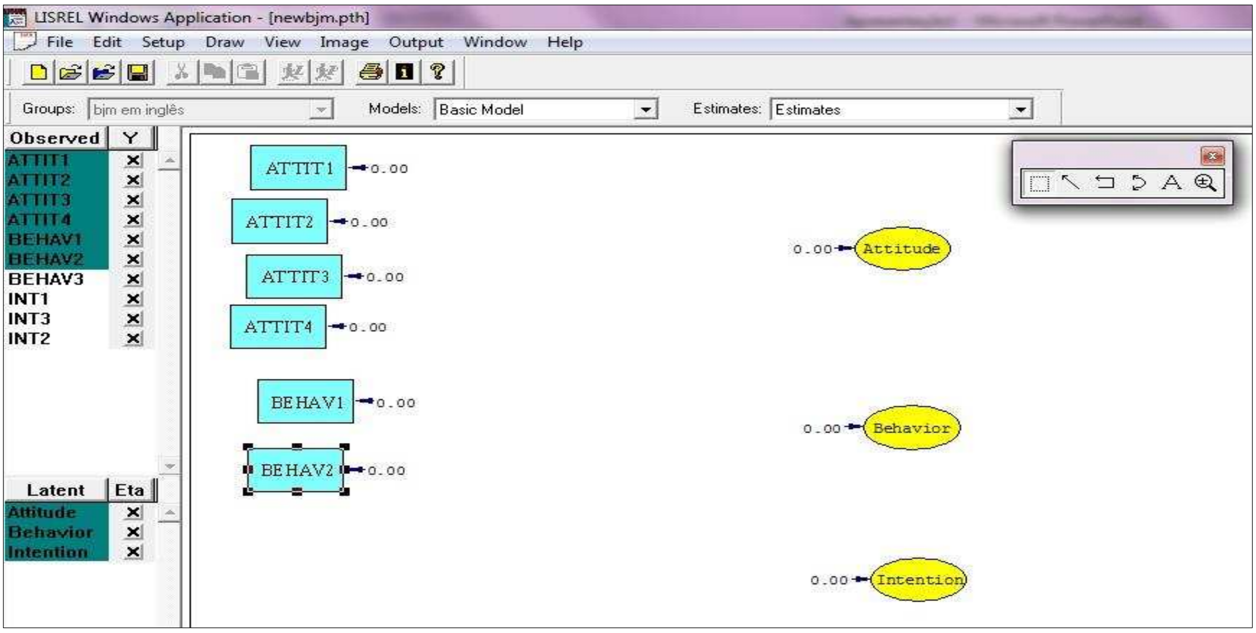

Figure 9 - Introduction of latent and manifest variables in LISREL

Because this is the measurement model, the theoretical relationships between the latent variables should not be listed at this stage. Once the layout of the measurement model is finalized through the F5 command, LISREL calculates and Lambda Phi check matrices for convergent and discriminant validity of the measurement model. As can be seen in Figure 9, the convergent validity was established, however the discriminant validity, not observed by the correction between attitude and behavior, was greater than 0.60 (ϕ = 0.65). With this, using SPSS, LISREL checked the manifest variables that showed the highest correlation coefficients and, consequently, must be causing the lack of discriminant validity between the constructs that operationalize.

