# *GSCA Pro 1.1* User's Manual

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Last updated June 25, 2021

DOI: 10.13140/RG.2.2.28162.61127

Website: www.gscapro.com

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Google Discussion Group: https://groups.google.com/g/gsca-pro

# Table of Contents

**I. Downloading and Opening GSCA Pro 1.1** p.2

**II. GSCA Pro Graphical Interface** p.3

**III. General Information** p.5

**IV. Pre-Analysis - Descriptive Statistics** p.9

**V. Analysis**

1. Basic GSCA: Single Group Analysis p.10
2. Basic GSCA with Constrained Parameters p.21
3. Basic GSCA: Multigroup Analysis p.23
4. GSCA with 2nd-order Components p.27
5. Nonlinear GSCA p.30
6. GSCA with Component Interactions p.31
7. Multilevel GSCA p.33
8. Regularized GSCA p.34
9. Integrated GSCA p.35

**VI. Post Analysis**

1. Model Comparison p.36
2. Moderation Analysis p.39
3. Conditional Process Analysis p.41

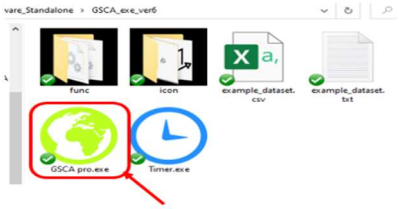
**VII. Preference – Estimation Options** p.43

**VIII. References** p.45

# Downloading and Opening GSCA Pro

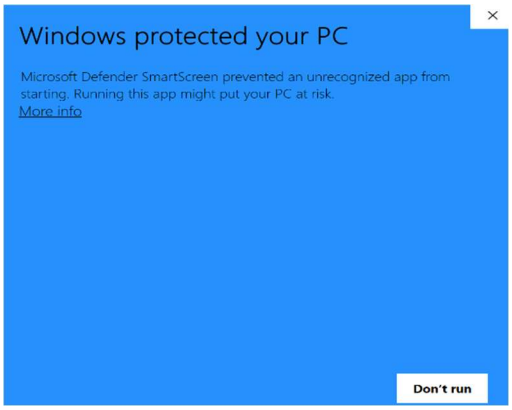
Users download **GSCA Pro 1.1.zip** from www.gscapro.com and **unzip** it. Please download the software only from this website.

Then, double-click on **GSCA Pro 1.1.exe** to open the software.




## Important Notices

- When double-clicking on GSCA Pro 1.1.exe, **Windows 10** users will receive the "**Windows protected your PC**" warning message, as shown on the right. Here is what they need to do:
    - Don't click on the "Don't run" option
    - Click on the "More info" option
    - A new popup window will then appear
    - Click on "Run anyway"



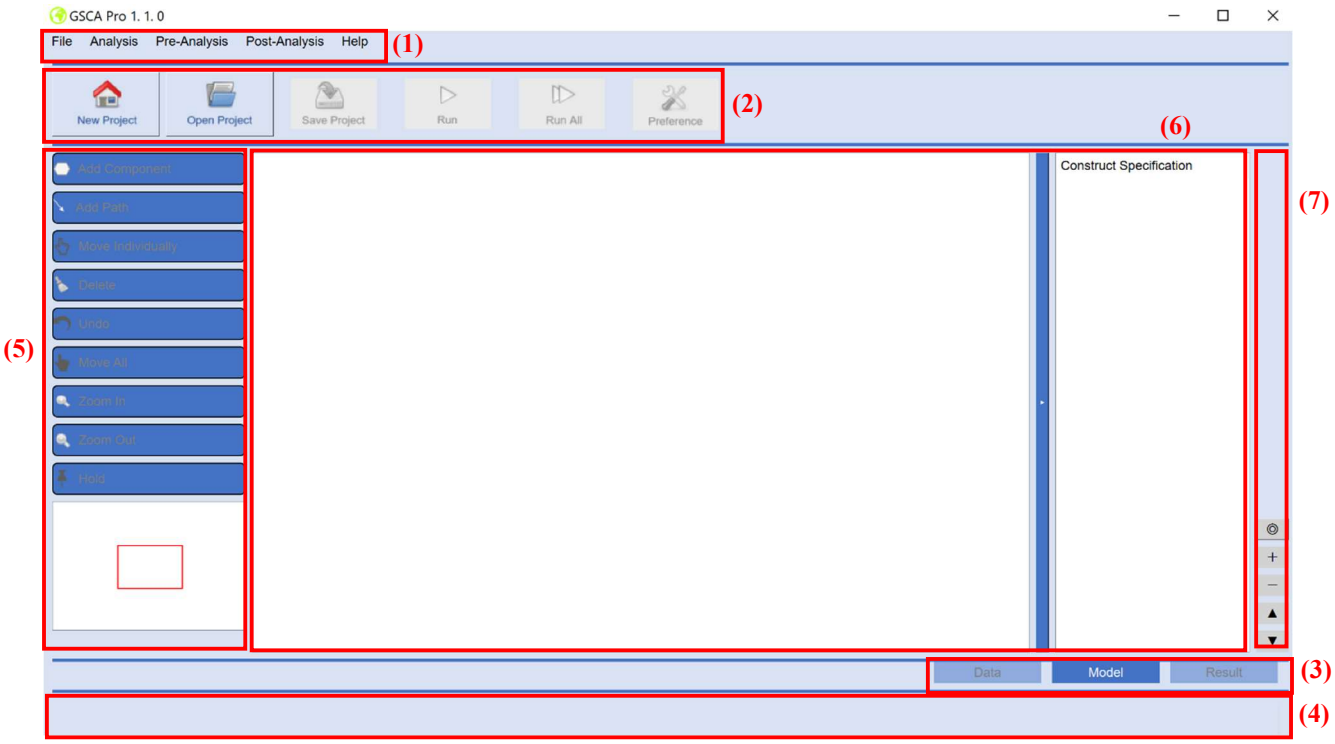

- An antivirus program on users' PC can prevent GSCA Pro 1.1 from running. Then, users need to temporarily disable their antivirus program, or add GSCA Pro 1.1 to the antivirus program's Trusted Program List. Below is how to add a trusted program to several antivirus programs.
    - Trend Micro: https://docs.trendmicro.com/all/ent/officescan/v11.1/en-us/osce_11.1_sp1_agent_olh/Trusted-Program-List.html
    - McAfee: https://community.mcafee.com/t5/SecurityCenter/How-to-add-programs-to-the-Trusted-List/td-p/72462
    - Norton: https://www.providesupport.com/help/troubleshooting/norton-internet-security

- **Windows 7** users may receive the "**Windows cannot access the specified device, path, or file**" warning message. Then, please refer to the following link: https://support.microsoft.com/en-us/topic/-windows-cannot-access-the-specified-device-path-or-file-error-when-you-try-to-install-update-or-start-a-program-or-file-46361133-47ed-6967-c13e-e75d3cc29657

- We do not recommend creating GSCA Pro's folder within an existing folder whose contents are synchronized by a cloud storage service (e.g., Dropbox's folder). This may interrupt the execution of the software or turn it off suddenly.

# GSCA Pro's Graphical Interface

Upon opening *GSCA Pro*, the following graphical interface will appear.




(1) **Menu Bar** contains top-level menus, including [File], [Analysis], [Pre-Analysis], [Post-Analysis], and [Help].

