ADANCO 2.0.1

User Manual

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Contents

Contents iii

List of Figures vi

List of Tables viii

1 Getting started 1
- 1.1 Variance-based structural equation modeling . . . 1
- 1.2 The ADANCO software . . . 1
  - 1.2.1 Implemented statistical techniques . . . 1
  - 1.2.2 How to cite ADANCO . . . 2
  - 1.2.3 Installing ADANCO . . . 2
  - 1.2.4 ADANCO Quickstart video guide . . . 2
- 1.3 Starting ADANCO . . . 2
  - 1.3.1 Create a new ADANCO project . . . 2
  - 1.3.2 Open a saved ADANCO project . . . 2
- 1.4 The program shell . . . 2
  - 1.4.1 The ADANCO modeling window . . . 2
  - 1.4.2 The menu . . . 6
- 1.5 Data . . . 8
  - 1.5.1 Import data . . . 8
  - 1.5.2 Data format . . . 8
  - 1.5.3 Standardization . . . 8

2 Model specification 11
- 2.1 Measurement model . . . 11
  - 2.1.1 Composite models (composite-formative measurement) . . . 11
  - 2.1.2 Common factor models (reflective measurement) . . . 12
  - 2.1.3 Single-indicator measurement . . . 12
  - 2.1.4 The dominant indicator . . . 12
  - 2.1.5 Weighting schemes . . . 12
  - 2.1.6 Implicit specifications . . . 13
- 2.2 Specifying the structural model . . . 13
- 2.3 Estimated vs. saturated model . . . 14
- 2.4 Ensuring identification . . . 14

3 Estimating the model parameters 15
- 3.1 The PLS path modeling algorithm . . . 15
- 3.2 Algorithm settings . . . 16

3.2.1 Inner weighting scheme . . . 17
3.2.2 Maximum number of iterations . . . 17
3.2.3 Stop criterion . . . 17
3.3 Treatment of missing values . . . 17
3.4 Bootstrapping . . . 17
3.5 Options . . . 18
3.5.1 View settings . . . 18
3.5.2 Configure output styles . . . 18

4 Estimation results **21**
4.1 Output shown in the graphical user interface . . . 21
4.2 Goodness of model fit . . . 21
4.2.1 Unweighted least squares discrepancy (d_{ULS}) . . . 22
4.2.2 Geodesic discrepancy (d_{G}) . . . 22
4.2.3 Standardized root mean squared residual (SRMR) . . . 23
4.3 Measurement model results . . . 23
4.3.1 Reliability of construct scores . . . 23
4.3.2 Average variance extracted . . . 24
4.3.3 Discriminant validity . . . 25
4.3.4 Indicator results . . . 28
4.3.5 Cross loadings . . . 30
4.4 Structural model results . . . 30
4.4.1 Inter-construct correlations . . . 30
4.4.2 R^2 and adjusted R^2 . . . 32
4.4.3 Path coefficients . . . 32
4.4.4 Indirect effects . . . 33
4.4.5 Total effects . . . 33
4.4.6 Effect size (Cohen's f^2) . . . 35
4.5 Bootstrap inference statistics . . . 36
4.6 Scores . . . 39
4.6.1 Standardized construct scores . . . 39
4.6.2 Unstandardized construct scores . . . 39
4.6.3 Original indicator scores . . . 39
4.6.4 Standardized indicator scores . . . 39
4.7 Diagnostic tools . . . 41
4.7.1 Empirical correlation matrix . . . 41
4.7.2 Implied correlation matrix . . . 41
4.8 Exporting results . . . 43
4.8.1 HTML export . . . 43
4.8.2 Excel export . . . 43
4.8.3 Graphic export . . . 43

5 Extensions **45**
5.1 Longitudinal studies . . . 45
5.2 Mediating effects . . . 45
5.3 Moderating effects . . . 45
5.4 Nonlinear effects . . . 45
5.5 Multigroup analysis . . . 46
5.6 Analyzing data from experiments . . . 46
5.7 Second-order constructs . . . 46
5.8 Prediction-oriented modeling . . . 46

5.9 Importance-performance matrix analysis 46
5.10 Other extensions 46

6 Help & support **47**
6.1 The ADANCO help system 47
6.2 Trouble shooting 47
6.3 Downloadable example files 48
6.3.1 Service Customization 48
6.3.2 European Customer Satisfaction Index 48
6.3.3 Organizational Identification 48
6.4 Selected ADANCO applications 48

Bibliography **49**

List of Figures

1.1 ADANCO Quickstart video guide . . . 3
1.2 Start screen . . . 4
1.3 Open file dialog . . . 4
1.4 The modeling window . . . 5
1.5 The menus . . . 7
1.6 Data import and preview . . . 8
1.7 Selecting the data file . . . 9

3.1 Run dialog . . . 16
3.2 Settings . . . 18
3.3 Configure output styles . . . 19

4.1 Goodness of fit . . . 22
4.2 Reliability coefficients . . . 24
4.3 Unidimensionality of reflective constructs . . . 25
4.4 Fornell-Larcker criterion . . . 26
4.5 Heterotrait-monotrait ratio of correlations (HTMT) . . . 27
4.6 95% quantile of bootstrapped HTMT . . . 27
4.7 Indicator weights . . . 28
4.8 Variance inflation factors (VIF) . . . 29
4.9 Loadings . . . 29
4.10 Indicator reliability . . . 30
4.11 Cross loadings . . . 31
4.12 Inter-construct correlations . . . 31
4.13 R^2 and adjusted R^2 values . . . 32
4.14 Path coefficients . . . 33
4.15 Indirect effects . . . 34
4.16 Total effects . . . 34
4.17 Effect overview and effect size . . . 35
4.18 Direct effect inference . . . 36
4.19 Indirect effect inference . . . 37
4.20 Total effect inference . . . 37
4.21 Loadings inference . . . 38
4.22 Weights inference . . . 38
4.23 Standardized construct scores . . . 39
4.24 Unstandardized construct scores . . . 40
4.25 Original indicator scores . . . 40
4.26 Standardized indicator scores . . . 41
4.27 Empirical correlations of indicators . . . 42

4.28 Implied correlations (estimated model) 42
4.29 Implied correlations (saturated model) 43

6.1 ADANCO help 47

List of Tables

4.1 A comparison of reliability coefficients 23
4.2 How to interpret f^2 values (Cohen, 1988) 35

One

Getting started

1.1 Variance-based structural equation modeling[1]

Structural equation modeling (SEM) is a family of statistical techniques that has become very popular in business and social sciences. Its ability to model latent variables, to take into account various forms of measurement error into account, and to test entire theories makes it useful for a plethora of research questions.

Two types of SEM can be distinguished: covariance- and variance-based SEM (Reinartz et al., 2009). Covariance-based SEM estimates model parameters using the empirical variance-covariance matrix. It is the method of choice if the hypothesized model consists of one or more common factors. In contrast, variance-based SEM first creates proxies as linear combinations of observed variables, and thereafter uses these proxies to estimate the model parameters. Variance-based SEM is the method of choice if the hypothesized model contains composites.

Of all the variance-based SEM methods, partial least squares path modeling (PLS) is regarded as the "most fully developed and general system" (McDonald, 1996, p. 240). PLS is widely used in information systems research (Marcoulides & Saunders, 2006), strategic management (Hulland, 1999), marketing (Hair et al., 2012), operations management (Peng & Lai, 2012), organizational behavior (Sosik et al., 2009), and beyond. Researchers across disciplines appreciate its ability to model both factors and composites. Whereas factors can be used to model latent variables of behavioral research, such as attitudes or personality traits, composites can be applied to model strong concepts (Höök & Löwgren, 2012), i.e. the abstraction of artifacts such as management instruments, innovations, or information systems. Consequently, PLS path modeling is the preferred statistical tool for success factor studies (Albers, 2010).

1.2 The ADANCO software

ADANCO ("advanced analysis of composites") is a software for variance-based structural equation modeling. Its first edition appeared in 2014. The current version is ADANCO 2.0.1.

1.2.1 Implemented statistical techniques

Variance-based structural equation modeling covers a plethora of statistical techniques, of which ADANCO 2.0.1 implements a relevant subset. The following are techniques that ADANCO 2.0.1 implements:

- partial least squares path modeling (PLS),
- consistent PLS (PLSc),
- confirmatory composite analysis (CCA),

[1] This section mainly reprints parts of Henseler et al. (2016).

- extraction of the first principal component (PCA),
- ordinary least squares regression (OLS),
- sum scores,
- canonical correlation analysis, and
- bootstrapping.

1.2.2 How to cite ADANCO

If you use ADANCO in a publication, please cite it as follows:

> Henseler, Jörg & Dijkstra, Theo K. (2015). ADANCO 2.0. Kleve, Germany: Composite Modeling.

1.2.3 Installing ADANCO

ADANCO 2.0.1 is available for Microsoft Windows and Apple Mac operating systems. It comes with an installation wizard. This installation wizard is self-explaining. Please note that administration rights may be required to install ADANCO 2.0.1.

1.2.4 ADANCO Quickstart video guide

A quickstart guide is available as a YouTube video:

`https://www.youtube.com/watch?v=okzSxcH6L9Y`.

Figure 1.1 shows the start of the video.

1.3 Starting ADANCO

Figure 1.2 depicts the start screen of ADANCO 2.0.1.

1.3.1 Create a new ADANCO project

One possibility when starting to work with ADANCO is to create a new project. ADANCO 2.0.1 will first request a file name to save the new project. ADANCO projects are saved by using the file extension `.cmq`. Once the project has been saved, ADANCO will show the modeling window.

1.3.2 Open a saved ADANCO project

Another possibility when starting to work with ADANCO is to open an existing ADANCO project. Figure 1.3 depicts the open file dialog of ADANCO 2.0.1. ADANCO projects have a `.cmq` file extension.

1.4 The program shell

1.4.1 The ADANCO modeling window

Figure 1.4 depicts the ADANCO 2.0.1 modeling window, which contains the following elements:

1. New project
2. Load project
3. Save project

Figure 1.1: ADANCO Quickstart video guide

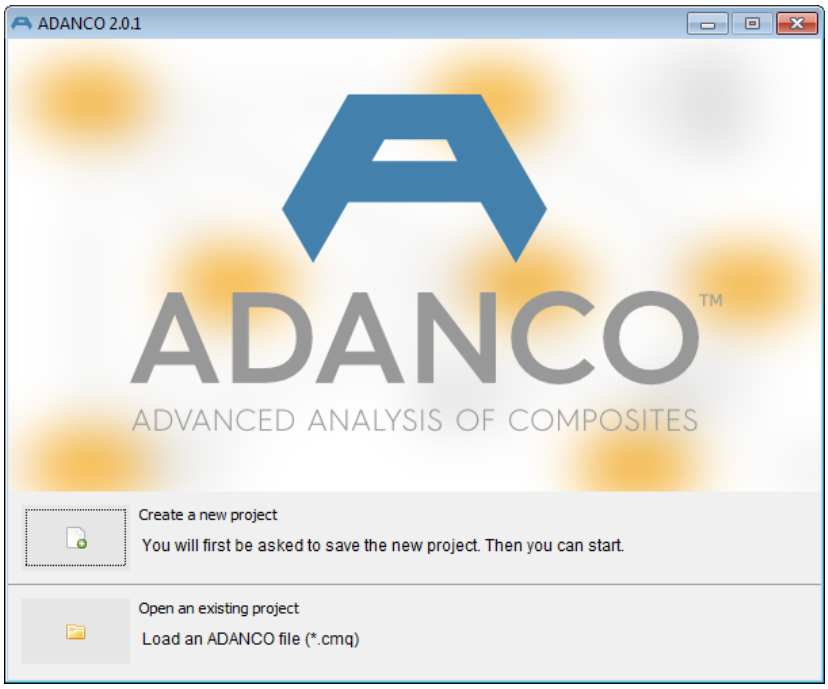


Figure 1.2: Start screen of ADANCO 2.0.1

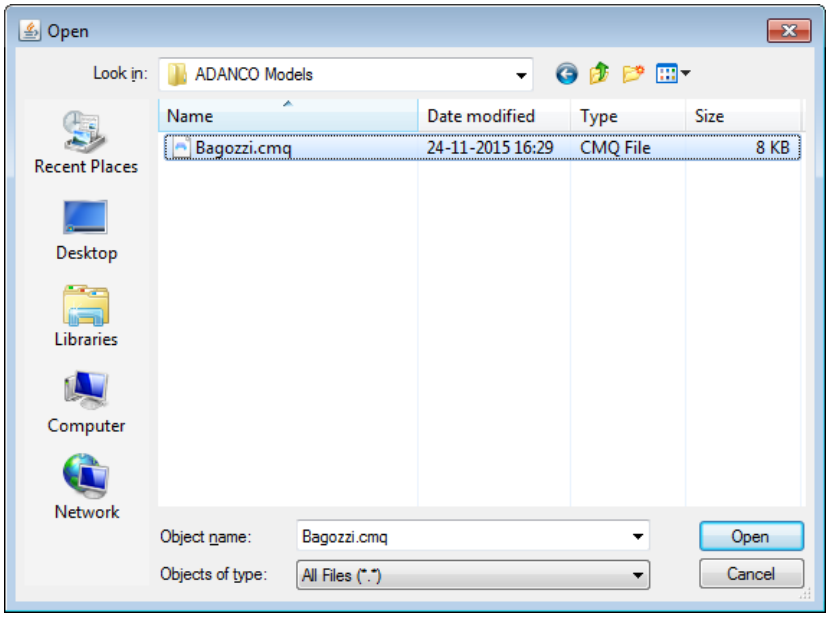


Figure 1.3: Open file dialog of ADANCO 2.0.1

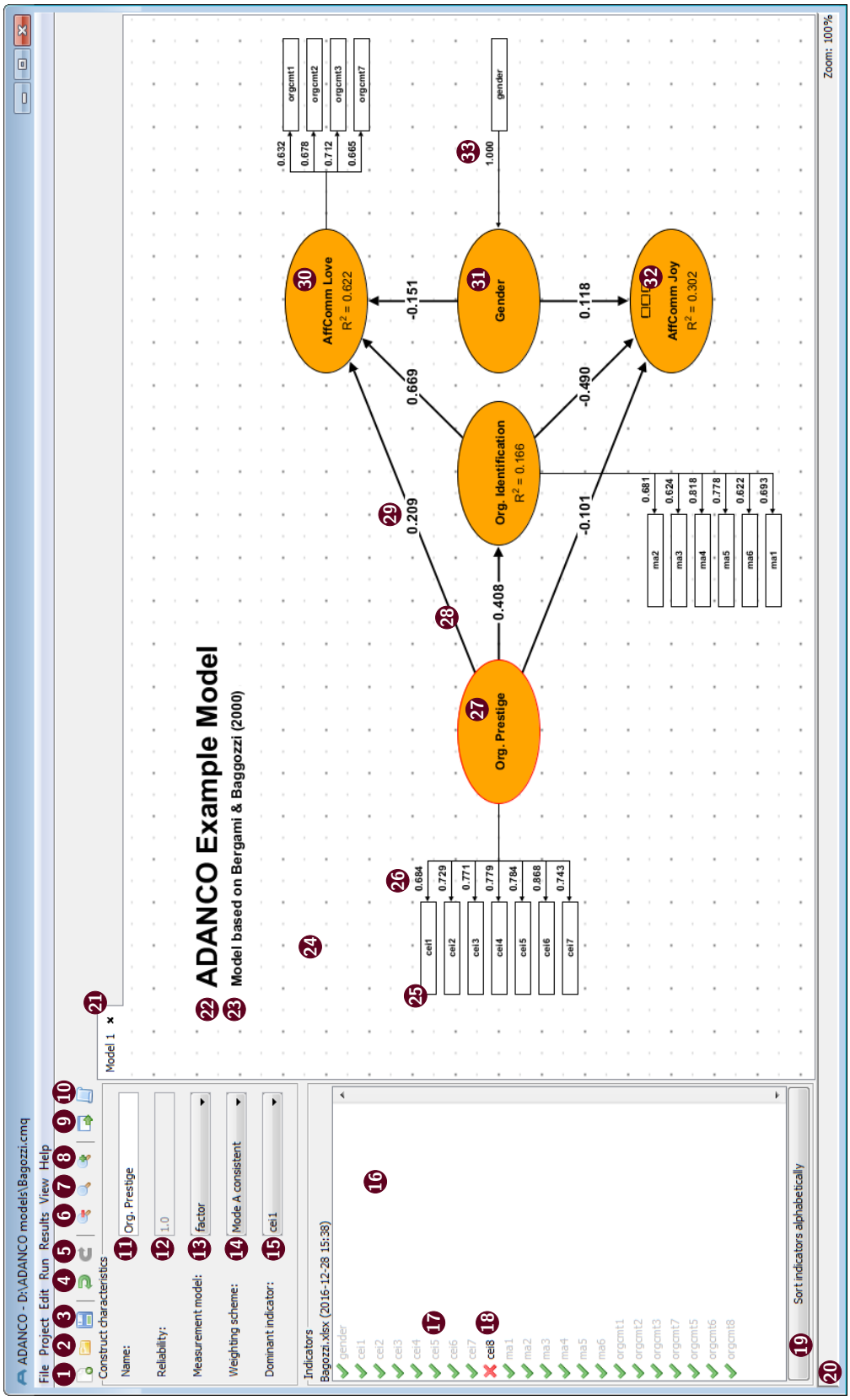
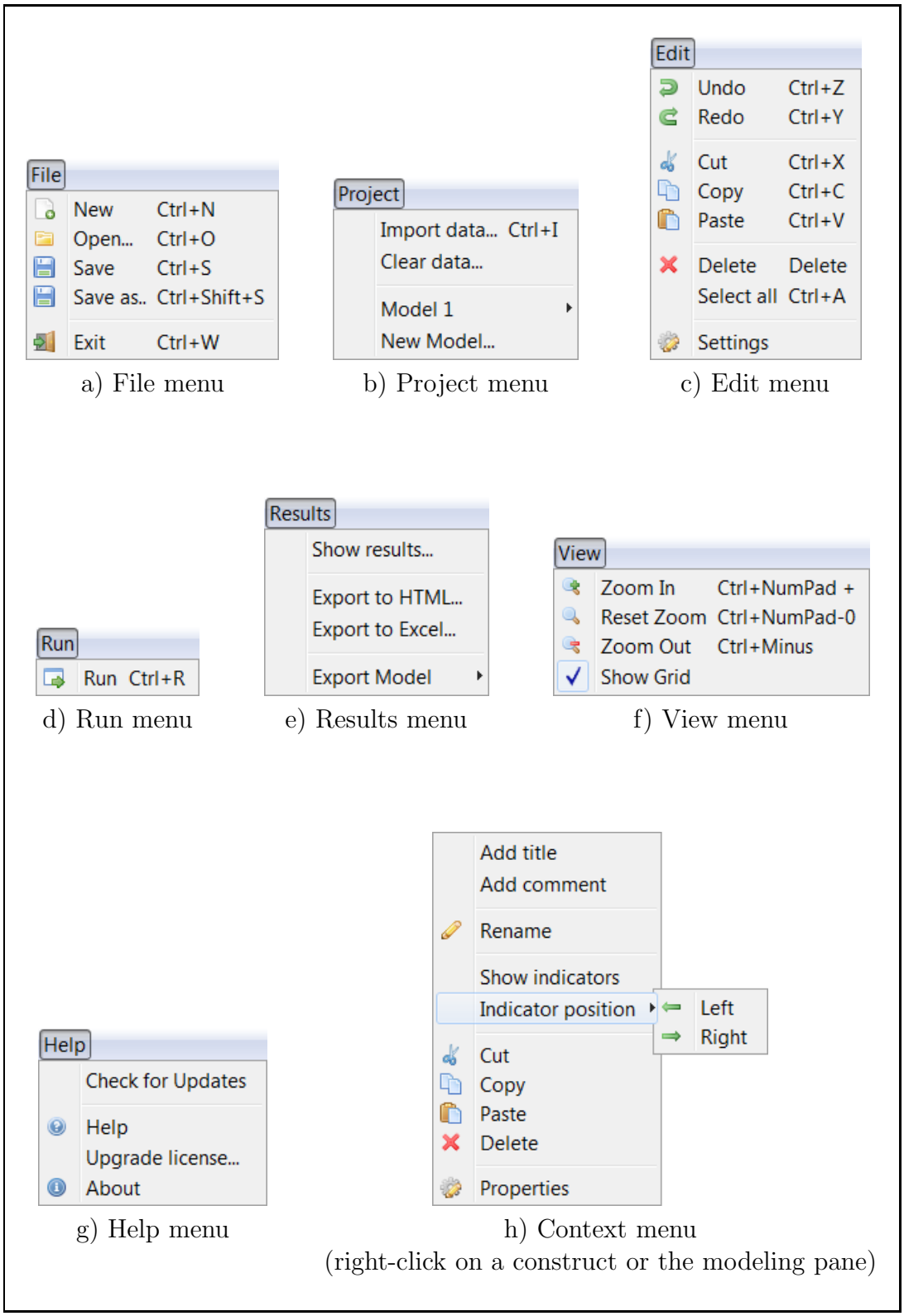