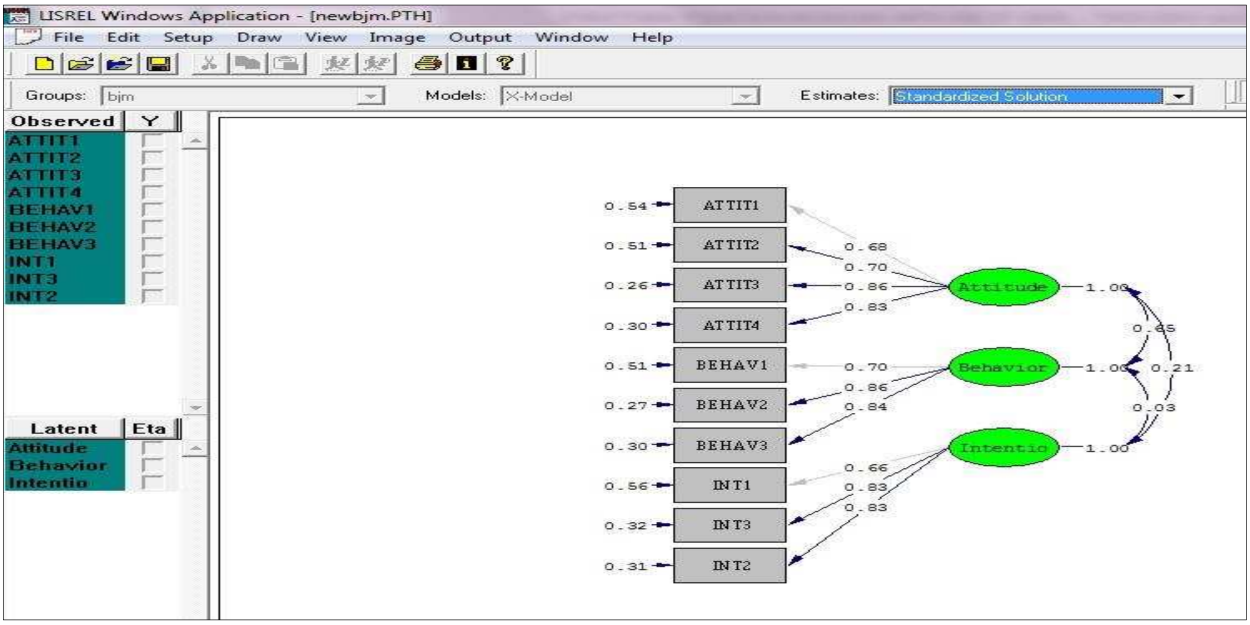

Figure 10 – Model of measures calculated.

With the identification of the obvious correlation between the two variables, items with higher cross-correlation between the constructs were removed.

Correlations

			attit1	attit2	attit3	attit4	Behav1	Behav2	Behav3
Spearman's rho	attit1	Correlation Coefficient	1,000	,528**	,481**	,447**	-,265**	-,380**	-,282**
		Sig. (2-tailed)	.	,000	,000	,000	,000	,000	,000
		N	750	750	750	750	750	750	750
	attit2	Correlation Coefficient	,528**	1,000	,419**	,441**	-,271**	-,315**	-,322**
		Sig. (2-tailed)	,000	.	,000	,000	,000	,000	,000
		N	750	750	750	750	750	750	750
	attit3	Correlation Coefficient	,481**	,419**	1,000	,617**	-,292**	-,456**	-,421**
		Sig. (2-tailed)	,000	,000	.	,000	,000	,000	,000
		N	750	750	750	750	750	750	750
	attit4	Correlation Coefficient	,447**	,441**	,617**	1,000	-,354**	-,395**	-,404**
		Sig. (2-tailed)	,000	,000	,000	.	,000	,000	,000
		N	750	750	750	750	750	750	750
	Behav1	Correlation Coefficient	-,265**	-,271**	-,292**	-,354**	1,000	,501**	,504**
		Sig. (2-tailed)	,000	,000	,000	,000	.	,000	,000
		N	750	750	750	750	750	750	750
	Behav2	Correlation Coefficient	-,380**	-,315**	-,456**	-,395**	,501**	1,000	,607**
		Sig. (2-tailed)	,000	,000	,000	,000	,000	.	,000
		N	750	750	750	750	750	750	750
	Behav3	Correlation Coefficient	-,282**	-,322**	-,421**	-,404**	,504**	,607**	1,000
		Sig. (2-tailed)	,000	,000	,000	,000	,000	,000	.
		N	750	750	750	750	750	750	750

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 11 - Matrix of bivariate correlation between attitude and behavior generated in SPSS v.18.

After the elimination of two manifest variables in the model, we can see that the correlation between attitude and behavior ($\phi = 0.52$) was within the proper limits. With this, we pass to the analysis of relations between the latent variables i.e., the analysis of the structural model.

