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Armando Luis Vieira

Interactive LISREL in Practice

Getting Started with a SIMPLIS Approach

Springer

Armando Luis Vieira
DEGEI/GOVCOPP
University of Aveiro
Campus Universitário de Santiago
3810-193 Aveiro
Portugal
e-mail: aluisvieira@ua.pt

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Preface

LISREL was created about 40 years ago by Karl Jöreskog and Dag Sörbom, among other researchers of the *Educational Testing Services*. It was soon acknowledged as the best solution for the estimation of structural models and also as a complex statistical computer program, hard to learn and use (e.g., Kenny 1979). Bearing this in mind, LISREL experts have been gradually producing more user friendly versions of the computer program, command languages, and handbooks. Nevertheless, the degree of difficulty is still perceived as high, especially for those in the beginning of their learning process, mostly due the absence of handbooks adopting a perspective that is both pragmatic and effective. Another typical problem of the early stages of the learning process is to figure out what and where is the essential and objective information. The risk of dispersion is considerable, given the large number and diversity of sources. This handbook aims at contributing to overcome those obstacles, by adopting a practical perspective of the utilisation of LISREL and pointing out the references considered essential for an effective learning process.

This handbook is particularly appropriate for those users who are not experts in statistics, but have some basic notions of multivariate data analysis that would allow them to use the following pages as a good first incursion into the realm of LISREL. Part I introduces the topic, presents the study that serves as the background for the explanation of matters, and launches the bases for parts II and III, which, in turn, explain the process of estimation of the measurement model and the structural model, respectively. The announcement of each part also includes a suggestion of the references considered essential to go along with the utilisation of the handbook. At the end, the reader will have acquired the basic notions on structural equation modelling, namely with the LISREL program. If, ideally, the reading of this handbook could be accompanied by an actual analysis, based on a real or simulation sample, the reader will get a more accurate idea of how LISREL works in practice and be better prepared to evolve in the learning process.

Good Luck!

Armando Luis Vieira

Contents

Part I
Introduction and Preparation of the Analysis

Indispensable Bibliography

- J.C. Anderson, D.W. Gerbing, Structural equation modeling in practice: a review and recommended two-step approach. Psychol. Bull. **103**(3), 411–423 (1988)
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At the Completion of Part I you will be able to:

- Understand what are SEM and LISREL, and why you need them;
- Distinguish latent versus manifest variables;
- Distinguish endogenous versus exogenous variables;
- Distinguish measurement versus structural (sub-)models;
- Perform the preliminary steps in order to prepare a SEM analysis using Interactive LISREL

Chapter 1
Introduction

Abstract This chapter introduces SEM and LISREL and elaborates on their practical usefulness. It distinguishes latent vs. manifest variables, endogenous vs. exogenous variables, as well as measurement vs. structural (sub-)models. It also illustrates the first two steps of a SEM analysis with Interactive LISREL.

Keywords Endogenous variables · Exogenous variables · Latent variables · Manifest variables · LISREL · Structural equation modelling

LISREL, an abbreviation of *Linear Structural Relationships*, is the designation of a computer program that is utilised in structural equation modelling (SEM). Although there are other statistical packages that can be used to analyse structural equation models, LISREL is considered by investigators as the most preferred statistical software. Indeed, the identification between SEM and LISREL is so marked that structural equation models are often referred to as LISREL models, regardless of the software that is being used. The SEM methodology is, in turn, viewed by researchers as one of the most sophisticated statistical tools. Therefore, it is perfectly reasonable to admit that those who understand the principles of LISREL will not experience serious difficulties in using alternative programs. The indispensable characteristics of LISREL models can be illustrated through the following example.

Let us suppose that we want to assess our willingness to interact with our account manager (or client manager, relationship manager, key contact, etc.) at a given service provider (e.g. in banking, insurance, telecommunications, etc.). Suppose, in addition, that the literature on the topic suggests that, probably, the willingness to interact is dependant, for the most part, on the importance of the relationship between the client and his/her client manager, as perceived by the client. In this case we have two constructs—*willingness to interact* and *relationship importance*—to assess, as well as the association between them. To test the hypothesis that relationship importance positively influences the willingness to interact, we need to collect data on both constructs. One of the problems is that it is

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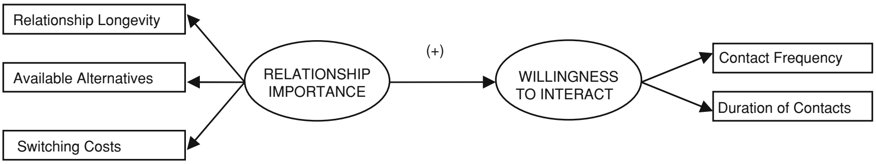

Fig. 1.1 Associations between latent variables and their indicators

not possible to directly observe, neither the willingness to interact, nor relationship importance—because they are *latent variables*. What we can do is to measure aspects of each construct that can be directly observed. Let us admit, for example, that a literature review and/or some empirical evidence led us to presuppose that both willingness to interact and relationship importance can be measured through some measurable indicators or *manifest variables*. In this context, we would have, for example, willingness to interact being reflected by the *frequency* and *duration* of contacts between both sides, and relationship importance being reflected by *relationship longevity*, the number of *available alternatives* in terms of service providers, and *switching costs*. Figure 1.1 illustrates the simple model that we have just described, i.e., the associations among the latent variables, and between these and their observable indicators.

Apparently, in conceptual terms, the model in Fig. 1.1 is similar to a simple regression model with a dependent variable (willingness to interact) and an independent variable (relationship importance). However, the fact that we are dealing with latent variables, which in turn are measured by more that one indicator, does not allow for the utilisation of traditional techniques such as regression, for example. Rather it requires an analysis approach at the level of SEM, which is a statistical technique that combines factor analysis (from a confirmatory perspective) with econometric modelling. SEM, namely through LISREL, allows for the simultaneous estimation of a number of separate, yet interdependent equations incorporating both latent and manifest variables, as well as direct, indirect and total associations, even if there are variables acting as both dependent and independent (Hair et al. 1998). The model is statistically tested through a simultaneous analysis of the whole system of variables in order to assess goodness of fit, that is, the compatibility between model and data. Put simply, the better the goodness of fit, the stronger the chances of confirmation of the hypotheses representing the associations among the variables (Byrne 1998).

Each LISREL model is normally comprised of two sub-models (also referred to as models, for simplification reasons): the *measurement model* and the *structural model*. The former shows us how each latent variable is measured by its indicators or, in other words, how each construct is *operationalised*; the latter characterises the associations between the variables, indicating the direction and statistical significance of each association, as well as the amount of variance in the endogenous variables explained by the respective proposed determinants. According to the literature (e.g. Anderson and Gerbing 1988), due to the complexity of some models and in order to achieve better results, the two components should be

Fig. 1.2 Steps in structural equation modelling with INTERACTIVE LISREL

analysed separately, starting with the assessment of the measurement model, which includes *dimensionality*, *validity* and *reliability* tests, and then moving on to the estimation of the structural model, which, ideally, should include *cross-validation*, *statistical power*, and *rival models* analyses. In spite of the existence of several versions of the steps suggested for LISREL modelling (see, for example, Diamantopoulos and Siguaw 2000; Hair et al. 1998), this handbook, which has a simultaneously pragmatic and effective approach as a first priority, adopts a sequence of 4 phases, which interact with one another, as presented in Fig. 1.2.

The first phase, or *Step 1—Model Development*, is about building a conceptual framework or theoretical model that supports the proposed associations among the variables, as well as between the variables and their observable indicators. These associations are represented by the research hypotheses suggested and justified by the mentioned conceptual structure, which, in turn, is based on the literature, preferably combined with empirical evidence. This first phase is crucial to the whole process. Indeed, the effectiveness of an analysis that follows the LISREL methodology, which is mainly confirmatory in nature, lies, to a great extent, on a sound theoretical conceptualisation.

Step 2—Path Diagram Construction, as the expression suggests, is nothing more than the graphical illustration of the links among the variables integrating the model, which correspond to the suggested hypotheses. Although, apparently, this step might seem as of minor importance, its inclusion in the process is highly recommended, bearing in mind the relevant role that it plays in LISREL modelling, as will become evident throughout the present handbook.

Figure 1.3 is an example of a graphical illustration of a model that resulted from the combination of the literature with empirical evidence on the *relationship quality*(RQ). construct and its determinants and dimensions (for a review on RQ, see Vieira et al. 2008). That is, the first step, model development, was accomplished (see Vieira 2009; 2010).

The model presented in Fig. 1.3 includes three exogenous variables—*communication*, *customer orientation*, and *relational net benefits*—and three endogenous variables—*commitment*, *mutual goals* and *relationship quality*. Exogenous variables are those variables that do not receive impacts from any other variable and act only as independent variables. Variables that are influenced by other variables in the model are designated endogenous variables. Endogenous variables can simultaneously influence other variables in the model, acting as independent and dependent variables at the same time (e.g. latent variables commitment and mutual goals in Fig. 1.3). In this case, the endogenous and latent variable relationship quality is the central construct in the model, in relation to which latent variables communication, commitment and customer orientation act as both direct and indirect determinants, latent

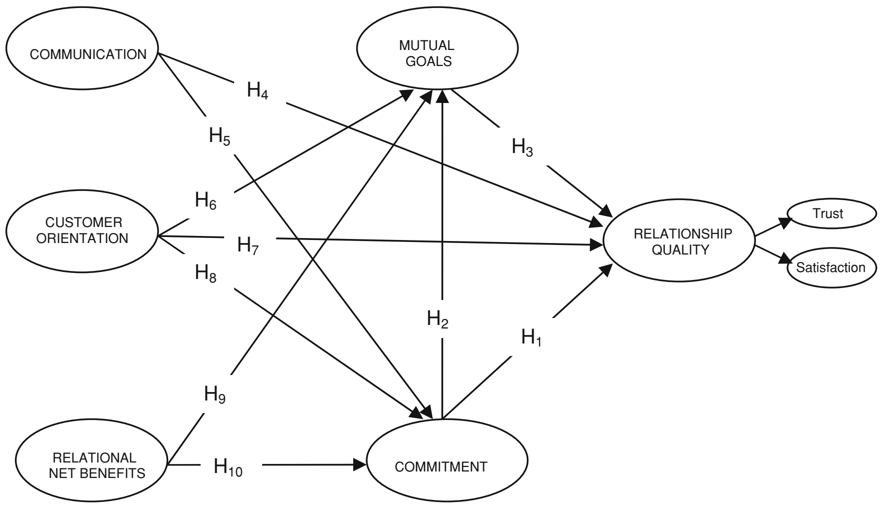

Fig. 1.3 Relationship quality model
Source Vieira (2009)

variable relational net benefits only as an indirect determinant, and latent variable mutual goals as a direct determinant only. Latent variables commitment and mutual goals also work as mediators of the effects exerted by other variables in the model. The former mediates the impacts of variables communication, customer orientation, and relational net benefits on relationship quality, whereas the latter mediates the influence of variables customer orientation, relational net benefits, and commitment, also on relationship quality. In addition, the literature review, combined with the results of an exploratory study, suggested the inclusion of two latent variables as dimensions of relationship quality: *trust* in the client manager, and *satisfaction* with the client manager's performance. The above described model corresponds to the following research hypotheses, which are formulated from the perspective of the client's perception:

H_1: The higher the level of commitment, the higher the level of RQ;
H_2: The higher the level of commitment, the higher the level of mutual goals;
H_3: The higher the level of mutual goals, the higher the level of RQ;
H_4: The higher the level of communication, the higher the level of RQ;
H_5: The higher the level of communication, the higher the level of commitment;
H_6: The higher the level of customer orientation, the higher the level of mutual goals;
H_7: The higher the level of customer orientation, the higher the level of RQ;
H_8: The higher the level of customer orientation, the higher the level of commitment;
H_9: The higher the level of relational net benefits, the higher the level of mutual goals;
H_{10}: The higher the level of relational net benefits, the higher the level of commitment.

Our journey through LISREL is going to be accomplished with reference to the model in Fig. 1.3 and respective research hypotheses, which, in turn, correspond to a set of regression equations that have to be estimated simultaneously. To this end, data was collected through questionnaires (containing 7-point Likert-type questions) sent to corporate clients of a hotel chain operating in Portugal. 948 usable cases were obtained. For simplification reasons, let us focus on the latent variables only. The model will be revealed in more detail (including, for example, the observable/manifest indicators, and the issue of error variance, both in measurement and structural equations), as we go through the LISREL steps presented in Fig. 1.2. The next chapter aims at preparing the analysis, as well as building bridges to the remaining components of the analysis process.

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Chapter 2
Preparation of the Analysis

Abstract This chapter describes the SEM analysis preparation procedures, including the choice of the input matrix and estimation technique, the selection of goodness-of-fit-indices, as well as a step-by-step, annotated illustration of how to conduct normality tests.

Keywords Data screening · Estimation technique · Goodness-of-fit indices · Input matrix · Level of abstraction · Two-step approach

The overall strategy concerning data analysis was divided in two main parts, taking advantage of a relatively large sample: model calibration and model (cross-)validation. For this purpose, the final sample of collected data was split in two random halves, the calibration sample and the validation sample. Within model calibration, the two-step approach suggested by Anderson and Gerbing (1988) was followed. In this context, the evaluation of the measurement model was carried out using factor analysis, both exploratory (EFA) and confirmatory (CFA). In a first instance, EFA was used as a procedure of measure purification, from a traditional (i.e., non-confirmatory) perspective (using SPSS), which was subsequently complemented with a confirmatory assessment of dimensionality, convergent validity, reliability, and discriminant validity, under the principles of SEM (using the *Interactive* LISREL software). Subsequently, the testing of the structural model, also with SEM, served as a confirmatory assessment of nomological validity. SEM was used as well for validating the structural model, on the validation sample, and for an analysis of alternative/rival models.

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Before moving on to the estimation of the measurement model, the following preliminary considerations are deemed pertinent.

2.1 Type of Input Matrix

In this respect, the choice is, basically, between using a correlation matrix or a covariance matrix. Several reasons informed the option for a covariance matrix as the input matrix in the present analysis. To begin with, Hair et al. (1998) defend that when the goal is to test a proposed theoretical framework, as is the case of the study that serves as the basis for this handbook, a covariance matrix should be used. Moreover, according to Bentler et al. (2001), most of the statistical theory behind SEM has been developed on the assumption that the analysis applies to a covariance matrix. In addition, Baumgartner and Homburg (1996) recommended the utilisation of covariance matrices in all analyses. Furthermore, there are some specific technical reasons in favour of using a covariance matrix. For instance, Bentler et al. (2001) stressed that covariance structure models (an alternative designation for structural equation models) have standardised solutions as well—thus the advantage is that a correlation metric is available even if a covariance matrix is used. Also, in general, when a correlation matrix is used, the chi-square test and standard errors are not correct (Bentler et al. 2001).

2.2 Estimation Technique

Maximum likelihood (ML) is the default estimation method in most statistical packages and it is also the more widely used estimation method (Anderson and Gerbing 1988; Baumgartner and Homburg 1996; Bollen 1989; Diamantopoulos and Siguaw 2000). ML is quite consistent at producing efficient estimation and is rather robust against moderate violations of the normality assumption (Diamantopoulos and Siguaw 2000), provided that the sample comprises 100 or more observations (Anderson and Gerbing 1988; Steenkamp and van Trijp 1991). Despite the existence of asymptotically distribution-free (ADF) methods, i.e., methods that make no assumptions on the distribution of the variables, ADF procedures are of little practical usefulness, because they imply the use of very large samples (Baumgartner and Homburg 1996; Diamantopoulos and Siguaw 2000; Steenkamp and van Trijp 1991). In addition, it has been proven that ADF techniques do not necessarily yield better performances even when they are theoretically considered more appropriate (Baumgartner and Homburg 1996). One option could be to use weighted least squares (WLS), an example of an ADF method, as the estimation technique on an asymptotic covariance matrix, which can be calculated with PRELIS—a pre-processor of LISREL (Jöreskog and Sörbom 2002; Jöreskog et al. 2001)—and try to collect as much data as possible.

However, again, it has been shown that WLS can be troublesome, namely regarding the chi-square test statistic, even with large samples (Diamantopoulos and Siguaw 2000). According to Steenkamp and van Trijp (1991), the utilisation of WLS requires a sample as large as at least 1.5*(number of items)*(number of items + 1), which, in the case of the present study, would require a final sample with more than 5,800 observations. In this context, for the purpose of the present handbook, ML was the selected estimation technique.

2.3 Two-Step Approach

In the present case, the measurement model was estimated separately and prior to the estimation of the structural model, following Anderson and Gerbing's (1988) two-step approach for structural equation modelling, as already mentioned. It was felt that this would be the most appropriate approach for the context of the present analysis, due to its advantages, as compared to the single-step analysis, which, on the contrary, involves the simultaneous estimation of both measurement and structural models. Essentially, this approach allows for unidimensionality assessments, and facilitates formal comparisons between the proposed model and alternative models (for a summary of the mentioned advantages see Anderson and Gerbing, 1988, p. 422).

2.4 Level of Abstraction

According to Baumgartner and Homburg (1996) there are three levels of abstraction in modelling latent variables: total aggregation, partial aggregation, and total disaggregation. The partial aggregation approach, in which subsets of items are combined into composites that are then treated as indicators of the constructs, was considered the most appropriate for testing the structural model, whereas the total disaggregation approach will be used for model calibration. The partial aggregation approach minimises model complexity, in comparison to the total disaggregation approach, in which the original items are used as indicators of each construct. The latter method, though useful for model development, becomes unmanageable for the purpose of testing the whole model, particularly with large sample sizes and when there are more than four or five manifest indicators (Bagozzi and Heatherton 1994; Baumgartner and Homburg 1996), which is the case of the study that serves as the basis for the present analysis. In addition, the partial aggregation approach considers reliability more clearly, while allowing for assessment of the unidimensionality of constructs, this way providing support for the combination of subsets of items into composites, as opposed to 'collapsing' all the items into a single composite, as in the total aggregation approach, where each construct has a single indicator (Baumgartner and Homburg 1996).

2.5 Summated Scales

Hunter and Gerbing (1982, p. 271) emphasise the practice of using composites by stating that "the usual method of finding the common thread through several responses is to add or average them". Moreover, these authors highlight the appropriateness of this practice by suggesting that computing composites means that the observed variables, for example, the items on a questionnaire, are organised into clusters or tests or scales, so that each cluster of observed variables corresponds to a single underlying latent variable. The average score across the items that define the cluster, the "cluster score", provides a level of analysis that is intermediate to the "molar and molecular" (Hunter and Gerbing 1982, p. 271).[1] The same authors go on to explain why averaged scores may lead to greater reliability: "if the items satisfy the empirical procedures of construct validation, then the composite is potentially a more reliable and valid estimate of the latent variable of interest than any of the component single item responses" (Hunter and Gerbing 1982, p. 271).

Therefore, in coherence with the option for the partial aggregation level of abstraction, composites were built for each of the latent variables. The creation of summated (or composite, or averaged) scales (or measures, or scores) is a widely used procedure, being "practically unavoidable" when there is a relatively large number of indicators (Baumgartner and Homburg 1996, p. 144), and presents two major advantages when compared to using single questions (original/individual items). In short, these two main advantages are the reduction of measurement error (i.e., greater reliability) and parsimony (Dillon et al. 2001; Grapentine 1995; Hair et al. 1998). In this case, the words of Dillon et al. (2001, pp. 63–64) are particularly pertinent:

> The formation of a composite (an average of a scale's items) may be preferred to the modelling of the individual component for two reasons: first, an average, whether over respondents or items, lends stability (literally enhanced reliability here) to the resultant composite variable (…); second, the composite can be simpler, both to conceptualize and communicate and to use in models. (…). Even a structural equation model (SEM), an approach to data analysis created as a perfect partnership of a measurement model and a structural model, seems to behave with somewhat more stability in the presence of parsimony (in this case, simplifying the measurement end of the model). (…) Although a composite is not the measurement of the construct, its greater reliability means that the particular idiosyncrasies of the component items have less power to yield misleading results.

In the present analysis, scores of the items pertaining to each construct that resulted from the measurement model evaluation carried out in the next chapter were averaged to form composites to be used in the assessment of the structural model, which is going to be conducted in Chap. 4. It was possible to combine items and use

[1] The molar level refers to latent variables, also referred to as "molar variables", and the molecular level refers to observed variables, also referred to as "molecular variables" (Hunter and Gerbing 1982, p. 270).

them as composites, due to, again, the proven psychometric properties of the measures, namely unidimensionality (Baumgartner and Homburg 1996; Dillon et al. 2001; Hair et al. 1998), as shown in Part II. In other words, items that pertained to the same cluster, which, after EFA and CFA procedures, were proven to form a unidimensional set, ended up resulting in a certain summated scale or composite that was then used within the process of assessing the structural model.

2.6 Goodness of Fit Indices

While there is no consensus on the appropriate index for assessing overall goodness-of-fit of a model (Ping 2004), the chi-square statistic has been the most widely used fit index (Bagozzi and Heatherton 1994; Baumgartner and Homburg 1996; Ping 2004). The chi-square test measures the discrepancy between a hypothesised model and data (Bagozzi and Heatherton 1994), by testing "the null hypothesis that the estimated variance–covariance matrix deviates from the sample variance–covariance matrix only because of sampling error" (Baumgartner and Homburg 1996, p. 149). Significant values of the chi-square test mean that there is a strong divergence between the data and the model, and that the latter should be rejected. However, the chi-square goodness-of-fit test tends to inflate as the sample size increases, leading to the rejection of models with only slight divergences from the data, which limits its practical usefulness (Baumgartner and Homburg 1996). In this context, it is advisable to report additional measures of fit (Bagozzi and Heatherton 1994; Baumgartner and Homburg 1996).

The following fit indices were chosen for this analysis, based on suggestions that can be found in previous studies (Baumgartner and Homburg 1996; Ping 2004). Four of these indices are absolute fit indices, which assess the overall model-to-data fit for structural and measurement models together (Bollen 1989; Hair et al. 1998): chi-square goodness-of-fit test (χ^2), ratio of χ^2 to degrees of freedom (χ^2/df), root mean squared error of approximation (RMSEA), goodness-of-fit index (GFI), and adjusted goodness-of-fit index (AGFI); whereas the remaining two are incremental fit indices, which means that they compare the target model to the fit of a baseline model, normally one in which all observed variables are assumed to be uncorrelated (Baumgartner and Homburg 1996): comparative fit index (CFI), and non-normed fit index (NNFI). Table 2.1 presents a description of these indices and suggested cut-offs.