Figure 1.4: The ADANCO 2.0.1 modeling window

4. Undo
5. Redo
6. Zoom out
7. Standard zoom and refresh graphical model
8. Zoom in
9. Run
10. View report
11. Name of the selected construct
12. Preset reliability of the selected construct
13. Measurement model of the selected construct
14. Weighting scheme of the selected construct
15. Dominant indicator of the selected construct
16. List of indicators
17. Used indicator
18. Unused indicator
19. Sort indicators button
20. Status bar
21. Model denominator
22. Model title
23. Model comment
24. Modeling pane with grid
25. Indicator
26. Loading
27. Exogenous construct (unselected)
28. Linear relationship between constructs
29. Path coefficient
30. Endogenous construct (unselected) and coefficient of determination
31. Exogenous construct (selected) modeled as composite
32. Endogenous construct (unselected) whose indicators are hidden
33. Indicator weight

1.4.2 The menu

Figure 1.5 shows the available menus.



a) File menu b) Project menu c) Edit menu

d) Run menu e) Results menu f) View menu

g) Help menu h) Context menu
(right-click on a construct or the modeling pane)

Figure 1.5: The menus

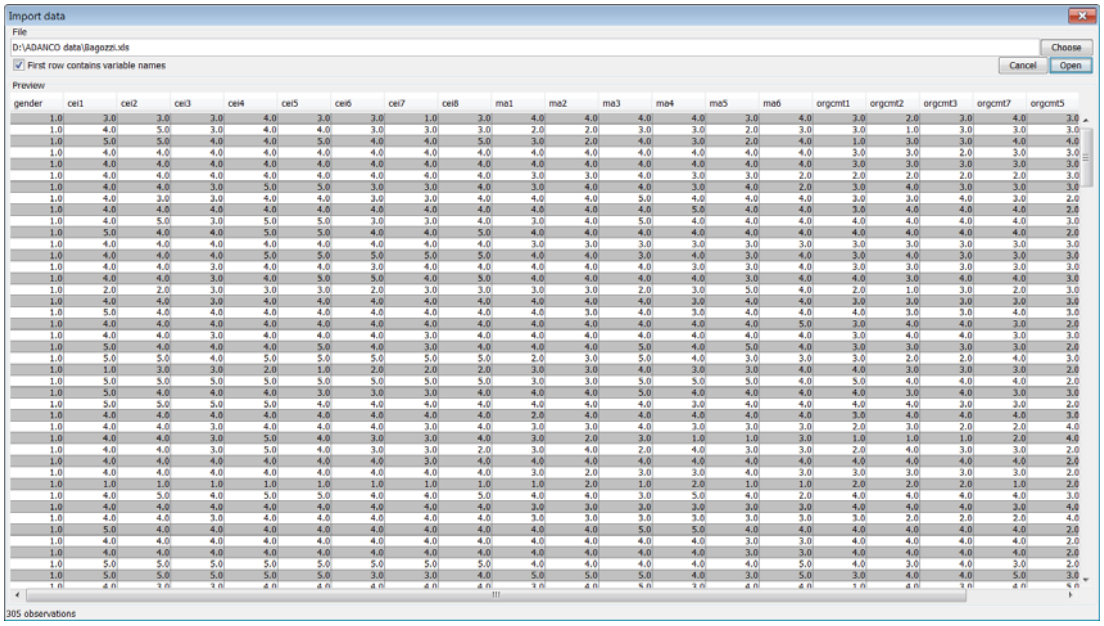


Figure 1.6: Data import and preview in ADANCO 2.0.1

1.5 Data

1.5.1 Import data

Figure 1.6 shows the main data import dialog, which automatically turns into a data previewer once a data file has been chosen. Missing data that ADANCO 2.0.1 has recognized as such will be marked by red cells.

1.5.2 Data format

ADANCO 2.0.1 can import Excel Workbooks (`*.xlsx`) and Excel 97-2003 Workbooks (`*.xls`) as depicted in Figure 1.7. The data files should have the following characteristics:

- The first row should contain the indicator names. If no indicator names are found, ADANCO will automatically generate indicator names.
- There should not be any empty column.
- The file should contain nothing but values. Specifically, it should not contain
  - equations,
  - pictures,
  - formatting (such as borders, colors, highlighted text).
- Cells containing missing data should be left empty or filled with a string, e.g. “NA.”

1.5.3 Standardization

ADANCO 2.0.1 estimates all parameters using standardized data. Standardization entails that an indicator is rescaled so that it is assigned a mean value of zero and a variance of one.

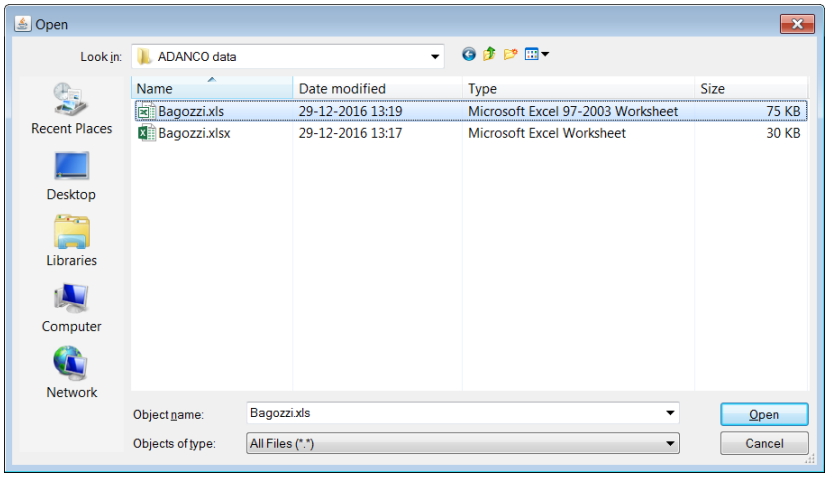


Figure 1.7: Selecting the data file

Two

Model specification

Structural equation models are formally defined by two sets of linear equations: the measurement model (also called the outer model) and the structural model (also called the inner model). The measurement model specifies the relations between a construct and its observed indicators (also called the manifest variables), whereas the structural model specifies the relationships between the constructs.

In the model graph, ovals denote constructs, and rectangles denote indicators. Constructs typically serve as unobservable conceptual variables' proxies.

2.1 Measurement model

The measurement model specifies the relationship between constructs and their indicators. Indicators are observed variables. Each indicator corresponds to a column in the data file.

ADANCO 2.0.1 can cope with various types of measurement models:

- Composite models,
- Common factor models (reflective measurement models),
- MIMIC models (causal-formative measurement),
- single-indicator measurement, and
- categorical exogenous variables.

The choice of a concrete type of measurement model (e.g., composite vs. reflective) has consequences for the weighting schemes' availability and for the reporting. No matter which type of measurement is chosen to measure a construct, PLS requires at least one available indicator. Constructs without indicators, called phantom variables (Rindskopf, 1984), cannot be included in PLS path models in general. An exception are second-order constructs, which should be modeled using a two-stage approach (see Section 5.7)

2.1.1 Composite models (composite-formative measurement)

PLS path modeling forms composites as linear combinations of their respective indicators (Henseler et al., 2014). The composite model does not impose any restrictions on the covariances between indicators of the same construct, i.e. it relaxes the assumption that a common factor explains all the covariation between a block of indicators. The composites serve as proxies of the scientific concept under investigation (Ketterlinus et al., 1989; Rigdon, 2012; Maraun & Halpin, 2008; Tenenhaus, 2008). Since composite models are less restrictive than factor models, they typically have a higher overall model fit (Landis et al., 2000). ADANCO 2.0.1 permits to manually define the reliability of constructs with a composite measurement model with one or more indicators.

2.1.2 Common factor models (reflective measurement)

The factor model hypothesizes that an unobserved variable (the common factor) and individual random errors can be perfectly explain the variance of a set of indicators. This model is the standard model of behavioral research. In order to obtain consistent estimate for reflective measurement models, analysts should rely on consistent PLS (PLSc, see Dijkstra & Henseler, 2015b) by choosing "Mode A consistent" as the weighting scheme.

2.1.3 Single-indicator measurement

If only one indicator measures a construct, one calls this a single-indicator measurement (Diamantopoulos et al., 2012). The construct scores are then identical to the standardized indicator values. In this case, it is not possible to determine the amount of random measurement error in the indicator. If an indicator is error-prone, the only possibility to account for the error is to utilize external knowledge about this indicator's reliability in order to manually define it.

To explicitly model random measurement error, analysts should specify a measurement model as a composite and define the reliability manually. ADANCO 2.0.1 will then correct for attenuation. Note that, in this case, the inter-construct correlations will differ from the correlations between the construct scores.

2.1.4 The dominant indicator

Sign-indeterminacy, in which the weight or loading estimates of a factor or a composite can only be determined jointly in terms of their value but not their sign, is a typical characteristic of factor-analytical tools and particularly SEM. For example, if a factor is extracted from the strongly negatively correlated customer satisfaction indicators "How satisfied are you with provider X?" and "How much does provider X differ from an ideal provider?" the method cannot "know" whether the extracted factor should correlate positively with the first or with the second indicator. Depending on the sign of the loadings, the meaning of the factor would either be "customer satisfaction" or "customer non-satisfaction." To avoid this ambiguity, it has become practice in SEM to determine one particular indicator per construct with which the construct scores are forced to correlate positively. Since this indicator dictates the orientation of the construct, it is called the "dominant indicator." While in covariance-based structural equation modeling this dominant indicator also dictates the construct's variance, in variance-based SEM, the construct variance is simply set to one.

For each construct, ADANCO 2.0.1 allows users to specify a dominant indicator, which is an indicator that must have a positive correlation with its corresponding construct. No default dominant indicator is selected.

The dominant indicator is a practical solution for SEM's sign-indeterminacy problem. ADANCO 2.0.1 forces the construct scores to have a positive correlation with the dominant indicator. If the construct scores have a negative correlation with the dominant indicator, ADANCO 2.0.1 will automatically multiply the construct scores by −1.

2.1.5 Weighting schemes

The weighting scheme defines how the indicator weights should be determined. The type of measurement model partly determines the choice of weighting scheme.

ADANCO 2.0.1 implements the following weighting schemes for *composite measurement models*:

- Mode A,
- Mode B, and
- sum scores.

. Mode A yields weights proportional to the correlations between the construct scores and the indicators. Multicollinearity does not affect these correlation weights, and they demonstrate a favorable out-of-sample prediction (Rigdon, 2012). However, they are inconsistent.

Mode B is essentially an ordinary least squares regression in which the construct scores are regressed on the construct's indicators. These regression weights are consistent (Dijkstra, 2010).

Sum scores means that the construct scores will be calculated as the sum of the (standardized) indicators multiplied by a scaling factor, which is needed to obtain standardized construct scores.

ADANCO 2.0.1 implements the following weighting schemes for *reflective measurement models*:¡/p¿

- Mode A consistent,
- Mode A, and
- sum scores.

. Mode A consistent is the recommended option for reflective measurement. It creates construct scores by using correlation weights. Consistent PLS (Dijkstra & Henseler, 2015a,b) is then used to obtain consistent inter-construct correlations, path coefficients, and loadings. Consistent PLS can be regarded as a correction for attenuation, using Dijkstra-Henseler's rho as a reliability estimate.

ADANCO 2.0.1 mainly provides Mode A for downward compatibility in order to emulate the results of older PLS software such as PLS-Graph, SmartPLS, and XLSTAT-PLS. Mode A does not correct for attenuation. Mode A provides inconsistent estimates for inter-construct correlations, path coefficients, and loadings; it is therefore not recommended for confirmatory research. However, it can be a viable option for predictive research.

Sum scores means that the construct scores will be calculated as the sum of the (standardized) indicators multiplied by a scaling factor required to obtain standardized construct scores. Sum scores are not corrected for attenuation.

2.1.6 Implicit specifications

Some model specifications are made automatically and cannot be manually changed: Measurement errors are assumed to be uncorrelated with all other variables and errors in the model; structural disturbance terms are assumed to be orthogonal to their predictor variables and to each other; correlations between exogenous variables are free. Because these specifications hold across models, it has become customary not to draw measurement errors and their correlations in PLS path models. As a consequence, measurement models in variance-based SEM may appear less detailed than those of covariance-based structural equation modeling; however, some specifications are implicit and are simply not visualized. Since ADANCO 2.0.1 does not allow either constraining or freeing factor models' error correlations, these model elements are not drawn.

2.2 Specifying the structural model

The structural model consists of exogenous and endogenous constructs as well as the relationships between them. The values of exogenous constructs are assumed to be given from outside the model. Consequently, other constructs in the model do not explain the exogenous variables, and the structural model should not contain any arrows pointing to exogenous constructs. In contrast, other constructs in the model at least partially explain endogenous constructs. Each endogenous construct must have at least one structural model arrow pointing to it.

In the model graph, ovals denote constructs, and arrows denote paths. The relationships between the constructs are usually assumed to be linear. The size and significance of path relationships are usually the focus of the scientific endeavors pursued in empirical research.

In ADANCO 2.0.1, structural models must be recursive. This means that there should be no causal loop. All residuals are assumed to be uncorrelated.

In ADANCO 2.0.1, structural models can consist of several unconnected pieces, i.e. constructs need not be connected with other constructs.

Construct names must be unique.

2.3 Estimated vs. saturated model

The estimated model is the model as graphically specified. Correlations between exogenous constructs cannot be drawn; exogenous constructs are always allowed to correlate. All endogenous constructs are assumed to have residuals. These are not only assumed to be uncorrelated, but also to be uncorrelated with factor models' measurement errors.

Next to the estimated model, ADANCO 2.0.1 automatically generates a saturated model. The saturated model has the same measurement model as the estimated model, but does not restrict the relationships between the constructs. In other words, in the saturated model, all the constructs are correlated. If the endogenous constructs in the structural model form a complete graph, the estimated and the saturated model will be equivalent. If all the construct measurements are composites, ADANCO 2.0.1 performs a confirmatory composite analysis (Henseler et al., 2014). If "Mode A consistent" is used as the weighting scheme for all the constructs, ADANCO 2.0.1 performs a confirmatory factor analysis.

2.4 Ensuring identification[1]

Identification has always been an important issue for SEM, although it was neglected in the PLS path modeling realm in the past. It refers to the necessity to specify a model such that only one set of estimates exists that yields the same model-implied correlation matrix. It is possible for a complete model to be unidentified, but only parts of a model can also be unidentified. In general, it is not possible to derive useful conclusions from unidentified (parts of) models.

In order to achieve identification, PLS fixes the variance of factors and composites to one. A called nomological net is an important composite model requirement. This means that composites cannot be estimated in isolation, but need at least one other variable (either observed or latent) with which to have a relation. Since PLS also estimates factor models via composites, this requirement applies to all factor models estimated by PLS. If a factor model has exactly two indicators, it does not matter which form of SEM is used – a nomological net is then required to achieve identification.

[1] This section mainly reprints parts of Henseler et al. (2016).

Three

Estimating the model parameters

3.1 The PLS path modeling algorithm[1]

The estimation of PLS path model parameters happens in four steps:

1. an iterative algorithm that determines the composite scores for each construct;
2. a correction for attenuation for those constructs modeled as factors (Dijkstra & Henseler, 2015b);
3. parameter estimation; and
4. bootstrapping for inference statistics.

Step 1. The iterative PLS algorithm creates a proxy as a linear combination of the observed indicators for each construct. The indicator weights are determined such that each proxy shares as much variance as possible with the causally related constructs' proxies. The PLS algorithm can be viewed at as an approach to extend canonical correlation analysis to more than two sets of variables; it can emulate several of Kettenring's 1971 techniques for the canonical analysis of several sets of variables (Tenenhaus & Esposito Vinzi, 2005). For a more detailed description of the algorithm see Henseler (2010). The proxies (i.e., composite scores), the proxy correlation matrix, and the indicator weights are the first step's main output.

Step 2. Correcting for attenuation is a required step if a model involves factors. If the indicators contain a random measurement error, the proxies will also. Consequently, proxy correlations are usually underestimations of the factor correlations. Consistent PLS (PLSc) corrects for this tendency (Dijkstra & Henseler, 2015a,b) by dividing a proxy's correlations by the square root of its reliability (the correction for attenuation). PLSc addresses the question: What would the correlation between the constructs be if there were no random measurement error? The main output of this second step is a consistent construct correlation matrix.

Step 3. Once a consistent construct correlation matrix is available, it is possible to estimate the model parameters. ADANCO 2.0.1 uses ordinary least squares (OLS) regression to obtain consistent parameter estimates for the structural paths. Next to the path coefficient estimates, this third step also provides estimates for loadings, indirect effects, total effects, and several model assessment criteria.

[1] This section mainly reprints parts of Henseler et al. (2016).

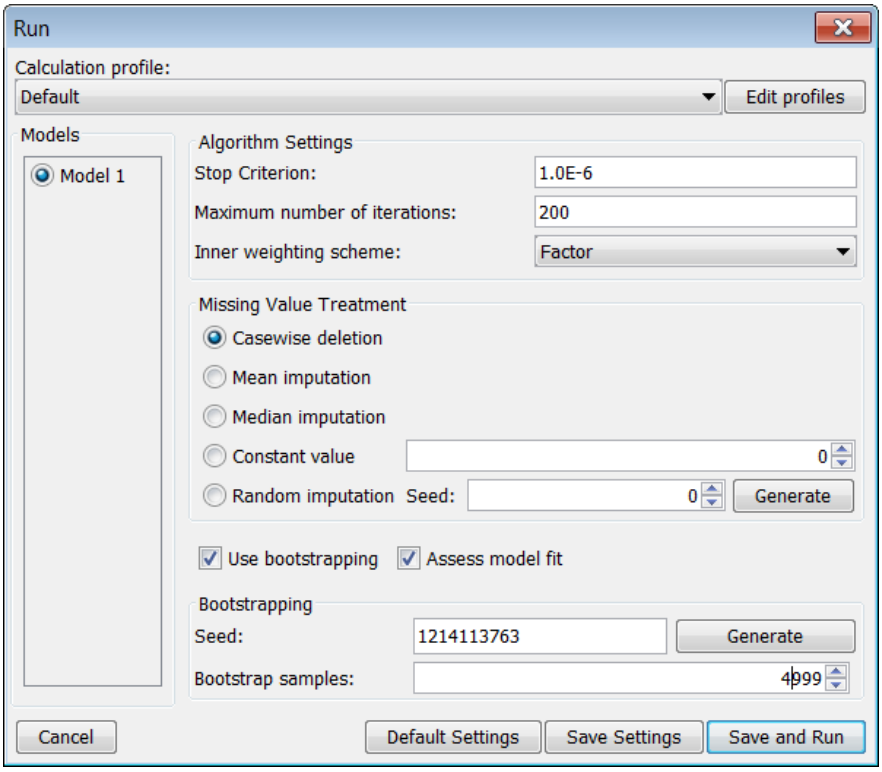


Figure 3.1: Run dialog of ADANCO 2.0.1

Step 4. Finally, bootstrapping is applied in order to obtain inference statistics for all the model parameters. Bootstrapping is a non-parametric inferential technique based on the assumption that the sample distribution conveys information about the population distribution. Bootstrapping is the process of drawing a large number of re-samples with replacement from the original sample. The model parameters of each bootstrap re-sample are estimated. The standard error of an estimate is inferred from the standard deviation of the bootstrap estimates.