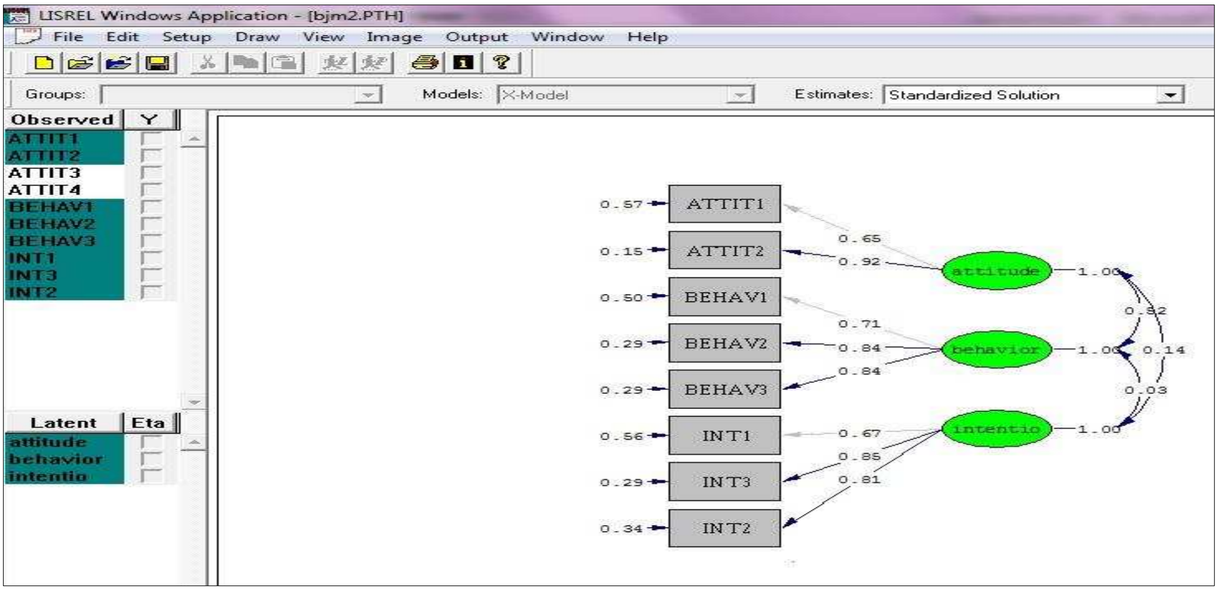

Figure 12 - Model of the variables measured after purification

Still in the LISREL screen, we established the relationship between the latent variables (structural paths) and, again through the F5 key request, the structural model. The result of this step is shown in Figure 13.

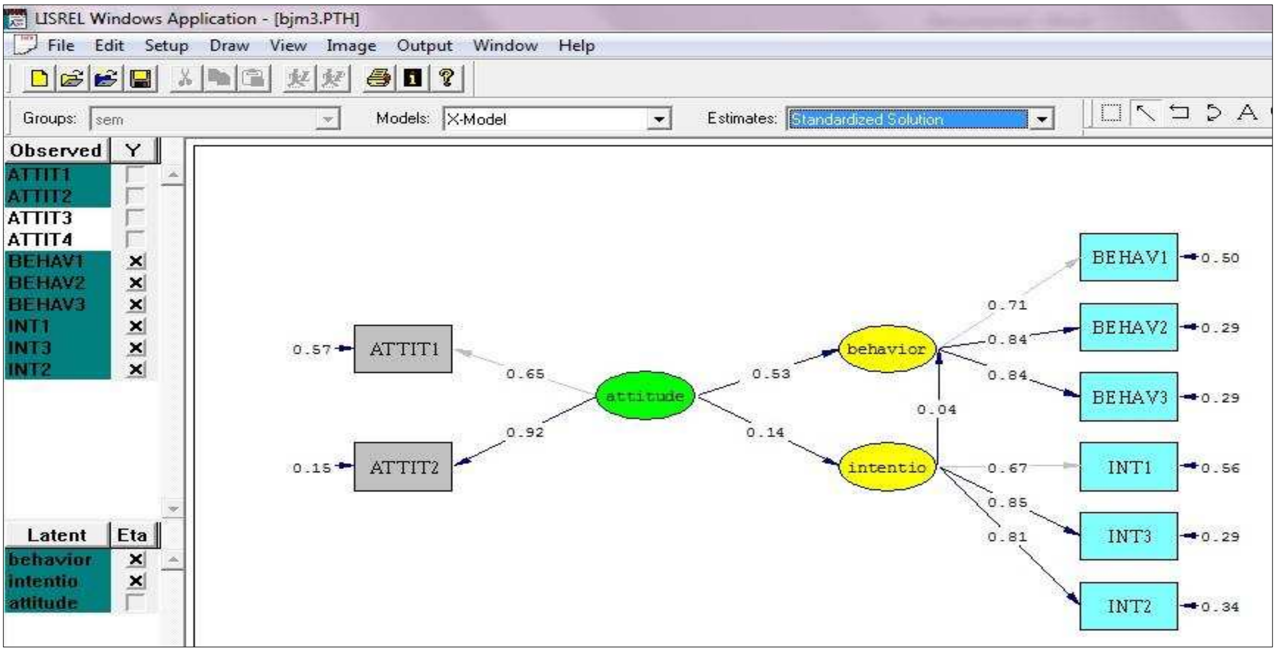

Figure 13 – Structural Model

Besides the path diagram, LISREL has an output with indicators of fit of the model as presented in Figure 14.