2.7 Data Screening Prior to Model Estimation and Testing

To begin with, the data matrix (built in SPSS support) was checked for coding errors. In those cases where coding errors were detected, the original questionnaire was used to correct these errors (Baumgartner and Homburg 1996; Churchill 1999;

Table 2.1 Descriptions and thresholds of goodness-of-fit indices used in the assessment of both measurement and structural models

Fit index	Description	Cut-offs
χ^2	Indicates the discrepancy between hypothesised model and data; Tests the null hypothesis that the estimated covariance–variance matrix deviates from the sample variance–covariance matrix only because of sampling error	$p > 0.05$
χ^2/df	Because the chi-square test is sensitive to sample size and is only meaningful if the degrees of freedom are taken into account, its value is divided by the number of degrees of freedom	2–1 or 3–1
RMSEA	Shows how well the model fits the population covariance matrix, taken the number of degrees of freedom into consideration	<0.05: good fit; <0.08: reasonable fit
GFI	Comparison of the squared residuals from prediction with the actual data, not adjusted for the degrees of freedom	>0.90
AGFI	GFI adjusted for the degrees of freedom	>0.90
NNFI	Shows how much better the model fits, compared to a baseline model, normally the null model, adjusted for the degrees of freedom (can take values greater than one)	>0.90
CFI	Shows how much better the model fits, compared to a baseline model, normally the null model, adjusted for the degrees of freedom	>0.90

Source Based on Bagozzi and Yi (1988), Baumgartner and Homburg (1996), Cote et al. (2001), Diamantopoulos and Siguaw (2000), MacCallum et al. (1996), Ping (2004)

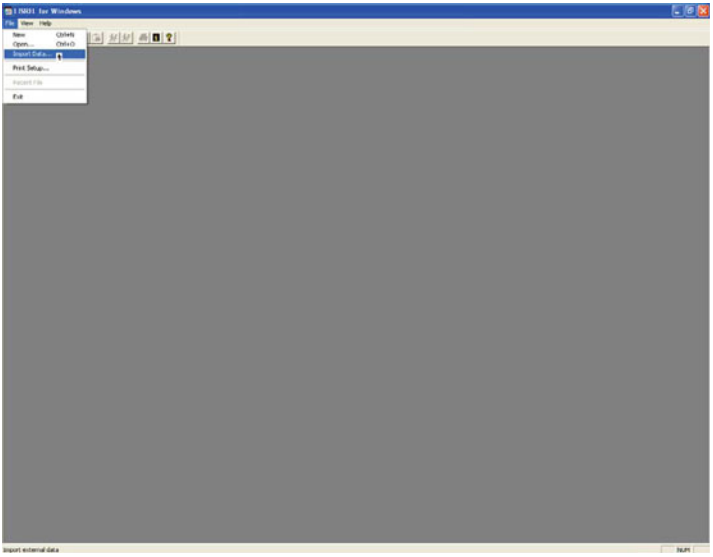
Green et al. 1988). Also, variables were recoded where necessary, namely regarding reverse coded items. Moreover, an inspection of the matrix was carried out with the objective of identifying extreme values that might pose some danger in terms of distorting influences, and no such values were found.

In addition, cases incorporating missing values were deleted prior to data analysis, following a listwise approach. There are several ways to approach missing values, like, for example, substitution (e.g., case substitution and mean substitution), imputation (e.g., cold deck imputation, regression imputation, and multiple imputation), and model-based procedures (Hair et al. 1998). All methods for dealing with missing data contain advantages and disadvantages (Hair et al. 1998; Streiner 2002). Moreover, the solutions offered in statistical packages, like, for instance, listwise and pairwise deletion, regression imputation, and expectation–maximization, included in the MVA (Missing Value Analysis) from SPSS Inc., seem to be insufficient and introduce bias in the analysis (Von Hippel 2004). Nevertheless, listwise case deletion is considered appropriate when the proportion of missing values is not too high (Hair et al. 1998), which is the case in this analysis, with around 5.4% of cases containing missing values. Taking also into consideration that this study's quantitative analysis is based on a relatively large sample, listwise deletion was the selected approach to missing values.

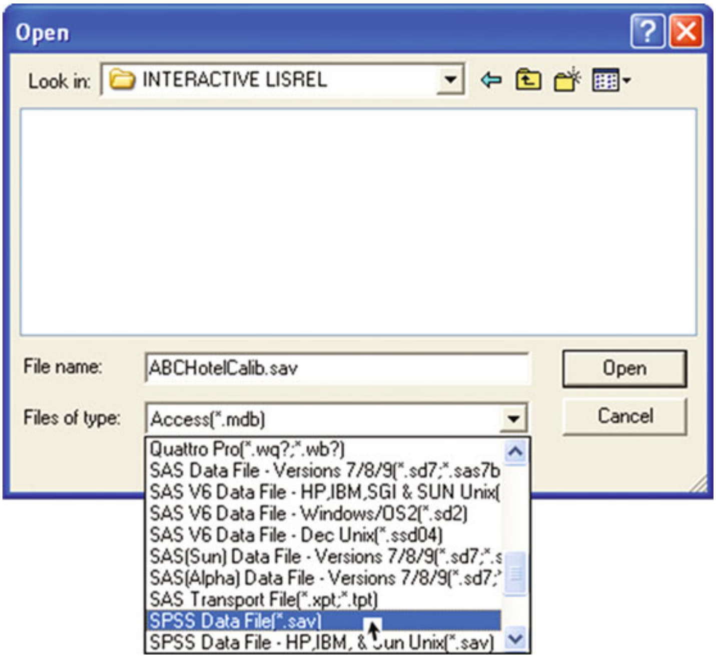
> **Hint**
>
> The above mentioned procedures can be carried out with SPSS, which is a more popular and fine tuned statistical package than PRELIS. The SPSS file with the data already (pre)prepared for the analysis can then be imported to LISREL 'via' PRELIS, as illustrated next.

In SEM it is always necessary to consider the issue of normality assumption. SEM is rather sensitive to the characteristics of the distribution of data, especially departures from multivariate normality. Severe violations of the normality assumption can be worrisome due to the possibility of inflating chi-square statistics, causing bias in critical values for determining coefficient significance, and affecting standard errors (Baumgartner and Homburg 1996; Hair et al. 1998; Steenkamp and van Trijp 1991). Also, one of the assumptions of the ML estimation technique is the normality of the variables (Cortina et al. 2001). Therefore, normality tests were conducted. As far as normality is concerned, PRELIS (version 2.80, a pre-processor incorporated in the 8.80 version of *Interactive* LISREL) was used to conduct the tests of normality with reference to the values of skewness and kurtosis of the observed variables (Bollen 1989). In order to perform normality tests, we should start by opening the LISREL program and clicking:

File—Import Data



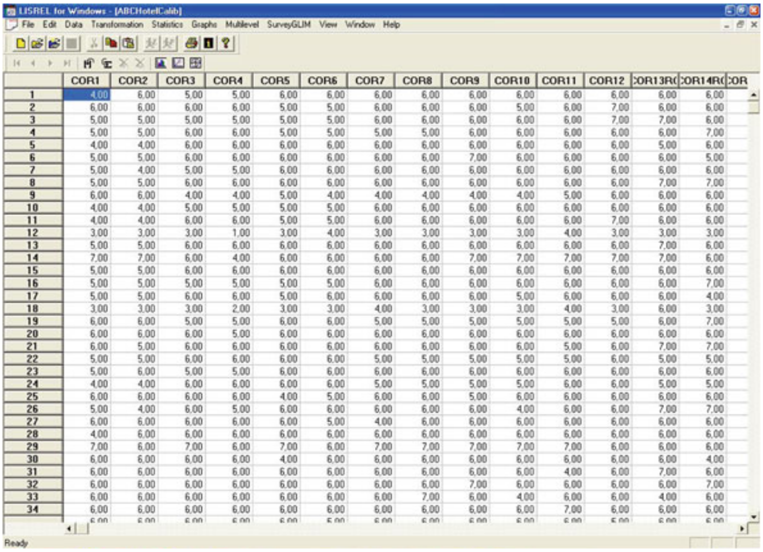
Then we should look for files of type *SPSS Data File* (*.*sav*):



We then choose the SPSS file and name it. In the present case the chosen name was ABC*HotelCalib* (calibration sample containing data on the quality of the relationships between ABC Hotels and their corporate clients). After doing this we get the following screen (of PRELIS, the above referred pre-processor incorporated in LISREL):

Hint

If possible, one should choose file names that are both short and revealing, and that stay unchanged through the whole analysis, from SPSS to PRELIS and LISREL.



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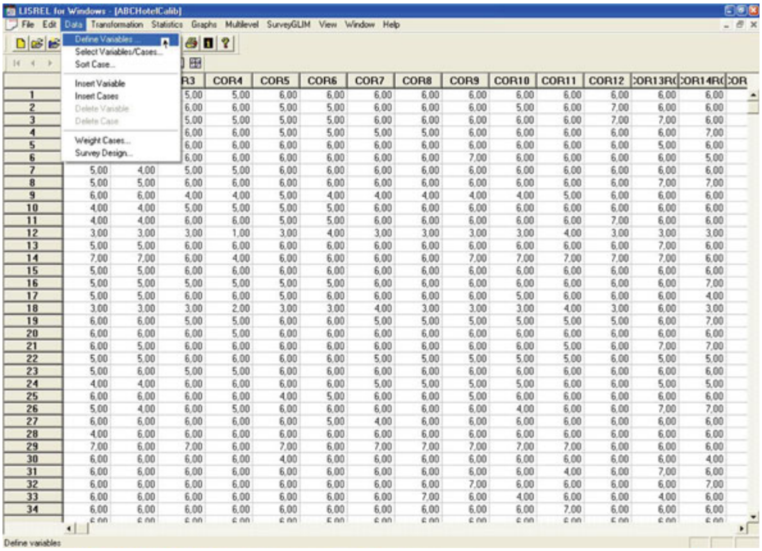
2	6.00	6.00	6.00	6.00	5.00	5.00	6.00	6.00	6.00	5.00	6.00	7.00	6.00	6.00	
3	5.00	5.00	5.00	5.00	5.00	5.00	6.00	6.00	6.00	6.00	6.00	7.00	7.00	6.00	
4	5.00	5.00	6.00	6.00	5.00	5.00	5.00	5.00	6.00	6.00	6.00	6.00	6.00	7.00	
5	4.00	4.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	5.00	6.00	
6	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	7.00	6.00	6.00	6.00	6.00	5.00	
7	5.00	4.00	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	
8	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	7.00	7.00	
9	6.00	6.00	4.00	4.00	5.00	4.00	4.00	4.00	4.00	4.00	5.00	6.00	6.00	6.00	
10	4.00	4.00	5.00	5.00	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	
11	4.00	4.00	6.00	6.00	5.00	5.00	6.00	6.00	6.00	6.00	6.00	7.00	6.00	6.00	
12	3.00	3.00	3.00	1.00	3.00	4.00	3.00	3.00	3.00	3.00	4.00	3.00	3.00	3.00	
13	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	7.00	6.00	
14	7.00	7.00	6.00	4.00	6.00	6.00	6.00	6.00	7.00	7.00	7.00	7.00	7.00	6.00	
15	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	
16	5.00	5.00	5.00	5.00	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	7.00	
17	5.00	5.00	6.00	6.00	5.00	6.00	6.00	6.00	6.00	5.00	6.00	6.00	6.00	4.00	
18	3.00	3.00	3.00	2.00	3.00	3.00	4.00	3.00	3.00	3.00	4.00	3.00	6.00	3.00	
19	6.00	6.00	5.00	5.00	6.00	6.00	5.00	5.00	5.00	5.00	5.00	5.00	6.00	7.00	
20	6.00	6.00	6.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	
21	6.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	5.00	6.00	7.00	7.00	
22	5.00	5.00	6.00	6.00	6.00	6.00	5.00	5.00	5.00	5.00	5.00	6.00	5.00	5.00	
23	5.00	6.00	5.00	5.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	
24	4.00	4.00	6.00	6.00	6.00	6.00	5.00	5.00	5.00	5.00	6.00	6.00	5.00	5.00	
25	6.00	6.00	6.00	6.00	4.00	5.00	6.00	6.00	5.00	6.00	6.00	6.00	6.00	6.00	
26	5.00	4.00	6.00	5.00	6.00	6.00	6.00	6.00	6.00	4.00	6.00	6.00	7.00	7.00	
27	6.00	6.00	6.00	6.00	6.00	5.00	4.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	
28	4.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	
29	7.00	6.00	7.00	6.00	7.00	6.00	7.00	7.00	7.00	7.00	7.00	6.00	6.00	6.00	
30	6.00	6.00	6.00	6.00	4.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	4.00	
31	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	4.00	6.00	7.00	6.00	
32	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	7.00	6.00	6.00	6.00	6.00	7.00	
33	6.00	6.00	6.00	6.00	6.00	6.00	6.00	7.00	6.00	4.00	6.00	6.00	4.00	6.00	
34	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	7.00	6.00	6.00	6.00	

Before conducting the actual normality tests, we need to define the variables in terms of level of measurement. In the study that serves as the basis for this analysis all the observable variables (items) were measured using seven-point Likert-type scales. Even though, from a pure technical perspective, Likert scales correspond to ordinal scales, its output is widely treated at an interval level (Malhotra 1996). This occurs in the majority of investigations in social sciences and it is considered an acceptable procedure (Kinnear and Taylor 1991). Similarly, in this study numeric values resulting from answers were treated as if they were obtained through metric scales. The reasonableness of this procedure is strengthened by the fact that the studied variables are indeed continuous and yet it is only possible to measure them as ordinal variables (Powers and Xie 2000).

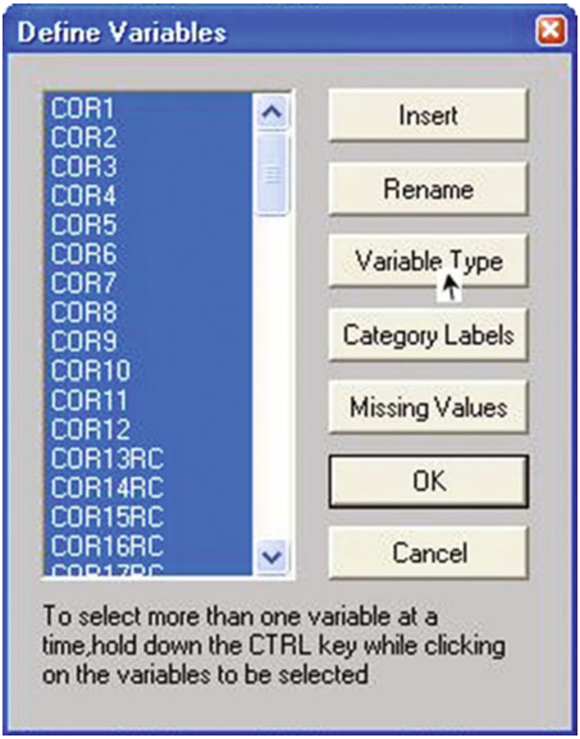
In order to define the variables as continuous we start by clicking:

Data—Define variables



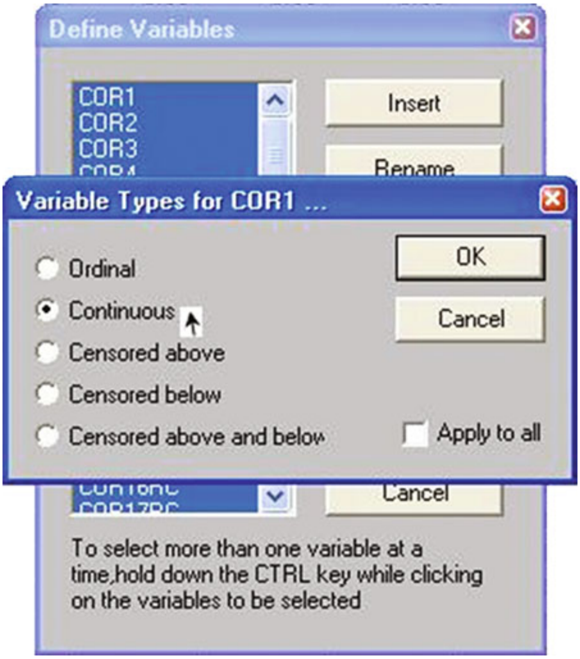
Then we get the following screen, where we select the variables to be defined and press:

Variable type



And in the following window press successively:

Continuous—OK—OK



Warning

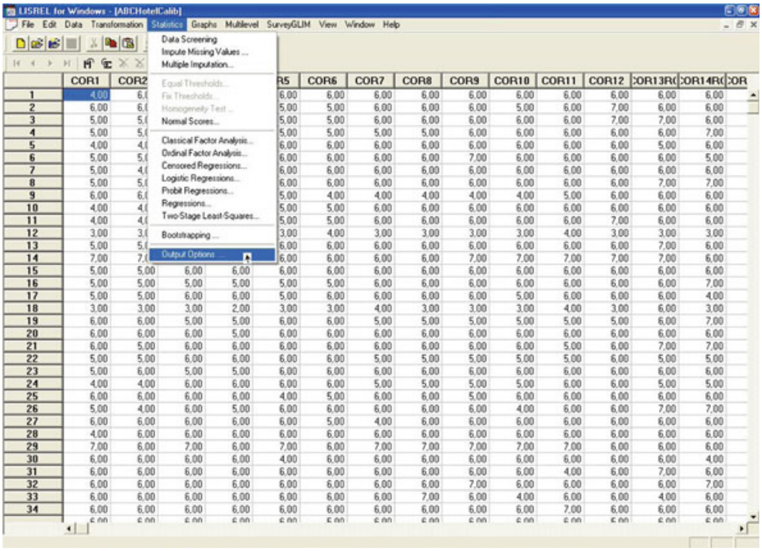
Do not forget to save the changes (this is very likely to happen). Failure to do so would mean that the subsequent steps would not take into account the definition of the variables you have just made, which would jeopardise the whole analysis.

Hint

It is strongly recommended that the whole process should be saved in the same location (for example, in the present case all of the procedures were saved in 'INTERACTIVE LISREL'). This facilitates the utilisation of LISREL on various aspects such as, for example, the location and identification of the covariance matrix that serves as the basis for the analysis, as we will see in Part II.

Let us move on to the normality tests:

Statistics—Output Options



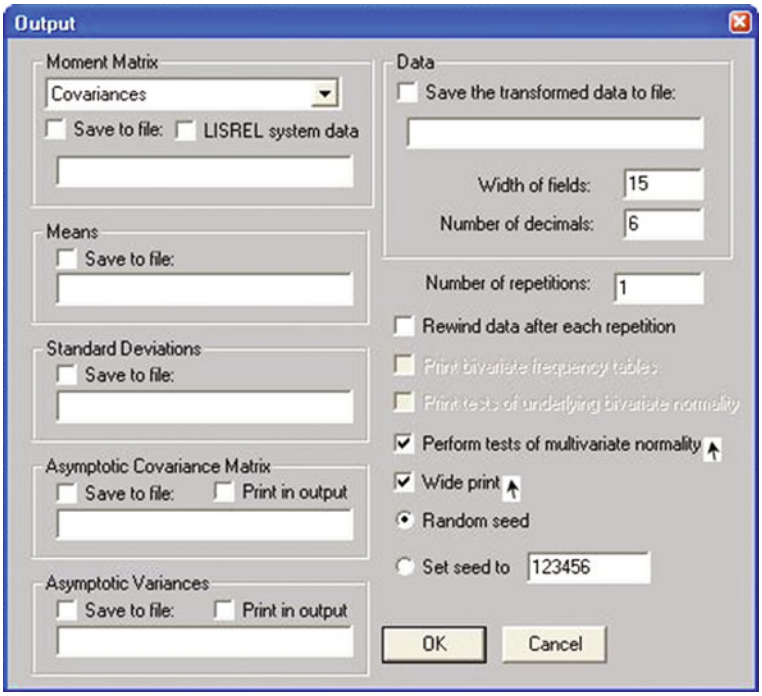
In the following window we will, for the moment, only choose:

Perform tests of multivariate normality

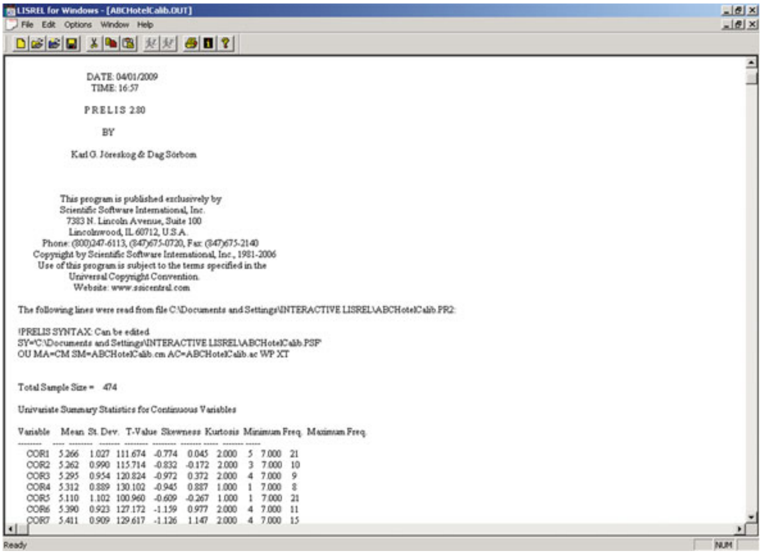
Because there are two or more continuous variables; and

Wide print

To reduce the extension of the output screens (even so, the outputs are rather lengthy and have some format inefficiencies, an aspect of PRELIS that needs some more fine-tuning).