The PLS path modeling algorithm has favorable convergence properties (Henseler, 2010). However, as soon as PLS path models involve common factors, Heywood cases (Krijnen et al., 1998) may occur, meaning that one or more variances that the model implies will be negative. An atypical or too-small sample or a misspecified model may cause Heywood cases.

3.2 Algorithm settings

ADANCO 2.0.1 relies on the PLS path modeling algorithm to determine the indicator weights. The algorithm settings include the following options:

- inner weighting scheme,
- maximum number of iterations, and
- stop criterion.

These options can be set in the run dialog as depicted in Figure 3.1. More information on the PLS path modeling algorithm can be found in Henseler (2010).

3.2.1 Inner weighting scheme

The inner weighting scheme is a characteristic of the iterative algorithm. This scheme determines how other constructs influence the estimation of construct weights (Henseler, 2010).

Two types of inner weighting schemes are available in ADANCO 2.0.1:

Centroid: All adjacent constructs have equal influence.

Factor: The influence of the adjacent constructs is proportional to their correlation.

3.2.2 Maximum number of iterations

ADANCO 2.0.1 allows users to limit the iterative algorithm in order to use a maximum, predefined number of iterations, the maximum number of iterations. This setting ensures that the algorithm is terminated in a controlled fashion.

If the maximum number of iterations has been reached, the algorithm will stop even if convergence has not been achieved. The maximum number of iterations must be an integer greater than zero.

3.2.3 Stop criterion

Analysts can manually specify a stop criterion. The stop criterion determines how large the smallest weight change from one iteration to another must be for the iterative algorithm to perform another iteration. The smaller the stop criterion, the more calculation time is needed. The stop criterion must have a value greater than zero. Its default value is 10^{-6}.

3.3 Treatment of missing values

ADANCO 2.0.1 offers a set of options to treat missing values:

Casewise deletion: Observations with missing values are dropped from the data matrix.

Mean imputation: Missing values are replaced by each indicator's mean.

Median imputation: Missing values are replaced by each indicator's median.

Constant value: Missing values are replaced by a predefined constant value.

Random imputation: Missing values are replaced by standard normal-distributed random numbers.

In general, users are recommended to estimate the model parameters by using different missing value treatments and comparing the results.

3.4 Bootstrapping

Bootstrapping is a non-parametric approach to obtain inference statistics for model parameter estimates. ADANCO 2.0.1 provides error probabilities and confidence intervals for path coefficients as well as indirect and total effects. In addition, it provides t-values for loadings and weights, as well as inference statistics for the HTMT.

Users are asked to determine the number of bootstrap samples. A good default value are 4,999 bootstrap samples. This number is sufficiently close to infinity for usual situations, is tractable with regard to computation time, and allows for an unanimous determination of empirical bootstrap confidence intervals (for instance, the 2.5% [97.5%] quantile would be the 125^{th} [4875^{th}] element of the sorted list of bootstrap values). To some extent, bootstrapping results depend on randomly drawn numbers. If the bootstrapping results differ greatly from

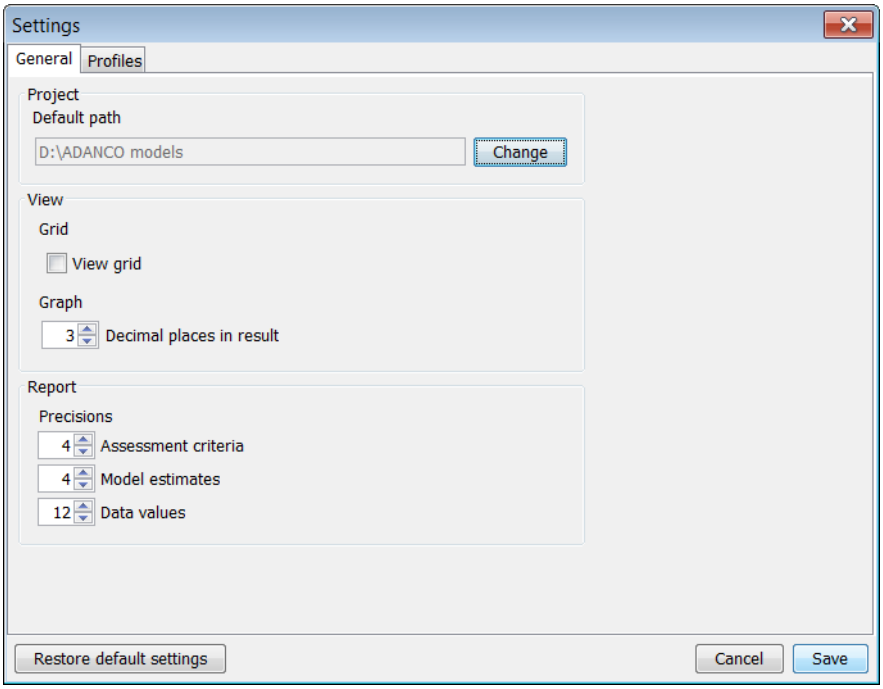


Figure 3.2: Settings of ADANCO 2.0.1

those of another run,[2] the number of bootstrap samples should be increased, for example, to 9,999.

More information on bootstrapping can be found in Henseler et al. (2009), Streukens & Leroi-Werelds (forthcoming), and (Chin, 2010).

3.5 Options

3.5.1 View settings

Figure 3.2 shows the settings that can be configured in ADANCO 2.0.1. It is possible to define the main folder in which ADANCO 2.0.1 has to search for model and data files, to toggle the grid in the modeling pane, and to adjust the number of decimal places used in the graphical output, as well as the different output tables.

3.5.2 Configure output styles

ADANCO 2.0.1 allows users to modify and define the output styles. In this way, users can customize the amount of output presented in the HTML and Excel reports. The fewer output ADANCO generates, the higher the calculation speed. ADANCO 2.0.1 includes a *complete profile*, comprising all possible outputs, and a *default profile*, which comprises all possible outputs with the exception of the indicator scores and certain technical outputs. Figure 3.3 shows how output styles can be configured in ADANCO 2.0.1. Result files with more output will be larger and need more preparation time.

[2] The random seed has to be varied for this comparison.

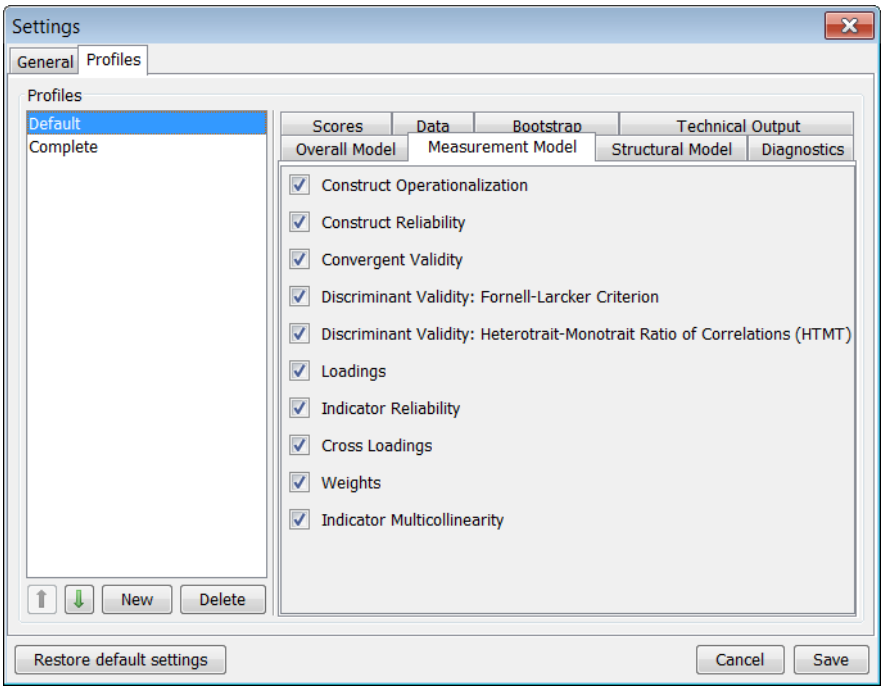


Figure 3.3: Configure output styles in ADANCO 2.0.1

Four

Estimation results

4.1 Output shown in the graphical user interface

After running the selected algorithm, the path coefficients will appear in the graphical model (on the arrows between the constructs). ADANCO 2.0.1 provides results instantly as long as a valid model has been specified. After running the selected algorithm, weights will appear near the indicators of composite measurement models, and loadings will appear near the indicators of reflective measurement models (on the arrows between the construct and its indicators).

4.2 Goodness of model fit

ADANCO 2.0.1 provides tests of model fit, which rely on bootstrapping to determine the likelihood of obtaining a discrepancy between the empirical and the model-implied correlation matrix that is as high as the one obtained for the sample at hand if the hypothesized model was indeed correct (Dijkstra & Henseler, 2015a). Bootstrap samples are drawn from modified sample data. This modification entails an orthogonalization of all variables and a subsequent imposition of the model-implied correlation matrix. In covariance-based SEM, this approach is known as the Bollen-Stine bootstrap (Bollen & Stine, 1992). If more than five percent (or a different percentage if an alpha-level different from 0.05 is chosen) of the bootstrap samples yield discrepancy values above those of the actual model, the sample data may indeed stem from a population that functions according to the hypothesized model. Consequently, the model cannot be rejected.

ADANCO 2.0.1 provides several ways of assessing the model's goodness of fit:

- the unweighted least squares discrepancy (d_{ULS}),
- the geodesic discrepancy (d_{G}), and
- the standardized root mean squared residual (SRMR),

Because different tests may have different results, a transparent reporting practice should include several tests.

Note that early suggestions for PLS-based goodness-of-fit measures such as the "goodness-of-fit" (GoF, see Tenenhaus et al., 2005) or the "relative goodness-of-fit" ($\mathrm{GoF}_{\mathrm{rel}}$, proposed by Esposito Vinzi et al., 2010) are – in contrast to what their name might suggest – not informative about the goodness of model fit (Henseler & Sarstedt, 2013; Henseler et al., 2014). Consequently, there is no reason to evaluate and report them if the analyst's aim is to test or to compare models, and they are not implemented in ADANCO.

Figure 4.1 shows how ADANCO 2.0.1 reports the goodness of fit. More information on the goodness of fit can be found in Henseler et al. (2016).

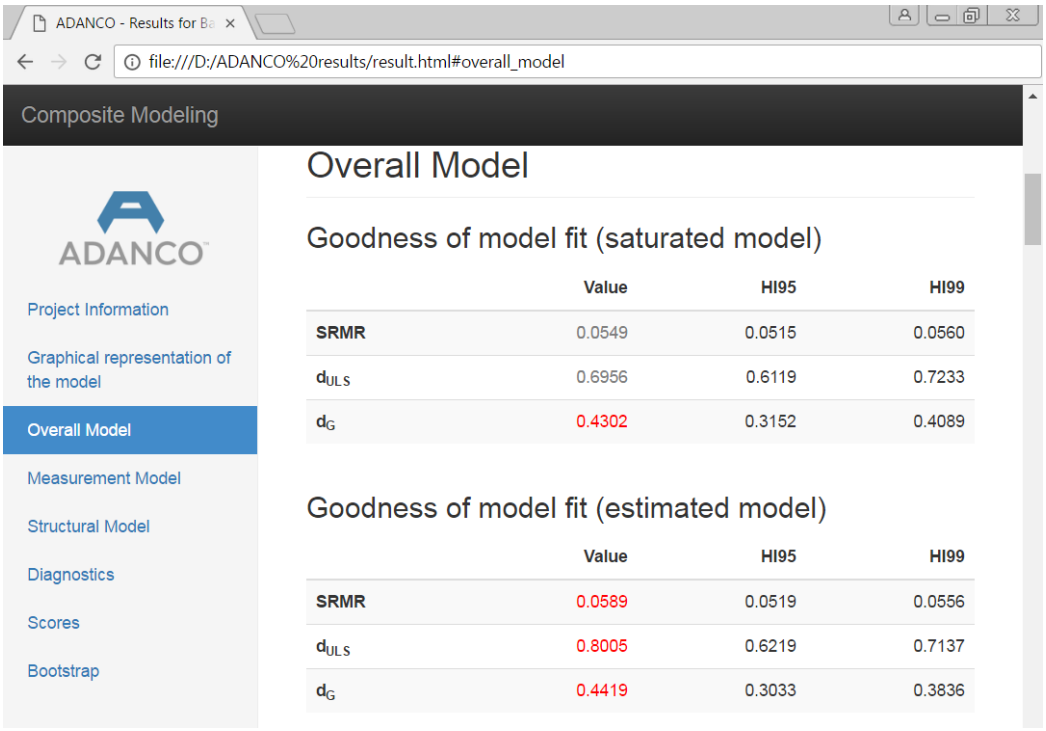


Figure 4.1: Goodness of fit reported by ADANCO 2.0.1

4.2.1 Unweighted least squares discrepancy (d_{ULS})

The unweighted least squares discrepancy (d_{ULS}) is a measure that quantifies how strongly the empirical correlation matrix differs from the model-implied correlation matrix. The lower the d_{ULS}, the better the theoretical model's fit.

The d_{ULS} is determined for the estimated model and the saturated model. In order to obtain the d_{ULS}, users must select the option "assess model fit" in the run dialog.

ADANCO 2.0.1 uses bootstrapping to provide the 95%-percentile ("HI95") and the 99%-percentile ("HI99") for the d_{ULS} if the theoretical model was true. If the d_{ULS} exceeds these values, it is unlikely that the model is true.

More information on the d_{ULS} can be found in Dijkstra & Henseler (2015a).

4.2.2 Geodesic discrepancy (d_{G})

The geodesic discrepancy (d_{G}) is another approach to quantify how strongly the empirical correlation matrix differs from the model-implied correlation matrix. The lower the d_{G}, the better the theoretical model's fit.

The d_{G} is determined for the estimated model and the saturated model. In order to obtain the d_{G}, users must select the option "assess model fit" in the Run dialog.

ADANCO 2.0.1 uses bootstrapping to provide the 95%-percentile ("HI95") and the 99%-percentile ("HI99") for the d_{G} if the theoretical model was true. If the d_{G} exceeds these values, it is unlikely that the model is true.

More information on the d_{G} can be found in Dijkstra & Henseler (2015a).

Reliability coefficient	Estimate for the reliability of...	Applicable to...
Dijkstra-Henseler's rho (ρ_A)	PLS construct scores	generic measurement
Composite reliability (ρ_c or ω)	sum scores	generic measurement
Cronbach's alpha (α)	sum scores	tau-equivalent measurement

Table 4.1: A comparison of reliability coefficients

4.2.3 Standardized root mean squared residual (SRMR)

Next to conducting the tests of model fit, it is also possible to determine the approximate model fit. Approximate model fit criteria help answer the question: How substantial is the discrepancy between the model-implied correlation matrix and the empirical correlation matrix? This question is particularly relevant if this discrepancy is significant.

The standardized root mean squared residual (SRMR Hu & Bentler, 1998) quantifies how strongly the empirical correlation matrix differs from the model-implied correlation matrix. As can be derived from its name, the SRMR is the square root of the sum of the squared differences between the model-implied correlation matrix and the empirical correlation matrix, i.e. the Euclidean distance between the two matrices. The lower the SRMR, the better the theoretical model's fit. A value of 0 for the SRMR would indicate a perfect fit and, generally, an SRMR value less than 0.05 indicates an acceptable fit (Byrne, 2013). A recent simulation study shows that even totally correctly specified models can yield SRMR values of 0.06 and higher (Henseler et al., 2014). Therefore, a cut-off value of 0.08, as proposed by Hu & Bentler (1999), appears to be better for variance-based SEM.

ADANCO 2.0.1 calculates the SRMR for the models as specified (the estimated model) and for a model in which all the constructs are allowed to freely covary (the saturated model). If the user has selected the option "assess model fit" in the run dialog, ADANCO 2.0.1 will provide bootstrap-based 95% ("HI95") and 99% percentiles ("HI99") for the SRMR if the theoretical model was true. If the SRMR exceeds these values, it is unlikely that the model is true.

4.3 Measurement model results

4.3.1 Reliability of construct scores

In absence of systematic error, the reliability equals the squared correlation between the true construct (which is usually unknown) and the construct scores. ADANCO 2.0.1 provides three reliability coefficients for reflective constructs with multiple indicators:

- Dijkstra-Henseler's rho (Dijkstra & Henseler, 2015b),
- Composite reliability (Werts et al., 1978), and
- Cronbach's alpha (Cronbach, 1951).

Table 4.1 compares the three reliability coefficients. Figure 4.2 shows how ADANCO 2.0.1 reports the reliability of constructs.

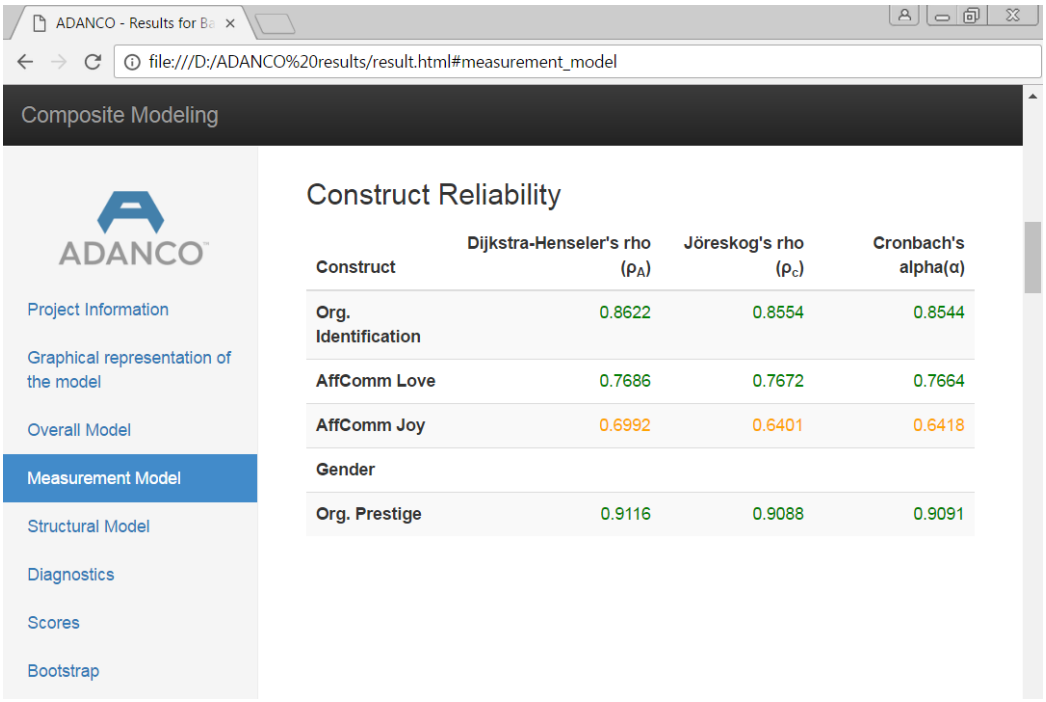


Figure 4.2: Reliability coefficients reported by ADANCO 2.0.1

Dijkstra-Henseler's rho (ρ_A)

Dijkstra-Henseler's rho (ρ_A) is an estimate of the reliability of construct scores pertaining to a reflective measurement model if PLS mode A was used to determine these scores. The ρ_A is only calculated for reflective measurement models in combination with the weighting scheme "Mode A consistent". Currently, the ρ_A is the only consistent estimate of the reliability of construct scores obtained through PLS path modeling.