- In [File], users can create a new project, open an old project, save a current project, save a project as a different file, or exit the program.
- In [Analysis], users can select various analytic features of GSCA.
- In [Pre-Analysis], users can calculate descriptive statistics.
- In [Post-Analysis], users can conduct a supplementary analysis after fitting models, including model comparison, mediation analysis, or conditional process analysis.
- In [Help], users can find information on the program, developers, or citation.

(2) **Shortcuts**

- [New Project] is used to create a new project.
- [Open Project] is used to open an existing project.
- [Save Project] is used to save a current project.
- [Run] is used to fit a specified model to data.
- [Run All] is used to fit all specified models to the same data at once.

- [Preference] is used for users to choose various estimation options (e.g., maximum number of iterations, number of bootstrap samples, missing data options, etc.)

(3) **View Tap**
- [Data] displays the data that users uploaded into GSCA Pro.
- [Model] is used to create or revise a model.
- [Result] displays results after estimating a model.

(4) **Status Bar** displays the names of the project and the analysis type that users currently select and conduct.

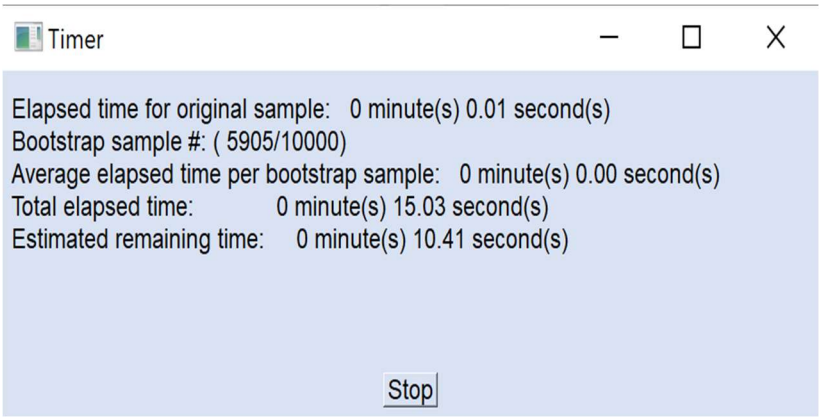
(5) **Tool Panel** contains all tools that users can use for specifying a model or conducting an analysis.

(6) **Main Window** displays users' data, models, or analysis results.

(7) **Model Bar** shows a list of models that users specified. Users can add (+), delete (-), move up (▲), or move down (▼) a model.

## Timer

When an analysis runs longer than 5 seconds, the below timer will appear, displaying how many bootstrap samples have been run and how much time the analysis will take to complete.



# General Information

## 1. How to Prepare Data for *GSCA Pro*

GSCA Pro is run on individual-level raw data. The raw data file can be prepared in various formats (.txt, .csv, or .xlsx). The specific data format for *GSCA Pro* is as follows:

- The first row can contain the names of indicators. The name of each indicator should be separated by a space, tab, comma, semicolon, or column (.xlsx). Refer to the example data files (*tutorial_data.txt*, *tutorial_data.csv*, and *tutorial_data.xls*).
- If the first row does not contain the names of indicators, by default, the indicators will be named V1, V2, …, and V*J* (*J* is the number of indicators).
- The data input begins on the second row. Data from an observation, or responses by an individual on each indicator, should be separated by a space (.txt), a comma (.csv), or a column (.xlsx).
- Data for each observation appear on a single row.
- Data must not include nonnumeric characters or blank cells.
- Data may include missing values. Any numeric value can be used to indicate missing values (the default value is -9999) and should be used consistently in the data.

### Exemplary Data and Model

Part of Bergami and Bagozzi's (2000) organizational identification data is used for illustrative purposes. The number of observations is 305. Figure 1 displays the model specified for the data. This model includes 4 components (**hexagons**) and 21 indicators (**boxes**): Organizational Prestige (OP) is associated with 8 indicators (cei1 – cei8), Organizational Identification (OI) with 6 indicators (ma1 – ma6), Affective Commitment-Joy ($AC_{Joy}$) with 4 indicators (orgcmt1, 2, 3 and 7), and Affective Commitment – Love ($AC_{Love}$) with 3 indicators (orgcmt5, 6, and 8).

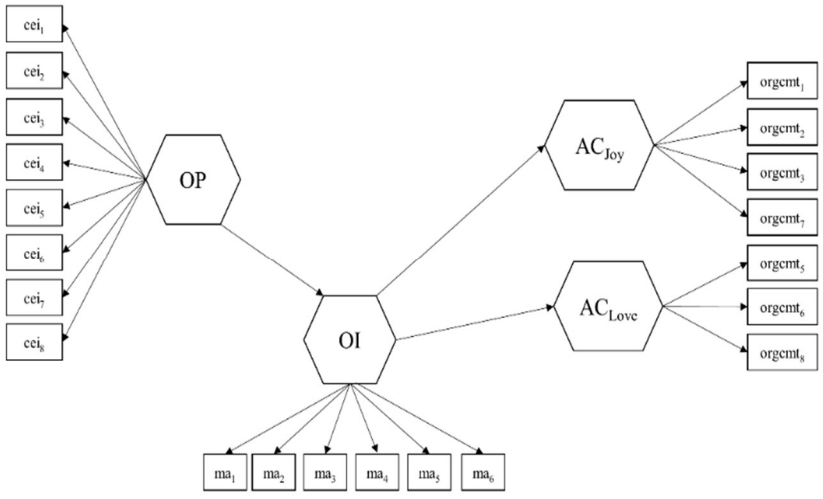
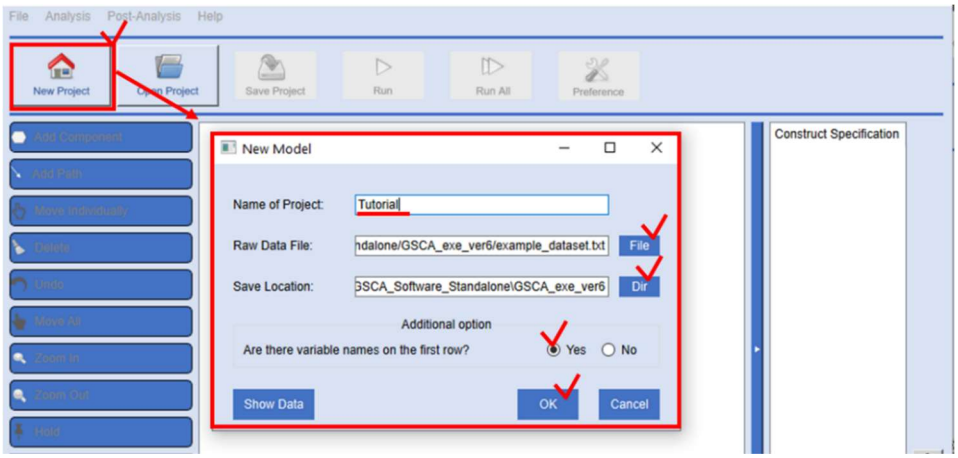