Results are obtained through an output screen that looks like this:



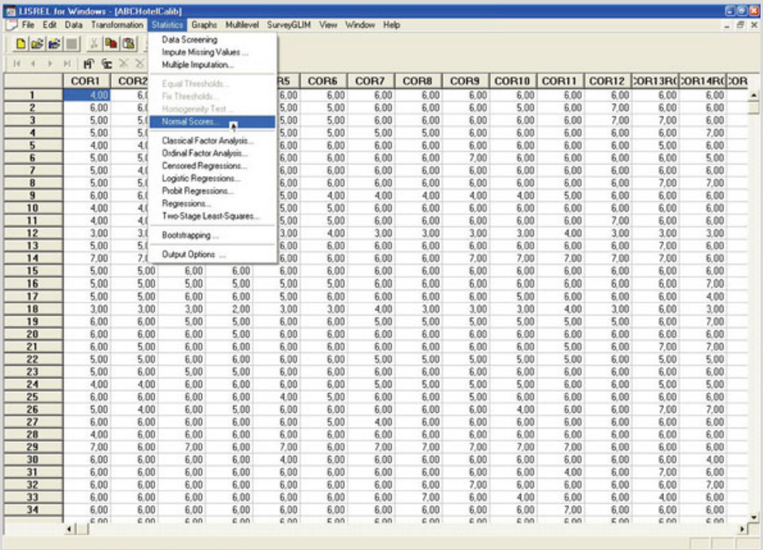
In the present case, all observed variables revealed significant kurtosis and skewness p-values, in terms of multivariate normality tests, which might suggest a potential departure from normality. Nevertheless, in the case under consideration, skewness seems to be more problematic than kurtosis, taking into consideration that, in terms of univariate normality tests, all p-values regarding the former are significant, contrary to what happens in relation to the latter, with several non-significant p-values. Still, this could constitute a problem, namely because of potential bias in parameter estimates and because it can raise questions related to the estimation technique used (as mentioned, ML depends on the assumption of multivariate normality). However, according to Hair et al. (1998), large sample sizes, which is the case in this analysis, tend to mitigate violations of the normality assumption caused by excessive kurtosis—which is more problematic than skewness, according to Bollen (1989)—namely by reducing biases in parameter estimates. In addition, also as already mentioned, the adopted estimation technique, ML, is robust against several types of the violation of the multivariate normality assumption (Bollen 1989). What is more, the ML estimator shows a superior performance in terms of "bias in parameter estimates, Type I error rates, and power" (Cortina et al. 2001, p. 326). Furthermore, specifically in relation to the calibration sample, the measure of relative multivariate kurtosis, printed by the PRELIS program (Jöreskog and Sörbom 2002) was 1.078. This value is considered relatively small and, therefore, it appears that, in spite of the items that do not show univariate normality, collectively the multivariate distribution is reasonably normal, similarly to what was concluded in previous analyses (e.g., Benson and Bandalos 1992).

Moreover, as Barnes et al. (2001, p. 80) put it, "variables are rarely normally distributed (…). Probably in strict terms the question is a non-issue from the beginning: virtually no variable follows the normal distribution". These authors go on to state that "by definition, data that come from 7-point scales are not normally distributed. In fact, the distribution of variables measured on such scales are often skewed toward one end of the scale, uniform, or even bimodal." (Barnes et al. 2001, p. 81). In this context, it is suggested that, for practical purposes, and if, as is the case of the data collected for this analysis, "the distributions of the sample variables are not wildly non-normal" (Barnes et al. 2001, p. 80), ML can be used, for its results are probably reliable in most situations. The option in this analysis was to follow this suggestion and not to transform non-normally distributed variables, given that this procedure could represent more problems by changing the meaning of actual responses (Anderson et al. 1987; Gassenheimer et al. 1998).

Note

In case we decide for the 'normalisation' of variables, we should start by pressing:

Statistics—Normal Scores



And then follow the steps described in Du Toit and Du Toit (2001, starting on p. 143).

As far as the sample size is concerned, it is noteworthy to mention that the final sample (either the total sample or each of the halves) contains a sufficient number of cases in relation to the parameters to be estimated. In SEM, the estimation and testing methods are based on asymptotic theory and the validity of the parameter estimates and test statistics depends on large samples (Baumgartner and Homburg 1996). While there is little empirical and theoretical indication of what is a large sample in this context, one rule of thumb is that, under normal distribution theory, “the ratio of sample size to the number of free parameters should be at least 5:1 to get trustworthy parameter estimates, and (…) higher (at least 10:1, say) to obtain appropriate significant tests” (Baumgartner and Homburg 1996, p. 146). The most stringent of these criteria is satisfied in this study, given that the most complex model (the second-order confirmatory factor analysis for the customer orientation construct, see Part II, 3.1.1) estimated 44 parameters, less than ten times the size of the calibration sample, which contains 474 cases.

After introducing the study that serves as the basis for the present handbook, and having described the preparation of the analysis, we will now move on to parts II and III, which will detail the necessary procedures to accomplish

Step 3—Assessment of measurement model and *Step 4*—Assessment of structural model, respectively.

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Part II
Assessment of Measurement Model

Essential Bibliography

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- K. Jöreskog, D. Sörbom, *LISREL 8: Structural Equation Modelling with the SIMPLIS Command Language* (Scientific Software International, Lincolnwood, 1993)
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At the completion of Part II you will be able to:

- Perform dimensionality tests;
- Build and test a second-order CFA model;
- Understand the basics of the SIMPLIS command language;
- Perform validity tests, both convergent and discriminant;
- Perform reliability tests;
- Interpret LISREL outputs.

Chapter 3
Assessment of Measurement Model

Abstract This chapter is concerned with the assessment of the measurement (sub-) model. It includes step-by-step, annotated illustrations of how to build and test a second-order CFA model, as well as how to perform dimensionality, reliability and validity tests. Chapter 3 also introduces the SIMPLIS command language and LISREL outputs

Keywords Convergent validity · Discriminant Validity · Measurement model · Reliability · Second-order CFA · Unidimensionality

3.1 Customer Orientation

The results of the EFA conducted for the 24 items measuring customer orientation (COR) identified a three-factor structure (see Appendix for a measurement summary, which includes the retained items). The values observed for the Bartlett's test of sphericity ($p = 0.000$) and the value of the Kaiser–Meyer–Olkin measure of sampling adequacy (KMO = 0.949) are strong and significant, suggesting that factor analysis is adequate for this data. An examination of both the eigenvalues and the scree plot helped inform the decision of retaining these three factors, accounting for a total variance explained of around 60%—in social sciences, an explained variance of 60%, and sometimes less, is acceptable, according to Hair et al. (1998). As far as communalities are concerned, the low values of items COR1 and COR24RC suggested the removal of these items. The examination of the inter-items correlations corroborated this scenario, with items COR1 and COR24RC showing the lowest correlations, irrespectively of the factor considered. The rest of the items loaded highly and significantly onto the respective factor—the lowest loading was observed for COR23 (0.687)—and correlated significantly with the other items pertaining to the same factor.

A. L. Vieira, *Interactive LISREL in Practice*, SpringerBriefs in Statistics,
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Taking into consideration both the precursor study by Saxe and Weitz (1982) and the content meaning of the questions included in each factor, factor 1 was named *problem solving behaviour* (PSB), which broadly refers to the ability of the client manager to provide expert counselling on the client's present and future needs (Crosby 1989), and factor 2 *selling orientation* (SO), in line with more recent propositions (Bejou et al. 1996; Periatt et al. 2004; Sirdeshmukh and Sabol 2002; Thomas et al. 2001; Wray et al. 1994). Factor 3 was named *selling ethics* (SE), again due to the content meaning implicit in the items comprising this factor, consistent with a perspective that can also be found in the literature (e.g. Bejou et al. 1998; Bejou et al. 1996; Dorsch et al. 1998; Lagace et al. 1991; Roberts et al. 2003; Wray et al. 1994). The tests with the Cronbach's alpha reliability coefficient suggested that all items should be retained in their respective factors, with the exception of the above mentioned COR1 and COR24RC.

3.1.1 Dimensionality Tests for COR

Anderson and Gerbing (1988, p. 414) expressed the importance of unidimensional measurement in the following terms:

> Achieving unidimensional measurement (…) is a crucial undertaking in theory testing and development. A necessary condition for assigning meaning to estimated constructs is that the measures that are posited as alternate indicators of each construct must be acceptably unidimensional. That is, each set of alternate indicators has only one underlying trait or construct in common (…).

EFA is generally acknowledged as insufficient for the assessment of dimensionality (Hunter and Gerbing 1982; Rubio et al. 2001). In this case, the EFA suggested three factors, which are correlated among them and seem to be measuring a higher-order construct, COR. In other words, the higher-order factor, COR, would account for the relation between the lower order factors, PSB, SO, and SE (Benson and Bandalos 1992; Hunter and Gerbing 1982; Rubio et al. 2001). According to Byrne (2001), in this case, the fit statistics resulting from the model will be equivalent, either if it is parameterised as a first-order or a second-order structure. The second-order model is equivalent to the first-order model, only the former is a special case of the latter, an alternative account of the association between the first-order factors (Byrne 2001; Kline 2005).

The decision on whether to model a certain measurement instrument as first or second-order structure relies ultimately on what theory suggests (Byrne 2001; Garver and Mentzer 1999). In this context, it was felt that a second-order structure should be tested, in line with previous approaches to COR (e.g. Periatt et al. 2004; Thomas et al. 2001).

EFA is not able to test models with higher-order factors (Hunter and Gerbing 1982; Rubio et al. 2001), but this can be done through confirmatory factor analysis, namely using SEM. For dimensionality purposes, EFA gives a valuable but insufficient indication that must be tested through CFA.

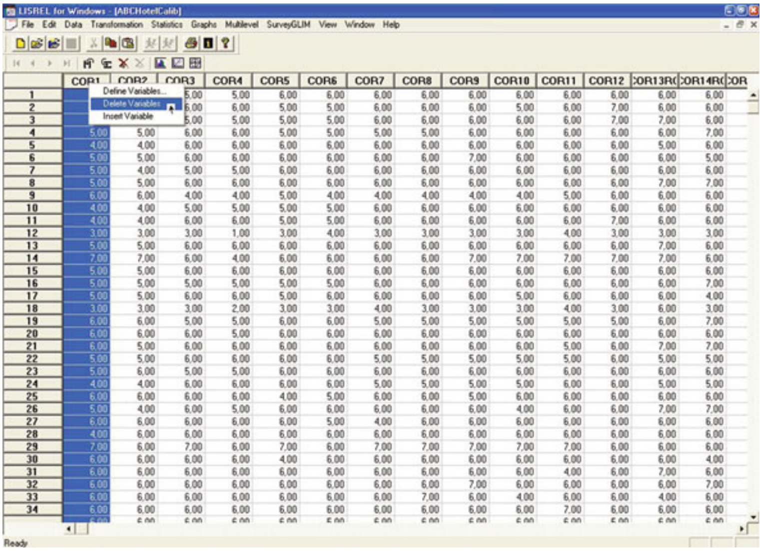
In the present case, EFA apparently suggests a second-order factor structure composed by a higher-order construct, COR, comprising three lower-order dimensions, PSB, SO, and SE—each of these being, in turn, unidimensional. The object of analysis is, therefore, whether unidimensionality holds for each of the first-order factors or dimensions (Steenkamp and van Trijp 1991). Thereby, despite the equivalence between first-order and second-order structure mentioned in the last paragraph, a second-order CFA using SEM was deemed useful for clarification purposes (and for illustration purposes in the context of the present manual). This CFA was performed on the items relating to COR, aiming at finding out whether there is support for the second-order factor structure, and for the unidimensionality of each of the three first-order constructs—being the latter the CFA's primary object of attention.

3.1.1.1 Second-Order CFA for COR

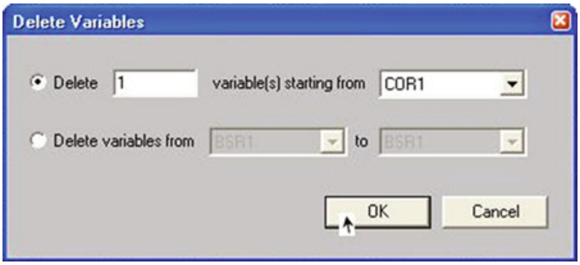
First of all, in order to execute a second-order CFA, we need to create a covariance matrix. To this end, let us go back to the *Interactive* LISREL program, and open the PRELIS file that we had created in Part I (ABCHotelCalib.psf). We start by eliminating from the database all the items that should be removed from the analysis, according to what was suggested by the EFA. Next, using the first item of COR as an example, we right click on 'COR1' and select:

> **Note**
>
> We can also eliminate all these items (i.e. in relation to which the EFA suggested removal) using SPSS, before importing the SPSS file to PRELIS.

Delete Variables

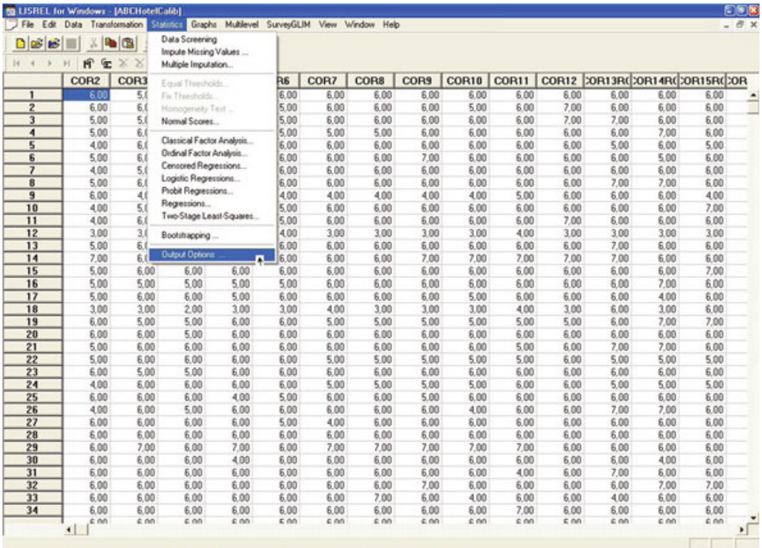


After having obtained the following window, we should click *OK*:

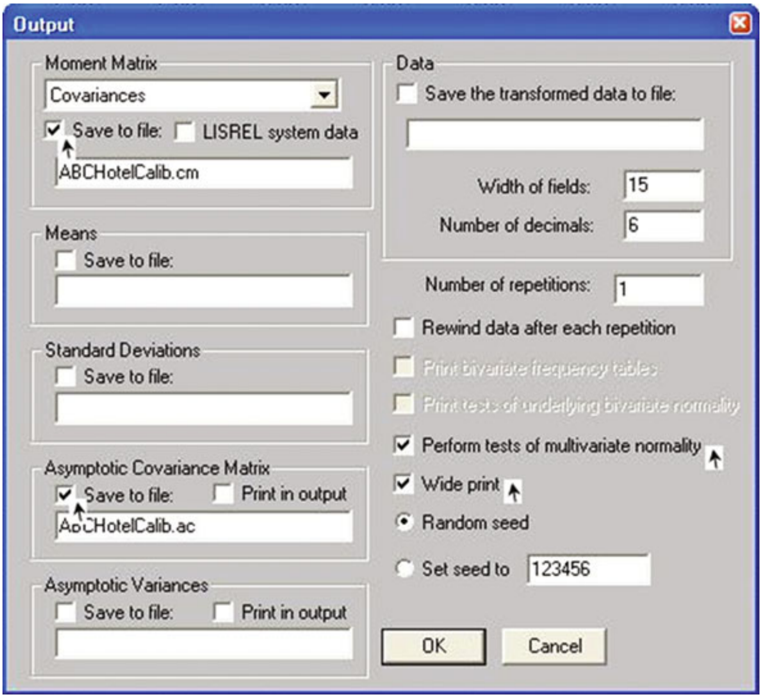


Then we save and proceed as follows:

Statistics—Output Options



We will now fill in the next window as follows:



Hint

At this point it is useful to designate the covariance matrix with the same name that we had chosen for the SPSS file (ABCHotelCalib), which was imported to PRELIS—and then do *Ctrl* + *C* (*Copy*) of this name so that we can do *Ctrl* + *V* (*Paste*) throughout the rest of the LISREL analysis.

As illustrated above, the difference between this step and the last step executed in Part I is that, in this step, we have additionally created the covariance matrix and saved it in file ABCHotelCalib.cm ('cm' for covariance matrix).

Note

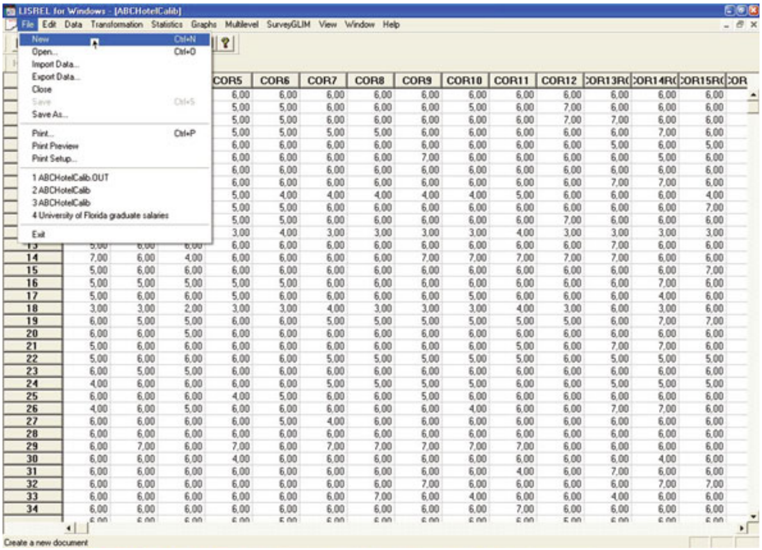
For illustration purposes, we have also saved an asymptotic covariance matrix (ABCHotelCalib.ac), which is necessary for those cases where there are also ordinal variables—and not only continuous variables, as in the present case (see Batista-Foguet and Coenders 2000, Chap. 6).

After clicking *OK* we should obtain an output map similar to that of the normality tests conducted in Part I, only now we will have a covariance matrix saved in a file that we will need to use while building path diagrams and testing the various LISREL models, which is what we will start doing in the next section (see more details on how to use PRELIS in Jöreskog and Sörbom 2002).

3.1.1.2 Path Diagram for COR

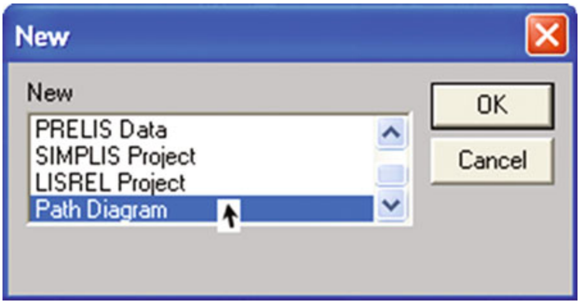
To start building the path diagram that corresponds to the second order CFA we need to close the output window and go back to the screen with the database. Then we press:

File—New

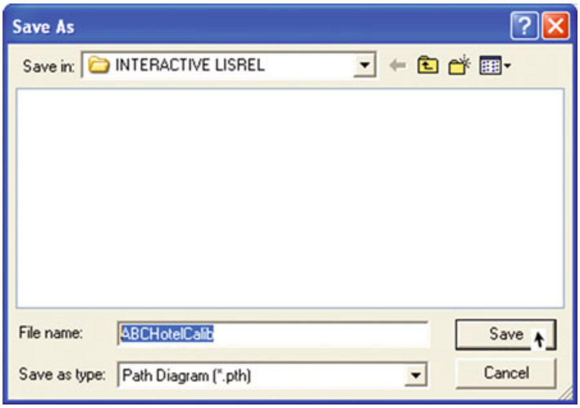


And in the following window we chose:

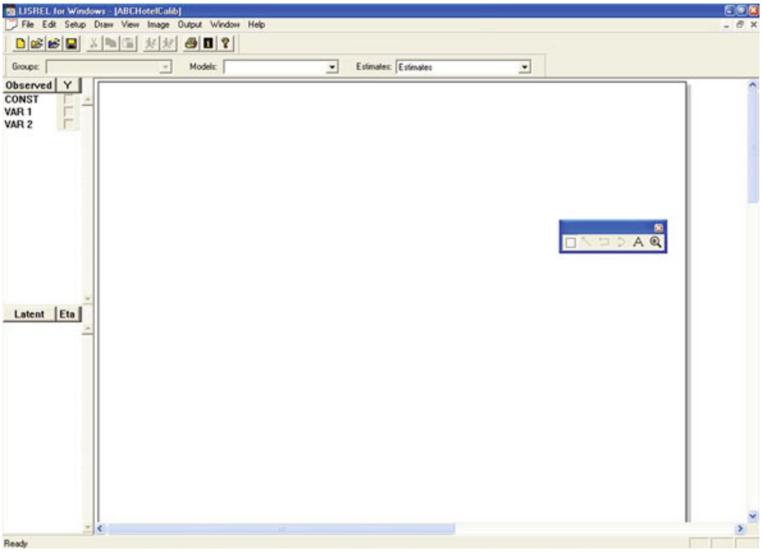
Path Diagram



After clicking *OK* we get a window in which we name the file—here, again, to *Paste* (*Ctrl* + *V*) 'ABCHotelCalib' comes in handy—and save:

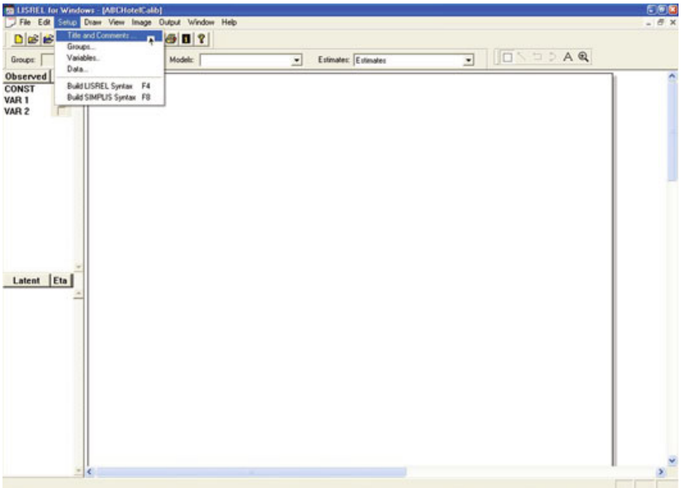


After clicking *save*, we will obtain the following screen:



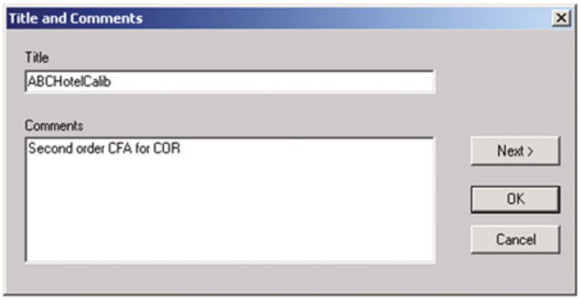
After ‘dragging’ the toolbar to the upper right corner, for our best convenience, we press:

Setup—Title and Comments



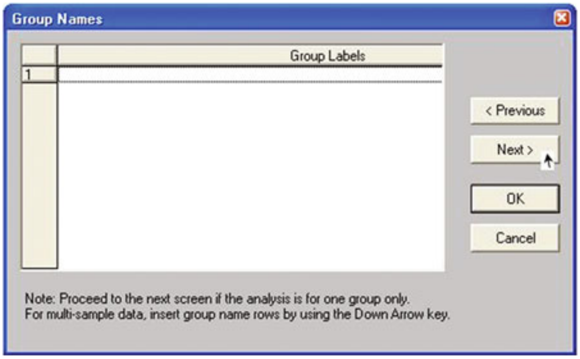
It is recommended that each model has its own title, which should be inserted it in the following window (we can also make some comments, if deemed necessary). Then we click:

Next



The following screen is appropriate for multi-group analysis, which is not the case of the present analysis. Therefore, we press again:

Next



In the following window we start by filling in the list of the observable variables. In order to do this, we start by clicking:

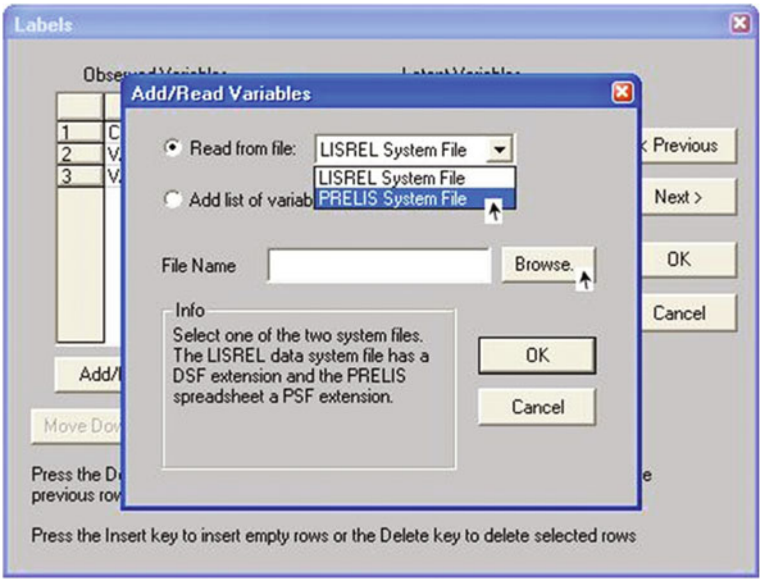
Add/Read Variables

Then, in the next window, we select:

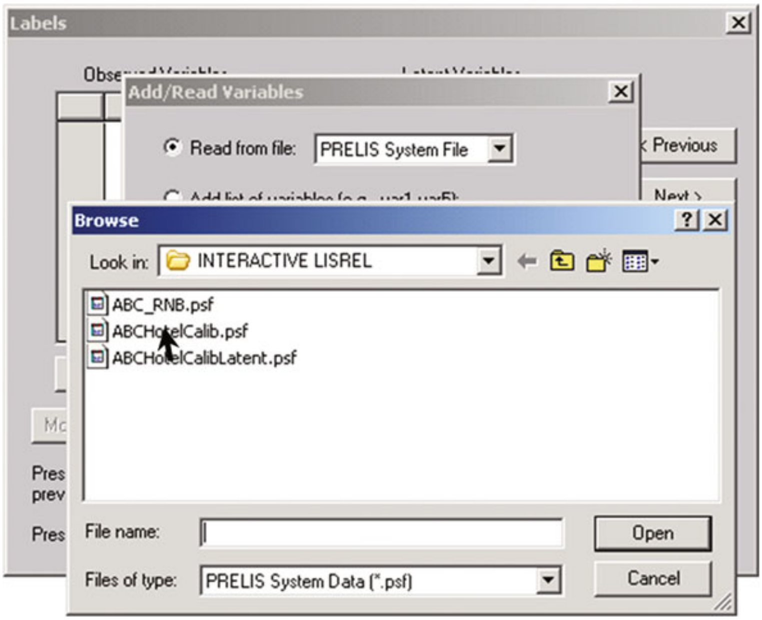
Read from File—PRELIS System File

And 'fetch' the data in the PRELIS file that we have been using, by doing:

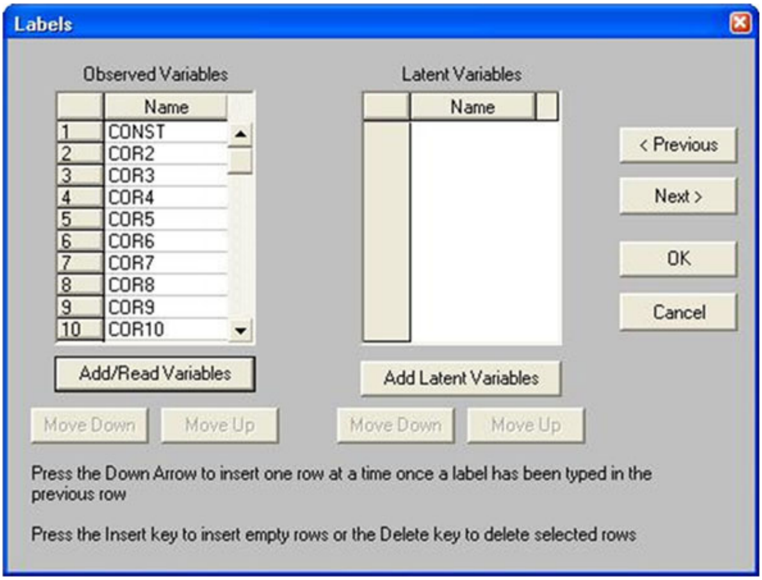
Browse



We should now click twice on the PRELIS file 'ABCHotelCalib' to open it.

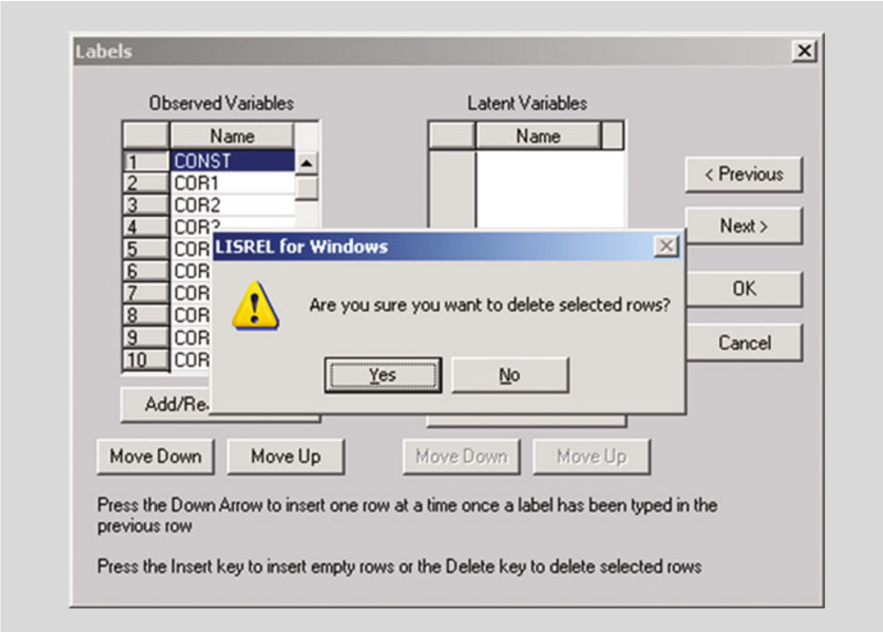


By pressing *OK* we will obtain the following window with the observable variables already inserted:



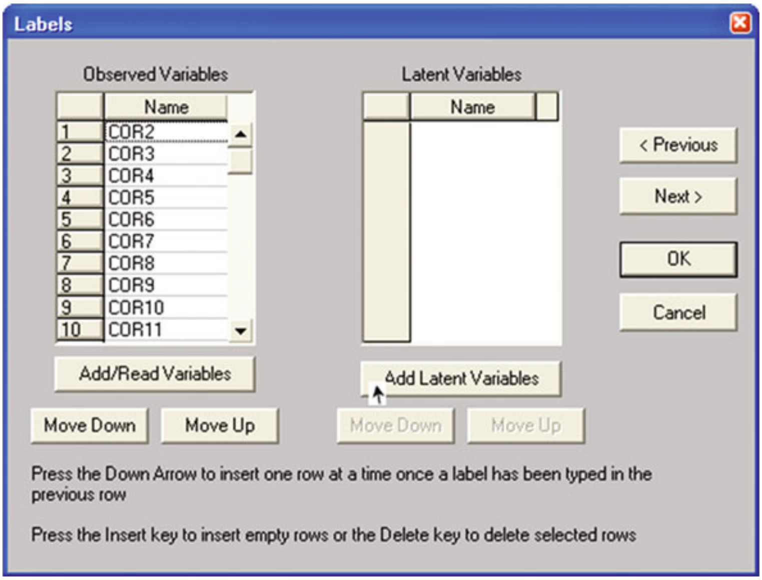
Hint

With the purpose of exemplifying how to eliminate a variable (which is sometimes needed), let us eliminate the variable 'CONST', which will not affect subsequent procedures. We can do this by clicking on '1' on the left hand side of the window. Then we press 'Del' and confirm.



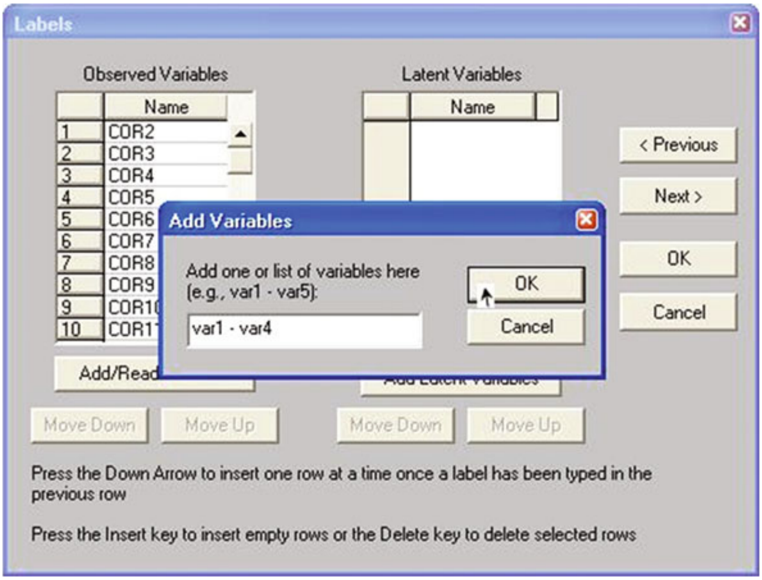
Let us now define the latent variables by clicking:

Add Latent Variables

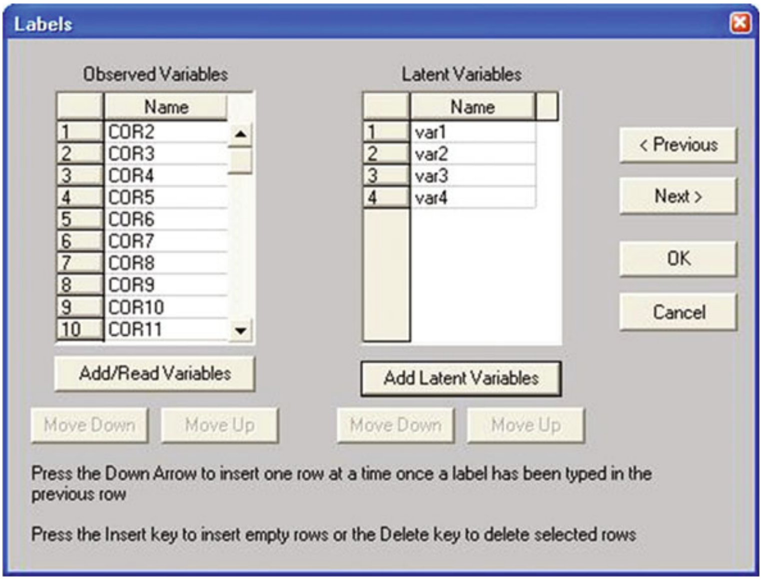


This will lead us to the following window, in which, taking into consideration that the second-order CFA model that we intend to test includes four latent variables (COR, PSB, SO and SE), we should write:

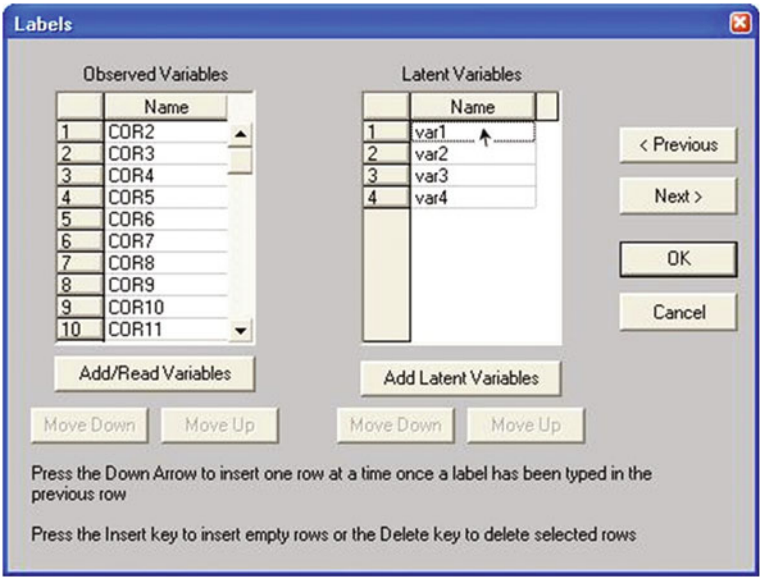
var1–var4



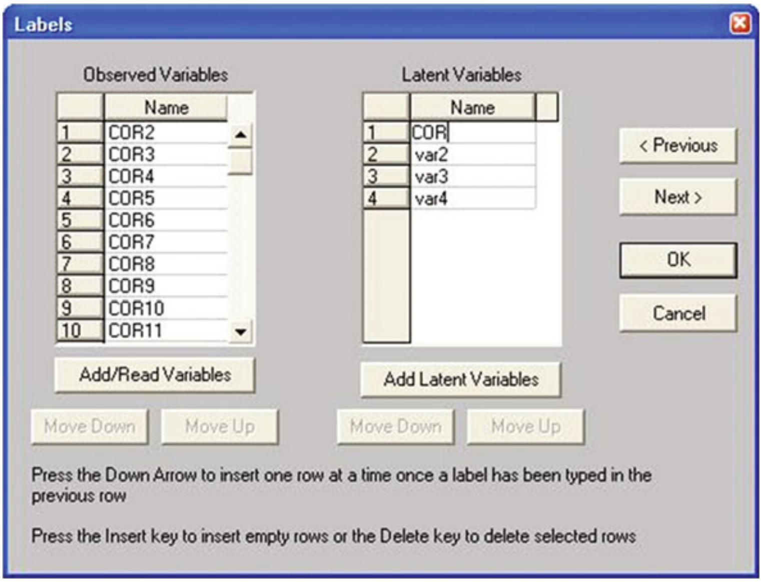
Clicking *OK* will lead us to the following window:



The variables should be defined one by one. For example, we begin by clicking on ‘var1’:

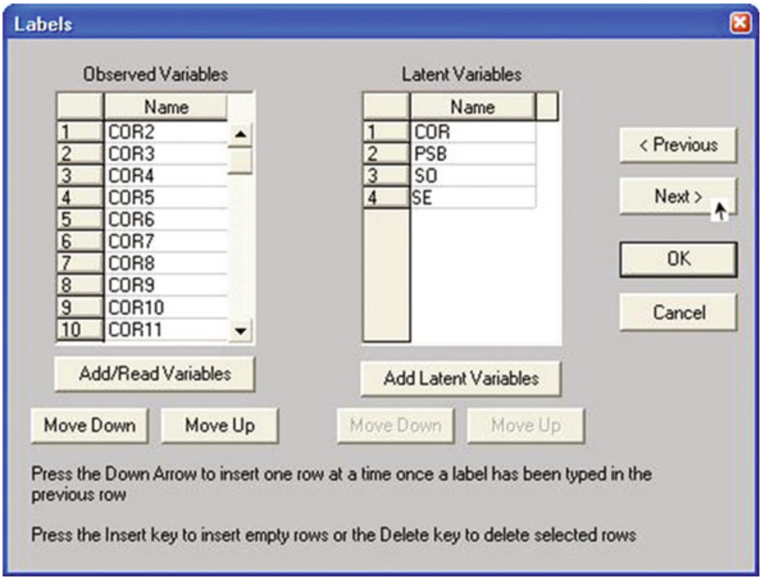


And then write the abbreviation for customer orientation:

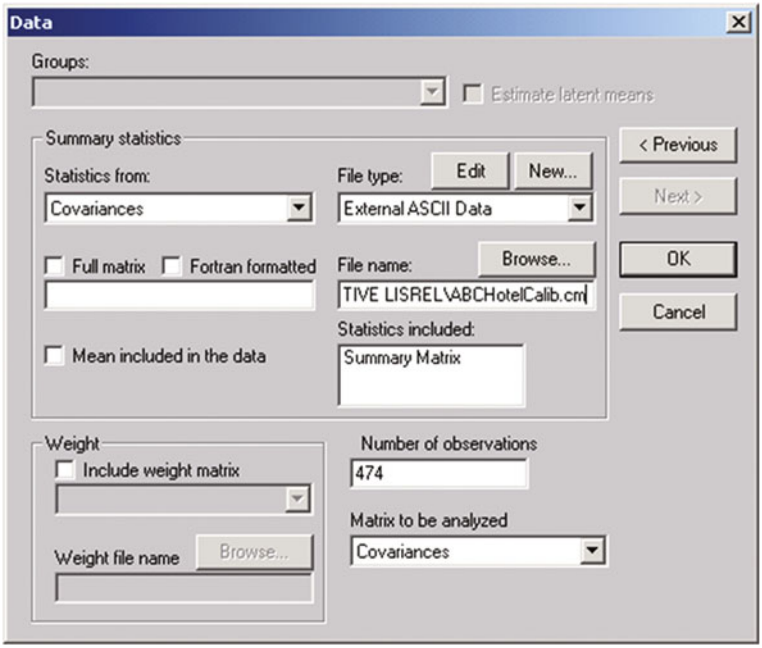


After inserting the abbreviations for all the latent variables we click:

Next



And get this window, which we should fill in as follows:



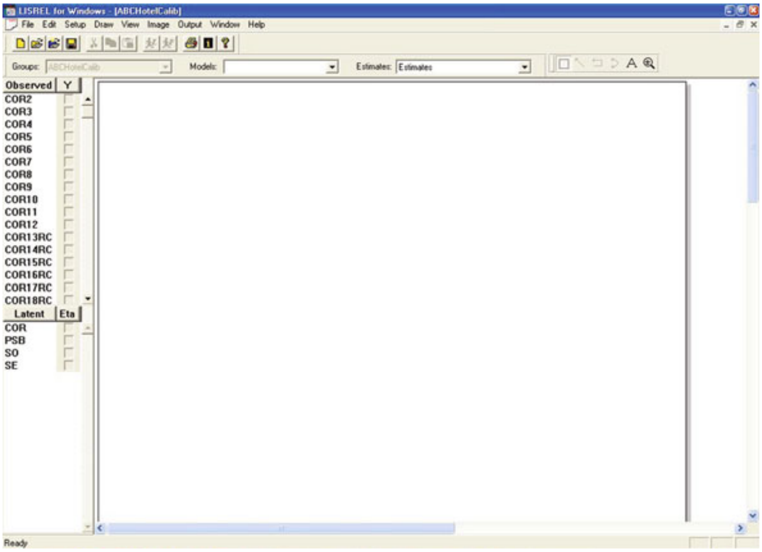
Hint

The field 'File name:' is where we indicate the file where the program should 'fetch' the covariance matrix. Analogous to what we have done when we defined the observable variables, we can use the *Browse* function to look for the file 'ABCHotelCalib.cm'. But it is much more practical to use what is already written in the field 'File name:' and simply change the file extension from '.psf' to '.cm' (one of the advantages of saving everything in the same location, as suggested previously).

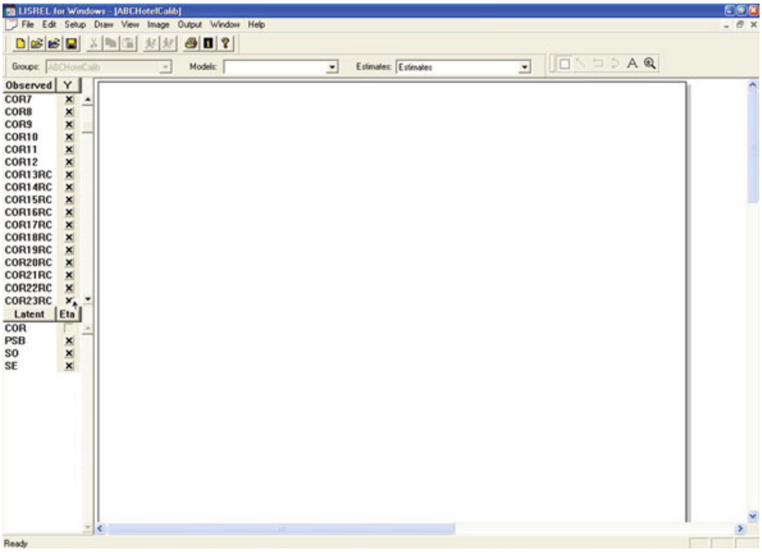
Warning

Do not forget to choose 'Covariances' and to indicate the number of observations, otherwise errors will appear in the LISREL output and you will be forced to go back to the above mentioned step.

After clicking *OK* the following screen will appear, where we will start drawing the path diagram that corresponds to the model that we are about to test, that is, the second-order CFA for the construct COR and its potential dimensions/first order constructs (PSB, SO, SE).

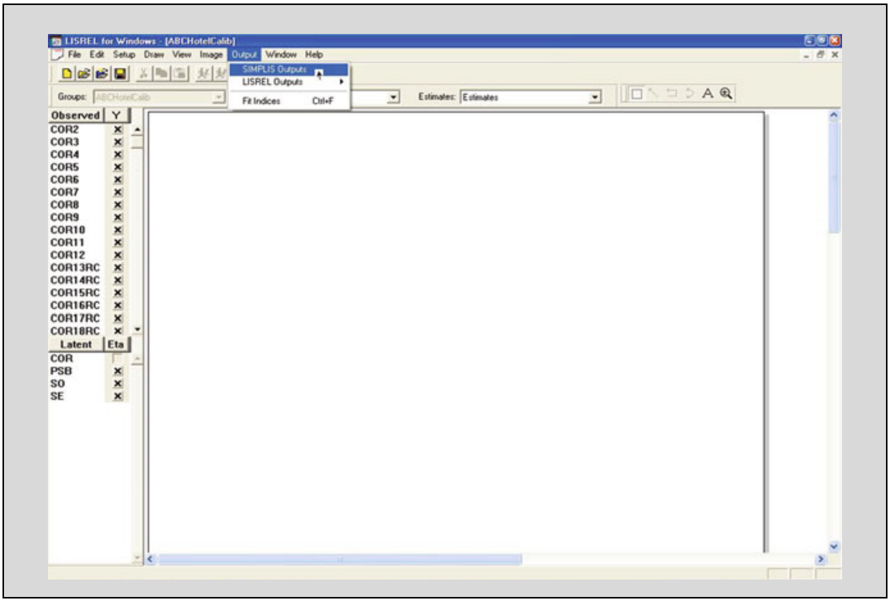


Here we should indicate which ones are the endogenous variables by ticking the respective boxes. In this case, all the variables are endogenous except for COR. Therefore, let us tick the boxes in front of PSB, SO, SE, as well as all the observable variables, from COR2 to COR23RC, inclusive.