Composite reliability (also called Dillon-Goldstein's rho, factor reliability, Jöreskog's rho, McDonald's ω)

The composite reliability is an estimate of the reliability of sum scores pertaining to a reflective measurement model. Other names for composite reliability are factor reliability, Dillon-Goldstein's rho, and Jöreskog's rho. The following symbols are typically used for composite reliability: ρ_c or ω.

More information on the coefficient of determination can be found in Henseler et al. (2009).

Cronbach's alpha (α)

Cronbach's alpha is a lower bound estimate of the reliability of sum scores pertaining to a reflective measurement model. The following symbol is typically used for Cronbach's alpha: α.

More information on Cronbach's alpha can be found in Henseler et al. (2009).

4.3.2 Average variance extracted

The average variance extracted (AVE) equals the average indicator reliability. It takes values between zero and one. The AVE is typically interpreted as a measure of unidimensionality.

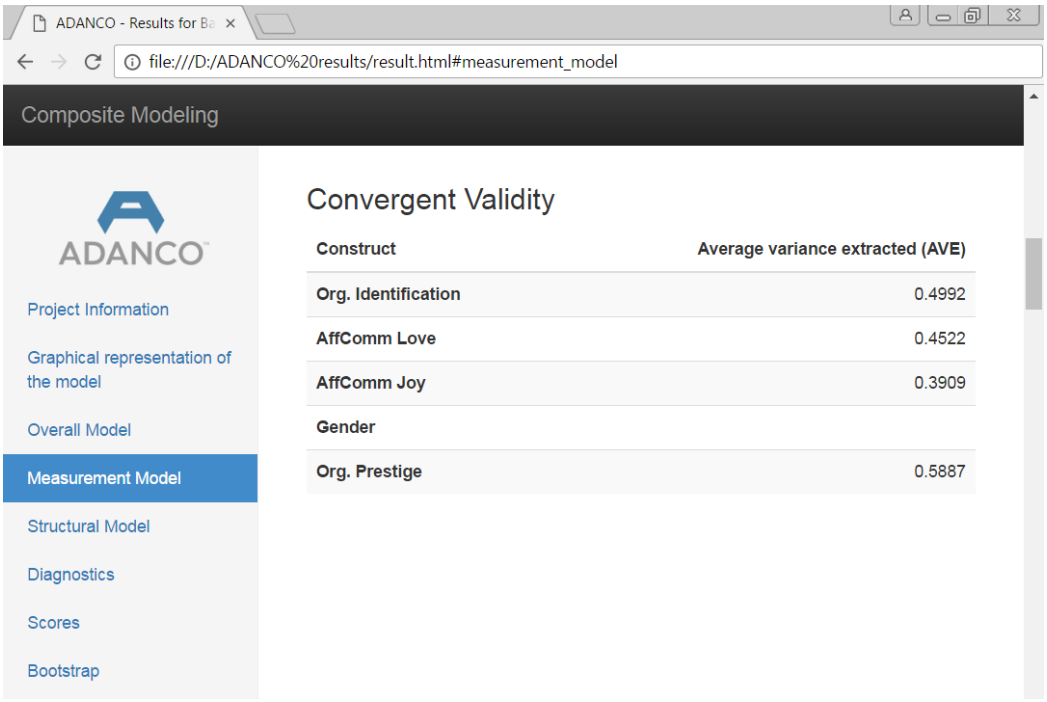


Figure 4.3: Unidimensionality of reflective constructs reported by ADANCO 2.0.1

Reflective constructs exhibit sufficient unidimensionality if their AVE exceeds 0.5 (Fornell & Larcker, 1981).

Figure 4.3 shows how ADANCO 2.0.1 reports constructs' unidimensionality. More information on the average variance extracted can be found in Henseler et al. (2009).

4.3.3 Discriminant validity

Discriminant validity means that two conceptually different constructs must also differ statistically. ADANCO 2.0.1 offers two approaches to assess the discriminant validity of reflective measures:

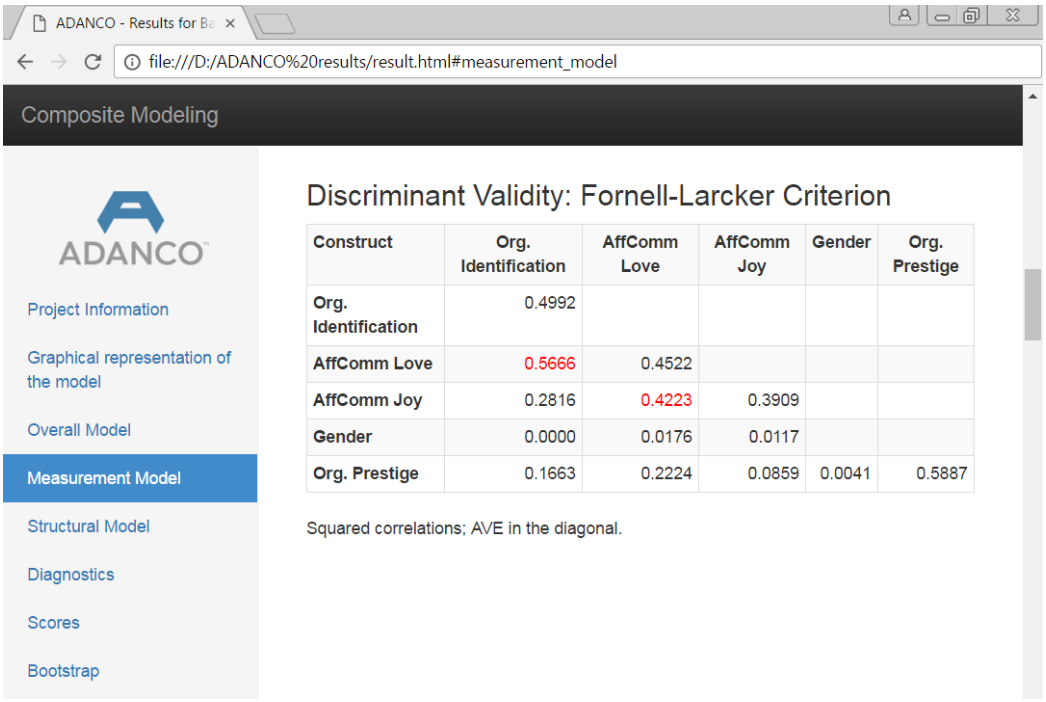
- the Fornell-Larcker criterion (Fornell & Larcker, 1981) and
- heterotrait-monotrait ratio of correlations (HTMT, see Henseler et al., 2015).

Fornell-Larcker criterion

The Fornell-Larcker criterion (Fornell & Larcker, 1981) postulates that a construct's average variance extracted should be higher than its squared correlations with all other constructs in the model.

ADANCO 2.0.1 includes a table, called "Discriminant Validity: Fornell-Larcker Criterion," containing the reflective constructs' average variance extracted in its main diagonal and the squared inter-construct correlations in the lower triangle (see Figure 4.4). Discriminant validity is regarded as given if the highest absolute value of each row and each column is found in the main diagonal.

Users are strongly recommended to use "Mode A consistent" as the weighting scheme for reflective constructs. If they fail to do so, the Fornell-Larcker criterion will not detect discriminant validity problems (Henseler et al., 2015).



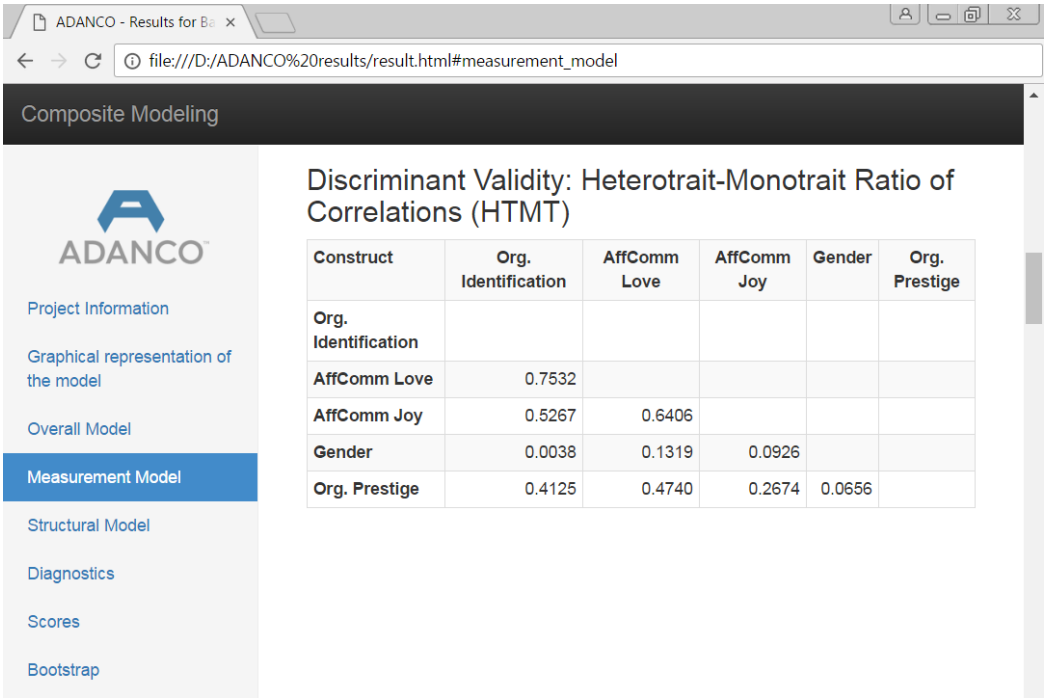
Construct	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
Org. Identification	0.4992				
AffComm Love	0.5666	0.4522			
AffComm Joy	0.2816	0.4223	0.3909		
Gender	0.0000	0.0176	0.0117		
Org. Prestige	0.1663	0.2224	0.0859	0.0041	0.5887

Figure 4.4: Fornell-Larcker criterion reported by ADANCO 2.0.1

Heterotrait-monotrait ratio of correlations (HTMT)

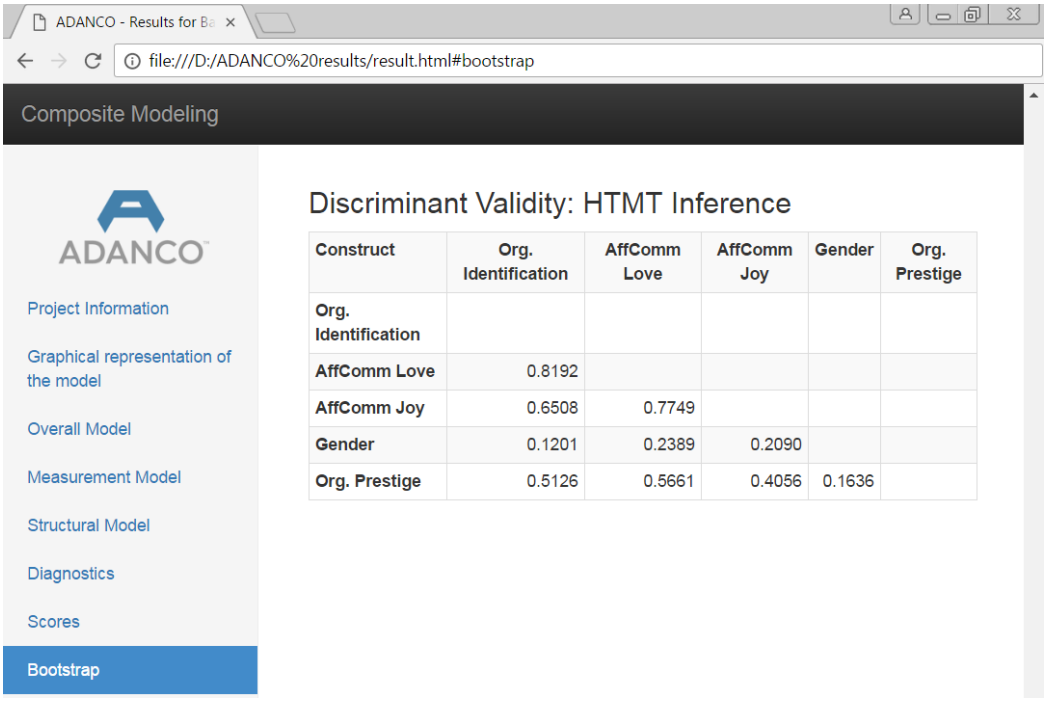
The heterotrait-monotrait ratio of correlations (HTMT) measures factors' discriminant validity. Henseler et al. (2015) suggested its use, as it often outperforms alternative approaches (according to a simulation study conducted by Voorhees et al., 2016). The smaller the HTMT of a pair of constructs, the more likely they are to be distinct. HTMT values should be below 0.9, or, better, below 0.85. Figure 4.5 shows how ADANCO 2.0.1 reports the HTMT.

If the bootstrap is performed, ADANCO 2.0.1 provides inference statistics for the HTMT values. The 95% quantile of bootstrapped HTMT values is part of the bootstrap output (Table "HTMT inference," see Figure 4.6). These values should be smaller than one; if they are not, there is a lack of discriminant validity.



Construct	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
Org. Identification					
AffComm Love	0.7532				
AffComm Joy	0.5267	0.6406			
Gender	0.0038	0.1319	0.0926		
Org. Prestige	0.4125	0.4740	0.2674	0.0656	

Figure 4.5: HTMT values reported by ADANCO 2.0.1



Construct	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
Org. Identification					
AffComm Love	0.8192				
AffComm Joy	0.6508	0.7749			
Gender	0.1201	0.2389	0.2090		
Org. Prestige	0.5126	0.5661	0.4056	0.1636	

Figure 4.6: 95% quantile of bootstrapped HTMT reported by ADANCO 2.0.1

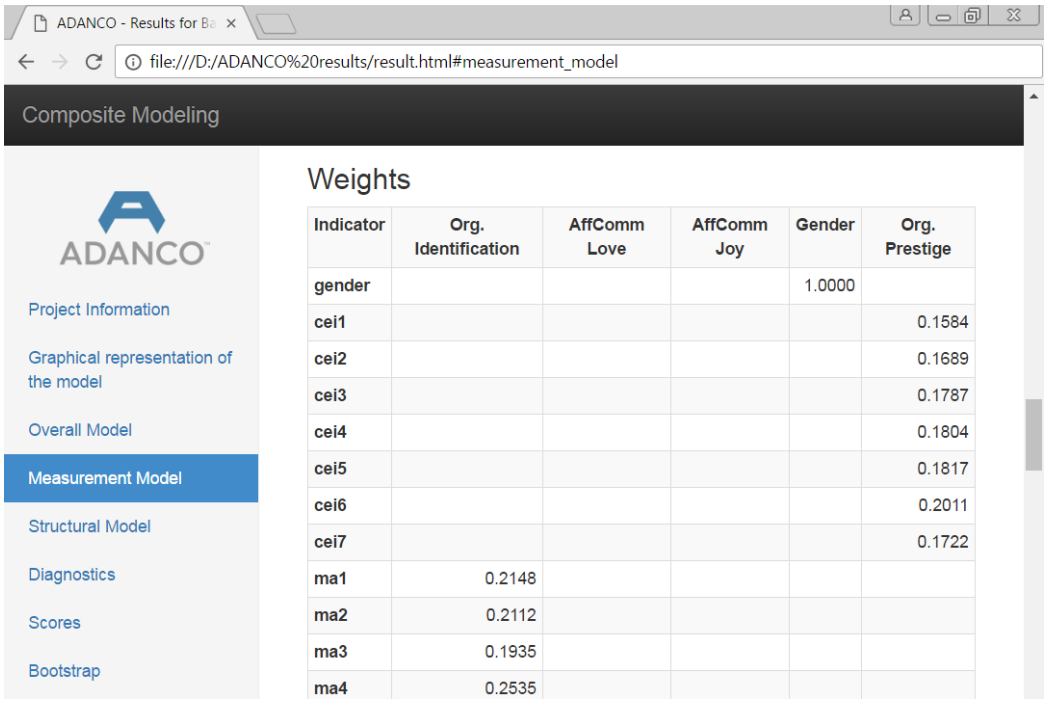


Figure 4.7: Indicator weights reported by ADANCO 2.0.1

4.3.4 Indicator results

Indicator weights

The indicator weights determine the construct scores as a weighted sum of their indicators. Using the weighting scheme option "sum score," users can set the indicator weights so that they all have the same value. After running the selected algorithm, the weights, with a composite measurement model, will appear in the graphical model for all constructs (on the arrows between the construct and its indicators). Figure 4.7 shows how ADANCO 2.0.1 reports the indicator weights.

Variance inflation factor (VIF)

If Mode B has been specified as a weighting scheme, multicollinearity may affect the indicator weights. As a diagnostic tool for quantifying the amount of multicollinearity, ADANCO 2.0.1 calculates the variance inflation factor (VIF) per set of indicators. The higher the variance inflation factor, the higher the degree of multicollinearity. Figure 4.8 shows how ADANCO 2.0.1 reports the variance inflation factors.

Loadings

The loading is the simple regression slope if an indicator is regressed on its construct. ADANCO 2.0.1 provides standardized loadings that equal the correlation between an indicator and its construct. The correlations between reflective constructs and their indicators usually have greater absolute values than the correlations between indicators and construct scores. Figure 4.9 shows how ADANCO 2.0.1 reports the loadings.