Goodness of Fit Statistics

```
Degrees of Freedom = 17
Minimum Fit Function Chi-Square = 50.57 (P = 0.0)
Estimated Non-centrality Parameter (NCP) = 389.56
90 Percent Confidence Interval for NCP = (327.59 ; 458.95)

Minimum Fit Function Value = 0.65
Population Discrepancy Function Value (F0) = 0.52
90 Percent Confidence Interval for F0 = (0.44 ; 0.61)
Root Mean Square Error of Approximation (RMSEA) = 0.07
90 Percent Confidence Interval for RMSEA = (0.06 ; 0.09)
P-Value for Test of Close Fit (RMSEA < 0.05) = 0.00

Expected Cross-Validation Index (ECVI) = 0.59
90 Percent Confidence Interval for ECVI = (0.51 ; 0.69)
ECVI for Saturated Model = 0.096
ECVI for Independence Model = 4.00

Chi-Square for Independence Model with 28 Degrees of Freedom =
2976.26
Independence AIC = 2992.26
Model AIC = 444.56
Saturated AIC = 72.00
Independence CAIC = 3037.22
Model CAIC = 551.34
Saturated CAIC = 274.32

Normed Fit Index (NFI) = 0.94
Non-Normed Fit Index (NNFI) = 0.94
Parsimony Normed Fit Index (PNFI) = 0.51
Comparative Fit Index (CFI) = 0.91
Incremental Fit Index (IFI) = 0.92
Relative Fit Index (RFI) = 0.93

Critical N (CN) = 52.33
Root Mean Square Residual (RMR) = 208.87
Standardized RMR = 0.02
Goodness of Fit Index (GFI) = 0.91
Adjusted Goodness of Fit Index (AGFI) = 0.95
Parsimony Goodness of Fit Index (PGFI) = 0.92
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Figure 14 - Indicators of structural fit model

After analyzing the suitability of the indicators of model fit, the researcher can analyze the coefficients and significance of the structural paths and verify the explanatory power of the model for the dependent variables of the study. At this stage, the researcher compares the structural relations with the previously conceived theoretical hypotheses.

The LISREL also provides the development of SEM through two programming languages - the LISREL and Simplis. Figures 15 and 16 show the practical example used in this article constructed in these two syntaxes. For details of this type of programming, we recommend reading Byrne (1998).

```
SYSTEM FILE from file 'C:\Users\ Desktop\ Remark
- Lopes, Veiga and Malhotra              REMARK.DSF'
Latent Variables  attitude behavior intention
Relationships
ATTIT1 = 1.00*attitude
ATTIT2 = attitude
BEHAV1 = 1.00*behavior
BEHAV2 = behavior
BEHAV3 = behavior
INT1 = 1.00*intention
INT3 = intention
INT2 = intention
behavior = attitude intention
intention = attitude
Path Diagram
End of Problem
```

```
TI Modelo de Mensuração - Remark - Lopes, Veiga
and Malhotra
DA NI=10 NO=750 MA=CM
LA
ATIT1 ATIT2 ATIT3 ATIT4 COMP1 COMP2
COMP3 INT1 INT3 INT2
 CM
FI='C:\Users\Evandro\Desktop\Lisrel_BJMmedida\re
mark.cm' SY
SE
 1 2 5 6 7 8 9 10 /
MO NY=8 NE=3 BE=FU PS=SY TE=SY
LE
attitude behavior intention
FR LY(2,1) LY(4,2) LY(5,2) LY(7,3) LY(8,3)
BE(2,1) BE(2,3) BE(3,1)
VA 1 LY(1,1)
VA 1 LY(3,2)
VA 1 LY(6,3)
PD
OU
```

4 FINAL THOUGHTS

Structural equation modeling used to estimate theoretical models is a common practice in applied research in the social sciences and especially in marketing research.

The use of covariance matrices is identified as most appropriate for the analysis of social phenomena. Covariance matrices contribute more information about behavior when compared with correlation matrices, which show only standardized data (Hair *et al*., 1998). Furthermore the most important algorithms for estimating structural models assume the use of covariance matrices. Therefore, the use of software that addresses these arrays is critical to scientific development. At the same time, LISREL is touted as a robust tool for this type of application.

The purpose of this article was to present, in a simple way, the characteristics of LISREL and the benefits of its use, in the hope of enlisting new researchers and reducing the perceived difficulty of using this software. We have also provided helpful guidelines to enable the proper use of this technique. Although we have not eliminated all doubts, we hope to have contributed, even modestly, to the spread and frequent use of this excellent structural equation modeling software.

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APPENDIX 1 – VARIABLES USED IN THE PRACTICAL STUDY

CODE	AFFIRMATIVE
Attit 1	The products of this brand have excellent quality.
Attit 2	I like a lot many of this brand’s products.
Attit 3	The evaluated brand is much better than other brands I know.
Attit 4	This brand attends to my consumer needs.
Int 1	I intend to keep consuming products of this brand.
Int 2	I will keep buying products of this brand even if other brands offer good deals.
Int 3	If I find this brand’s products in the supermarket, I will certainly buy them.
Behav1	I always bought products of this brand.
Behav2	When I go to the supermarket, I always buy products of this brand.
Behav3	I will always recommend this brand’s products to my relatives and friends.