

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.

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 $1.5 \times (\text{number of items}) \times (\text{number of items} + 1)$, 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.

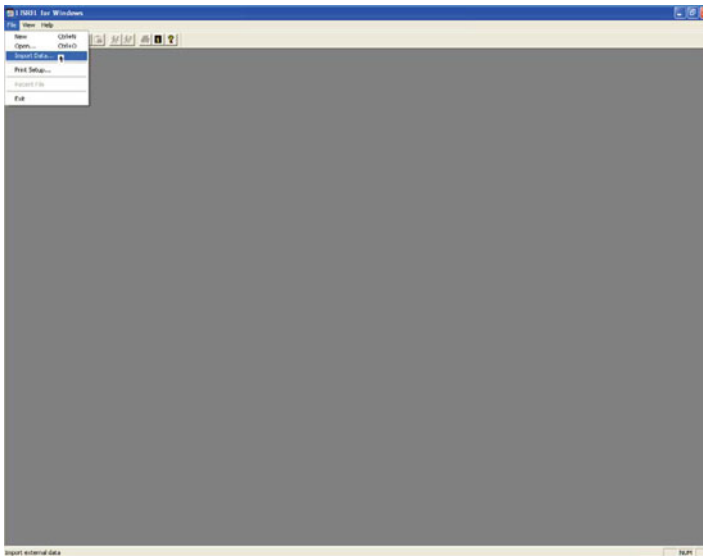
In addition, cases incorporating missing values were deleted prior to data analysis, following a listwise approach. There are several ways to approach missing values, like, for example, substitution (e.g., case substitution and mean substitution), imputation (e.g., cold deck imputation, regression imputation, 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

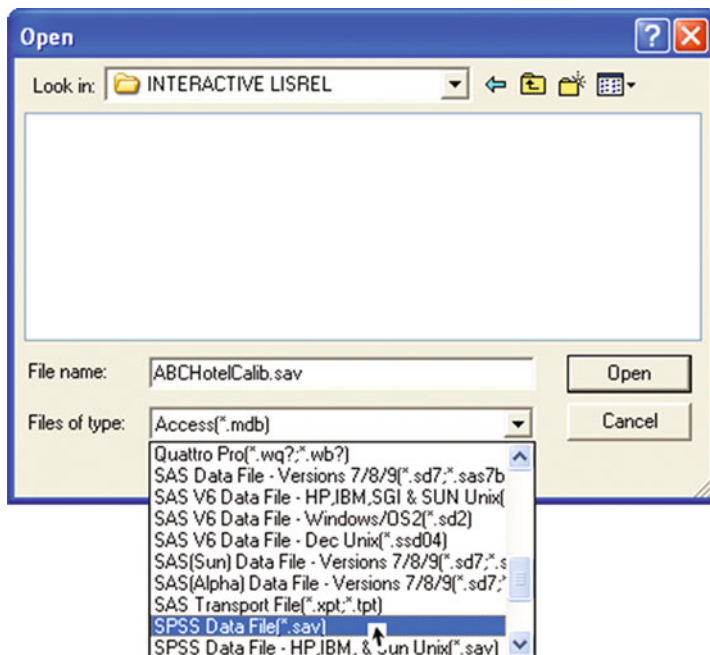
The above mentioned procedures can be carried out with SPSS, which is a more popular and fine tuned statistical package than PRELIS. The SPSS file with the data already (pre)prepared for the analysis can then be imported to LISREL ‘via’ PRELIS, as illustrated next.

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 *ABCHotelCalib* (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):