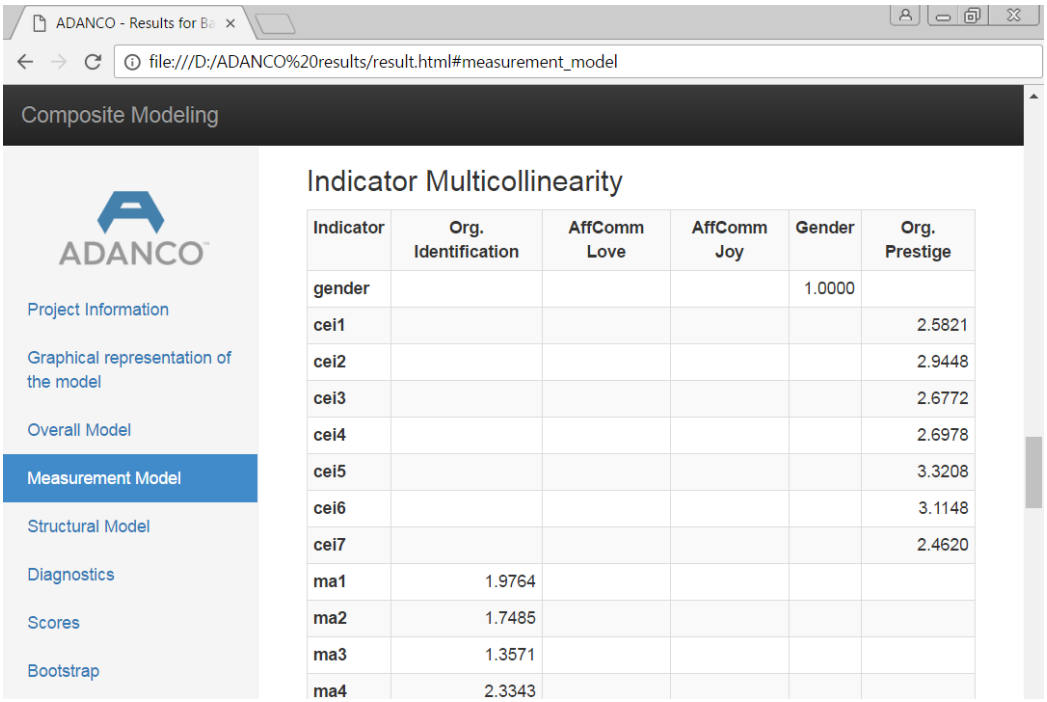


Figure 4.8: Variance inflation factors (VIF) reported by ADANCO 2.0.1

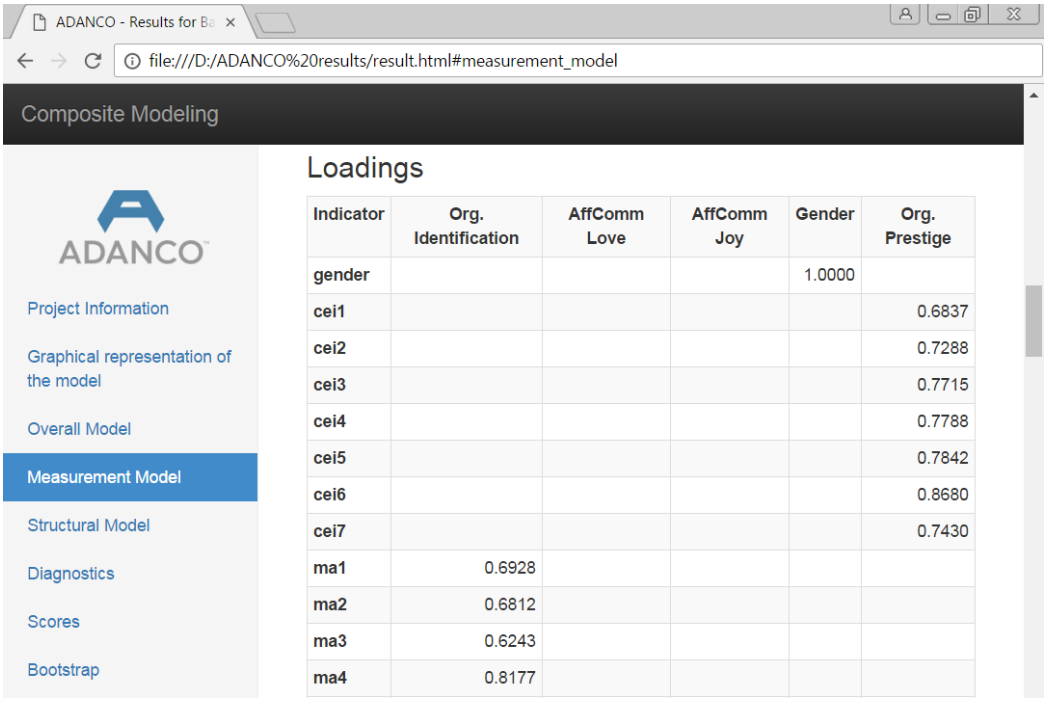
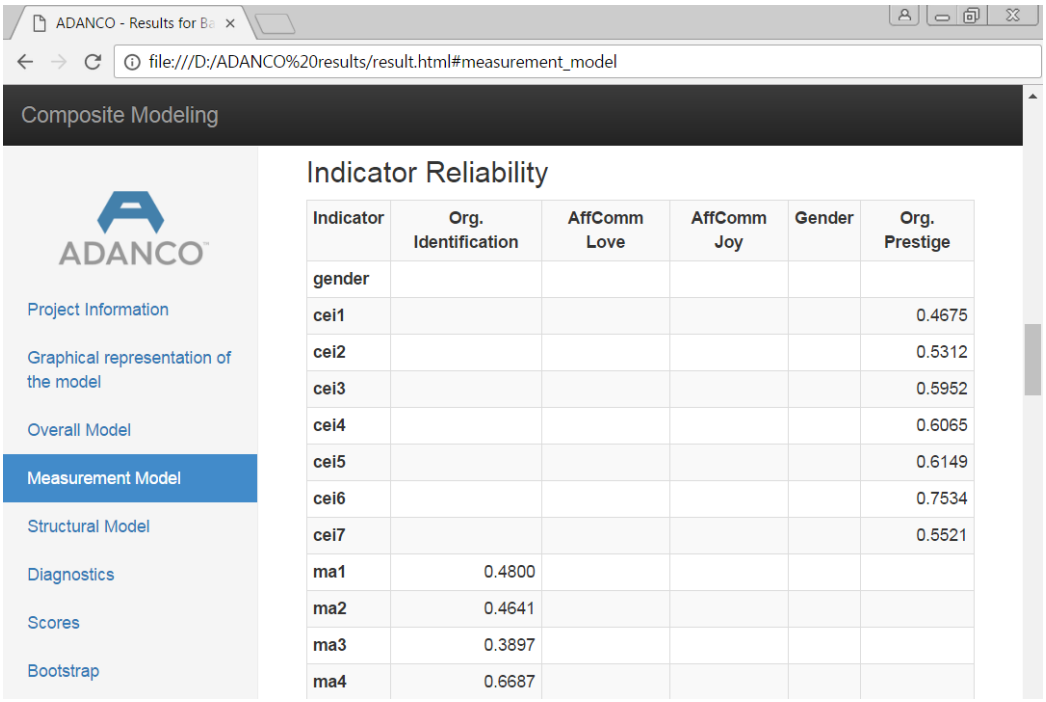


Figure 4.9: Loadings reported by ADANCO 2.0.1



Indicator	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
gender					
cei1					0.4675
cei2					0.5312
cei3					0.5952
cei4					0.6065
cei5					0.6149
cei6					0.7534
cei7					0.5521
ma1	0.4800				
ma2	0.4641				
ma3	0.3897				
ma4	0.6687				

Figure 4.10: Indicator reliability reported by ADANCO 2.0.1

Indicator reliability

The indicator reliability is the squared standardized loading of an indicator. It takes values between zero and one.

Figure 4.10 shows how ADANCO 2.0.1 reports the indicator reliability. More information on the indicator reliability can be found in Henseler et al. (2009).

4.3.5 Cross loadings

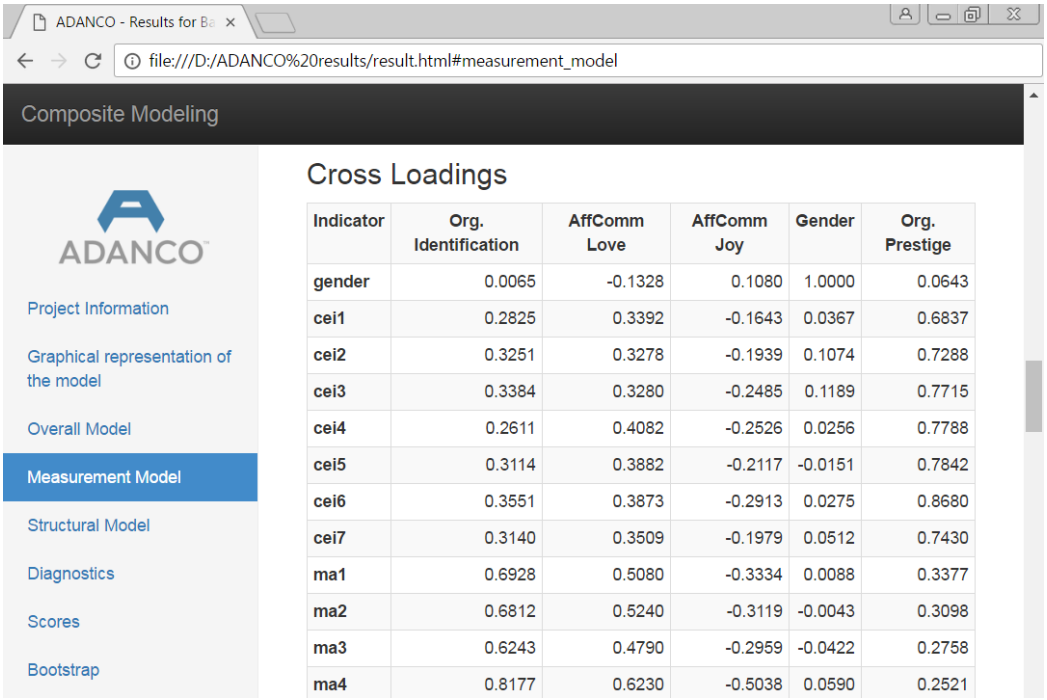
In ADANCO 2.0.1, the cross loadings matrix contains the correlations between indicators and constructs. Owing to the correction for attentuation, the cross loadings can differ from the correlations between indicators and construct scores. Figure 4.11 shows how ADANCO 2.0.1 reports the cross loadings.

4.4 Structural model results

4.4.1 Inter-construct correlations

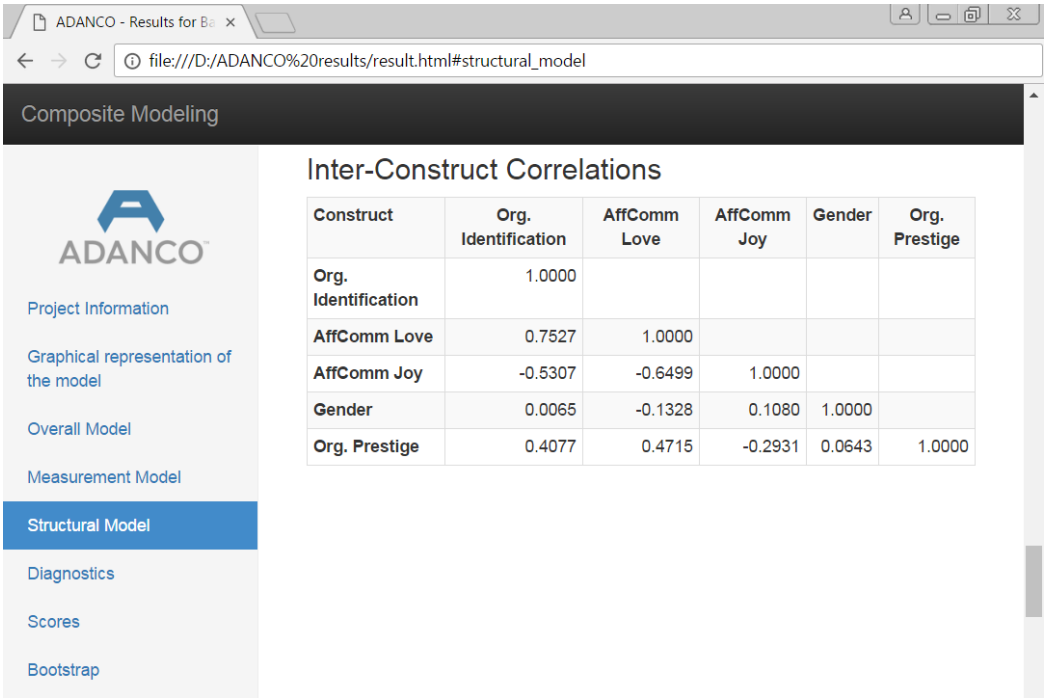
The inter-construct correlation matrix contains the estimated correlations between constructs. Owing to symmetry, only the lower triangle of the inter-construct correlation matrix is shown. Figure 4.12 shows how ADANCO 2.0.1 reports the inter-construct correlations.

The inter-construct correlations can differ from the correlations between the construct scores. This will occur if one or more constructs have "Mode A consistent" as a weighting scheme, or if one or more composite measurement models are assumed to have a random measurement error (i.e., the reliability was manually set to a value different from one).



Indicator	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
gender	0.0065	-0.1328	0.1080	1.0000	0.0643
cei1	0.2825	0.3392	-0.1643	0.0367	0.6837
cei2	0.3251	0.3278	-0.1939	0.1074	0.7288
cei3	0.3384	0.3280	-0.2485	0.1189	0.7715
cei4	0.2611	0.4082	-0.2526	0.0256	0.7788
cei5	0.3114	0.3882	-0.2117	-0.0151	0.7842
cei6	0.3551	0.3873	-0.2913	0.0275	0.8680
cei7	0.3140	0.3509	-0.1979	0.0512	0.7430
ma1	0.6928	0.5080	-0.3334	0.0088	0.3377
ma2	0.6812	0.5240	-0.3119	-0.0043	0.3098
ma3	0.6243	0.4790	-0.2959	-0.0422	0.2758
ma4	0.8177	0.6230	-0.5038	0.0590	0.2521

Figure 4.11: Cross loadings reported by ADANCO 2.0.1



Construct	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
Org. Identification	1.0000				
AffComm Love	0.7527	1.0000			
AffComm Joy	-0.5307	-0.6499	1.0000		
Gender	0.0065	-0.1328	0.1080	1.0000	
Org. Prestige	0.4077	0.4715	-0.2931	0.0643	1.0000

Figure 4.12: Inter-construct correlations reported by ADANCO 2.0.1

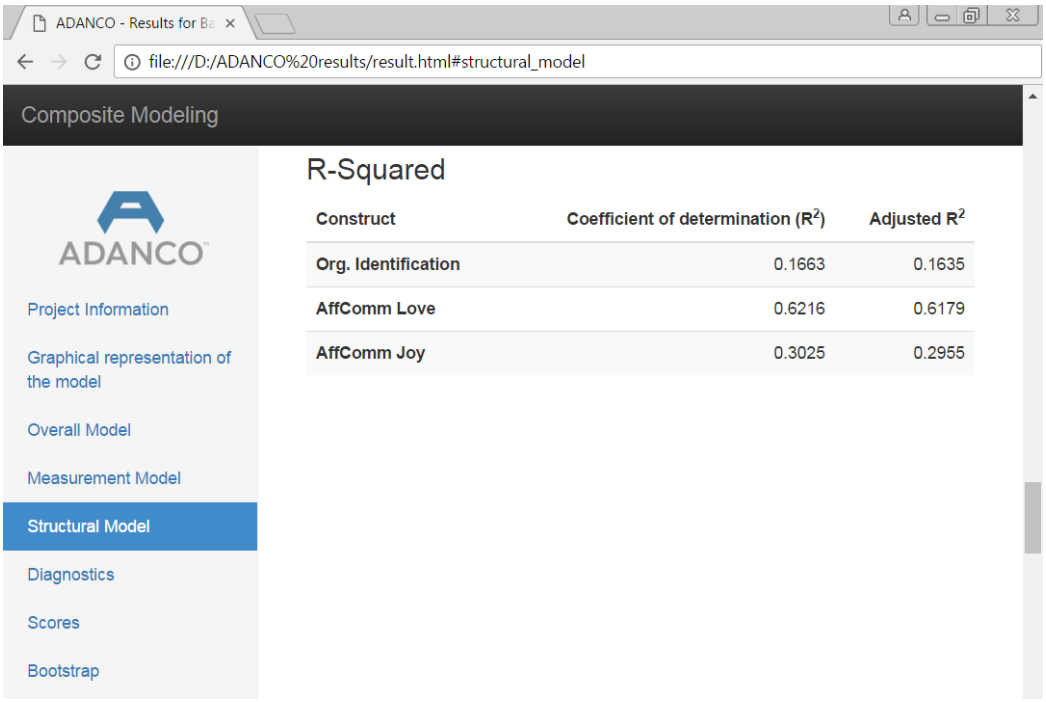


Figure 4.13: R^2 and adjusted R^2 values reported by ADANCO 2.0.1

4.4.2 R^2 and adjusted R^2

For every endogenous construct, ADANCO 2.0.1 determines the R^2 and the adjusted R^2. The R^2 values are printed in the model's graphical representation. Figure 4.13 shows how ADANCO 2.0.1 reports the R^2 and the adjusted R^2 in the HTML output.

R^2

The coefficient of determination (R^2) quantifies the proportion of an endogenous variable's variance that the independent variables explain. Possible R^2 values range from zero to one. The R^2 is not calculated for exogenous constructs. More information on the coefficient of determination can be found in Henseler et al. (2009).

Adjusted R^2

The adjusted R^2 is a modification of the R^2 that takes the sample size into account and compensates for the independent variables added to the model. The adjusted R^2 will never exceed the R^2. It can be negative. The adjusted R^2 is not calculated for exogenous constructs.

4.4.3 Path coefficients

The path coefficients are standardized regression coefficients (beta values). A path coefficient quantifies the direct effect of an independent variable on a dependent variable. Path coefficients are interpreted as the increase in the dependent variable if the independent variable were increased by one standard deviation and all the other independent variables in the equation remained constant. Figure 4.14 shows how ADANCO 2.0.1 reports the path coefficients.

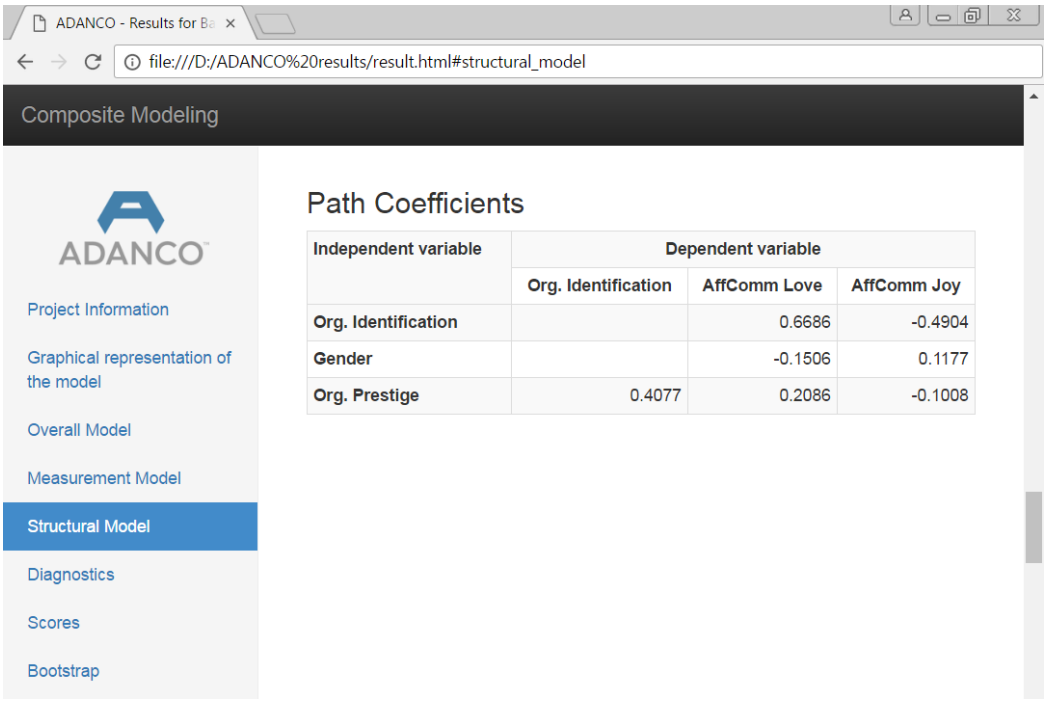


Figure 4.14: Path coefficients reported by ADANCO 2.0.1

4.4.4 Indirect effects

If a variable X has an effect A on the variable M, and the variable M has an effect B on the variable Y, then the indirect effect of X on Y is $A \times B$. Indirect effects are an important element of mediation analysis (Nitzl et al., 2016). Figure 4.15 shows how ADANCO 2.0.1 indicates the indirect effects.

4.4.5 Total effects

The total effect of one variable on another is the sum of the direct effect and all the indirect effects. The value of the total effect is interpreted as the increase in the dependent variable if the independent variable were increased by one standard deviation. Total effects are particularly useful in business success factor research (Albers, 2010). Figure 4.16 shows how ADANCO 2.0.1 reports the total effects.