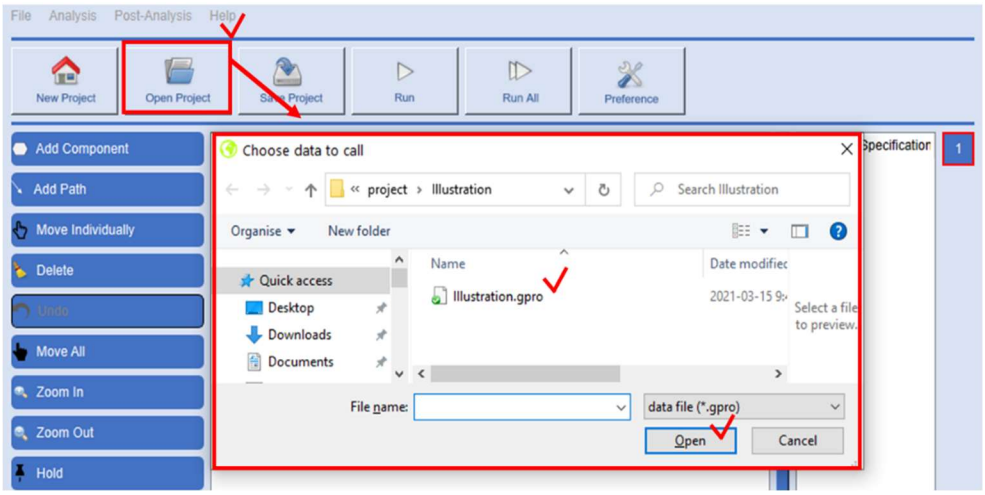

Figure 1. The specified model for the example data.

## 2. How to Start New Project or Open Old Project

- To start a new project, click on the **[New Project]** shortcut. Users name a new project, upload a data file, set a directory for saving the project, and indicate whether the names of indicators appear in the first row of the data file (default). Then, click on [OK].

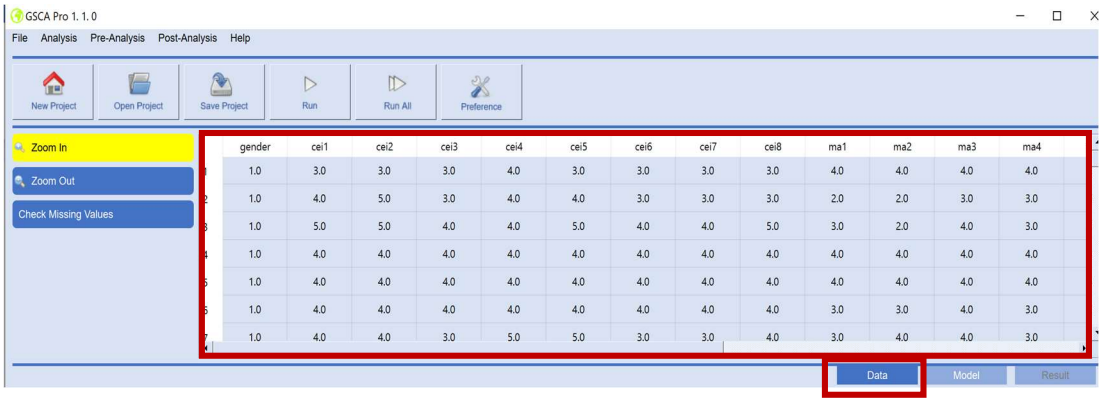



- To open an old project, click on the **[Open Project]** shortcut, search the directory that contains a project file of interest, click on the file, and click on [Open].



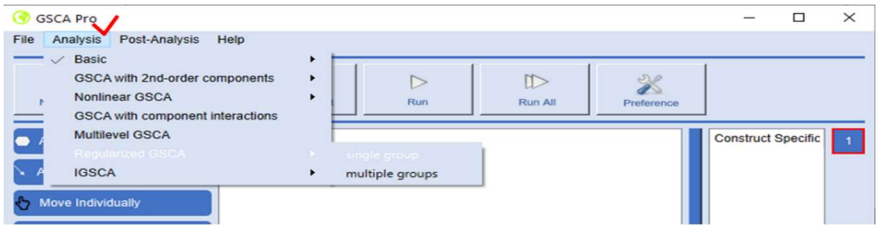

## 3. How to Check Uploaded Data

- To review uploaded data, click on the **[Data]** tap.
- Users can increase or decrease cell size by clicking on [Zoom in] or [Zoom Out] on the left-hand window.
- Users can check the number of missing values per observation or variable by clicking on [Check Missing Values] on the left-hand window.



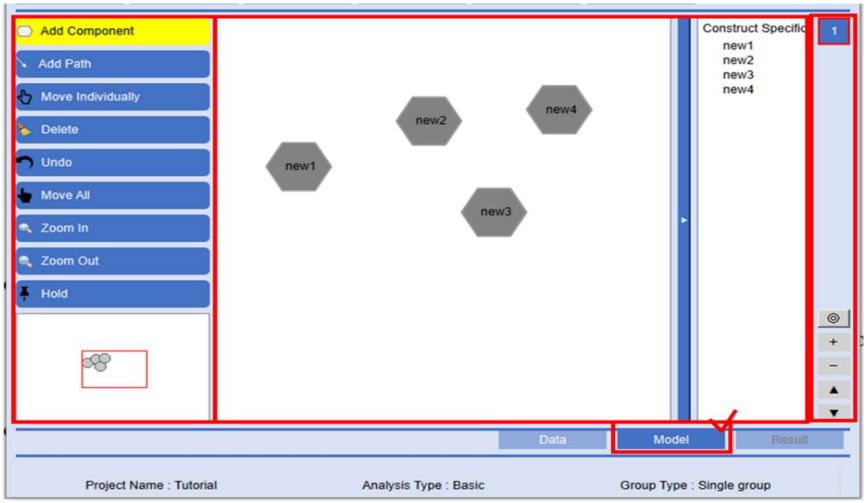

## 4. How to Choose Analysis Type

- Users can choose an analysis type in [**Analysis**] on the Menu Bar.



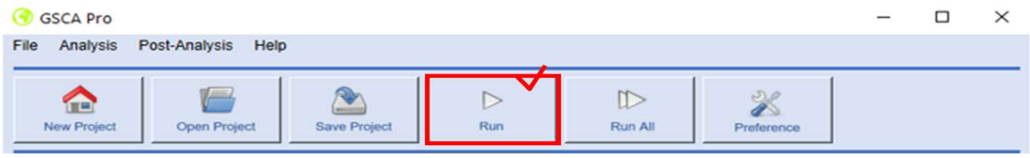

## 5. How to Specify Model

- Users can specify a model on the Main Window. When they have viewed their data or analysis results, they can click on the **[Model]** tap to specify or view a model.
- Users can specify a model with tools in the Tool Panel. A detailed description of model specification is provided in the following chapters.