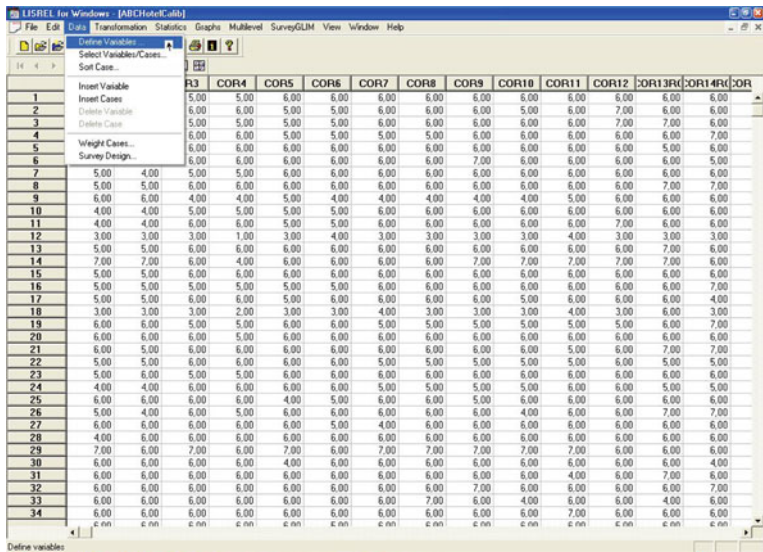
Hint

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.

	COR1	COR2	COR3	COR4	COR5	COR6	COR7	COR8	COR9	COR10	COR11	COR12	COR13	COR14
1	4.00	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
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	6.00	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	5.00	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	7.00	6.00	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	6.00	6.00	6.00	6.00

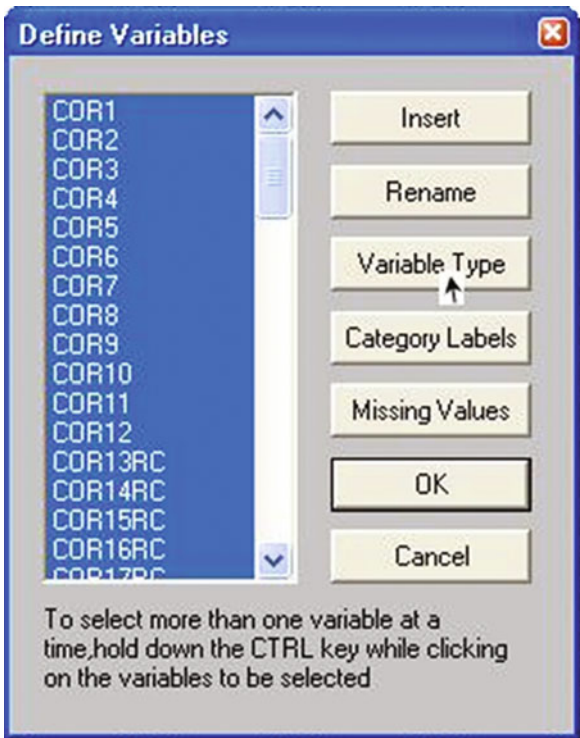
Before conducting the actual normality tests, we need to define the variables in terms of level of measurement. In the study that serves as the basis for this analysis all the observable variables (items) were measured using seven-point Likert-type scales. Even though, from a pure technical perspective, 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



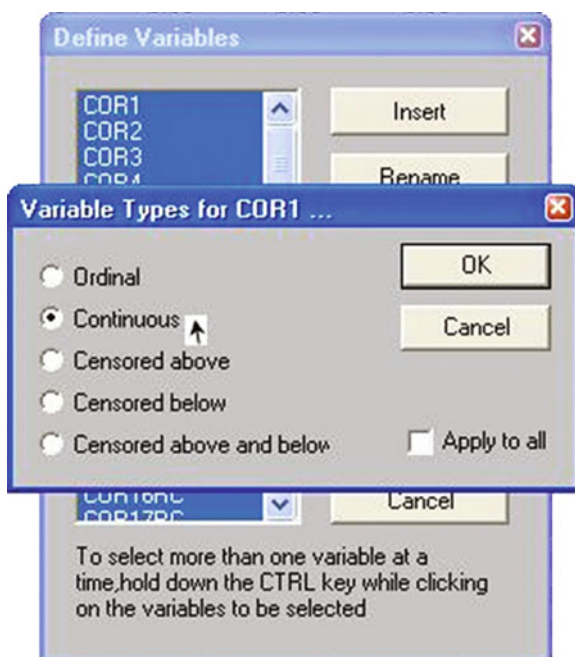
Then we get the following screen, where we select the variables to be defined and press:

Variable type



And in the following window press successively:

Continuous—OK—OK



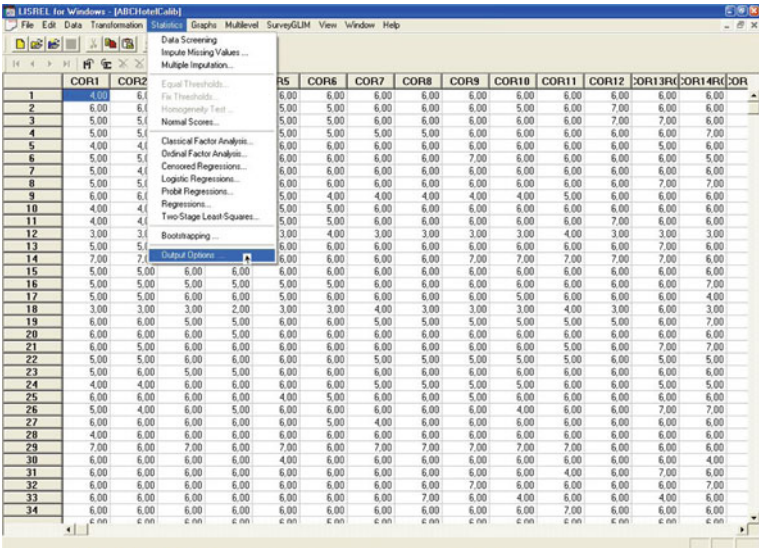
Warning

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).

Output

Moment Matrix:
 Covariances
☐ Save to file: ☐ LISREL system data

Means:
☐ Save to file:

Standard Deviations:
☐ Save to file:

Asymptotic Covariance Matrix:
☐ Save to file: ☐ Print in output

Asymptotic Variances:
☐ Save to file: ☐ Print in output

Data:
☐ Save the transformed data to file:
 Width of fields: 15
 Number of decimals: 6
 Number of repetitions: 1
☐ Rewind data after each repetition
☐ Print bivariate frequency tables
☐ Print tests of underlying bivariate normality
☒ Perform tests of multivariate normality
☒ Wide print
☒ Random seed
☐ Set seed to 123456

OK Cancel

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

LISREL for Windows - [ABCHotelCah.DAT]

File Edit Options Window Help

DATE: 04/01/2009
 TIME: 16:57
 PRELIS 2.00
 BY
 Karl O. 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, (647)675-0720, Fax: (647)675-2140
 Copyright by Scientific Software International, Inc., 1991-2006
 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\ABCHotelCah.FP2:

PRELIS SYNTAX: Can be edited
 SYNTAX Documents and Settings\INTERACTIVE\LISREL\ABCHotelCah.FP2
 OU MA=CM SM=ABCHotelCah.cm AC=ABCHotelCah.ac WP XT

Total Sample Size = 474

Univariate Summary Statistics for Continuous Variables

Variable	Mean	St. Dev.	T-Value	Skewness	Kurtosis	Minimum	Maximum	Freq.	Maximum Freq.
COB1	5.266	1.027	111.674	-0.774	0.045	2.000	5	7.000	21
COB2	5.262	0.990	115.714	-0.832	-0.172	2.000	3	7.000	10
COB3	5.295	0.954	120.824	-0.972	-0.372	2.000	4	7.000	9
COB4	5.312	0.889	130.102	-0.945	-0.857	1.000	1	7.000	8
COB5	5.110	1.102	100.960	-0.609	-0.267	1.000	1	7.000	21
COB6	5.390	0.923	127.172	-1.159	0.977	2.000	4	7.000	11
COB7	5.411	0.909	129.617	-1.126	1.147	2.000	4	7.000	15

Ready

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:

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

References

- 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)
- E. Anderson, L.M. Lodish, B. Weitz, Resource allocation behavior in conventional channels. *J. Market. Res.* **24**(1), 85–97 (1987)
- R.P. Bagozzi, T.F. Heatherton, A general approach to representing multifaceted personality constructs: application to state self-esteem. *Struct. Equ. Model.* **1**(1), 35–67 (1994)
- R.P. Bagozzi, Y. Yi, On the evaluation of structural equation models. *J. Acad. Market. Sci.* **16**, 74–94 (1988)
- J. Barnes, J. Cote, R. Cudeck, E. Malthouse, Factor analysis—checking assumptions of normality before conducting factor analysis. *J. Consum. Psychol.* **10**(1,2), 79–81 (2001)
- H. Baumgartner, C. Homburg, Applications of structural equation modeling in marketing and consumer research: a review. *Int. J. Res. Mark.* **13**, 139–161 (1996)
- J. Benson, D.L. Bandalos, Second-order confirmatory factor analysis of the reactions to tests scale with cross-validation. *Multivar. Behav. Res.* **27**(3), 459–487 (1992)
- P. Bentler, R.P. Bagozzi, R. Cudeck, D. Iacobucci, Structural equation modeling—SEM using correlation or covariance matrices. *J. Consum. Psychol.* **10**(1,2), 85–87 (2001)
- K.A. Bollen, *Structural equations with latent variables* (Wiley, New York, 1989)
- G. Churchill, *Marketing Research: Methodological Foundations* (Dryden Press, Orlando, 1999)
- J. Cortina, G. Chen, W. Dunlap, Testing interaction effects in LISREL: examination and illustration of available procedures. *Org. Res. Methods* **4**(4), 324–360 (2001)
- J. Cote, R. Netemeyer, P. Bentler, Structural equation modeling—improving model fit by correlating errors. *J. Consum. Psychol.* **10**(1, 2), 87–88 (2001)
- A. Diamantopoulos, J. Siguaw, *Introducing LISREL* (SAGE, London, 2000)
- W.R. Dillon, R.P. McDonald, D. Iacobucci, Measurement—how to combine multiple items into a composite measure. in ed. by D. Iacobucci *J. Consum. Psychol.* **10**(1&2), pp. 55–59 (2001)
- M. Du Toit, S. Du Toit *Interactive LISREL: User's Guide*. (Scientific Software International, Lincolnwood, 2001)
- J. Gassenheimer, J.D. Davis, R. Dahlstrom, Is dependent what we want to be? *J. Retail.* **74**(2), 247–271 (1998)
- T. Grapentine, Dimensions of an attribute. *Market. Res.* **7**(3), 19–27 (1995)
- P.E. Green, D.T. Tull, G. Albaum, *Research for Marketing Decisions*, 5th edn. (Prentice Hall, New Jersey, 1988)
- J. Hair, R. Anderson, R. Tatham, W. Black, *Multivariate Data Analysis*, 5th edn. (Prentice Hall International, London, 1998)
- J.E. Hunter, D.W. Gerbing in *Unidimensional Measurement, Second-Order Factor Analysis, and Causal Models* ed. by B.M. Staw, L.L. Cummings. *Research in Organizational Behavior* (JAI Press, Greenwich, 1982)
- K. Jöreskog, D. Sörbom, *PRELIS 2: User's Reference Guide* (Scientific Software International, Lincolnwood, 2002)
- K. Jöreskog, D. Sörbom, S. Du Toit, M. Du Toit, *LISREL 8: New Statistical Features* (Scientific Software International, Lincolnwood, 2001)
- T. Kinnear, J. Taylor, *Marketing Research: An Applied Approach* (McGraw-Hill, New York, 1991)

- R.C. MacCallum, M.W. Browne, H.M. Sugawara, Power analysis and determination of sample size for covariance structure modeling. *Psychol. Methods* **1**(2), 130–149 (1996)
- N.K. Malhotra, *Marketing Research: An Applied Orientation* (Prentice Hall, New Jersey, 1996)
- R.A. Ping Jr, On assuring valid measures for theoretical models using survey data. *J. Bus. Res.* **57**, 125–141 (2004)
- D. Powers, Y. Xie, *Statistical Methods for Categorical Data Analysis* (Academic Press, London, 2000)
- J. Steenkamp, H. van Trijp, The use of LISREL in validating marketing constructs. *Int. J. Res. Mark.* **8**, 283–299 (1991)
- D.L. Streiner, The case of the missing data: methods of dealing with dropouts and other research Vagaries. *Can. J. Psychiatr.* **47**(1), 70–77 (2002)
- P. Von Hippel, Biases in SPSS 12.0 missing value analysis. *Am. Stat.* **58**(2), 160–164 (2004)



<http://www.springer.com/978-3-642-18043-9>

Interactive LISREL in Practice

Getting Started with a SIMPLIS Approach

Vieira, A.L.

2011, VIII, 90 p., Softcover

ISBN: 978-3-642-18043-9