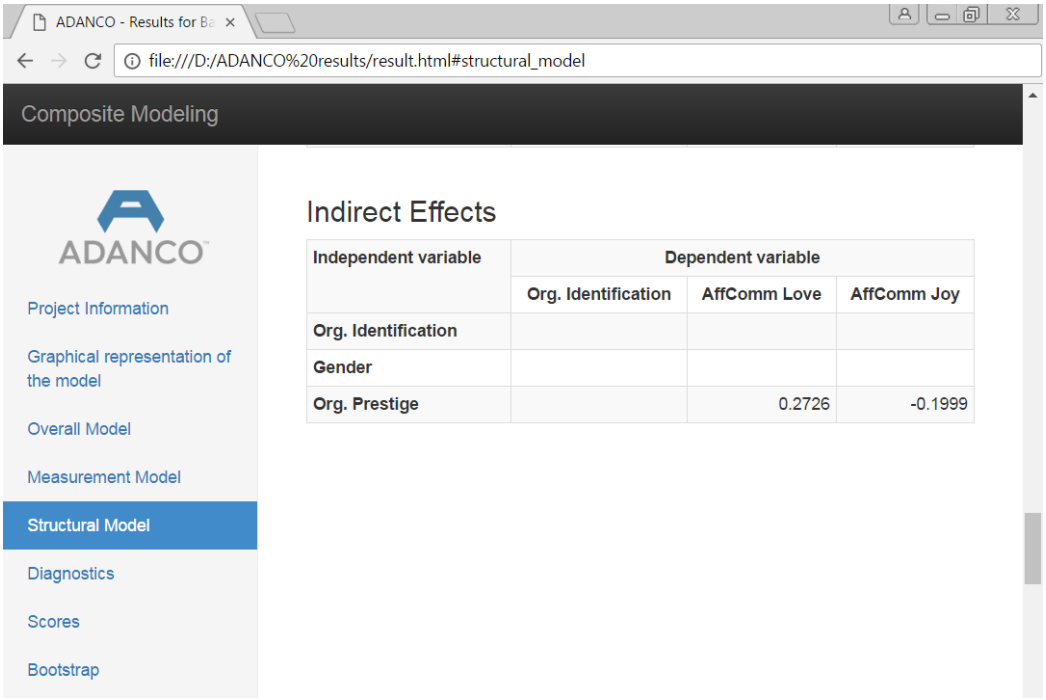


Figure 4.15: Indirect effects reported by ADANCO 2.0.1

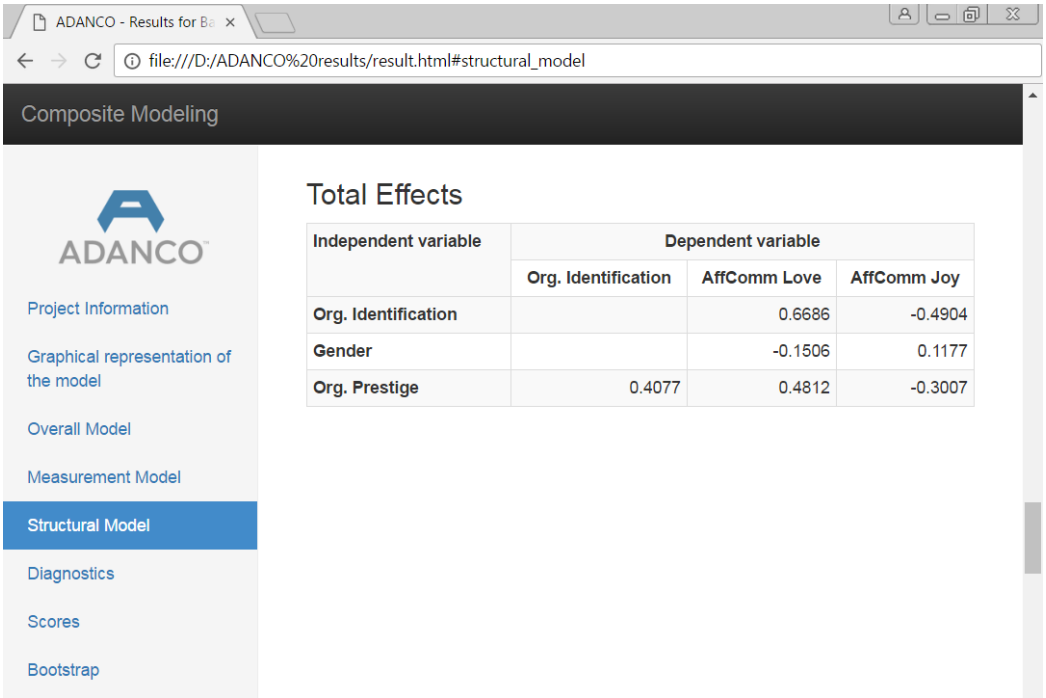


Figure 4.16: Total effects reported by ADANCO 2.0.1

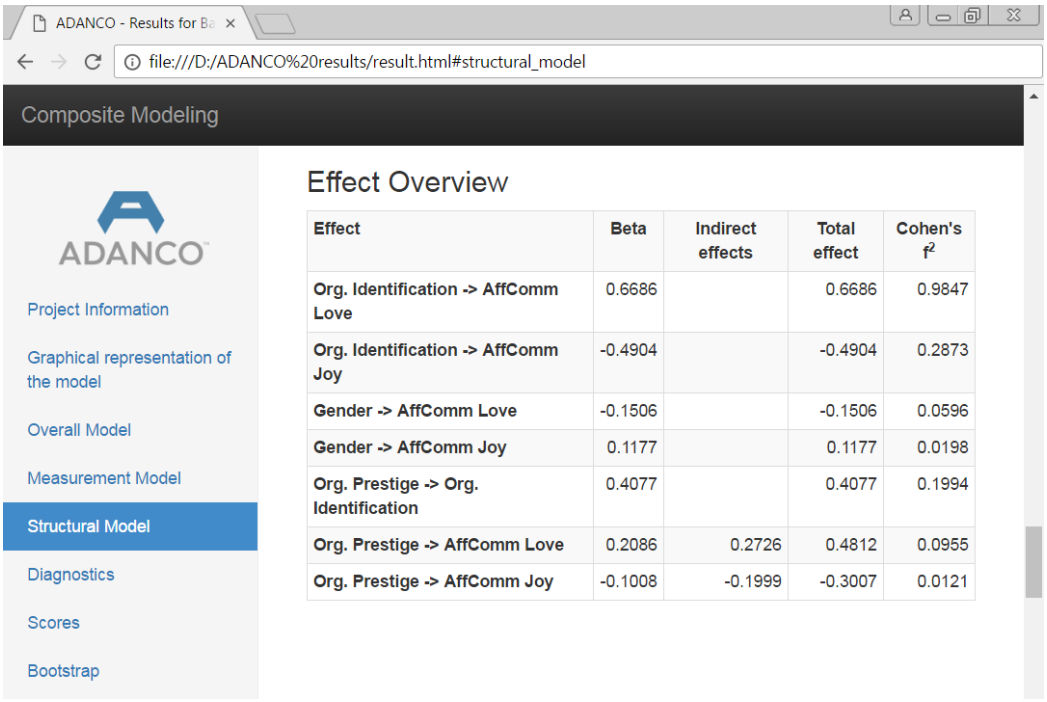


Figure 4.17: Effect overview provided by ADANCO 2.0.1

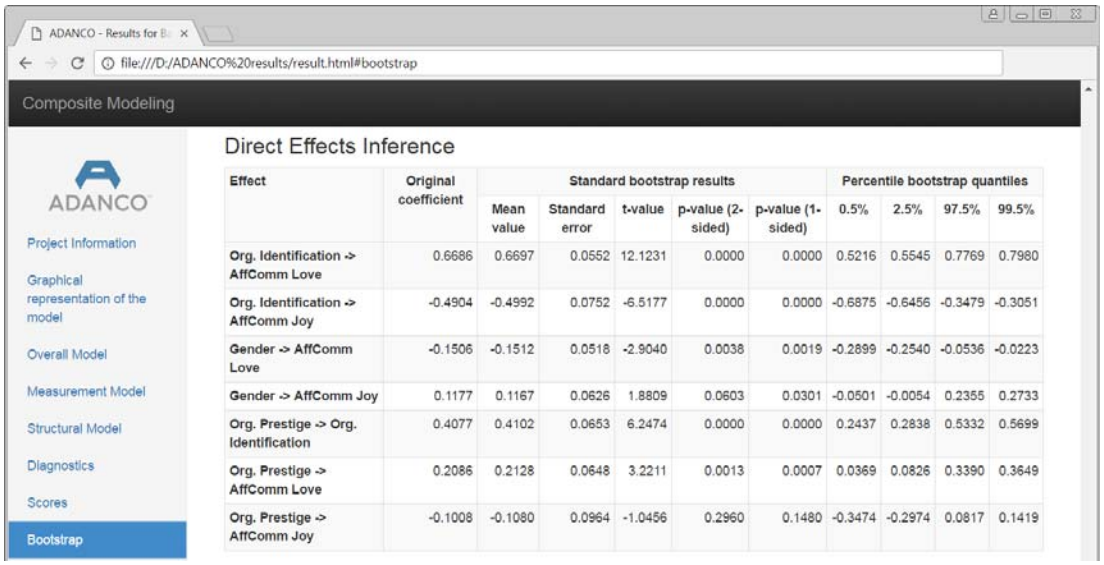
4.4.6 Effect size (Cohen's f^2)

The effect size indicates how substantial a direct effect is. Its values can be greater than or equal to zero. The following symbol is typically used for the effect size: f^2.

Table 4.2 describes how to interpret f^2 values. More information on the effect size can be found in Henseler et al. (2009). ADANCO 2.0.1 reports the effect size of each effect as part of an effect overview, as depicted in Figure 4.17.

Table 4.2: How to interpret f^2 values (Cohen, 1988)

Effect size	Interpretation
$f^2 \geq 0.35$	strong effect
$0.15 \leq f^2 < 0.35$	moderate effect
$0.02 \leq f^2 < 0.15$	weak effect
$f^2 < 0.02$	unsubstantial effect



Effect	Original coefficient	Standard bootstrap results					Percentile bootstrap quantiles			
		Mean value	Standard error	t-value	p-value (2-sided)	p-value (1-sided)	0.5%	2.5%	97.5%	99.5%
Org. Identification -> AffComm Love	0.6686	0.6697	0.0552	12.1231	0.0000	0.0000	0.5216	0.5545	0.7769	0.7980
Org. Identification -> AffComm Joy	-0.4904	-0.4992	0.0752	-6.5177	0.0000	0.0000	-0.6875	-0.6456	-0.3479	-0.3051
Gender -> AffComm Love	-0.1506	-0.1512	0.0518	-2.9040	0.0038	0.0019	-0.2899	-0.2540	-0.0536	-0.0223
Gender -> AffComm Joy	0.1177	0.1167	0.0626	1.8809	0.0603	0.0301	-0.0501	-0.0054	0.2355	0.2733
Org. Prestige -> Org. Identification	0.4077	0.4102	0.0653	6.2474	0.0000	0.0000	0.2437	0.2838	0.5332	0.5699
Org. Prestige -> AffComm Love	0.2086	0.2128	0.0648	3.2211	0.0013	0.0007	0.0369	0.0826	0.3390	0.3649
Org. Prestige -> AffComm Joy	-0.1008	-0.1080	0.0964	-1.0456	0.2960	0.1480	-0.3474	-0.2974	0.0817	0.1419

Figure 4.18: Direct effect inference reported by ADANCO 2.0.1

4.5 Bootstrap inference statistics

If the analyst's aim is to generalize from a sample to a population, the path coefficients should be evaluated for significance. To obtain inference statistics, analysts must open the run dialog. Inference statistics include the empirical bootstrap confidence intervals, as well as p-values for one-sided or two-sided tests. A path coefficient is regarded as significant (i.e., unlikely to purely result from sampling error) if its confidence interval does not include the value of zero, or if the p-value is below the pre-defined alpha level. Despite strong pleas for the use of confidence intervals (Cohen, 1994), the reporting of p-values still seems to be more common in business research.

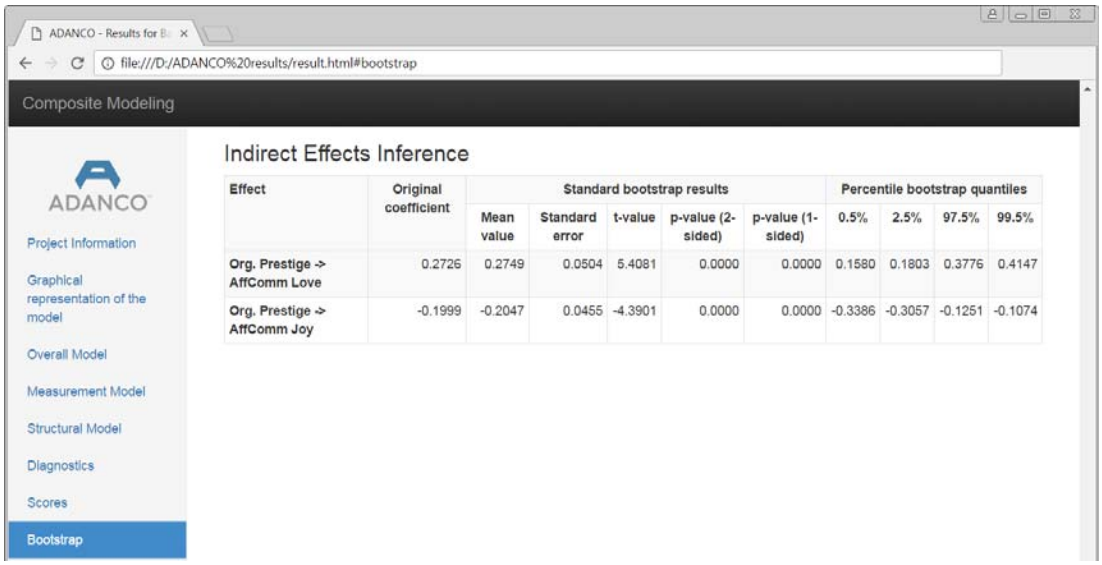
Figure 4.18 shows how ADANCO 2.0.1 reports the direct effects' bootstrap results. ADANCO 2.0.1 provides p-values for one-sided and two-sided tests as well as the lower and upper bounds of 95% and 99% confidence intervals.

Figure 4.19 shows how ADANCO 2.0.1 reports the indirect effects' bootstrap results. ADANCO 2.0.1 provides p-values for one-sided and two-sided tests as well as the lower and upper bounds of 95% and 99% confidence intervals.

Figure 4.20 shows how ADANCO 2.0.1 reports the total effects' bootstrap results. ADANCO 2.0.1 provides p-values for one-sided and two-sided tests as well as the lower and upper bounds of 95% and 99% confidence intervals.

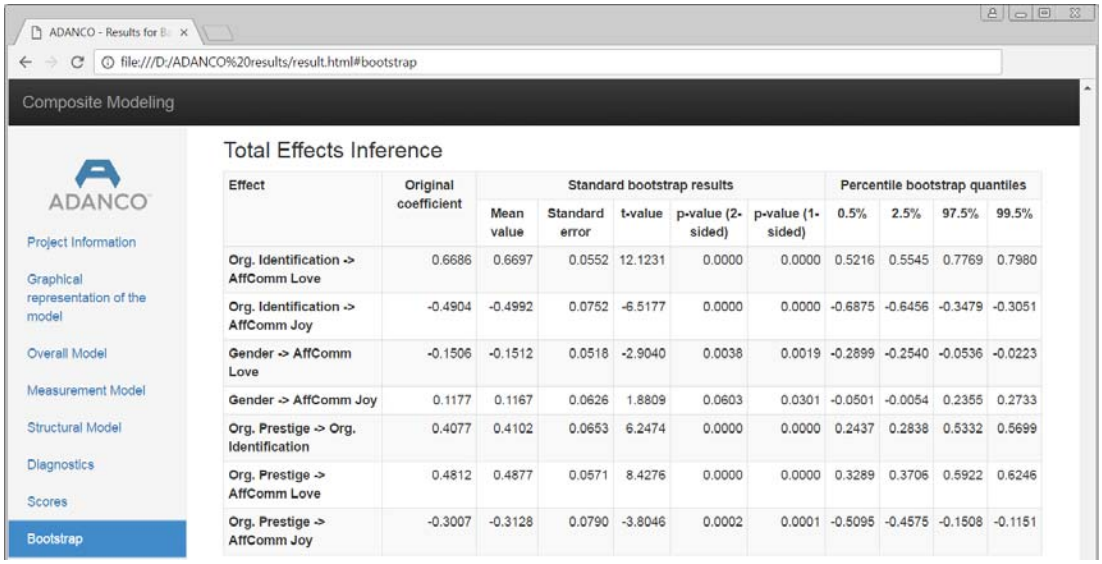
Figure 4.21 shows how ADANCO 2.0.1 reports the loadings' bootstrap results. Only Student t-values are provided.

Figure 4.22 shows how ADANCO 2.0.1 reports the indicator weights' bootstrap results. Only Student t-values are provided.



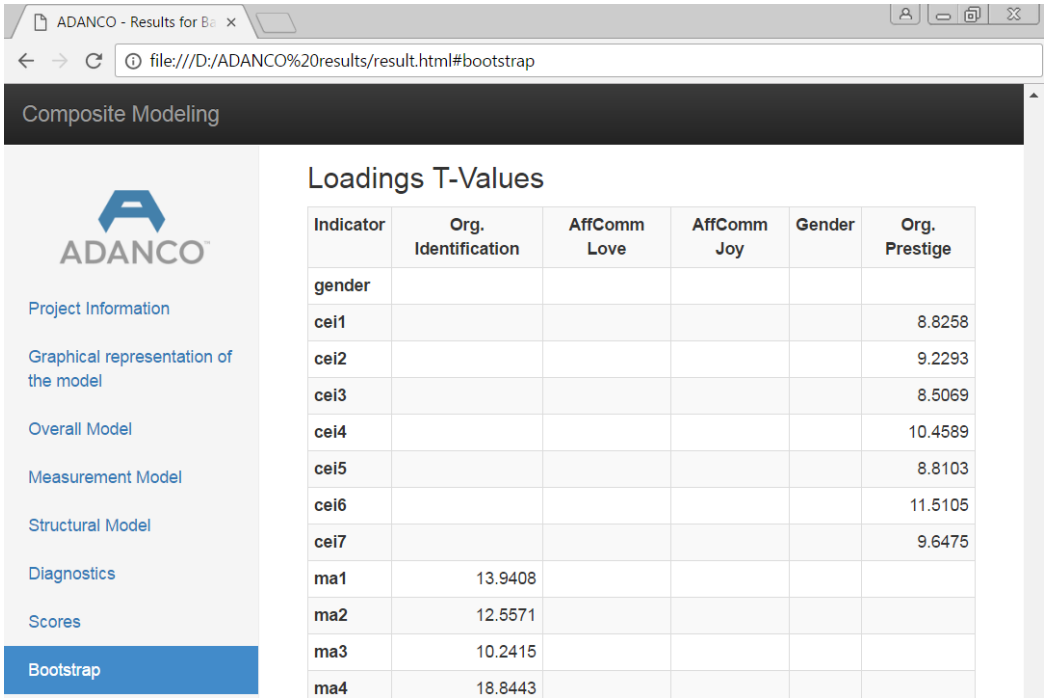
Effect	Original coefficient	Standard bootstrap results					Percentile bootstrap quantiles			
		Mean value	Standard error	t-value	p-value (2-sided)	p-value (1-sided)	0.5%	2.5%	97.5%	99.5%
Org. Prestige -> AffComm Love	0.2726	0.2749	0.0504	5.4081	0.0000	0.0000	0.1580	0.1803	0.3776	0.4147
Org. Prestige -> AffComm Joy	-0.1999	-0.2047	0.0455	-4.3901	0.0000	0.0000	-0.3386	-0.3057	-0.1251	-0.1074