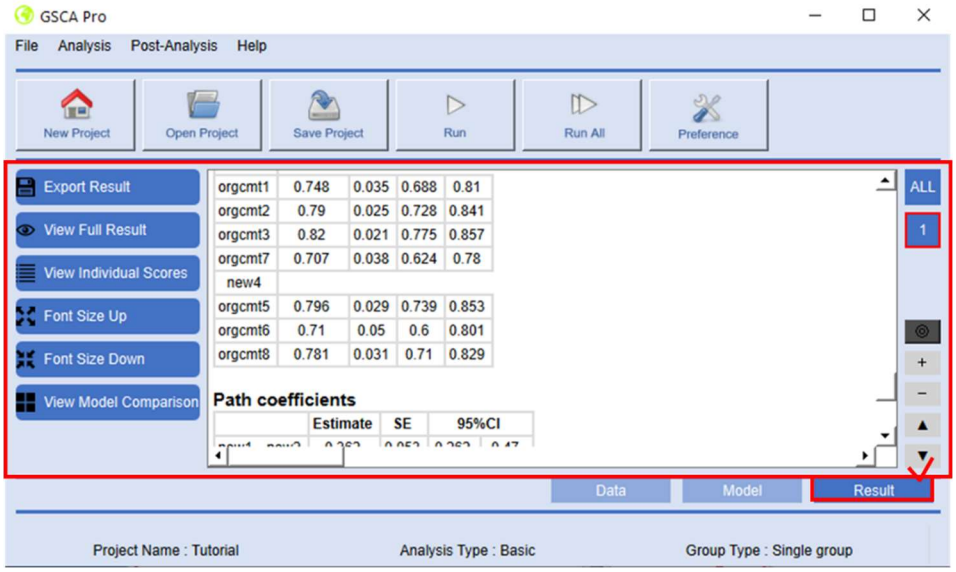

## 6. How to Fit Model

- Click on the **[Run]** shortcut to fit a specified model to the uploaded data.



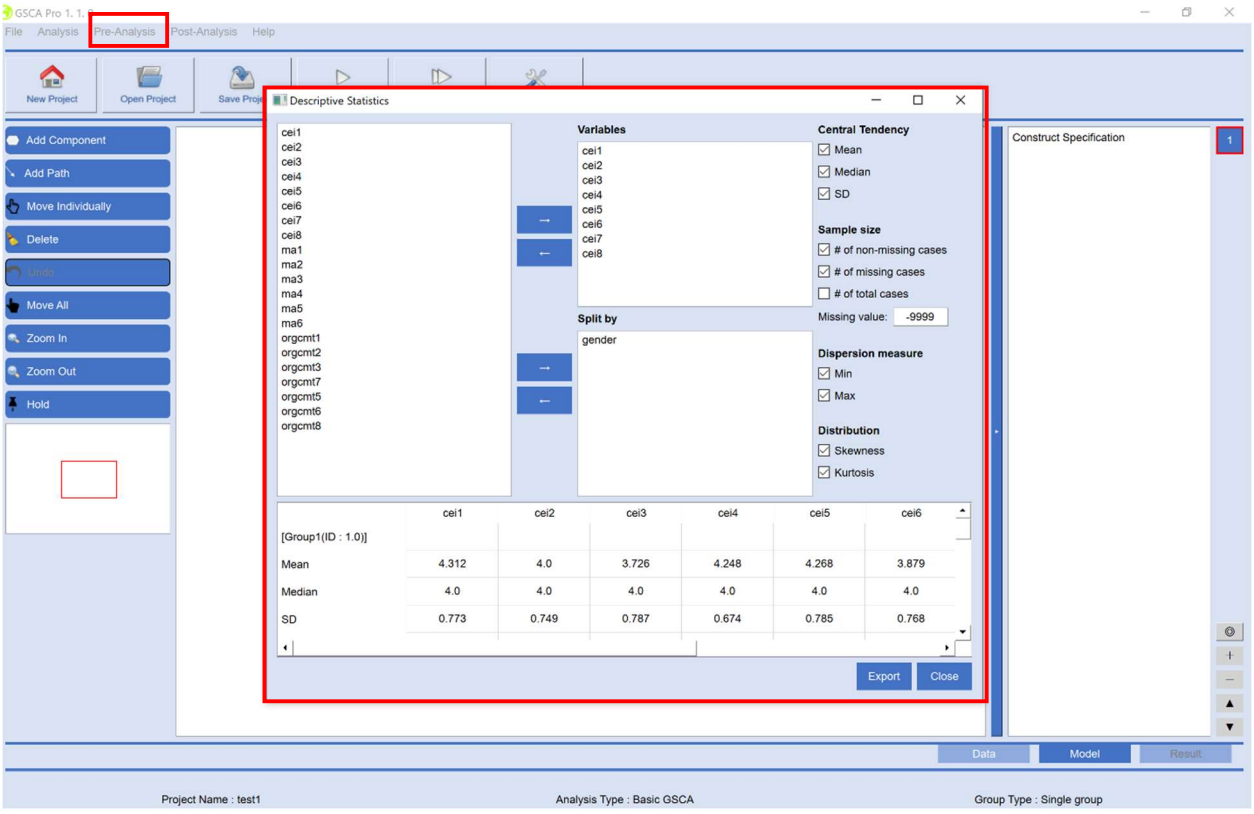

## 7. How to View Analysis Result

- *GSCA Pro* automatically displays analysis results after fitting a model. Users can also click on the **[Result]** tab to view the results.



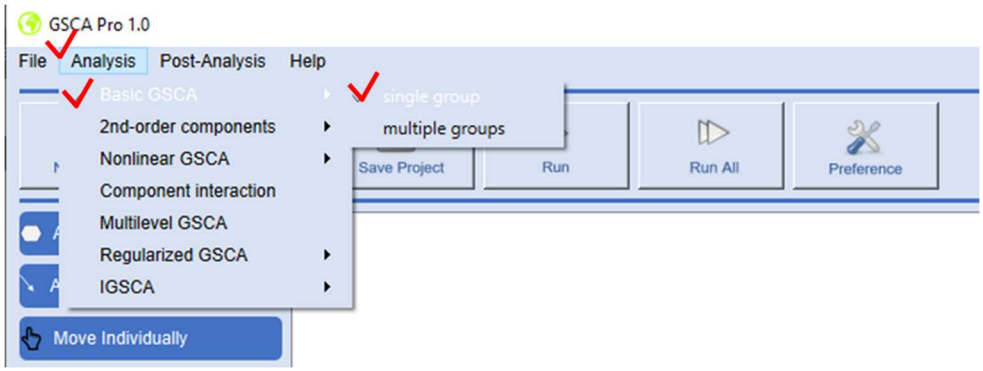
# Pre-Analysis – Descritive Statistics

- To calculate descriptive statistics for the data, select "**Pre-Analysis → Descriptive Statistics**"
    - Select variables on the left-hand window and move them to the upper right-hand window labelled "**Variables**."
    - Choose which descriptive statistics are calculated for the selected variables.
    - Users can calculate descriptive statistics for the variables in different groups by moving a grouping variable (e.g., gender) to the the lower right-hand window labelled "**Split by**."
    - Users can export the calculated descriptive statistics in csv format by clicking on the icon **[Export]** on the bottom.



# Analysis – Basic GSCA: Single Group Analysis

- To begin, select "**Analysis → Basic GSCA → single group**" under the [**Analysis**] menu.