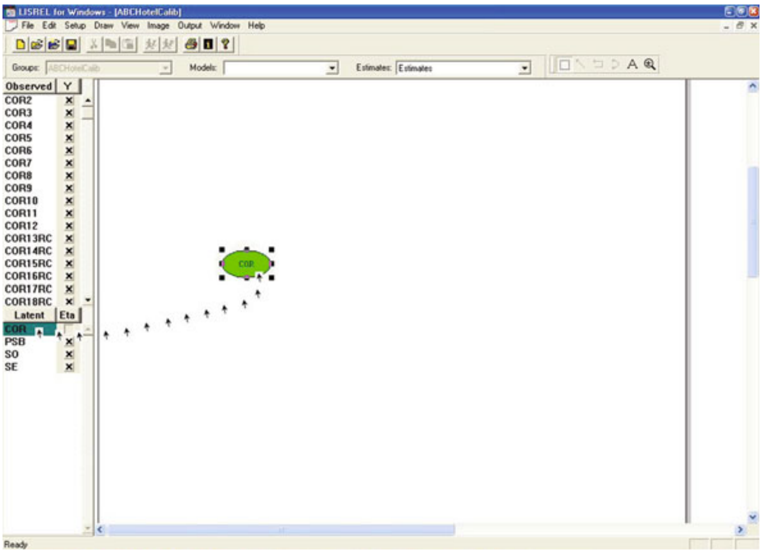


Notes

- As mentioned earlier, the default estimation method is ML (Maximum Likelihood). To change it, we can use the option 'SIMPLIS Outputs' (SIMPLIS is the command language that we are going to use in this handbook—to be addressed in the next sub-section), which can also be used to make various changes other than the estimation method:
- To know the meaning of symbols like 'Y' or 'Eta', among others, see, for example, Diamantopoulos and Siguaw (2000), Appendix 3A.
- Let us focus on the observable variables related to COR, although the list includes variables measuring other constructs.



To draw the path diagram, we begin by using the mouse to 'drag' the variables to the 'canvas' (after ensuring that the 'square' in the tool bar—upper right corner—is selected). Using the variable COR as an example:

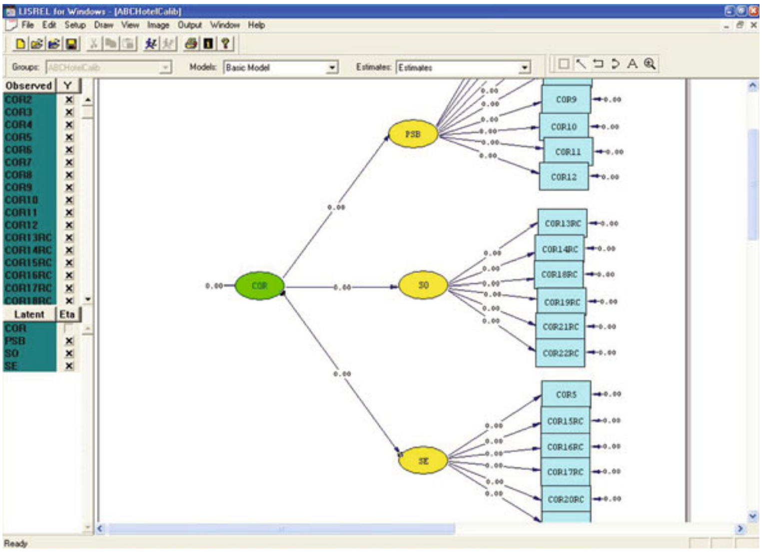


After ‘dragging’ all the variables, we are now going to connect them according to the associations implied by the model and suggested by the conducted EFA (for further details, see Vieira 2010, Chap. 6). To this end, we should click on the rectilinear arrow in the tool bar and link the variables by clicking on the ‘origin variable’ and ‘dragging’ the mouse to the ‘destination variable’, according to the impacts proposed in the model.

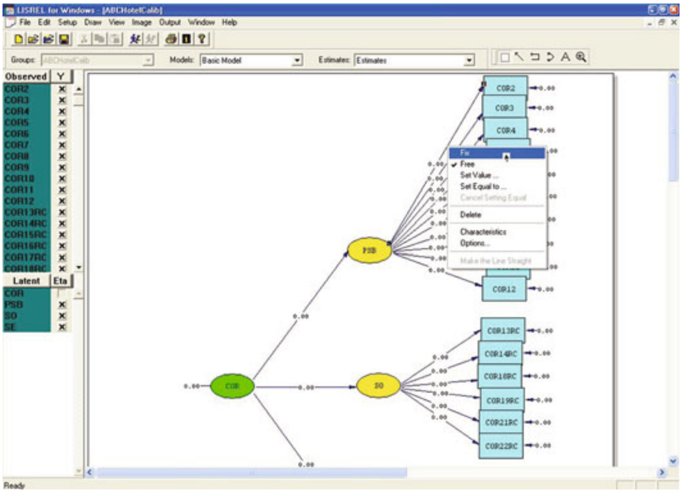
Hint

To eliminate a link, we can either press ‘Del’ immediately after its creation, or click on the square in the tool bar and then on the link to be eliminated and press ‘Del’.

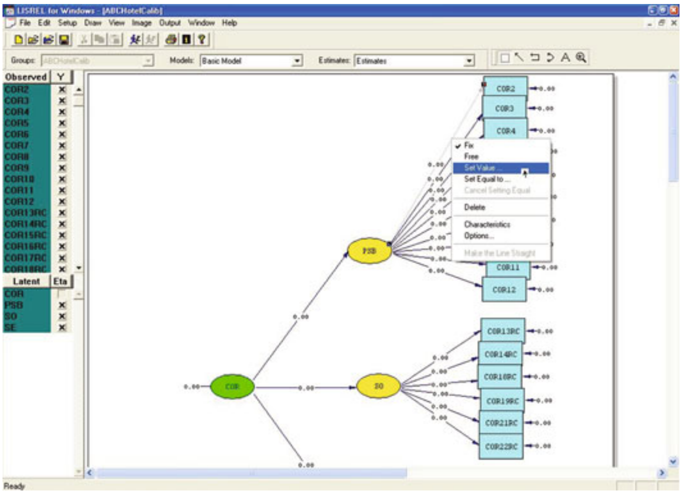
We will now obtain a diagram that looks like the one in the following picture:



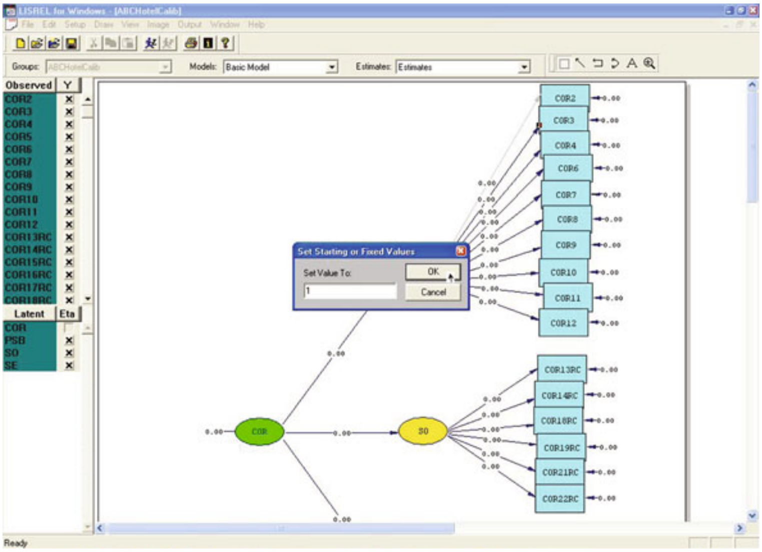
Given that, by definition, a latent variable is not observable and, therefore, has no scale of its own, its origin and unit of measurement need to be defined. The origin is defined by assuming that the mean of the variable is zero. As for the unit of measurement, there are two alternatives: either we assume that it is a standardised variable, with the variance fixed to unity, or we define the unit of the latent variable with reference to one of its observable indicators, by ‘fixing’ one of the coefficients to ‘1’ and choosing for this purpose the indicator which, according to the most adequate criteria selected by the researchers, best represents the latent variable (see also Diamantopoulos and Siguaw 2000, pp. 34–35). In our example, the option was the former alternative for the variable COR, and the latter for each of its dimensions (PSB, SO and SE). To 'fix' parameters, we should proceed as follows: we click on the 'square' in the tool bar and place the cursor on the parameter to be 'fixed'. Then we right click and select 'fix':



We will now perform the same operation, only this time we need to choose 'Set Value':



At this stage we will obtain the following window, in which we define the value ‘1’ and press *OK*:



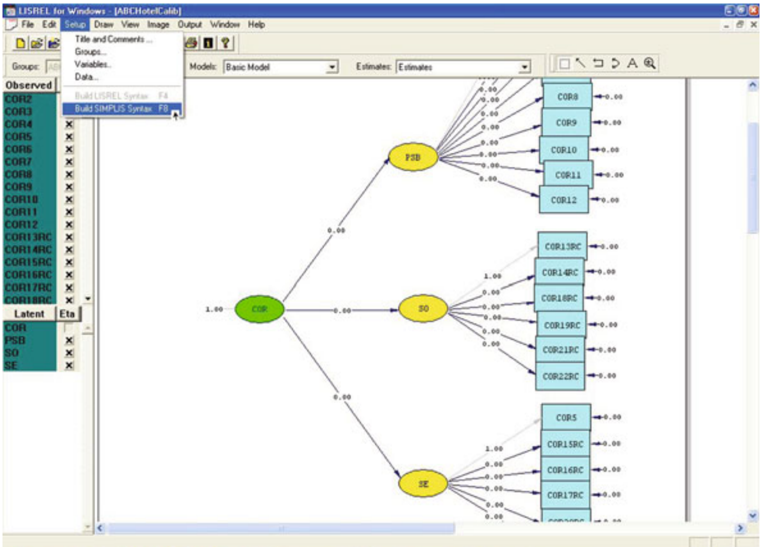
Note

Sometimes the ‘fixing’ procedure is also used for reasons pertaining to the identification of models/parameters (see Diamantopoulos and Siguaw 2000, from p. 48 and/or Batista-Foguet and Coenders 2000, from p. 67). The ‘fixing’ procedure does not affect the standardised solution, as evidenced throughout the present analysis.

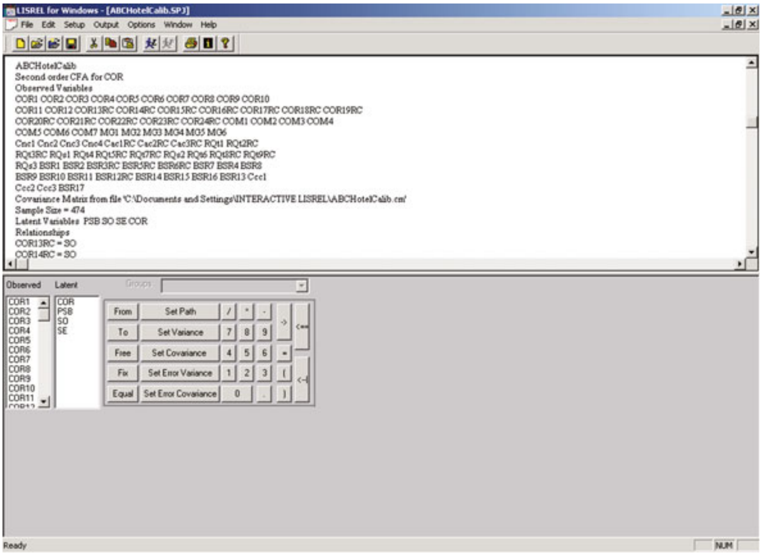
Once all the parameters are ‘fixed’ we will obtain the following screen, in which we should select:

Setup—Build SIMPLIS Syntax

In order to generate the syntax of the program that corresponds to the drawn path diagram, in SIMPLIS command language (to be briefly addressed in the next sub-section—see Jöreskog and Sörbom 1993, for a more detailed approach).



This is how the screen with the SIMPLIS program looks like:



3.1.1.3 SIMPLIS Command Language—Brief Notions

In the above presented screen we have the possibility of re-programming the displayed program using a command language that is simpler than the original LISREL language (as the designation 'SIMPLIS' suggests). (As a matter of fact, up until not so long ago, when there were no interactive versions of LISREL, to write the program—in LISREL syntax—and run it on the computer was the only option available). Let us begin by interpreting each of the lines of the following program:

```
ABCHotelCalib
Second Order CFA for COR
Observed Variables
COR2 COR3 COR4 COR5 COR6 COR7 COR8 COR9 COR10 COR11
COR12 COR13RC COR14RC COR15RC COR16RC COR17RC COR18RC COR19RC
COR20RC
COR21RC COR22RC COR23RC COM1 COM2 COM3 COM4 COM5 COM6
COM7 MG1 MG2 MG3 MG4 MG5 MG6 Cnc1 Cnc2
Cnc3 Cnc4 Cac1RC Cac2RC Cac3RC RQt1 RQt2RC RQt3RC RQs1
RQt4 RQt5RC RQt7RC RQs2 RQt6 RQt8RC RQt9RC RQs3 BSR1
BSR2 BSR3RC BSR5RC BSR6RC BSR7 BSR4 BSR8 BSR9 BSR10
BSR11 BSR12RC BSR14 BSR15 BSR16 BSR13 Ccc1 Ccc2 Ccc3
BSR17
Covariance Matrix from file 'C:\Documents and Settings\INTERACTIVE
LISREL\ABCHotelCalib.cm'
Sample Size = 474
Latent Variables  PSB SO SE COR
Relationships
COR2 = 1.00*PSB
COR3 = PSB
COR4 = PSB
COR5 = 1.00*SE
COR6 = PSB
COR7 = PSB
COR8 = PSB
COR9 = PSB
COR10 = PSB
COR11 = PSB
COR12 = PSB
COR13RC = 1.00*SO
COR14RC = SO
COR15RC = SE
COR16RC = SE
COR17RC = SE
COR18RC = SO
COR19RC = SO
COR20RC = SE
COR21RC = SO
COR22RC = SO
COR23RC = SE
PSB = COR
SO = COR
SE = COR
Set the Variance of COR to 1.00
Path Diagram
End of Problem
```

The first two lines reproduce the title and subtitle (comments) that we attributed to the analysis. The next line 'announces' the observable variables. As we can see, the program shows all the observable variables that are included in the database. This has advantages and disadvantages. For example, one disadvantage is that we do not need all the variables for the present analysis and, therefore, the variables that do not relate to COR are just occupying space in the program. On the advantages side we have, for example, the possibility of running several analyses on different variables, based on the same PRELIS file, given that the 'extra' variables do not represent any problem at all, apart from the space occupation. In any case, we can always simply delete them from the SIMPLIS program, as we would do in a Word file or, alternatively, in the earlier phases of the analysis, we could build databases (in PRELIS, or even in SPSS) specifically tailored for each analysis. The next line is the command line indicating where the program is supposed to 'fetch' the covariance matrix (Covariance Matrix from file).

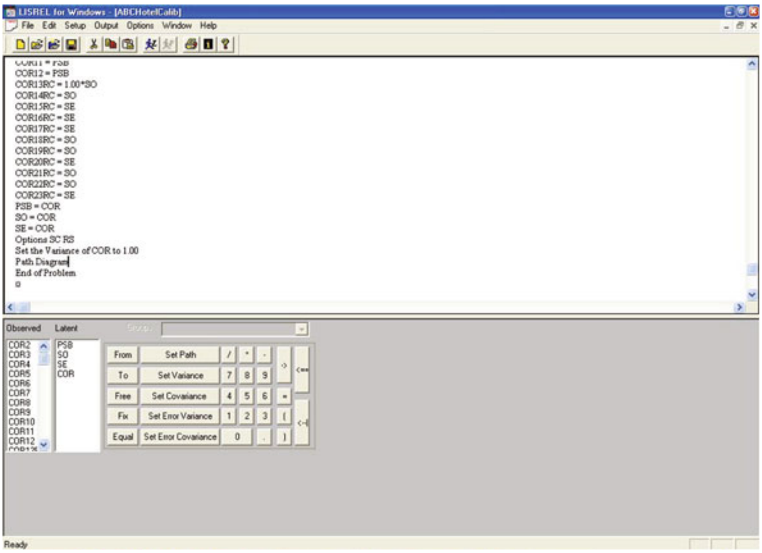
Warning

Here the 'short-and-revealing' rule applies again, both in relation to the abbreviations of the variables and the location of the file that contains the covariance matrix (see other useful suggestions in Diamantopoulos and Siguaw 2000, Chap. 4). In the case illustrated above, the location 'C:\Documents and Settings\INTERACTIVE LISREL\ABCHotelCalib.cm' fits in the respective line. When it does not fit, because it is too lengthy, the program will not fully reproduce it, which will originate error messages in the output map, which, in turn, will hinder the rest of the analysis. There are various types of error messages (see most common error messages and respective solutions as suggested in Diamantopoulos and Siguaw (2000), Appendix 6A), although normally these problems can be solved by thoroughly verifying (letter by letter, character by character) the SIMPLIS program and correcting it—for example, by completing 'by hand' a lengthy location. If none of these remedies work, an option is to go back to the very beginning and do it all over again, ensuring that there are no flaws along the process. Indeed, apart from the possible errors and/or omissions up to this point, errors and/or omissions may occur while drawing the path diagram. Besides that, some versions of the LISREL program contain 'bugs', i.e. they do not reproduce exactly what has been determined by the drawn path diagram. This reinforces the idea that it is very important for us to have at least some basic notions on the SIMPLIS command language.

After the command line that indicates the sample size (Sample Size =) we have a line containing the latent variables (Latent Variables). The next line

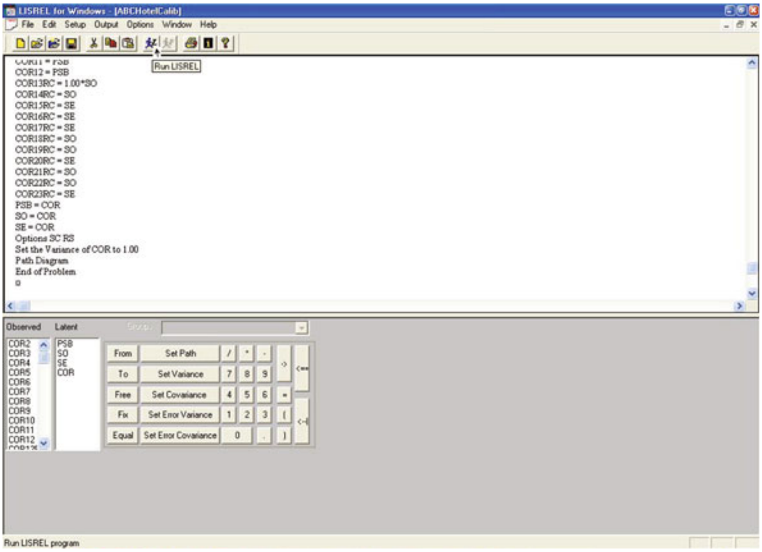
(Relationships) introduces the associations between the variables, which are presented in the form of (regression) equations containing the dependent variables on the left hand side, and the independent variables on the right hand side. Let us observe an important detail in this regard: the majority of the equations contain free parameters, i.e., parameters that need to be estimated, whereas the equations 'COR2 = 1.00*PSB', 'COR5 = 1.00*SE' and 'COR13RC = 1.00*SO' have 'fixed' parameters ('fixed' to the vale of '1'), as we had determined while drawing the path diagram.

Finally, we have the reproduction (in the form of the SIMPLIS command language) of the 'fixed' parameter that corresponds to the variance of COR, and the command line that 'asks for' the path diagram that will illustrate the results of the estimation process. These last two lines are in the section of the program that contains the output options. One of the possibilities in terms of additional functions to be programmed by the user (not least because it is not possible to do it via path diagram) is to add the command line 'Options' right after the equations and to 'order' the program to include more information in the output, for example, the completely standardised solution (SC) and the residual analysis (RS) (for more examples of additional functions, see Diamantopoulos and Siguaw 2000, Chaps. 4 and 6). After introducing these changes, the screen with the SIMPLIS program would look like this:

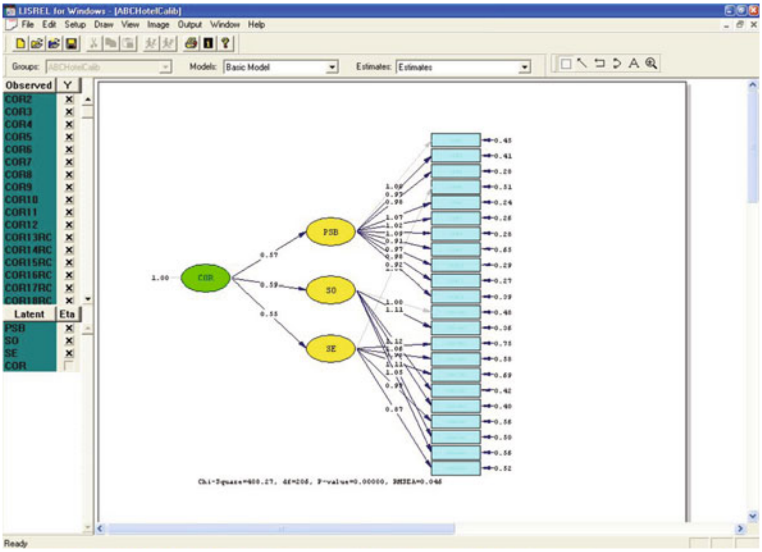


We will be back to SIMPLIS programming later in this analysis, namely regarding the rival models analysis, to be addressed in Part III. For the moment, after double checking all the program lines and ensuring that there are no syntax errors, we should click on ‘Run LISREL’, in order to obtain the path diagram resultant from the estimation process:

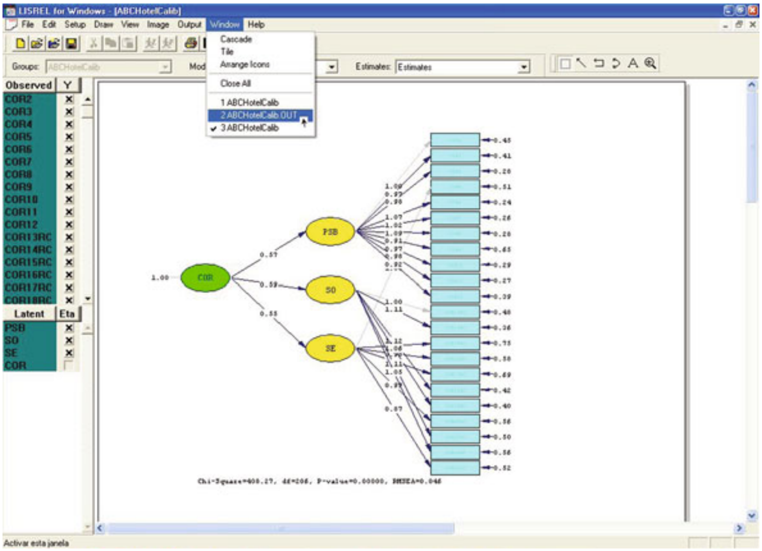
> **Note**
>
> Alternatively to the ‘manual’ programming, we can also use the virtual keyboard further down on the screen. In this case, all we need to do to perform the functions that are displayed is to click on the respective key and the lines will appear in the program.