Figure 4.19: Indirect effect inference reported by ADANCO 2.0.1



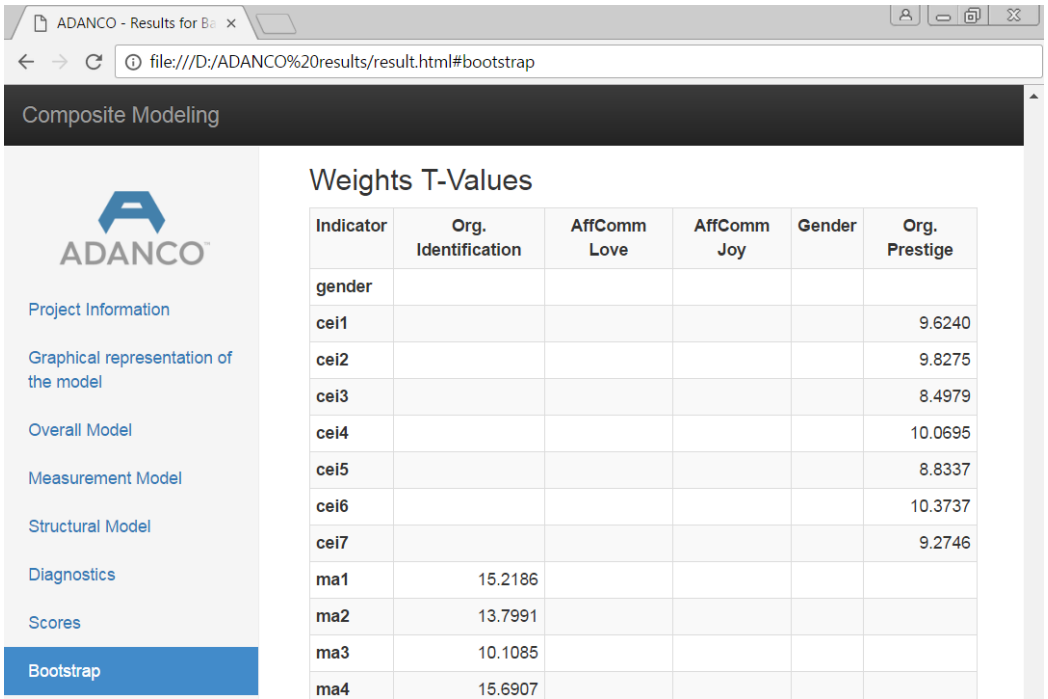
Effect	Original coefficient	Standard bootstrap results					Percentile bootstrap quantiles			
		Mean value	Standard error	t-value	p-value (2-sided)	p-value (1-sided)	0.5%	2.5%	97.5%	99.5%
Org. Identification -> AffComm Love	0.6686	0.6697	0.0552	12.1231	0.0000	0.0000	0.5216	0.5545	0.7769	0.7980
Org. Identification -> AffComm Joy	-0.4904	-0.4992	0.0752	-6.5177	0.0000	0.0000	-0.6875	-0.6456	-0.3479	-0.3051
Gender -> AffComm Love	-0.1506	-0.1512	0.0518	-2.9040	0.0038	0.0019	-0.2899	-0.2540	-0.0536	-0.0223
Gender -> AffComm Joy	0.1177	0.1167	0.0626	1.8809	0.0603	0.0301	-0.0501	-0.0054	0.2355	0.2733
Org. Prestige -> Org. Identification	0.4077	0.4102	0.0653	6.2474	0.0000	0.0000	0.2437	0.2838	0.5332	0.5699
Org. Prestige -> AffComm Love	0.4812	0.4877	0.0571	8.4276	0.0000	0.0000	0.3289	0.3706	0.5922	0.6246
Org. Prestige -> AffComm Joy	-0.3007	-0.3128	0.0790	-3.8046	0.0002	0.0001	-0.5095	-0.4575	-0.1508	-0.1151

Figure 4.20: Total effect inference reported by ADANCO 2.0.1



Indicator	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
gender					
cei1					8.8258
cei2					9.2293
cei3					8.5069
cei4					10.4589
cei5					8.8103
cei6					11.5105
cei7					9.6475
ma1	13.9408				
ma2	12.5571				
ma3	10.2415				
ma4	18.8443				

Figure 4.21: Loadings inference reported by ADANCO 2.0.1



Indicator	Org. Identification	AffComm Love	AffComm Joy	Gender	Org. Prestige
gender					
cei1					9.6240
cei2					9.8275
cei3					8.4979
cei4					10.0695
cei5					8.8337
cei6					10.3737
cei7					9.2746
ma1	15.2186				
ma2	13.7991				
ma3	10.1085				
ma4	15.6907				

Figure 4.22: Weights inference reported by ADANCO 2.0.1

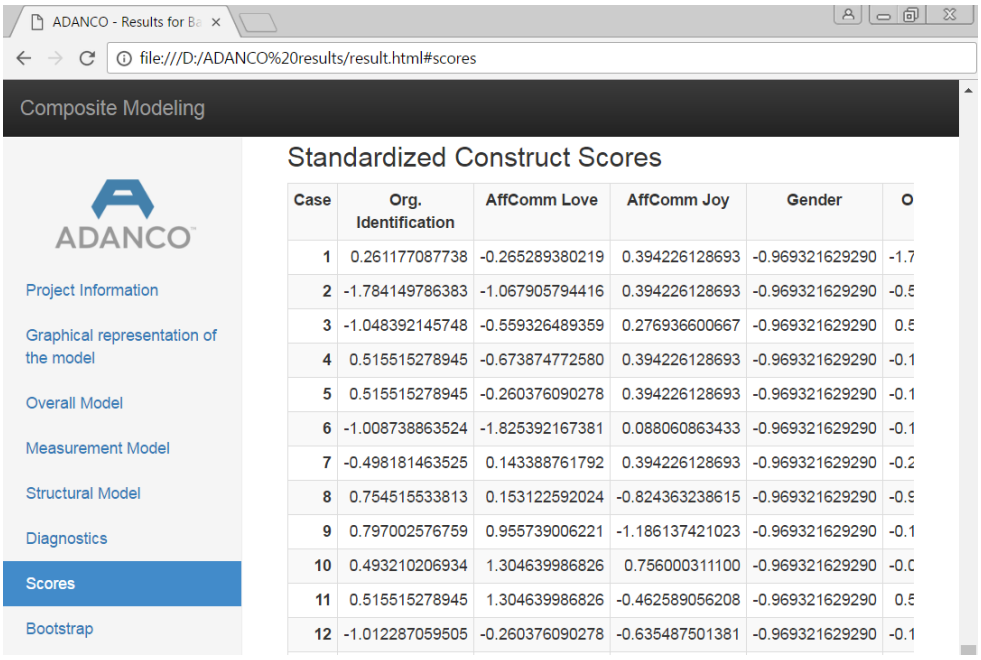


Figure 4.23: Standardized construct scores reported by ADANCO 2.0.1

4.6 Scores

4.6.1 Standardized construct scores

The construct scores are the weighted sum of a construct's indicators. The construct scores often serve as a latent variable proxy. If a construct has only one indicator (single-indicator measurement), the construct scores will be equal to the standardized indicator. Figure 4.23 shows how ADANCO 2.0.1 reports the standardized construct scores.

4.6.2 Unstandardized construct scores

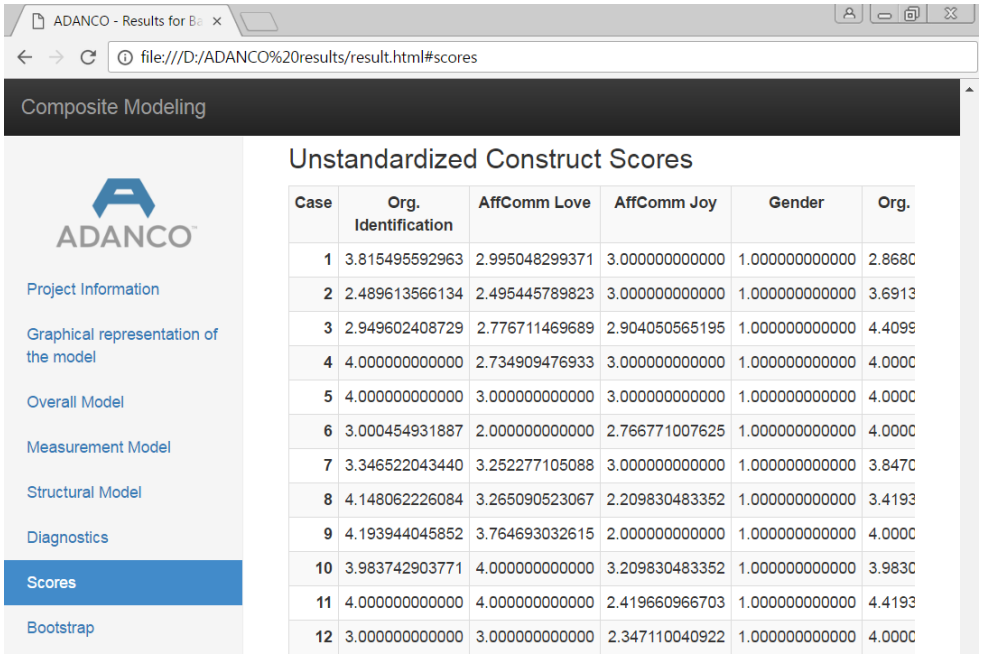
If all of a construct's weights are positive, ADANCO 2.0.1 determines unstandardized construct scores. Unstandardized construct scores are only meaningful if all of a construct's indicators have been measured on the same scale. The construct scores will then be on the same scale. Figure 4.24 shows how ADANCO 2.0.1 reports the unstandardized construct scores.

4.6.3 Original indicator scores

The original indicator scores represent the data after missing value treatment. If there are no missing values, the original indicator scores will equal the imported data. If missing values have been imputed, the imputed values can be found in the indicator scores. Figure 4.25 shows how ADANCO 2.0.1 reports the original construct scores (if the "complete" profile is used).

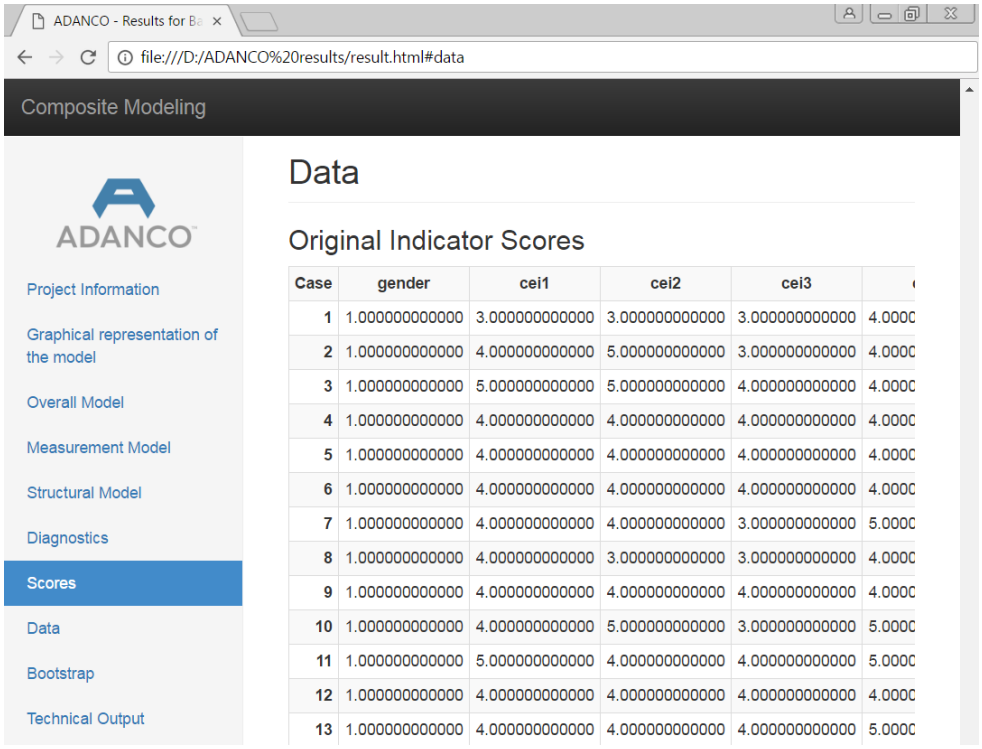
4.6.4 Standardized indicator scores

The standardized indicator scores are derived from the original indicator scores. The mean of the original indicator scores of each indicator is subtracted and the result divided by these scores' standard deviation. Figure 4.26 shows how ADANCO 2.0.1 reports the standardized construct scores (if the "complete" profile is used).



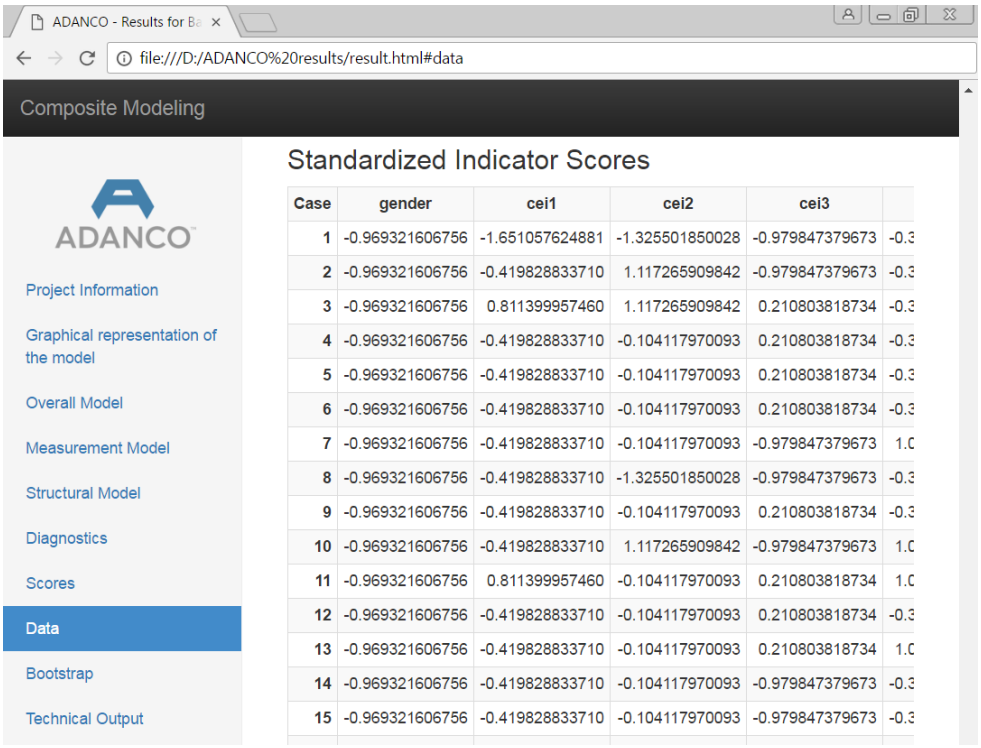
Case	Org. Identification	AffComm Love	AffComm Joy	Gender	Org.
1	3.815495592963	2.995048299371	3.000000000000	1.000000000000	2.8680
2	2.489613566134	2.495445789823	3.000000000000	1.000000000000	3.6913
3	2.949602408729	2.776711469689	2.904050565195	1.000000000000	4.4099
4	4.000000000000	2.734909476933	3.000000000000	1.000000000000	4.0000
5	4.000000000000	3.000000000000	3.000000000000	1.000000000000	4.0000
6	3.000454931887	2.000000000000	2.766771007625	1.000000000000	4.0000
7	3.346522043440	3.252277105088	3.000000000000	1.000000000000	3.8470
8	4.148062226084	3.265090523067	2.209830483352	1.000000000000	3.4193
9	4.193944045852	3.764693032615	2.000000000000	1.000000000000	4.0000
10	3.983742903771	4.000000000000	3.209830483352	1.000000000000	3.9830
11	4.000000000000	4.000000000000	2.419660966703	1.000000000000	4.4193
12	3.000000000000	3.000000000000	2.347110040922	1.000000000000	4.0000

Figure 4.24: Unstandardized construct scores reported by ADANCO 2.0.1



Case	gender	cei1	cei2	cei3	
1	1.000000000000	3.000000000000	3.000000000000	3.000000000000	4.0000
2	1.000000000000	4.000000000000	5.000000000000	3.000000000000	4.0000
3	1.000000000000	5.000000000000	5.000000000000	4.000000000000	4.0000
4	1.000000000000	4.000000000000	4.000000000000	4.000000000000	4.0000
5	1.000000000000	4.000000000000	4.000000000000	4.000000000000	4.0000
6	1.000000000000	4.000000000000	4.000000000000	4.000000000000	4.0000
7	1.000000000000	4.000000000000	4.000000000000	3.000000000000	5.0000
8	1.000000000000	4.000000000000	3.000000000000	3.000000000000	4.0000
9	1.000000000000	4.000000000000	4.000000000000	4.000000000000	4.0000
10	1.000000000000	4.000000000000	5.000000000000	3.000000000000	5.0000
11	1.000000000000	5.000000000000	4.000000000000	4.000000000000	5.0000
12	1.000000000000	4.000000000000	4.000000000000	4.000000000000	4.0000
13	1.000000000000	4.000000000000	4.000000000000	4.000000000000	5.0000

Figure 4.25: Original indicator scores reported by ADANCO 2.0.1



Case	gender	cei1	cei2	cei3	
1	-0.969321606756	-1.651057624881	-1.325501850028	-0.979847379673	-0.3
2	-0.969321606756	-0.419828833710	1.117265909842	-0.979847379673	-0.3
3	-0.969321606756	0.811399957460	1.117265909842	0.210803818734	-0.3
4	-0.969321606756	-0.419828833710	-0.104117970093	0.210803818734	-0.3
5	-0.969321606756	-0.419828833710	-0.104117970093	0.210803818734	-0.3
6	-0.969321606756	-0.419828833710	-0.104117970093	0.210803818734	-0.3
7	-0.969321606756	-0.419828833710	-0.104117970093	-0.979847379673	1.0
8	-0.969321606756	-0.419828833710	-1.325501850028	-0.979847379673	-0.3
9	-0.969321606756	-0.419828833710	-0.104117970093	0.210803818734	-0.3
10	-0.969321606756	-0.419828833710	1.117265909842	-0.979847379673	1.0
11	-0.969321606756	0.811399957460	-0.104117970093	0.210803818734	1.0
12	-0.969321606756	-0.419828833710	-0.104117970093	0.210803818734	-0.3
13	-0.969321606756	-0.419828833710	-0.104117970093	0.210803818734	1.0
14	-0.969321606756	-0.419828833710	-0.104117970093	-0.979847379673	-0.3
15	-0.969321606756	-0.419828833710	-0.104117970093	-0.979847379673	-0.3

Figure 4.26: Standardized indicator scores reported by ADANCO 2.0.1

4.7 Diagnostic tools

If the model fit is deemed low, the discrepancy between the empirical correlation matrix and the model-implied correlation matrix may point to relevant issues in the statistical model.

4.7.1 Empirical correlation matrix

The empirical correlation matrix contains the Pearson correlations between the indicators. Figure 4.27 shows how ADANCO 2.0.1 reports the empirical correlation matrix.