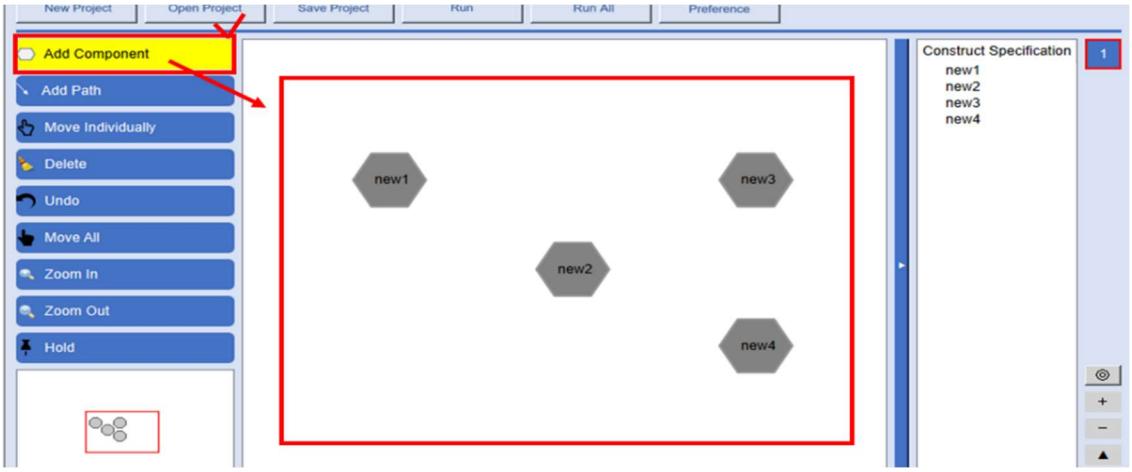

## 1. Specify a structural equation model

Users can specify their structural equation model with the following steps.

**Step 1: Draw components**

Users are to draw components before assigning variables them as follows:

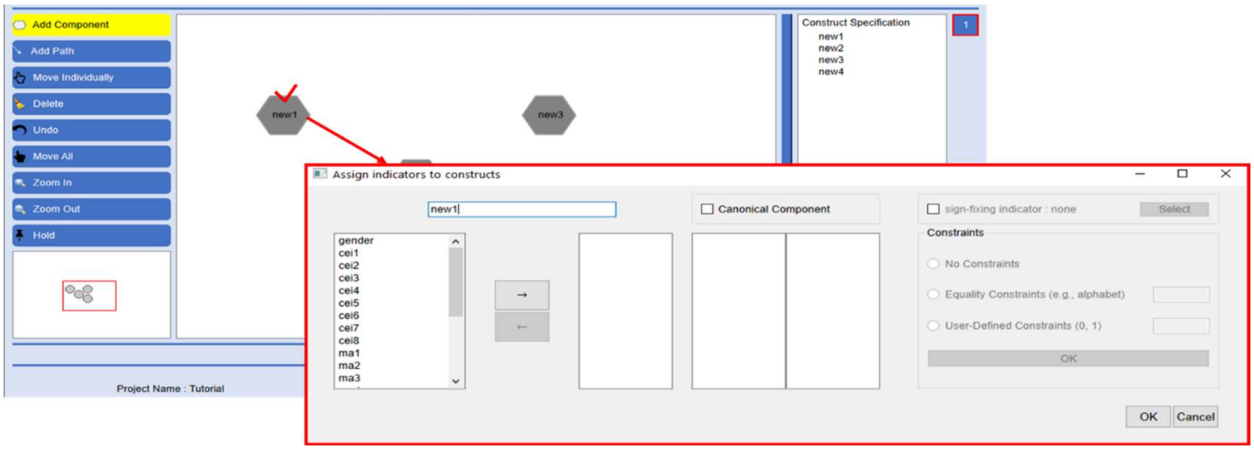
- Click once on **[Add Component]** in the Tool Panel.
- Click the left mouse button with the cursor placed in the Main Window as many times as the number of components. In the present example, four clicks resulted in the creation of four components. By default, the four components were initially named *new1* to *new4*.



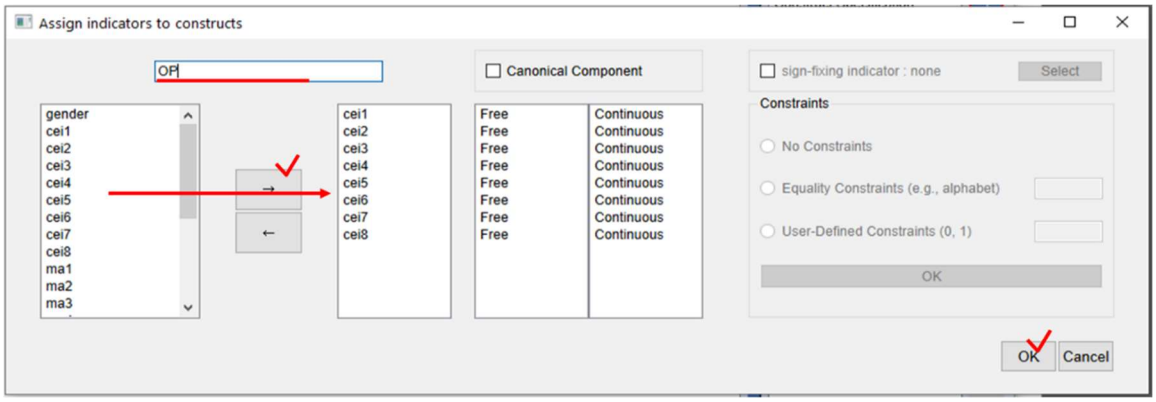

**Step 2: Assign indicators to components (measurement model)**

After drawing components, users are to specify their measurement model as follows:

- Double-click on an individual component (a hexagon). Then, the "**Assign Indicators to Constructs**" window will appear.




- In the "**Assign Indicators to Constructs**" window,
  - Users can rename the component by typing a new name.
  - User select the appropriate indicators in the list, which appears on the left-hand dialog window, and move them to the right-hand dialog window ("**Free**" means a free loading to be estimated).
  - Optionally,
    - Users can choose whether the component is specified as a canonical component, often known as a formative component, which does not involve loadings.
    - If users want to align the sign of each indicator's weight with the correlation of a certain indicator (a sign-fixing indicator) with the component, they can indicate which indicator is used as the sign-fixing indicator.
    - Users can constrain certain loadings to be equal (Equality Constraints) or to a constant (User-Defined Constraints). Refer to page 18.
  - Click on OK.

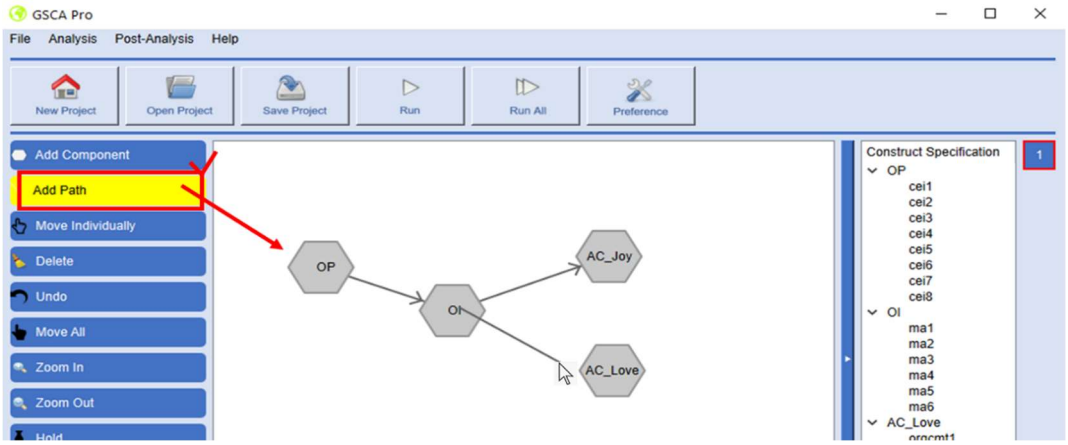



- Repeat the above steps for the remaining components.