We will now obtain the following path diagram:



This diagram already contains some statistical information resulting from the estimation, but to carry out the actual analysis we need to access the output map, using the ‘Window’ option (which allows us to commute between ‘Path Diagram’, ‘SIMPLIS Syntax’ and ‘Output’):



3.1.1.4 Interpreting the LISREL Output

The last procedure will take us to the output map. For the reader's convenience, we will discuss the output map in several stages, that is, we will focus on the most relevant information for the analysis, section by section. Let us start with the first part of the map, which, after the copyright information, reproduces the syntax of the SIMPLIS program that has been generated, followed by the covariance matrix (and, therefore, we will excuse ourselves from adding any further comments at this point):

```
L I S R E L  8.80
                              BY
                  Karl G. Jöreskog & Dag Sörbom

              This program is published exclusively by
              Scientific Software International, Inc.
                7383 N. Lincoln Avenue, Suite 100
                 Lincolnwood, IL 60712, U.S.A.
         Phone: (800)247-6113, (847)675-0720, Fax: (847)675-2140
       Copyright by Scientific Software International, Inc., 1981-2006
        Use of this program is subject to the terms specified in the
                 Universal Copyright Convention.
                  Website: www.ssicentral.com

 The following lines were read from file C:\Documents and Settings\INTERACTIVE
LISREL\ABCHotelCalib.SPJ:

 ABCHotelCalib
Second Order CFA for COR
SYSTEM FILE from file 'C:\Documents and Settings\ INTERACTIVE
LISREL\ABCHotelCalib.DSF'
 Sample Size = 474
 Latent Variables  PSB SO SE COR
 Relationships
 COR2 = 1.00*PSB
(...)
COR23RC = SE
 PSB = COR
 SO = COR
 SE = COR
 Options SC RS
 Set the Variance of COR to 1.00
 Path Diagram
 End of Problem

Sample Size =   474

 ABCHotelCalib

       Covariance Matrix

            COR2     COR3     COR4     COR5     COR6     COR7
         -------- -------- -------- -------- -------- --------
    COR2     0.98
(...)
       Covariance Matrix

          COR20RC  COR21RC  COR22RC  COR23RC
         -------- -------- -------- --------
  COR20RC     1.25
  COR21RC     0.39     1.16
  COR22RC     0.38     0.65     1.14
  COR23RC     0.62     0.29     0.28     1.05
```

The next information is on the number of necessary iterations that had to be carried out so that the estimation process could be completed or, in other words, so that the 'solution' was 'admitted' or 'converged'. After this, the equations that correspond to the measurement model (associations between the latent variables and respective observable variables) are presented, followed by the equations that represent the structural model (associations between latent variables). Close to each equation there is also information on the variance of the measurement error (error variance in measurement equations), and the variance of the residual term (error variance in structural equations). The way the issue of error is treated within SEM/LISREL is highlighted in the literature as one of the most important distinctive features of this methodology when compared to traditional techniques (e.g., Baptista-Foguet and Coenders 2000; Diamantopoulos and Siguaw 2000). Below each estimated parameter (regression coefficients and error variances) we can see the respective standard errors (between round brackets) and *t*-values (with some formatting inefficiencies, an aspect in which the LISREL 8.80 version still has room for improvement).

Hint

We can improve the formatting by changing the font to `Courier New` (or just `Courier`), size 10, as illustrated in the next extract of the output.

For example, in the measurement equation linking COR3 and PSB, the standard error that corresponds to the regression coefficient (0.97) is 0.059 and the *t*-value is 16.35; similarly, this time in relation to the error variance (0.41), the standard error is 0.029 and the *t*-value 14.30. Finally, it should be noted that this output section also includes the squared multiple correlations (R^2) for each equation, that is, the amount of variance in the dependent variables explained by independent variables.

```
Number of Iterations = 35

 LISREL Estimates (Maximum Likelihood)

         Measurement Equations


     COR2 = 1.00*PSB, Errorvar.= 0.45  , R² = 0.55
                                (0.031)
                                 14.31

     COR3 = 0.97*PSB, Errorvar.= 0.41  , R² = 0.55
           (0.059)              (0.029)
            16.35                14.30

     COR4 = 0.98*PSB, Errorvar.= 0.28  , R² = 0.65
           (0.055)              (0.020)
            17.96                13.72

(…)

  COR20RC = 0.99*SE, Errorvar.= 0.56  , R² = 0.55
           (0.063)             (0.044)
            15.87               12.59

  COR21RC = 1.11*SO, Errorvar.= 0.50  , R² = 0.57
           (0.070)             (0.038)
            15.83               13.11

  COR22RC = 1.05*SO, Errorvar.= 0.56  , R² = 0.51
           (0.070)             (0.041)
            15.00               13.59

  COR23RC = 0.87*SE, Errorvar.= 0.52  , R² = 0.51
           (0.058)             (0.040)
            15.11               13.10


         Structural Equations


      PSB = 0.57*COR, Errorvar.= 0.21  , R² = 0.61
           (0.044)              (0.035)
            13.01                5.94

       SO = 0.59*COR, Errorvar.= 0.19  , R² = 0.65
           (0.046)              (0.036)
            12.88                5.21

       SE = 0.55*COR, Errorvar.= 0.40  , R² = 0.43
           (0.048)              (0.051)
            11.42                7.80

(…)
```

We are now moving on to one of the most important sections of the output: the goodness of fit statistics.

```
(…)
Goodness of Fit Statistics

Degrees of Freedom = 206
Minimum Fit Function Chi-Square = 410.13 (P = 0.00)
Normal Theory Weighted Least Squares Chi-Square = 408.27 (P = 0.00)
Estimated Non-centrality Parameter (NCP) = 202.27
90 Percent Confidence Interval for NCP = (148.64 ; 263.68)

Minimum Fit Function Value = 0.87
Population Discrepancy Function Value (F0) = 0.43
90 Percent Confidence Interval for F0 = (0.31 ; 0.56)
Root Mean Square Error of Approximation (RMSEA) = 0.046
90 Percent Confidence Interval for RMSEA = (0.039 ; 0.052)
P-Value for Test of Close Fit (RMSEA < 0.05) = 0.87

Expected Cross-Validation Index (ECVI) = 1.06
90 Percent Confidence Interval for ECVI = (0.95 ; 1.19)
ECVI for Saturated Model = 1.07
ECVI for Independence Model = 42.10

Chi-Square for Independence Model with 231 Degrees of Freedom = 19871.62
Independence AIC = 19915.62
Model AIC = 502.27
Saturated AIC = 506.00
Independence CAIC = 20029.17
Model CAIC = 744.84
Saturated CAIC = 1811.79

Normed Fit Index (NFI) = 0.98
Non-Normed Fit Index (NNFI) = 0.99
Parsimony Normed Fit Index (PNFI) = 0.87
Comparative Fit Index (CFI) = 0.99
Incremental Fit Index (IFI) = 0.99
Relative Fit Index (RFI) = 0.98

Critical N (CN) = 296.40


Root Mean Square Residual (RMR) = 0.038
Standardized RMR = 0.035
Goodness of Fit Index (GFI) = 0.93
Adjusted Goodness of Fit Index (AGFI) = 0.91
Parsimony Goodness of Fit Index (PGFI) = 0.75
(…)
```

The overall model fit statistics in LISREL are within the generally accepted thresholds and suggest an acceptable goodness-of-fit (see Table 3.1). In fact, although the Chi-square test is significant ($\chi^2 = 408.207$, $p = 0.0000$), the ratio chi-square/degrees of freedom is below 2 (df = 206, χ^2/df = 1.98)—normally a ratio in the range of 2–1 or 3–1, is indicative of an acceptable fit (Cote et al. 2001). In addition, the goodness of fit index (GFI = 0.93), the adjusted goodness of fit index (AGFI = 0.91), the non-normed fit index (NNFI = 0.99), and the comparative fit index (CFI = 0.99), as well as the root mean square error of approximation (RMSEA = 0.046) are indicating good fit (Diamantopoulos and Siguaw 2000; MacCallum et al. 1996).

Although these results seem to suggest sufficient support for both the second-order factor structure and unidimensionality of each of the first-order constructs, it is advisable to further investigate potential threats to unidimensionality. A possible evidence of potential threats to unidimensionality is the number of absolute values above 2.58 in the matrix of standardised residuals, which may indicate that the model might not satisfactorily estimate the relationship between a given pair of variables. The 'standard' cut-off is a standardised residual above 2.58, corresponding to a p-value < 0.01 (Gerbing and Anderson 1988; Jöreskog and Sörbom 2001; Steenkamp and van Trijp 1991). Although standardised residuals with an absolute value >3 have been also mentioned as the cut-off in this context (Jöreskog and Sörbom 1993), the researcher adopts herein the more stringent criteria. Modification indices above five may also be another sign of potential threats to unidimensionality (Anderson and Gerbing 1988; Gefen 2003). If the event that the LISREL output suggests potential dimensionality problems, unidimensionality can be improved by tackling the most problematic pairs of items, being the addition of error covariances between items the most commonly used way of improving the model fit (Baumgartner and Homburg 1996; Diamantopoulos and Siguaw 2000; Ping 2004). The pairs of items should be analysed one at a time, for a high degree of shared variance between a pair of items can affect the shared variance between other pairs. However, it is crucial that the researcher is cautious enough neither to cause the overfitting of the model nor to be data driven, but rather driving the analysis primarily through theory (Gerbing and Anderson 1988).

In the present analysis, the standard residuals above 2.58 represent <6% of the total of pairs of the matrix of standard residuals and modification indices above 5.0 also <6% of the total of pairs. The following extract shows the potentially problematic cases. For a better clarification of this issue, let us suppose that we decide to add a covariance error for the pair 'COR9 - - - COR2'. In this case the decrease in chi-square would be around 18.0 and the new parameter estimate would be, approximately, 0.11 (and we would lose one degree of freedom, for this procedure is equivalent to turning a 'fixed' a parameter—to the value '0'—into a free parameter).

Table 3.1 CFA for COR

Items and standardised factor coefficients*	PSB	SO	SE
COR2 Client manager tries to achieve his/her goals by satisfying us	0.74		
COR3 Our client manager has our best interest in mind	0.74		
COR4 Client manager tries to get us to discuss our needs with him/her	0.81		
COR6 Our client manager recommends suitable solutions for us	0.85		
COR7 Our client manager tries to find best services for us	0.82		
COR8 Our client manager answers our questions correctly	0.83		
COR9 Our client manager tries to match the hotel's solutions with our problems	0.63		
COR10 Our client manager is willing to disagree with us in order to help us make a better decision	0.80		
COR11 Our client manager tries to give us an accurate expectation of what the product will do for us	0.81		
COR12 Our client manager tries to figure out our needs	0.73		
COR13RC Our client manager tries to sell us all (s)he convinces us to buy, even if we think it is more than a wise customer would buy		0.73	
COR14RC Our client manager tries to sell as much as (s)he can rather than to satisfy us		0.80	
COR18RC Our client manager paints too rosy a picture of his/her services, to make them sound as good as possible		0.78	
COR19RC Our client manager spends more time trying to persuade us to buy than trying to discover our needs		0.77	
COR21RC Our client manager pretends to agree with us to please us		0.76	
COR22RC Our client manager implies to us that something is beyond his/her control when it is not		0.72	
COR5 Our client manager tries to influence by information rather than by pressure			0.76
COR15RC Our client manager keeps alert for weaknesses on a person's personality so (s)he can use them to put pressure to buy			0.67
COR16RC Our client manager if (s)he is not sure a service is right for us, (s)he will still apply pressure to get us to buy			0.73
COR17RC Our client manager decides what services to offer on the basis of what (s)he can convince us to buy, not on what will satisfy us			0.69
COR20RC Our client manager stretches a truth in describing a service			0.74
COR23RC Our client manager begins the sales talk for a service before exploring our needs			0.71
Composite Reliability	0.939	0.892	0.866
Goodness of fit statistics $\chi^2 = 408.207$ ($p = 0.00$), df $= 206$, (χ^2/df) $= 1.98$, RMSEA $= 0.046$, GFI $= 0.93$, AGFI $= 0.91$, NNFI $= 0.99$, CFI $= 0.99$			
Correlation between factors	PSB↔SO 0.63	PSB↔SE 0.53	SO↔SE 0.51
χ^2 Differences for Standard versus 'non-discriminant' CFA models (Δdf $= 1$, $p = 0.000$)	PSB↔SO 1408.22	PSB↔SE 1312.12	SO↔SE 1270.27

*All values statistically significant at the level of $p < 0.05$. *PSB* problem solving behaviour, *SO* selling orientation, *SE* selling ethics, *RC* reverse coded

```
(...)
 Summary Statistics for Standardized Residuals

 Smallest Standardized Residual =   -5.15
   Median Standardized Residual =    0.00
  Largest Standardized Residual =    7.09
(…)
 Largest Negative Standardized Residuals
 Residual for     COR9 and     COR6  -3.49
 Residual for    COR11 and     COR6  -2.59
 Residual for  COR15RC and     COR6  -3.25
 Residual for  COR17RC and     COR5  -5.15
 Residual for  COR18RC and    COR10  -3.11
 Residual for  COR20RC and  COR15RC  -3.11
 Residual for  COR22RC and     COR3  -2.61
 Largest Positive Standardized Residuals
 Residual for     COR9 and     COR2   4.24
 Residual for    COR11 and     COR3   2.91
 Residual for    COR12 and     COR9   3.19
 Residual for  COR16RC and  COR15RC   3.20
 Residual for  COR20RC and  COR17RC   7.09
 Residual for  COR23RC and     COR2   2.77
 Residual for  COR23RC and     COR4   2.58
 Residual for  COR23RC and     COR6   2.89
 Residual for  COR23RC and     COR8   2.71
(…)
        The Modification Indices Suggest to Add the
  Path to  from      Decrease in Chi-Square    New Estimate
 COR8      SE              8.2              0.12
 COR23RC   PSB              11.9              0.21

 The Modification Indices Suggest to Add an Error Covariance
  Between    and     Decrease in Chi-Square    New Estimate
 COR9      COR2             18.0              0.11
 COR9      COR6             12.1             -0.07
 COR11     COR3              8.5              0.05
 COR12     COR9             10.2              0.08
 COR13RC   COR2              8.4             -0.07
 COR15RC   COR6             12.9             -0.08
 COR16RC   COR15RC          10.2              0.12
 COR17RC   COR5             26.5             -0.18
 COR18RC   COR10            10.9             -0.06
 COR18RC   COR11             7.9              0.05
 COR20RC   COR15RC           9.7             -0.11
 COR20RC   COR17RC          50.3              0.25
 COR22RC   COR3             14.3             -0.09
```

The question is thus whether the number of potential problematic cases justifies the addition of error covariances. In this context, no error covariances were allowed between items, a decision that was mainly based on the following criteria: first, there was no evidence in the literature suggesting the addition of error covariances, and doing so would only be capitalising on chance (Cote et al. 2001); second, some authors argue that the existence of within-factor correlated measurement errors may prevent the constructs from being unidimensional

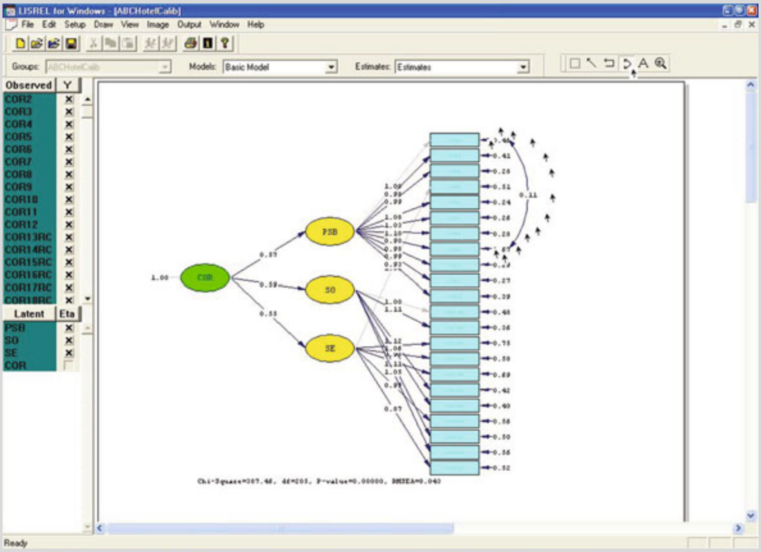
(Cote et al. 2001); third, the addition of error covariances would only serve to improve this particular model's fit, given that the structural model is going to be tested (in Part III) under the partial aggregation model approach (as explained in Part I) and, thus, the addition of error covariances will become irrelevant as soon as summated scales are computed.

Overall, in sum, taking also into consideration that the items loaded strongly and significantly onto unique factors, results suggest sufficient evidence of unidimensionality for each of the three dimensions of COR, PSB, SO, and SE.

Because unidimensionality is a crucial and necessary, but not sufficient, condition for construct validity (Anderson and Gerbing 1988), the following subsections address the issues of convergent and discriminant validity, as well as reliability.

Note

In case we decide to add error covariances, we can do as follows: on the screen with the path diagram we click on the curbed arrow in the tool bar and 'drag' it between the chosen pair of items, as in the following example:



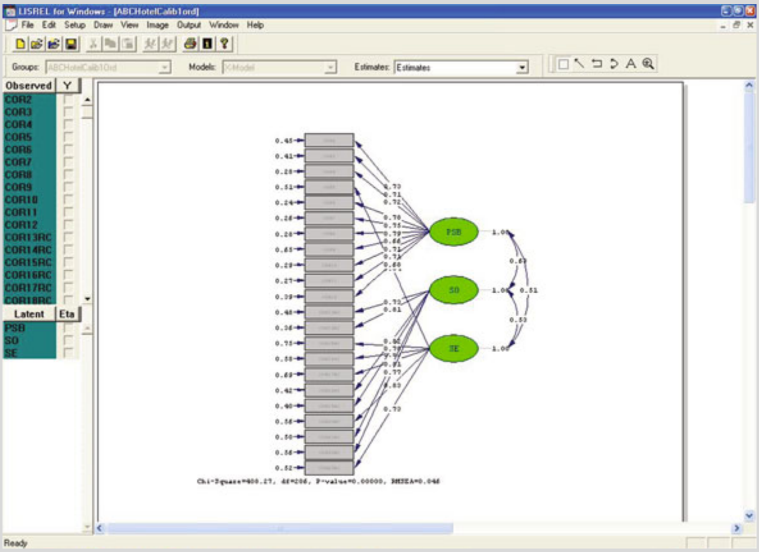
Before that, to help support subsequent discussions, Table 3.1 shows a synthesis of the CFA results (see also Vieira 2010), which are mainly based on the last section of the output (and, therefore, its reproduction here would be redundant) which, in turn, corresponds to the 'SC' command in the 'Options' line of the SIMPLIS program. In addition to the goodness of fit statistics and the loadings based on the completely standardised solution (where we can see the retained items and its factorial distribution), Table 3.1 also includes the correlations between the dimensions (or first-order factors) of the COR construct, the composite reliability,[1] as well as the results of the chi-square difference tests for the first-order factors, to be addressed later on.

3.1.2 Convergent Validity Tests for COR

In first-order models, convergent validity is supported if each observable variable loads significantly (i.e., t-value > |1.96| or, in other words, coefficients must be

Note

The path diagram for a first-order CFA would look like this:



[1] Composite reliability is calculated by using the information from LISREL's completely standardised solution and applying the following formula: $\rho_c = (\sum\lambda)^2/[(\sum\lambda)^2 + \sum(\theta)]$, where ρ_c = composite reliability, λ = indicator loadings, θ = indicator error variances, and $\sum$ = summation over the indicators of the latent variable (Diamantopoulos and Siguaw 2000).