4.7.2 Implied correlation matrix

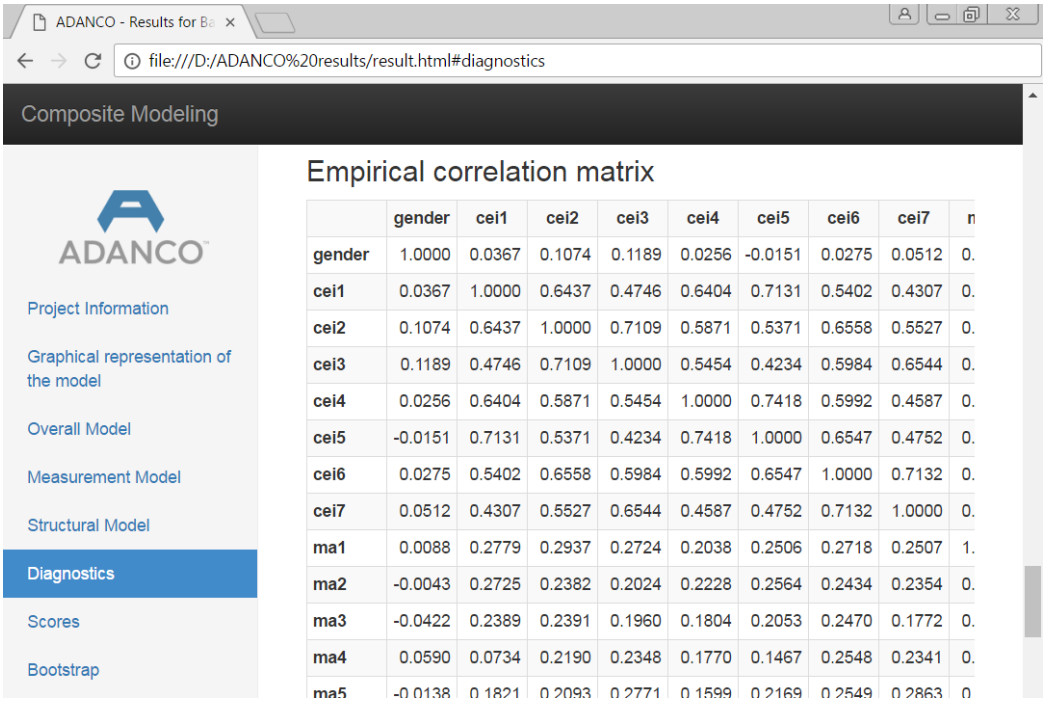
The model-implied correlation matrix contains the Pearson correlations that one would obtain if the model were true. Since ADANCO 2.0.1 determines the model fit for the estimated and for the saturated model (see Section 2.3), there are two implied correlation matrices.

Implied correlation matrix of the estimated model

Figure 4.28 shows how ADANCO 2.0.1 reports the implied correlation matrix of the estimated model.

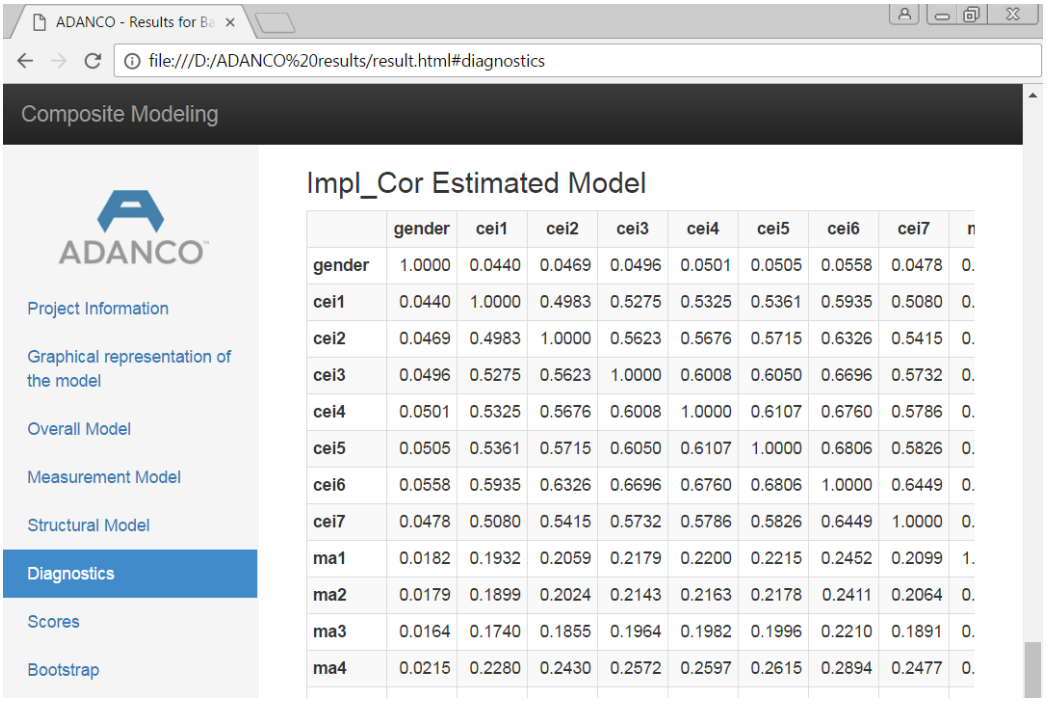
Implied correlation matrix of the saturated model

Figure 4.29 shows how ADANCO 2.0.1 reports the implied correlation matrix of the saturated model.



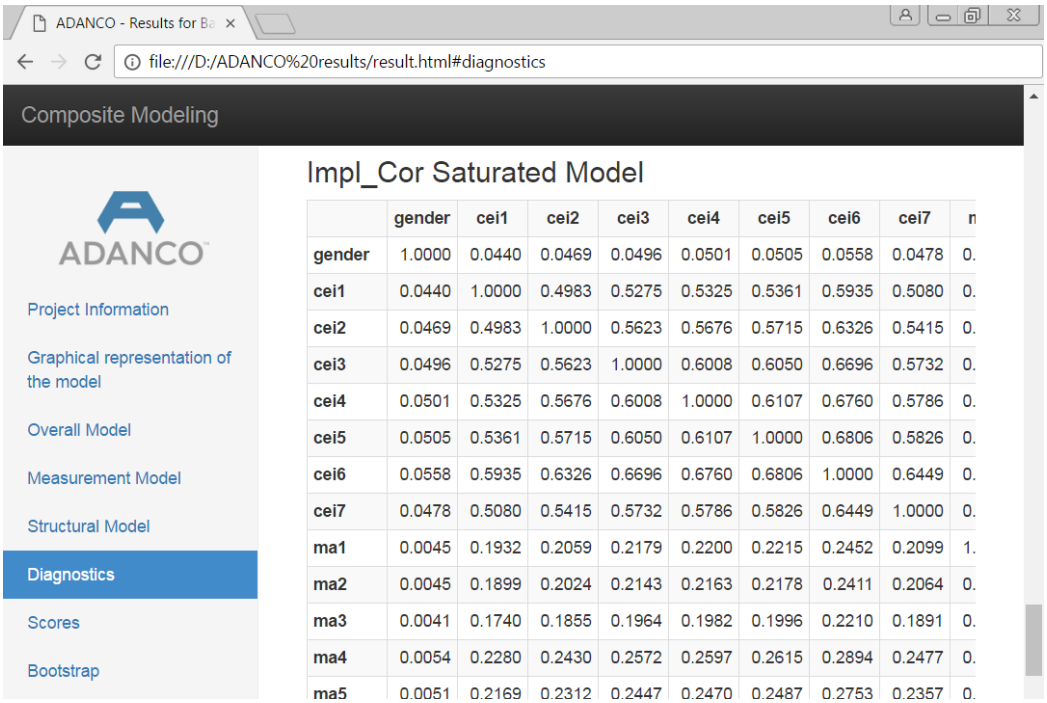
	gender	cei1	cei2	cei3	cei4	cei5	cei6	cei7	n
gender	1.0000	0.0367	0.1074	0.1189	0.0256	-0.0151	0.0275	0.0512	0.
cei1	0.0367	1.0000	0.6437	0.4746	0.6404	0.7131	0.5402	0.4307	0.
cei2	0.1074	0.6437	1.0000	0.7109	0.5871	0.5371	0.6558	0.5527	0.
cei3	0.1189	0.4746	0.7109	1.0000	0.5454	0.4234	0.5984	0.6544	0.
cei4	0.0256	0.6404	0.5871	0.5454	1.0000	0.7418	0.5992	0.4587	0.
cei5	-0.0151	0.7131	0.5371	0.4234	0.7418	1.0000	0.6547	0.4752	0.
cei6	0.0275	0.5402	0.6558	0.5984	0.5992	0.6547	1.0000	0.7132	0.
cei7	0.0512	0.4307	0.5527	0.6544	0.4587	0.4752	0.7132	1.0000	0.
ma1	0.0088	0.2779	0.2937	0.2724	0.2038	0.2506	0.2718	0.2507	1.
ma2	-0.0043	0.2725	0.2382	0.2024	0.2228	0.2564	0.2434	0.2354	0.
ma3	-0.0422	0.2389	0.2391	0.1960	0.1804	0.2053	0.2470	0.1772	0.
ma4	0.0590	0.0734	0.2190	0.2348	0.1770	0.1467	0.2548	0.2341	0.
ma5	-0.0138	0.1821	0.2093	0.2771	0.1599	0.2169	0.2549	0.2863	0

Figure 4.27: Empirical correlations of indicators reported by ADANCO 2.0.1



	gender	cei1	cei2	cei3	cei4	cei5	cei6	cei7	n
gender	1.0000	0.0440	0.0469	0.0496	0.0501	0.0505	0.0558	0.0478	0.
cei1	0.0440	1.0000	0.4983	0.5275	0.5325	0.5361	0.5935	0.5080	0.
cei2	0.0469	0.4983	1.0000	0.5623	0.5676	0.5715	0.6326	0.5415	0.
cei3	0.0496	0.5275	0.5623	1.0000	0.6008	0.6050	0.6696	0.5732	0.
cei4	0.0501	0.5325	0.5676	0.6008	1.0000	0.6107	0.6760	0.5786	0.
cei5	0.0505	0.5361	0.5715	0.6050	0.6107	1.0000	0.6806	0.5826	0.
cei6	0.0558	0.5935	0.6326	0.6696	0.6760	0.6806	1.0000	0.6449	0.
cei7	0.0478	0.5080	0.5415	0.5732	0.5786	0.5826	0.6449	1.0000	0.
ma1	0.0182	0.1932	0.2059	0.2179	0.2200	0.2215	0.2452	0.2099	1.
ma2	0.0179	0.1899	0.2024	0.2143	0.2163	0.2178	0.2411	0.2064	0.
ma3	0.0164	0.1740	0.1855	0.1964	0.1982	0.1996	0.2210	0.1891	0.
ma4	0.0215	0.2280	0.2430	0.2572	0.2597	0.2615	0.2894	0.2477	0.

Figure 4.28: Implied correlations (estimated model) reported by ADANCO 2.0.1



	gender	cei1	cei2	cei3	cei4	cei5	cei6	cei7	n
gender	1.0000	0.0440	0.0469	0.0496	0.0501	0.0505	0.0558	0.0478	0.
cei1	0.0440	1.0000	0.4983	0.5275	0.5325	0.5361	0.5935	0.5080	0.
cei2	0.0469	0.4983	1.0000	0.5623	0.5676	0.5715	0.6326	0.5415	0.
cei3	0.0496	0.5275	0.5623	1.0000	0.6008	0.6050	0.6696	0.5732	0.
cei4	0.0501	0.5325	0.5676	0.6008	1.0000	0.6107	0.6760	0.5786	0.
cei5	0.0505	0.5361	0.5715	0.6050	0.6107	1.0000	0.6806	0.5826	0.
cei6	0.0558	0.5935	0.6326	0.6696	0.6760	0.6806	1.0000	0.6449	0.
cei7	0.0478	0.5080	0.5415	0.5732	0.5786	0.5826	0.6449	1.0000	0.
ma1	0.0045	0.1932	0.2059	0.2179	0.2200	0.2215	0.2452	0.2099	1.
ma2	0.0045	0.1899	0.2024	0.2143	0.2163	0.2178	0.2411	0.2064	0.
ma3	0.0041	0.1740	0.1855	0.1964	0.1982	0.1996	0.2210	0.1891	0.
ma4	0.0054	0.2280	0.2430	0.2572	0.2597	0.2615	0.2894	0.2477	0.
ma5	0.0051	0.2169	0.2312	0.2447	0.2470	0.2487	0.2753	0.2357	0.

Figure 4.29: Implied correlations (saturated model) reported by ADANCO 2.0.1

4.8 Exporting results

Results can be exported in various formats.

4.8.1 HTML export

The HTML export saves an HTML file, including all the output defined by the selected output style.

4.8.2 Excel export

The Excel export saves an Excel file, including all the output defined by the selected output style.

4.8.3 Graphic export

The graphic export saves the graphical model as bitmap (`.png` or `.jpg`) or vector graphic (`.svg`).

Five

Extensions

ADANCO 2.0.1 can also be used to analyze more complex models. Various extensions have been proposed. The following sections point to literature that provides state-of-the-art guidelines.

5.1 Longitudinal studies

Roemer (2016) provide the most current guidelines on how to employ variance-based SEM in longitudinal studies. An example application is found in Ajamieh et al. (2016).

5.2 Mediating effects

Nitzl et al. (2016) provide the most current guidelines on how to model mediating effects using variance-based SEM. Analysts should ensure that the mediator's reliability is sufficiently taken into account; if it is not, wrong conclusions may result (Henseler, 2012b). If the mediator is a latent variable (using reflective measurement), a correction for attenuation is strongly recommendable. ADANCO 2.0.1 provides all the information required for mediation analysis.

5.3 Moderating effects

There are many ways of modeling the moderating effects (interaction effects) of multi-item constructs (Dijkstra & Henseler, 2011). Fassott et al. (2016) provide the most current guidelines on how to model the moderating effects of composites. In order to avoid multicollinearity issues in the context of moderating effects, users can orthogonalize the interaction term (see Henseler & Chin, 2010). Analysts using ADANCO 2.0.1 should use a two-stage approach to model moderating effects:

1. Estimate the model without the interaction. Extract the construct scores. Create an interaction term.
2. Estimate the model, including the interaction.

5.4 Nonlinear effects

Henseler et al. (2012) provide the most current guidelines on how to model nonlinear effects using variance-based SEM. In order to avoid multicollinearity issues in the context of nonlinear effects, users can orthogonalize the nonlinear terms (see Henseler & Chin, 2010). Analysts using ADANCO 2.0.1 should use a two-stage approach to model nonlinear effects:

1. Estimate the model without nonlinear terms. Extract the construct scores. Create the nonlinear term(s).
2. Estimate the model including the nonlinear term(s).

5.5 Multigroup analysis

Multigroup analysis can be regarded as a special type of moderation analysis, in which the moderator is a categorical variable (Henseler & Fassott, 2010). Sarstedt et al. (2011) and Henseler (2012a) provide the most current guidelines on how to conduct multigroup analysis using variance-based SEM.

5.6 Analyzing data from experiments

Streukens et al. (2010) and Streukens & Leroi-Werelds (2016) provide the most current guidelines on how to analyze data from experiments by using variance-based SEM.

5.7 Second-order constructs

Van Riel et al. (2017) provide the most current guidelines on how to model second-order constructs using variance-based SEM. Analysts using ADANCO 2.0.1 should use a two-stage approach to model second-order constructs:

1. Estimate the model containing only the first-order constructs. Extract the construct scores.
2. Estimate the model containing the second-order construct(s). Use the construct scores of the first-order constructs as indicators of the second-order construct(s). If necessary, adjust the reliability of the second-order construct manually.

5.8 Prediction-oriented modeling

Variance-based structural equation modeling can be used for confirmatory research and for predictive research. Shmueli et al. (2016) provide the most current guidelines on how to conduct predictive research using variance-based SEM. Cepeda Carrión et al. (2016) show how to assess the predictive validity of path models by using holdout samples.

5.9 Importance-performance matrix analysis

The importance-performance matrix analysis is a special form of reporting the results of variance-based structural equation modeling, which is popular for assessing the performance of business success factors. Importance-performance matrix analysis is essentially a xy-plot, in which business success factors are plotted such that their total effects on a business performance measure ("importance") serve as x-values, and the means of the business success factors' unstandardized construct scores ("performance") serve as y-values. It is common to scale all the relevant variables as if they were measured on a 0-to-100 scale. Martensen & Grønholdt (2003) provide an example of an importance-performance matrix analysis using variance-based structural equation modeling.

5.10 Other extensions

Variance-based SEM can also be used to model circumplex constructs (c.f. Furrer et al., 2012).

Six

Help & support

6.1 The ADANCO help system

Figure 6.1 shows the ADANCO 2.0.1 help system. It can be accessed via the main program menu. The help system contains short explanations of all of ADANCO's elements and its output.

6.2 Trouble shooting

In general, the program is pretty stable. Nevertheless, problems cannot be ruled out completely. The following steps might help users to overcome such problems.

Outdated version. Via the menu entry "Check for updates" it is possible to verify whether the installed version of ADANCO is the most currently available version. If a newer ADANCO version is available, the dialog offers to download and install this newer version.

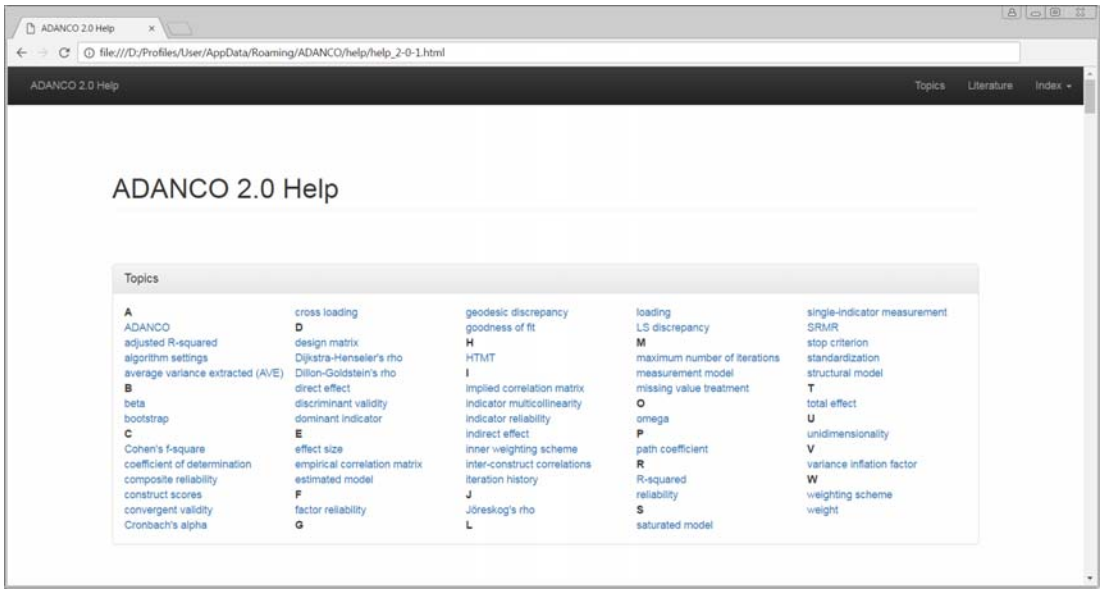


Figure 6.1: ADANCO help

Display problems. In case of display problems (incomplete graphs, exaggerated zoom, invisible areas etc.), try to reset the zoom (Element 7 in Figure 1.4).

Program instability. In case of instability try to restart the program.

6.3 Downloadable example files

ADANCO 2.0.1 provides three example projects dedicated to the three topics "Service Customization", "European Customer Satisfaction Index", and "Organizational Identification". The latter was used for many screenshots in this manual.

6.3.1 Service Customization

The file `Coelho & Henseler 2012 Banking.zip` contains the ADANCO model file (`*.cmq`) and the data belonging to the banking study described in Coelho & Henseler (2012).

The data are made available with Pedro S. Coelho's permission.

6.3.2 European Customer Satisfaction Index

The file `ECSI.zip` contains the ADANCO model file (`*.cmq`) and the data belonging to the European Customer Satisfaction Index study described in Tenenhaus et al. (2005).

The data are made available with Michel Tenenhaus's permission.

6.3.3 Organizational Identification

The file `Bagozzi.zip` contains the ADANCO model file (`*.cmq`) and the data belonging to the study described in Hwang & Takane (2004). The data originates from Bergami & Bagozzi (2000).

The data are made available with Richard Bagozzi's permission.

6.4 Selected ADANCO applications

Scientific work that has relied on ADANCO as modeling tool is a good source of information and learning. The following list contains a selection of empirical studies that have used ADANCO:

- Ajamieh et al. (2016)
- Ziggers & Henseler (2016)
- Gelhard & von Delft (2016)
- Lancelot-Miltgen et al. (2016)

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