## Step 3: Draw path coefficients (structural model)

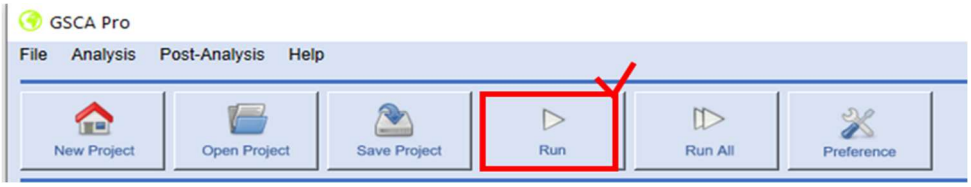
Path coefficients are to be drawn as follows:

- Click once on **[Add Path]** in the Tool Panel.
- Drag a path from an independent component to the corresponding dependent component. Repeat the above steps until all paths are drawn.



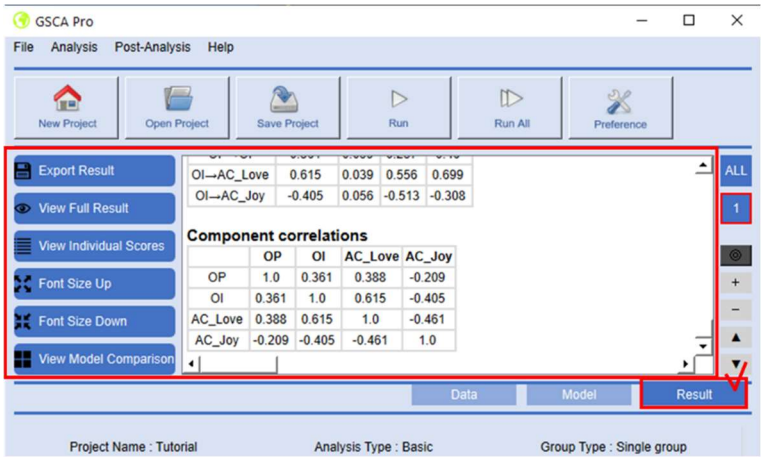

## 2. Run *GSCA Pro*

- Once the above steps are complete, users can run *GSCA Pro* for fitting the specified model to the data. This is done by clicking on the **[Run]** shortcut.




## 3. View and Interpret Basic Results

- When the program is finished running, basic analysis results are displayed in the "**Result**" tab.




- The basic analysis results of our example are below.

==========

Model Number : 1

Analysis Type : Basic / Single group
Execution Date : Wed Feb 24 14:13:05 2021
Number of bootstrap samples : 100

The ALS algorithm converged in 4 iterations (convergence criterion = 0.0001)

Elapsed time for original sample: 0 minute(s) 0.01 second(s)
Average elapsed time per bootstrap sample: 0 minute(s) 0.00 second(s)
Total elapsed time: 0 minute(s) 0.30 second(s)
==========

## Model fit measures

| FIT | AFIT | FITs | FITm | GFI | SRMR | OPE | OPEs | OPEm |
|---|---|---|---|---|---|---|---|---|
| 0.54 | 0.195 | 0.605 | 0.536 | 0.986 | 0.047 | 0.469 | 0.824 | 0.401 |

The above table provides various model fit measures in GSCA.

- **FIT** indicates the total variance of all variables (indicators and components) explained by a particular model specification. Like R squared in linear regression, the values of FIT range from 0 to 1. The larger this value, the more variance in the variables is accounted for by the specified model. For example, FIT = .50 indicates that 50% of the total variance of all variables is explained by the model. There is no rule of thumb cutoff for FIT, which is indicative of an acceptable fit.
- **AFIT** (Adjusted FIT) is similar to FIT but takes model complexity into account. Like Adjusted R-squared in linear regression, AFIT cannot be interpreted in the same way as FIT (i.e., the proportion of the total variance explained). Instead, it can be used only for comparing competing models. The model with the largest AFIT value may be chosen among competing models.
- **FIT$_S$** indicates the total variance of all components explained by a particular structural model specification. The values of FIT$_S$ range from 0 to 1. The larger this value, the more variance in the components is accounted for by the specified structural model.
- **FIT$_M$** indicates the total variance of all indicators explained by a particular measurement model specification. The values of FIT$_M$ range from 0 to 1. The larger this value, the more variance in the indicators is accounted for by the specified measurement model.
- **GFI** (goodness-of-fit index) and **SRMR** (standardized root mean squared residual). Both are proportional to the difference between the sample covariances and the covariances reproduced by the parameter estimates of GSCA. A recent study suggested the following rules-of-thumb cutoff criteria for GFI and SRMR in GSCA (Cho, Hwang, Sarstedt, & Ringle, 2020)

    - When sample size = 100, a GFI $\geq$ .89 and an SRMR $\leq$ .09 indicate an acceptable fit. Although both indexes can be used to assess model fit, using the SRMR with the above cutoff value may be better than using the GFI with the suggested cutoff

value. Also, if SRMR ≤ .09, then a GFI cutoff value of ≥ .85 may still be indicative of an acceptable fit.

- When sample size > 100, a GFI ≥ .93 or an SRMR ≤ .08 indicates an acceptable fit. In this case, there is no preference for one index over the other, or for using a combination of the indexes over using them separately. Each index's suggested cutoff value may be used independently to assess the model fit.

- **OPE** (out-of-sample prediction error) indicates prediction power of a specified model for unseen observations (Cho, Jung, & Hwang, 2019). The OPE can be used for comparing different models in terms of prediction power.
- **OPE**$_S$ indicates prediction power of a specified structural model and **OPE**$_M$ indicates prediction power of a specified measurement model.

**Weights**

| | Estimate | SE | 95%CI | |
|---|---|---|---|---|
| OP | | | | |
| cei1 | 0.15 | 0.008 | 0.132 | 0.163 |
| cei2 | 0.16 | 0.01 | 0.139 | 0.181 |
| cei3 | 0.157 | 0.009 | 0.137 | 0.173 |
| cei4 | 0.147 | 0.008 | 0.131 | 0.164 |
| cei5 | 0.162 | 0.01 | 0.146 | 0.186 |
| cei6 | 0.168 | 0.009 | 0.15 | 0.187 |
| cei7 | 0.15 | 0.008 | 0.134 | 0.165 |
| cei8 | 0.154 | 0.008 | 0.139 | 0.172 |
| OI | | | | |
| ma1 | 0.219 | 0.017 | 0.183 | 0.249 |
| ma2 | 0.211 | 0.02 | 0.164 | 0.25 |
| ma3 | 0.194 | 0.018 | 0.158 | 0.231 |
| ma4 | 0.261 | 0.02 | 0.222 | 0.3 |
| ma5 | 0.237 | 0.021 | 0.205 | 0.279 |
| ma6 | 0.184 | 0.021 | 0.134 | 0.223 |
| AC_Joy | | | | |
| orgcmt1 | 0.302 | 0.019 | 0.266 | 0.342 |
| orgcmt2 | 0.33 | 0.017 | 0.297 | 0.363 |
| orgcmt3 | 0.364 | 0.02 | 0.33 | 0.4 |
| orgcmt7 | 0.304 | 0.022 | 0.253 | 0.343 |
| AC_Love | | | | |
| orgcmt5 | 0.453 | 0.025 | 0.412 | 0.502 |
| orgcmt6 | 0.388 | 0.025 | 0.329 | 0.437 |
| orgcmt8 | 0.466 | 0.022 | 0.421 | 0.509 |