With a SIMPLIS syntax including the following extract (which can be obtained by 'manually' adjusting the 2nd-order syntax and clicking 'Run LISREL'):

```
(...)
Latent Variables PSB SO SE
Relationships
COR2 = PSB
COR3 = PSB
COR4 = PSB
COR5 = SE
COR6 = PSB
COR7 = PSB
COR8 = PSB
COR9 = PSB
COR10 = PSB
COR11 = PSB
COR12 = PSB
COR13RC = SO
COR14RC = SO
COR15RC = SE
COR16RC = SE
COR17RC = SE
COR18RC = SO
COR19RC = SO
COR20RC = SE
COR21RC = SO
COR22RC = SO
COR23RC = SE
Set the Variance of PSB to 1.00
Set the Variance of SO to 1.00
Set the Variance of SE to 1.00
Path Diagram
End of Problem
```

greater than approximately twice its standard error) onto the latent variable that they are purported to measure (Anderson and Gerbing 1988; Hair et al. 1998; Steenkamp and van Trijp 1991), which is the case here, regarding all the 22 items retained (10 for PSB, 6 for SO, and 6 for SE). This evidence of convergent validity was reinforced by the substantial—that is, larger than 0.50 (Hildebrandt 1987; Steenkamp and van Trijp 1991)—loadings for all items. A benchmark of 0.70 has also been suggested for a parameter estimate indicating convergent validity to be considered as exhibiting substantial magnitude (Garver and Mentzer 1999). This is true for the majority of the parameter estimates. Exceptions are items COR15RC (0.67) and COR17RC (0.69). The evidence of convergent validity is further strengthened by the good overall fit of the model (Steenkamp and van Trijp 1991). In second-order CFA, however, an additional requirement has to be accomplished for assessing convergent validity: the relationships between the first-order factors

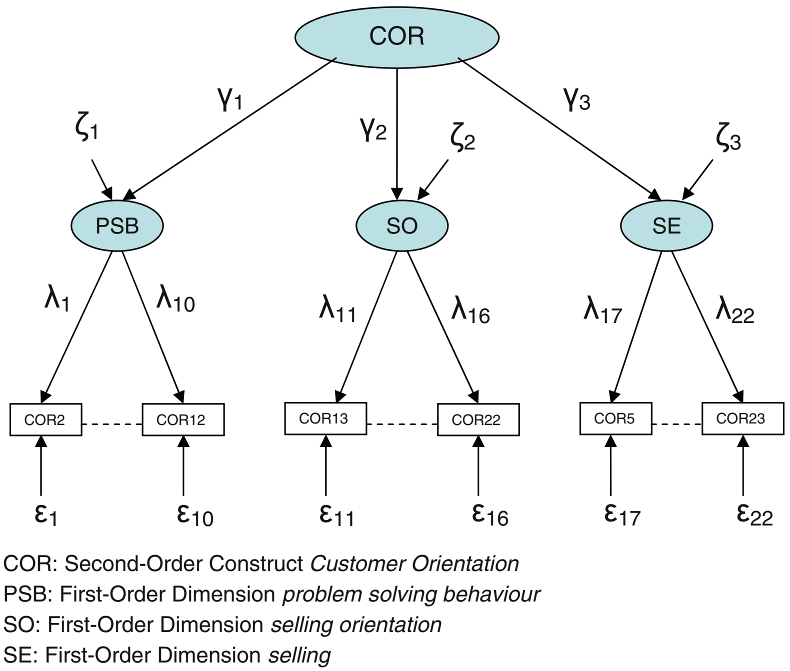


Fig. 3.1 Second-order CFA for COR
Source Vieira (2010)

and the second-order factor (i.e., the coefficients γ in Fig. 3.1) must be significant (Benson and Bandalos 1992). This is also true for the model under analysis ($\gamma_1 = 0.57$, sd = 0.044, *t*-value = 13.01; $\gamma_2 = 0.59$, sd = 0.046, *t*-value = 12.88; $\gamma_3 = 0.55$, sd = 0.048, *t*-value = 11.42), suggesting that there is sufficient evidence of convergent validity.

3.1.3 Reliability Tests for COR

Reliability was examined after assessing unidimensionality and convergent validity, given that a construct can exhibit an acceptable reliability even if it does not meet the convergent validity criteria (Steenkamp and van Trijp 1991). Cronbach's alpha should be assessed only after unidimensionality has been proven (Gerbing and Anderson 1988), namely because, as Hunter and Gerbing (1982, p. 281) state, "coefficient alpha provides an unbiased estimate of the reliability of the cluster score only if the scale is unidimensional". Also, as Hulin et al. (2001) stated, it is possible for a number of items to be interrelated (i.e., show internal consistency) and still not be homogeneous (i.e. not be unidimensional). As can be observed in Table 3.1, Cronbach's alphas are above Nunnally's (1978) 0.70 threshold, suggesting adequate reliability. In addition, as can be read also from

Table 3.1, composite reliability for each of the components exceed Bagozzi and Yi's (1988) 0.60 cut-off, thus providing additional support for the constructs' acceptable reliability.

3.1.4 Discriminant Validity Tests for COR

Results suggest support for discriminant validity. To begin with, the correlation between the factors did not exceed 0.70, a signal of measure distinctness (Ping 2004). In fact, correlations are significantly different from unity, which suggests evidence for discriminant validity, according to Steenkamp and van Trijp (1991).

In addition, a series of CFA models were performed for each pair of constructs, in order to examine the Chi-Square differences between the standard model and the model with the correlations between the factors constrained to 1.0, i.e., the 'non-discriminant' model. The null hypothesis is that the constructs are indistinct. Discriminant validity is supported in case of rejection of the null hypothesis. The statistic of interest is the change in the χ^2 between the two models, for each pair. As can be read from Table 3.1, the difference is significant for all three pairs, thus providing further support for discriminant validity.

Having applied analogous procedures to all the constructs, it can be observed that, in general, results are satisfactory, even considering that a (relatively small) number of items were removed from the analysis (14 out of 75). This process revealed two higher-order structures, COR and relational net benefits, in addition to RQ, which had already been included as a higher-order construct in the model development phase (see Appendix) and was confirmed within the measurement model assessment.

The analysis of the measurement model presented in this chapter resulted in the model structure depicted in Fig. 3.2, which is consistent with the partial aggregation approach adopted in the present analysis, to be tested in the next chapter.

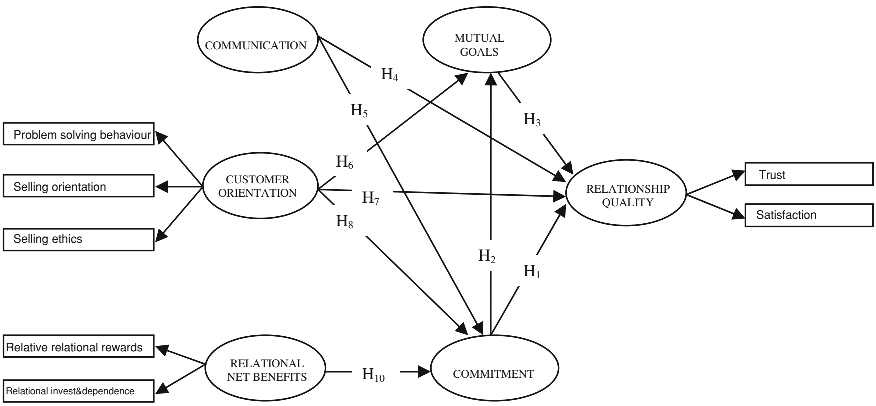


Fig. 3.2 Proposed RQ model structure

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Part III
Assessment of Structural Model

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At the completion of Part III you will be able to:

- Assess structural models;
- Compare rival models;
- Move on to the next level of your learning process.

Chapter 4
Assessment of Structural Model

Abstract This chapter addresses the assessment of the structural model. It includes a step-by-step, annotated illustration of the testing of the whole model (i.e., the model integrating both the measurement and the structural components), as well as its cross-validation, assessment of statistical power, and comparison to a rival model.

Keywords Calibration sample · Competing models analysis · Model cross-validation · Power analysis · Structural model · Validation sample

Begin at the beginning and go on till you come to the end; then stop.

Lewis Carroll, *Alice in Wonderland.*

Building on the results of the assessment of the measurement model carried out in Part II, and continuing to follow Anderson and Gerbing's (1988) two-step approach for structural equation modelling (SEM), the structural model, that is, the proposed set of associations among the latent variables, will be tested in this chapter, constituting, at the same time, an assessment of nomological validity (Steenkamp and van Trijp 1991).

4.1 Assessment of Structural Model Based on the Calibration Sample

In examining the structural model, the attention is on the proposed hypotheses that reflect the relationships between the latent variables. The purpose is assessing whether the data supports the proposed conceptualisation. The issues of interest are: (i) whether the directions of the relationships between the constructs are as hypothesised, which can be examined looking at the signs of the respective parameters; (ii) the strength of the hypothesised links, reflected by the estimated parameters, which should be at least significant, i.e., their respective t-values should be greater than $|1.96|$; and, (iii) the amount of variance in the endogenous

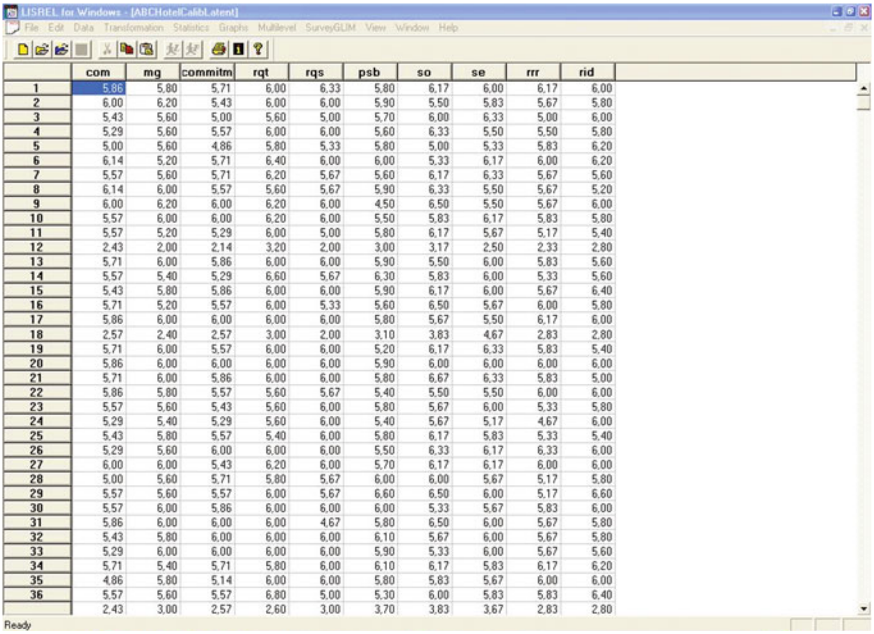
A. L. Vieira, *Interactive LISREL in Practice*, SpringerBriefs in Statistics,
DOI: 10.1007/978-3-642-18044-6_4,

variables explained by the respective proposed determinants, which can be evaluated looking at the squared multiple correlations (R^2) for the structural equations.

In order to test the structural model, in coherence with the partial aggregation approach, we need a database containing the information organised according to the constructs that resulted from the assessment of the measurement model, as described in Part II (see Fig. 3.2). In other words, it is necessary to create the summated scales or composites of items (by computing the average of the respective retained items) that correspond to the following latent variables: communication (COM)—unidimensional construct; problem solving behaviour (PSB), selling orientation (SO), selling ethics (SE)—the three dimensions of customer orientation (COR); relative relational rewards (RRR), relational investment and dependence (RID)—the two dimensions of relational net benefits (RNB); commitment (COMMIT)—unidimensional construct; mutual goals (MG)—unidimensional construct; trust (RQT) and satisfaction (RQS)—the two dimensions of relationship quality (RQ). The database resulting from this procedure, which we have named 'ABCHotel-CalibLatent', looks like this in PRELIS:

Hint

Analogous to what we have suggested earlier, the creation of the summated scales and respective database can be carried out in SPSS, and then imported to PRELIS.

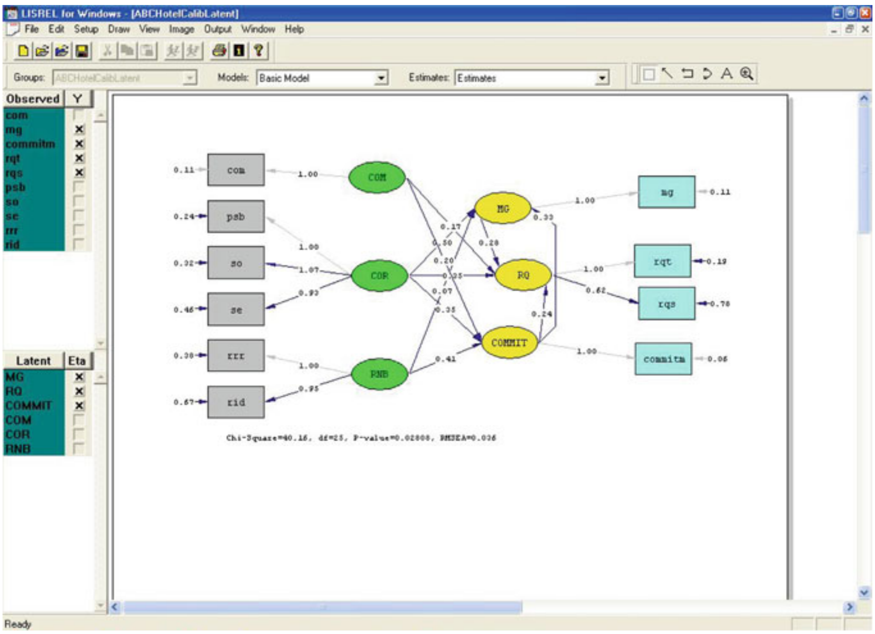


	com	mg	commitm	rqt	rqs	psb	so	se	rrr	rid
1	5,86	5,80	5,71	6,00	6,33	5,80	6,17	6,00	6,17	6,00
2	6,00	6,20	5,43	6,00	6,00	5,90	5,50	5,83	5,67	5,80
3	5,43	5,60	5,00	5,60	5,00	5,70	6,00	6,33	5,00	6,00
4	5,29	5,60	5,57	6,00	6,00	5,60	6,33	5,50	5,50	5,80
5	5,00	5,60	4,86	5,80	5,33	5,80	5,00	5,33	5,83	6,20
6	6,14	5,20	5,71	6,40	6,00	6,00	5,33	6,17	6,00	6,20
7	5,57	5,60	5,71	6,20	5,67	5,60	6,17	6,33	5,67	5,60
8	6,14	6,00	5,57	5,60	5,67	5,90	6,33	5,50	5,67	5,20
9	6,00	6,20	6,00	6,20	6,00	4,50	6,50	5,50	5,67	6,00
10	5,57	6,00	6,00	6,20	6,00	5,50	5,83	6,17	5,83	5,80
11	5,57	5,20	5,29	6,00	5,00	5,80	6,17	5,67	5,17	5,40
12	2,43	2,00	2,14	3,20	2,00	3,00	3,17	2,50	2,33	2,80
13	5,71	6,00	5,86	6,00	6,00	5,90	5,50	6,00	5,83	5,60
14	5,57	5,40	5,29	6,60	5,67	6,30	5,83	6,00	5,33	5,60
15	5,43	5,80	5,86	6,00	6,00	5,90	6,17	6,00	5,67	6,40
16	5,71	5,20	5,57	6,00	5,33	5,60	6,50	5,67	6,00	5,80
17	5,86	6,00	6,00	6,00	6,00	5,80	5,67	5,50	6,17	6,00
18	2,57	2,40	2,57	3,00	2,00	3,10	3,83	4,67	2,83	2,80
19	5,71	6,00	5,57	6,00	6,00	5,20	6,17	6,33	5,83	5,40
20	5,86	6,00	6,00	6,00	6,00	5,90	6,00	6,00	6,00	6,00
21	5,71	6,00	5,86	6,00	6,00	5,80	6,67	6,33	5,83	5,00
22	5,86	5,80	5,57	5,60	5,67	5,40	5,50	5,50	6,00	6,00
23	5,57	5,60	5,43	5,60	6,00	5,80	5,67	6,00	5,33	5,80
24	5,29	5,40	5,29	5,60	6,00	5,40	5,67	5,17	4,67	6,00
25	5,43	5,80	5,57	5,40	6,00	5,80	6,17	5,83	5,33	5,40
26	5,29	5,60	6,00	6,00	6,00	5,50	6,33	6,17	6,33	6,00
27	6,00	6,00	5,43	6,20	6,00	5,70	6,17	6,17	6,00	6,00
28	5,00	5,60	5,71	5,80	5,67	6,00	6,00	5,67	5,17	5,80
29	5,57	5,60	5,57	6,00	5,67	6,60	6,50	6,00	5,17	6,60
30	5,57	6,00	5,86	6,00	6,00	6,00	5,33	5,67	5,83	6,00
31	5,86	6,00	6,00	6,00	4,67	5,80	6,50	6,00	5,67	5,80
32	5,43	5,80	6,00	6,00	6,00	6,10	5,67	6,00	5,67	5,80
33	5,29	6,00	6,00	6,00	6,00	5,90	5,33	6,00	5,67	5,60
34	5,71	5,40	5,71	5,80	6,00	6,10	6,17	5,83	6,17	6,20
35	4,86	5,80	5,14	6,00	6,00	5,80	5,83	5,67	6,00	6,00
36	5,57	5,60	5,57	6,80	5,00	5,30	6,00	5,83	5,83	6,40
	2,43	3,00	2,57	2,60	3,00	3,70	3,83	3,67	2,83	2,80

After accomplishing *all* steps needed for building the path diagram and generating the SIMPLIS program, as described earlier (review Sect. 3.1.1.2) and applied this time to database 'ABCHotelCalibLatent', we will obtain the following screen:

Note

In the context of the partial aggregation approach, the composites of items were treated as indicators of constructs. Error variances of the single-indicator constructs—i.e., constructs with only one dimension—were 'fixed' to (1-reliability) times the variance of the indicator (Bagozzi and Heatherton 1994; Baumgartner and Homburg 1996). The paths between each single-indicator construct and respective dimension were fixed to '1'; in those cases where constructs have more than one dimension, the link with the indicator that best represents the construct was chosen to be 'fixed' to '1' (Diamantopoulos and Siguaw 2000). It should be stressed that these procedures do not affect the results of the analysis, as evidenced by the standardised solutions.



By switching to the output map, we can observe that, in terms of overall fit, the model's goodness of fit indices are within thresholds indicating good fit: $\chi^2 = 40.16$ ($p = 0.028$), df = 25, χ^2/df = 1.61, RMSEA = 0.036, GFI = 0.98, AGFI = 0.96, NNFI = 0.99, CFI = 0.99. These results suggest that, at least as far as the calibration sample is concerned, the model fits well and corresponds to a close representation of the population of interest.

In effect, as illustrated by Table 4.1, the results of the test of the structural model on the calibration sample indicate that the signs of the parameters representing the hypotheses incorporated in the model are as expected, or, in other words, all signs of the associations between constructs in the model under analysis were in accordance with hypothesised relationships. In addition, all but one of the parameter estimates—the one correspondent to the link between relational net benefits and mutual goals (H_9)—were statistically significant at $p < 0.05$ or better and the square multiple correlations are acceptable. However, it should be acknowledged that, although the majority of the significant associations are reasonable, one of them gives reasons for caution. Indeed, the direct link between communication and RQ is below 0.20, the threshold for a path to be considered practically meaningful (Echambadi et al. 2006), though it should be noted that the global impact on RQ is within acceptable thresholds—see also Table 4.2, which contains the aggregated effects (i.e. direct, indirect, and total effects) exerted by both exogenous and endogenous variables.

The results presented above correspond to a scenario where the variables customer orientation, communication, and commitment exert both direct and indirect effects on RQ, mutual goals exerts direct effects only, and relational net benefits indirect effects only. In principle, these results constitute sufficient evidence that the proposed conceptual framework is supported by the data, and provide support for the nomological validity of the constructs that comprise the model.

Table 4.1 Structural model assessment—calibration sample, proposed model

Parameter	Path	Estimate	Std-error	*t*-value	R^2	Hyp.	Result
COMMIT → RQ	β_{13}	0.24	0.052	4.59		H_1	Supported
MG → RQ	β_{12}	0.28	0.053	5.39		H_3	Supported
COM → RQ	γ_{11}	0.17	0.044	3.93		H_4	Supported
COR → RQ	γ_{12}	0.35	0.010	3.48		H_7	Supported
					0.42		
COMMIT → MG	β_{23}	0.33	0.060	5.50		H_2	Supported
COR → MG	γ_{22}	0.50	0.099	5.04		H_6	Supported
RNB → MG	γ_{23}	0.07	0.063	1.09		H_9	Non-supp.
					0.30		
COM → COMMIT	γ_{31}	0.20	0.044	4.68		H_5	Supported
COR → COMMIT	γ_{32}	0.35	0.095	3.71		H_8	Supported
RNB → COMMIT	γ_{33}	0.41	0.058	7.16		H_{10}	Supported
					0.45		

Table 4.2 Decomposition of structural effects—calibration sample

	Direct	Indirect	Total
Effect on RQ			
COMMIT	0.240	0.092	0.332
MG	0.280		0.280
COM	0.170	0.070	0.240
COR	0.350	0.260	0.610
RNB		0.160	0.160
Effect on MG			
COMMIT	0.330		0.330
COM		0.067	0.067
COR	0.500	0.120	0.620
RNB	0.069	0.131	0.200
Effect on COMMIT			
COM	0.200		0.200
COR	0.350		0.350
RNB	0.410		0.410

These suppositions are going to be put to the test next in this chapter, within the process of cross-validation.

4.2 Assessment of Structural Model Based on the Validation Sample

The steps in the LISREL software that are necessary to build the model that corresponds to the estimation of the structural model on the validation sample are analogous to those described previously, only now we use the other half of the sample, that is, the validation sample (in this case named 'ABCHotelValidLatent'). In the present analysis, the results of the test of the structural model on the validation sample (see Table 4.3) seem to corroborate those based on the calibration sample. In effect, when tested on the validation sample, the model also showed a good overall fit: $\chi^2 = 49.80$ ($p = 0.0023$), df = 25, χ^2/df = 1.99, RMSEA = 0.046, GFI = 0.98, AGFI = 0.95, NNFI = 0.98, CFI = 0.99. In addition, using the validation sample, all signs of the associations between constructs were also in accordance with hypothesised relationships. Analogous to the calibration sample, results of the validation sample support all but one (H_9) of the hypothesised relationships—that is, H_1 to H_8, and H_{10}. Indeed, as can be read from Table 4.3, all parameter estimates were also significant at $p < 0.05$ or better (again with the exception of the link correspondent to H_9).

In effect, these results also corroborate the scenario suggested by the calibration phase, in terms of both the magnitude and the statistical significance of the links between constructs, as well as in relation to the amount of explained variance (although the R^2 are slightly lower than those of the calibration sample). Analogous

Table 4.3 Structural model assessment—validation sample, proposed model

Parameter	Path	Estimate	Std-error	*t*-value	R^2	Hyp.	Result
COMMIT → RQ	β_{13}	0.32	0.052	6.26		H_1	Supported
MG → RQ	β_{12}	0.21	0.054	3.87		H_3	Supported
COM → RQ	γ_{11}	0.12	0.046	2.62		H_4	Supported
COR → RQ	γ_{12}	0.43	0.100	4.18		H_7	Supported
					0.36		
COMMIT → MG	β_{23}	0.21	0.055	3.73		H_2	Supported
COR → MG	γ_{22}	0.53	0.110	4.96		H_6	Supported
RNB → MG	γ_{23}	0.07	0.060	1.18		H_9	Non-Supp.
					0.23		
COM → COMMIT	γ_{31}	0.26	0.050	5.55		H_5	Supported
COR → COMMIT	γ_{32}	0.43	0.100	4.28		H_8	Supported
RNB → COMMIT	γ_{33}	0.20	0.060	3.46		H_{10}	Supported
					0.31		

Table 4.4 Decomposition of structural effects—validation sample

	Direct	Indirect	Total
Effect on RQ			
COMMIT	0.320	0.044	0.366
MG	0.210		0.210
COM	0.120	0.100	0.220
COR	0.430	0.270	0.700
RNB		0.086	0.086
Effect on MG			
COMMIT	0.210		0.210
COM		0.055	0.055
COR	0.530	0.090	0.620
RNB	0.070	0.040	0.110
Effect on COMMIT			
COM	0.260		0.260
COR	0.430		0.430
RNB	0.200		0.200

to the calibration phase, Table 4.4 presents the direct, indirect, and aggregated effects exerted by endogenous and exogenous variables.

As far as the non-significant link is concerned, which corresponds to the proposed association between relational net benefits and mutual goals reproduced in hypothesis H_9, the estimated parameter is very low and worryingly close to zero, posing questions on whether or not to include it in the model. Diamantopoulos and Siguaw (2000) suggest that the fact that a parameter estimate does not deviate significantly from zero would mean that the we cannot reject the hypothesis that it is zero, and recommend to fix this parameter value at zero. In this context, a version of the model without the non-significant link was tested. Both model's goodness of fit indices are very similar and within thresholds indicating good fit: $\chi^2 = 52.17$ ($p = 0.0017$), df = 26, χ^2/df = 2.00, RMSEA = 0.046, GFI = 0.98, AGFI = 0.95, NNFI = 0.98, CFI = 0.99 for the revised model; and $\chi^2 = 49.80$ ($p = 0.0023$), df = 25, χ^2/df = 1.99, RMSEA = 0.046, GFI = 0.98, AGFI = 0.95, NNFI = 0.98, CFI = 0.99 for the initial model, i.e., the proposed model based on the validation sample. Indeed, the results of this adjusted version of the model are not much different from those of the initial model, as can be observed in Tables 4.5 and 4.6.

In this context, the revision of the model was undertaken to improve the model, not in terms of fit, but for the sake of simplicity/parsimony. This kind of model modification is only appropriate when the revised model is as substantively interpretable and fits almost as well as the initial model (Diamantopoulos and Siguaw 2000), which is the case here.

Table 4.5 Structural model assessment—validation sample, final model

Parameter	Path	Estimate	Std-error	*t*-value	R^2	Hyp.	Result
COMMIT → RQ	β_{13}	0.32	0.050	6.27		H_1	Supported
MG → RQ	β_{12}	0.21	0.060	3.79		H_3	Supported
COM → RQ	γ_{11}	0.12	0.050	2.61		H_4	Supported
COR → RQ	γ_{12}	0.43	0.100	4.20		H_7	Supported
					0.36		
COMMIT → MG	β_{23}	0.22	0.050	4.06		H_2	Supported
COR → MG	γ_{22}	0.57	0.100	5.57		H_6	Supported
					0.22		
COM → COMMIT	γ_{31}	0.27	0.050	5.57		H_5	Supported
COR → COMMIT	γ_{32}	0.43	0.100	4.23		H_8	Supported
RNB → COMMIT	γ_{33}	0.20	0.060	3.44		H_{10}	Supported
					0.31		

Table 4.6 Decomposition of structural effects—final model

	Direct	Indirect	Total
Effect on RQ			
COM	0.320	0.046	0.366
MG	0.210		0.210
COM	0.120	0.100	0.220
COR	0.430	0.280	0.710
RNB		0.072	0.072
Effect on MG			
COMMIT	0.220		0.220
COMM		0.058	0.058
COR	0.570	0.090	0.660
RNB		0.043	0.043
Effect on COMMIT			
COM	0.270		0.270
COR	0.430		0.430
RNB	0.200		0.200

The next sub-section, which corresponds to the last part of our journey through LISREL, describes the comparison of the final (or revised) with an alternative/rival model.

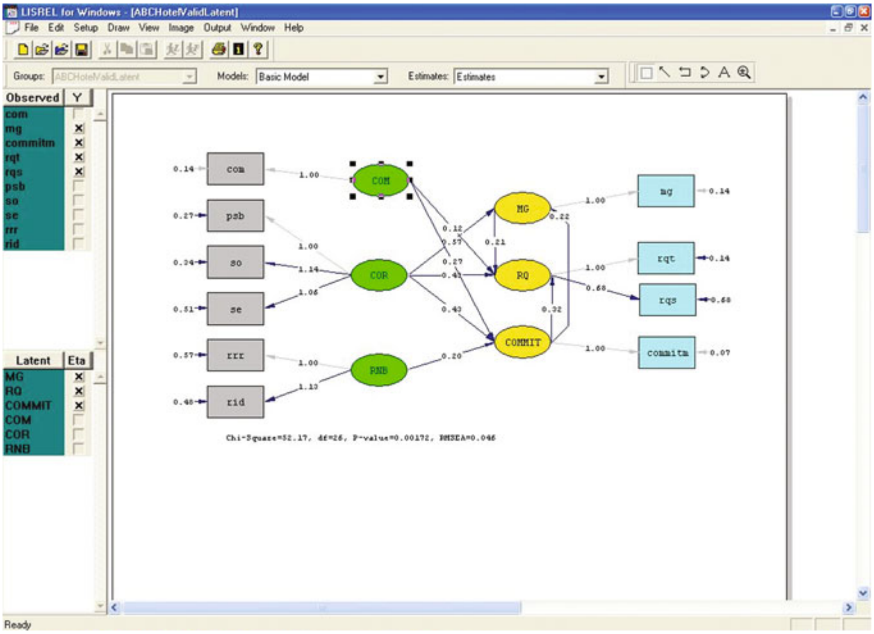
Note

According to Diamantopoulos and Siguaw (2000), the assessment of statistical power is an important, but often neglected, aspect related to the test of the model. The Chi-Square test only deals with the Type I error, that is, the probability of rejecting a correct model, whereas the statistical power of the test is associated with the Type II error, the probability of not rejecting an incorrect model. More specifically, the power of the test is the likelihood of avoiding Type II error, indicating the probability of rejecting an incorrect model. Both tests are used in a complementary way, and the power test is important due to the influence of sample size, namely because large samples tend to amplify small specification errors, leading to the rejection of the model (and vice-versa). A high power of the test means that any relevant specification errors would be detected. If, in addition, the Chi-Square is not significant, the model can be accepted without reservations. One way of evaluating the power of the test is to consult MacCallum et al. (1996, p. 144, Table 4), and check the minimum necessary sample size for a given level of statistical power of the test. The model under analysis has 25 degrees of freedom. For this particular case, the above mentioned table states that, for attaining a power level of 0.80, which is considered sufficient 'for most practical purposes' (Diamantopoulos and Siguaw 2000, p. 96), with 25 degrees of freedom, when testing for close fit, the size needed is $N = 363$. This is clearly exceeded by the sample size used in both the calibration and the validation phases ($N = 474$ each), meaning that the probability of detecting major misspecifications is at least 0.80 and, in addition, that there would be sufficient power to test the model with a sample more than 20% smaller. The values of the chi-square statistic and the power of the test, taken together, offer strong reasons to believe that there are no serious discrepancies between the hypothesised model and the data, or, in other words, that the data fit the model.

4.2.1 Comparison of the Final Model Versus a Rival Model

Even if a given proposed model exhibits an acceptable fit and cross-validates well, there may be alternative models, containing different associations among the variables, which could show the same level of goodness-of-fit. Thus, to compare one's model to alternative models is a fundamental practice in SEM (Bagozzi and Yi 1988; Diamantopoulos and Siguaw 2000; Hair et al. 1998). Although, ideally, the final model should be tested against more than one rival model, in this handbook only one comparison will be presented, just for the purpose of exemplifying the LISREL steps that are necessary to conduct such comparison tests.

Our final model is illustrated by the following path diagram:

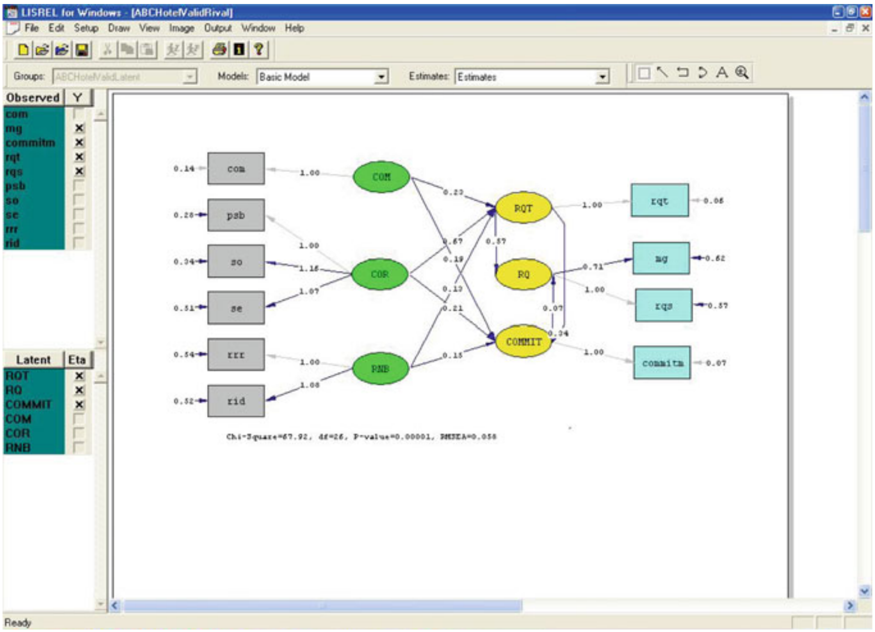


This, in turn, corresponds to the following SIMPLIS syntax:

```
ABCHotelValidLatent
Estimation of Structural Model—Validation Sample
Observed Variables
com mg commitm rqt rqs psb so se rrr rid
Covariance Matrix from file 'C:\Documents and Settings\INTERACTIVE
LISREL\ABCHotelValidLatent.cm'
Sample Size = 474
Latent Variables MG RQ COMMIT COM COR RNB
Relationships
mg = 1.00*MG
commitm = 1.00*COMMIT
rqt = 1.00*RQ
rqs = RQ
com = 1.00*COM
psb = 1.00*COR
so = COR
```

```
se = COR
rrr = 1.00*RNB
rid = RNB
MG = COMMIT
RQ = MG COMMIT
MG = COR
COMMIT = COM COR RNB
RQ = COM COR
Set the Error Variance of mg to 0.14
Set the Error Variance of commitm to 0.07
Set the Error Variance of com to 0.14
Path Diagram
End of Problem
```

The rival model that was chosen model for comparison is based on Morgan and Hunt (1994), whose 'Commitment-Trust Theory of Relationship Marketing' has inspired several authors that have developed RQ models (e.g. Huntley 2006; Wong and Sohal 2002). Building on our final model and adjusting it according to Morgan and Hunt's (1994) theory, i.e., establishing the constructs trust (RQT) and commitment (COMMIT) as mediators of the effects of the exogenous variables on RQ, we obtain the following alternative model:



This model corresponds to the following SIMPLIS syntax:

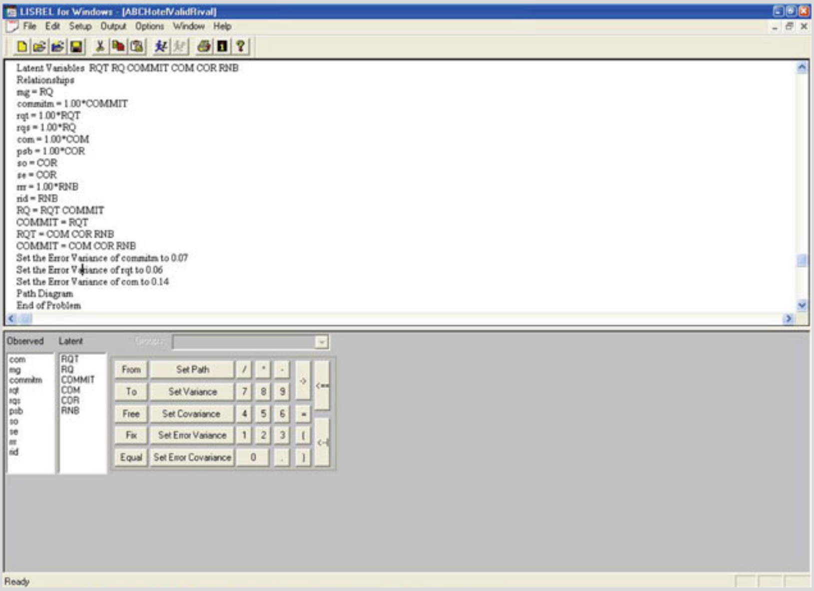
```
ABCHotelValidRival
Estimation of Structural Model—Validation Sample
Observed Variables
com mg commitm rqt rqs psb so se rrr rid
Covariance Matrix from file 'C:\Documents and Settings\INTERACTIVE
LISREL\ABCHotelValidLatent.cm'
Sample Size = 474
Latent Variables RQT RQ COMMIT COM COR RNB
Relationships
mg = RQ
commitm = 1.00*COMMIT
rqt = 1.00*RQT
rqs = 1.00*RQ
com = 1.00*COM
psb = 1.00*COR
so = COR
se = COR
rrr = 1.00*RNB
rid = RNB
RQ = RQT COMMIT
COMMIT = RQT
RQT = COM COR RNB
COMMIT = COM COR RNB
Set the Error Variance of commitm to 0.07
Set the Error Variance of rqt to 0.06
Set the Error Variance of com to 0.14
Path Diagram
End of Problem
```

Hint

Alternatively to the process described in Part II for the construction of a LISREL model, for the purpose of comparing models we can build on the existent syntax and adjust it in order to obtain the alternative model (not least because the models are exactly the same, except for the way some of the variables connect). To this end, we should proceed as follows: we start by saving the syntax of our model with another name (*save as*), for example, 'ABCHotelValidRival'. Then we change some parts of the program. In this case we adjust:

- The title and subtitle (comments);
- The line '`Latent Variables`', where we remove 'MG' (in the rival model, the variable mutual goals assumes the role of a RQ dimension) and add 'RQT' (the variable trust assumes the role of a latent variable);
- What is under the line '`Relationships`', given that the associations between the variables have to be adjusted (it should be noted that the program is 'case sensitive', i.e., for example, it reads 'RQT' as a model component that is different from 'rqt');
- The 'fixing' of error variances, by removing the one corresponding to MG, and adding the one corresponding to the 'new' latent variable trust.

After these adjustments, we will obtain a screen that looks like this:



In which we should click 'Run LISREL' to obtain the path diagram of the above presented alternative/rival model.

The models are going to be compared on the following criteria: AIC (Akaike's Information Criterion), considered particularly appropriate for comparing rival models—the lower the value, the better the performance of the model (Alden et al.

Table 4.7 Summary of alternative models evaluation—validation sample

Comparison criteria	Alternative models	
	Final model	Rival model
ECVI (expected cross validation index)	0.23	0.27
AIC (Akaike's information criterion)	110.2	125.96
PNFI (parsimonious normed fit index)	0.56	0.56
CFI (comparative fit index)	0.99	0.98
Percentage of significant parameters	100	92
ASMC (average squared multiple correlations)	0.297	0.293
χ^2 (Chi-square goodness-of-fit test)	52.17	67.92
p-value	0.002	0.000
df (Degrees of freedom)	26	26
Ratio χ^2/df	2.00	2.61
RMSEA (root mean squared error of approximation)	0.046	0.058
GFI (goodness-of-fit index)	0.98	0.97
AGFI (adjusted goodness-of-fit index)	0.95	0.94
NNFI (non-normed fit index)	0.98	0.96

2006; Williams and Holahan 1994); ECVI (Expected Cross Validation Index), as an indicator of a model's overall fit—the lower the value, the better the potential of replication/generalisation of the model; and parsimony, as measured by PNFI, the Parsimonious Normed Fit Index—also, the lower the value, the better the model's performance (Diamantopoulos and Siguaw 2000). These first three criteria are especially adequate when competing models comparison involves nonnested models, i.e., models that differ in number of constructs or indicators, in which cases the researcher must rely on criteria that take into account, not only fit, but parsimony as well (Hair et al. 1998; Jöreskog and Sörbom 1993). Complementarily, overall fit as measured also by CFI (Comparative Fit Index) was used for comparison purposes, as well as two other comparison indicators that have been used previously for comparing competing models (e.g. Morgan and Hunt 1994): comparative percentage of hypothesised statistically significant parameters; and average squared multiple correlations for the endogenous constructs (ASMC). Other goodness-of-fit indices, namely the ones used in previous stages of this analysis, are also included to complement the comparative analysis between the final structural model cross-validated on the validation sample and the rival model. Table 4.7 presents a synthesis of the results of the comparison process.

As can be inferred by the above presented values, the final model performs better than the rival model regarding practically all comparison indices (except for PNFI, which is the same for both models). These results contribute to strengthen the robustness of the model and suggest that there is a high probability that the final model is the most correct for the population of interest (for a more detailed analysis, see Vieira (2010)).

This is how our journey through INTERACTIVE LISREL ends. The purpose was to help with the 'kick-off' for the learning process. The bibliographic references listed at the end of each chapter of this handbook (which include, not only those that were highlighted in the beginning of each chapter of the three parts of this handbook, but also other references that may help to better understand LISREL) can be useful to readers interested in improving their knowledge on SEM in general, and on LISREL in particular.

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Appendix

Measurement Summary—Calibration Phase (Adapted from Vieira 2010)

Constructs and their *Dimensions* (alpha/mean/std. deviation)	Questionnaire Items
Customer Orientation (COR)	
Problem Solving Behaviour (*PSB*) (.94/5.34/.75)	COR2 Client manager tries to achieve his/her goals by satisfying us
	COR3 Our client manager has our best interest in mind
	COR4 Client manager tries to get us to discuss our needs with him/her
	COR6 Our client manager recommends suitable solutions for us
	COR7 Our client manager tries to find best services for us
	COR8 Our client manager answers our questions correctly
	COR9 Our client manager tries to match the hotel's solutions with our problems
	COR10 Our client manager is willing to disagree with us in order to help us make a better decision
	COR11 Our client manager tries to give us an accurate expectation of what the product will do for us
	COR12 Our client manager tries to figure out our needs
Selling Orientation (*SO*) (.89/5.33/.83)	COR13RC Our client manager tries to sell us all (s)he convinces us to buy, even if we think it is more than a wise customer would buy
	COR14RC Our client manager tries to sell as much as (s)he can rather than to satisfy us
	COR18RC Our client manager paints too rosy a picture of his/her services, to make them sound as good as possible
	COR19RC Our client manager spends more time trying to persuade us to buy than trying to discover our needs

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Constructs and their *Dimensions* (alpha/mean/std. deviation)	Questionnaire Items
	COR21RC Our client manager pretends to agree with us to please us
	COR22RC Our client manager implies to us that something is beyond his/her control when it is not
Selling Ethics (*SE*) (.86/5.16/.86)	COR5 Our client manager tries to influence by information rather than by pressure
	COR15RC Our client manager keeps alert for weaknesses on a person's personality so (s)he can use them to put pressure to buy
	COR16RC Our client manager if (s)he is not sure a service is right for us, (s)he will still apply pressure to get us to buy
	COR17RC Our client manager decides what services to offer on the basis of what (s)he can convince us to buy, not on what will satisfy us
	COR20RC Our client manager stretches a truth in describing a service
	COR23RC Our client manager begins the sales talk for a service before exploring our needs
Communication (COM) (.89/5.28/1..09)	COM1 Our client manager genuinely enjoys helping us
	COM2 Our client manager is easy to communicate with
	COM3 Our client manager likes to help clients
	COM4 Our client manager is a cooperative person
	COM5 Our client manager tries to establish a personal relationship
	COM6 Our client manager seems interested in us not only as a clients, but also as persons
	COM7 Our client manager is friendly
Relational Net Benefits (RNB)	
Relational Relative Rewards (*RRR*) (.94/5.00/1.12)	RNB1 This relationship is extremely rewarding
	RNB3RC This relationship is extremely costly
	RNB9 We like this partner very much
	RNB10 We have high consideration for this partner
	RNB11 We are extremely satisfied with this relationship
	RNB17 Overall, the benefits of this relationship outweigh the costs
Relational Investment and Dependence (*RID*) (.92/5.03/1.21)	RNB7 All things considered, there are many benefits associated with this relationship that we would lose if the relationship were to end
	RNB8 In general, we have invested a great deal in this relationship
	RNB12RC It is extremely likely that we will end this relationship in the near future

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Constructs and their *Dimensions* (alpha/mean/std. deviation)	Questionnaire Items
	RNB14 An alternative relationship would have to be extremely attractive for us to adopt it and end this relationship
	RNB16 We are extremely committed to this relationship
Mutual Goals (MG) (.89/5.13/.99)	MG1 We share a joint vision with our client manager of what is necessary for mutual success
	MG3 We know with certainty what our client manager expects of us
	MG4 We work proactively with our client manager to establish annual goals
	MG5 We can state with certainty that our client manager has the same basic beliefs about running a business than we do
	MG6 Overall, our goals are compatible with the goals of our client manager
Commitment (COMMIT) (.94/5.48/.97)	COMMIT1 Even if it were to our advantage, we do not feel it would be right to leave our client manager now
	COMMIT2 Thus client manager deserves our loyalty
	COMMIT3 We would feel guilty if we left our client manager now
	COMMIT4 We would not leave this client manager right now because we have a sense of obligation to him
	COMMIT5RC We do not feel 'emotionally attached' to our client manager
	COMMIT6RC We do not feel like 'part of the family' with our client manager
	COMMIT7RC We do not feel a strong sense of 'belonging' to our client manager
Relationship Quality (RQ)	
Trust (RQT) (.96/5.53/.99)	RQT1 Our client manager can be relied upon to keep his/her promises
	RQT2RC There are times when we find our client manager to be a bit insincere
	RQT3RC We find it necessary to be cautious in dealing with our client manager
	RQT4 Our client manager is trustworthy
	RQT6 Our client manager puts our interests before his/her own
	RQT7RC Our client manager is capable of bending the facts to create the impression he/she wants

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Constructs and their *Dimensions* (alpha/mean/std. deviation)	Questionnaire Items
	RQT9RC We suspect that our client manager has sometimes withheld certain pieces of information that might have affected my decision-making
Satisfaction (RQS) (.85/4.99/1.05)	RQS1 We are satisfied with the performance of our client manager
	RQS2 We are pleased with the performance of our client manager
	RQS3 We have a favourable opinion on our client manager's performance

RC: Reverse coded

Reference

A.L. Vieira, Modelling business-to-business relationship quality, European conference on research methodology for business and management studies, Madrid, 24–25 June 2010