**Loadings**

| | Estimate | SE | 95%CI | |
|---|---|---|---|---|
| OP | | | | |
| cei1 | 0.781 | 0.026 | 0.726 | 0.828 |
| cei2 | 0.825 | 0.016 | 0.797 | 0.852 |
| cei3 | 0.77 | 0.025 | 0.708 | 0.809 |
| cei4 | 0.804 | 0.035 | 0.729 | 0.865 |
| cei5 | 0.801 | 0.029 | 0.733 | 0.849 |
| cei6 | 0.843 | 0.022 | 0.794 | 0.879 |
| cei7 | 0.776 | 0.024 | 0.727 | 0.811 |
| cei8 | 0.801 | 0.033 | 0.748 | 0.854 |
| OI | | | | |
| ma1 | 0.787 | 0.025 | 0.741 | 0.827 |
| ma2 | 0.758 | 0.029 | 0.703 | 0.813 |
| ma3 | 0.637 | 0.034 | 0.564 | 0.703 |
| ma4 | 0.823 | 0.024 | 0.781 | 0.863 |
| ma5 | 0.811 | 0.024 | 0.751 | 0.851 |
| ma6 | 0.743 | 0.032 | 0.676 | 0.798 |
| AC_Joy | | | | |
| orgcmt1 | 0.748 | 0.033 | 0.671 | 0.801 |
| orgcmt2 | 0.79 | 0.028 | 0.723 | 0.835 |
| orgcmt3 | 0.82 | 0.022 | 0.776 | 0.86 |
| orgcmt7 | 0.707 | 0.04 | 0.599 | 0.775 |
| AC_Love | | | | |
| orgcmt5 | 0.796 | 0.027 | 0.742 | 0.848 |
| orgcmt6 | 0.71 | 0.045 | 0.621 | 0.787 |
| orgcmt8 | 0.781 | 0.031 | 0.72 | 0.842 |

The above two tables display the estimates of component weights and component loadings of indicators per component. They also show the bootstrap standard errors (SE) and bootstrap 95% confidence intervals (95% CI) of the weight and loading estimates. The 95% confidence intervals

can be used for testing the significance of an estimate (i.e., an estimate may be considered statistically significant at .05 level, if its confidence interval does not include 0). When a component is specified as a canonical component, its indicators' loadings will not be reported. Note that GSCA Pro does not provide a t-test (Estimate/SE) and its p value because this test is a parametric test assuming the normality of a parameter estimate. Such a parametric test is not consistent with GSCA which typically does not require a distributional assumption. No literature is available that shows that GSCA's estimates are normally distributed.

**Path coefficients**

| | Estimate | SE | 95%CI | |
|---|---|---|---|---|
| OP→OI | 0.362 | 0.059 | 0.234 | 0.476 |
| OI→AC_Joy | 0.614 | 0.035 | 0.559 | 0.686 |
| OI→AC_Love | -0.404 | 0.051 | -0.515 | -0.307 |

This table shows the estimates of path coefficients and their bootstrap standard errors (SE) and 95% confidence intervals (95% CI).

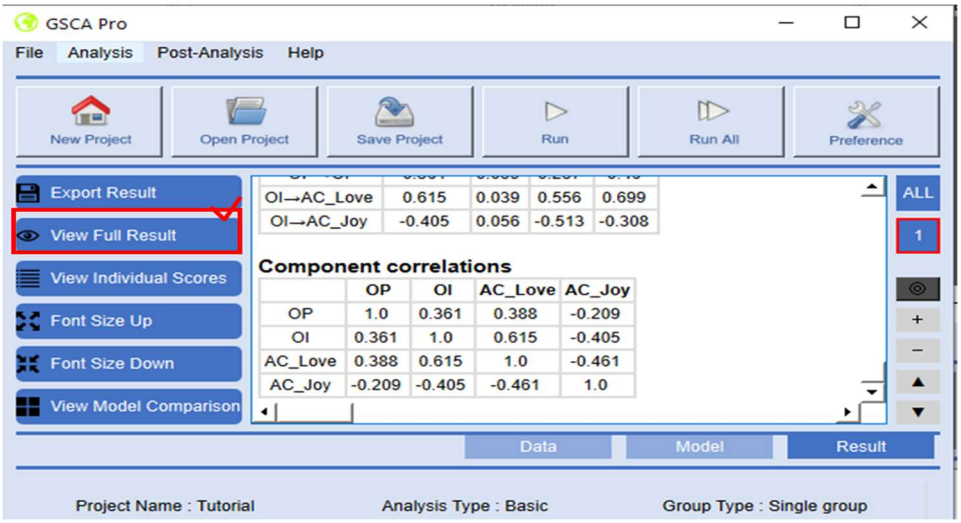
**Component correlations**

| | OP | OI | AC_Joy | AC_Love |
|---|---|---|---|---|
| **OP** | 1.1 | 0.362 | 0.388 | -0.209 |
| **OI** | 0.362 | 1.1 | 0.614 | -0.404 |
| **AC_Joy** | 0.388 | 0.614 | 1.1 | -0.461 |
| **AC_Love** | -0.209 | -0.404 | -0.461 | 1.1 |

This table shows the correlations among components.

## 4. View and Interpret Full Results

- To view more detailed results, click on [**View Full Result**] on the left-hand window. Then, more detailed analysis results are displayed.




- Below are the additional results that are not displayed in the "**Result**" tab.

**HTMT**

| | |
|---|---|
| OP ↔ OI | 0.409 |
| OP ↔ AC_Joy | 0.467 |
| OP ↔ AC_Love | 0.26 |
| OI ↔ AC_Joy | 0.753 |
| OI ↔ AC_Love | 0.527 |
| AC_Joy ↔ AC_Love | 0.641 |

This table shows the heterotrait-monotrait (HTMT) ratio per pair of components, which is defined as the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct. Discriminant validity problems are present when HTMT values are high. Henseler et al. (2015) propose a threshold value of 0.90 for structural models with constructs that are conceptually very similar. In such a setting, an HTMT value above 0.90 would suggest that discriminant validity is not present. But when constructs are conceptually more distinct, a lower, more conservative, threshold value is suggested, such as 0.85 (Henseler, Ringle, & Sarstedt, 2015).

Rönkkö and Cho (2020) show that the HTMT ratio is based on the parallel assumption of each block of indicators, i.e., the variances of the indicators are the same and the covariances of indicators are the same. The parallel assumption is not made in GSCA and hardly met in practice. Thus, in general, we do not recommend relying on the HTMT ratios for assessing unidimensionality or discriminant validity in GSCA.

**Construct quality measures**

| | **OP** | **OI** | **AC_Joy** | **AC_Love** |
|---|---|---|---|---|
| PVE | 0.641 | 0.581 | 0.589 | 0.583 |
| Alpha | 0.92 | 0.854 | 0.766 | 0.642 |
| Rho | 0.934 | 0.892 | 0.851 | 0.807 |
| Dimensionality | 1.1 | 1.1 | 1.1 | 1.1 |

The **PVE** (Proportion of Variance Explained) is the average amount of the total variance of indicators that is explained by their corresponding component, as in principal components analysis. If a single component explains 70% or higher of the total variance of a block of indicators, this may be indicative of unidimensionality for the block (Jolliffe & Cadman, 2016). The **Alpha** indicates Cronbach's alpha. The **Rho** is Dillon-Goldstein's rho or the composite reliability. Note that although Cronbach's alpha is used for assessing the reliability of sum scores, this metric assumes the equal covariances of a block of indicators, i.e., tau-equivalence (Benitez et al., 2020), which is not made in GSCA. Dillon-Goldstein's rho should be calculated based on factor loadings rather than component loadings (Benitez et al., 2020). Thus, this metric is not suitable for GSCA. Instead, the Rho can be used for factors when applying IGSCA. The **Dimensionality** indicates the number of eigenvalues greater than 1 for a set of indicators per component. If Dimensionality > 1, more than one component may be considered for a set of indicators.

**Fornell-Larcker criterion values**

| | **OP** | **OI** | **AC_Joy** | **AC_Love** |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| OP | 0.8 | 0.0 | 0.0 | 0.0 |
| OI | 0.362 | 0.762 | 0.0 | 0.0 |
| AC_Joy | 0.388 | 0.614 | 0.767 | 0.0 |
| AC_Love | -0.209 | -0.404 | -0.461 | 0.763 |

Fornell and Larcker (1981) proposed the traditional metric and suggested that each factor's AVE (average variance extracted) should be compared to the squared inter-factor correlation (as a measure of shared variance) of that same factor and all other factors in the structural model. The shared variance for all factors should not be larger than their AVEs. However, AVE and the Fornell-Larcker criterion do not apply to GSCA because they are calculated based on factor loadings (Benitez et al., 2020). Instead, these metrics may be used for factors when applying IGSCA.

**R squared values of indicators in measurement model**

| cei1 | cei2 | cei3 | cei4 | cei5 | cei6 | cei7 | cei8 | ma1 | ma2 | ma3 | ma4 | ma5 | ma6 | orgcmt1 | orgcmt2 | orgcmt3 | orgcmt7 | orgcmt5 | orgcmt6 | orgcmt8 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.609 | 0.68 | 0.593 | 0.646 | 0.642 | 0.711 | 0.603 | 0.642 | 0.619 | 0.575 | 0.405 | 0.678 | 0.657 | 0.552 | 0.559 | 0.624 | 0.672 | 0.5 | 0.633 | 0.504 | 0.61 |

This table shows how much variance of each indicator is explained by the indicator's component. When a canonical component is chosen for a set of indicators, the indicators' R squared values are not provided.

**R squared values of components in structural model**

| OP | OI | AC_Joy | AC_Love |
|---|---|---|---|
| 0.0 | 0.131 | 0.377 | 0.163 |

This table shows how much variance of each component is explained by its independent components. When a component is exogenous (e.g., OP in the present example), its R squared value is equal to zero.

GSCA Pro also provides the **variance inflation factor** (**VIF)** for the structural model if any component is affected by more than one component. Although no clear rule of thumb is available, a VIF value greater than 5 (Hair, Ringle, & Sarstedt, 2011) or 10 (Myers, 1990, p. 369) has often been taken as evidence to raise some concern. Also, if the measurement model contains a "canonical component", the VIF values of its corresponding indicators are calculated.

**F squared values**

| | OP | OI | AC_Joy | AC_Love |
|---|---|---|---|---|
| OP | 0.0 | 0.15 | 0.0 | 0.0 |
| OI | 0.0 | 0.0 | 0.604 | 0.195 |
| AC_Joy | 0.0 | 0.0 | 0.0 | 0.0 |
| AC_Love | 0.0 | 0.0 | 0.0 | 0.0 |

This table shows the $f^2$ effect size of each predictor component. As a rule of thumb, the $f^2$ values of 0.02, 0.15 and 0.35 may be considered small, medium, and large effect sizes, respectively (Cohen, 1988).

**Unstandardized component means**

| OP | OI | AC_Joy | AC_Love |
|---|---|---|---|
| 4.078 | 3.663 | 3.164 | 2.79 |

This table shows the averages of unstandardized components in the same scales as their original indicators.

**Unstandardized component variances**

| OP | OI | AC_Joy | AC_Love |
|---|---|---|---|
| 0.411 | 0.427 | 0.409 | 0.377 |

This table shows the variances of unstandardized components in the same scales as their original indicators.

**Sample correlations (lower diagonal) & Residual correlations (upper diagonal)**

| | cei1 | cei2 | cei3 | cei4 | cei5 | cei6 | cei7 | cei8 | ma1 | ma2 | ma3 | ma4 | ma5 | ma6 | orgcmt1 | orgcmt2 | orgcmt3 | orgcmt7 | orgcmt5 | orgcmt6 | orgcmt8 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| cei1 | 0.0 | -0.0 | -0.317 | 0.035 | 0.234 | -0.35 | -0.46 | -0.137 | 0.091 | 0.139 | 0.103 | -0.282 | -0.069 | 0.037 | -0.012 | -0.047 | -0.017 | 0.072 | 0.143 | -0.035 | -0.102 |
| cei2 | 0.644 | 0.0 | 0.21 | -0.225 | -0.366 | -0.129 | -0.25 | -0.226 | 0.048 | -0.025 | 0.052 | 0.045 | -0.093 | -0.037 | 0.097 | -0.066 | -0.147 | 0.114 | 0.03 | -0.161 | 0.123 |
| cei3 | 0.475 | 0.711 | 0.0 | -0.193 | -0.507 | -0.147 | 0.147 | -0.26 | -0.028 | -0.127 | -0.053 | 0.049 | 0.073 | 0.095 | 0.12 | -0.019 | -0.02 | -0.075 | -0.017 | -0.031 | 0.045 |
| cei4 | 0.64 | 0.587 | 0.545 | 0.0 | 0.275 | -0.244 | -0.43 | -0.16 | -0.068 | 0.054 | 0.006 | 0.061 | -0.091 | 0.037 | -0.071 | 0.001 | 0.029 | 0.037 | -0.134 | 0.08 | 0.051 |
| cei5 | 0.713 | 0.537 | 0.423 | 0.742 | 0.0 | -0.065 | -0.402 | -0.162 | -0.038 | 0.052 | -0.003 | -0.14 | -0.033 | 0.193 | -0.14 | -0.027 | 0.163 | -0.002 | 0.124 | 0.043 | -0.157 |
| cei6 | 0.54 | 0.656 | 0.598 | 0.599 | 0.655 | 0.0 | 0.181 | -0.224 | -0.083 | -0.072 | 0.031 | 0.094 | -0.023 | 0.047 | -0.039 | 0.076 | 0.0 | -0.035 | 0.034 | 0.022 | -0.052 |
| cei7 | 0.425 | 0.551 | 0.657 | 0.463 | 0.471 | 0.716 | 0.0 | 0.179 | -0.036 | -0.004 | -0.066 | 0.104 | 0.135 | -0.153 | 0.033 | 0.094 | -0.023 | -0.096 | -0.105 | 0.019 | 0.082 |
| cei8 | 0.574 | 0.584 | 0.517 | 0.587 | 0.584 | 0.603 | 0.689 | 0.0 | 0.112 | -0.011 | -0.063 | 0.082 | 0.087 | -0.23 | 0.007 | -0.01 | 0.008 | -0.005 | -0.085 | 0.065 | 0.019 |
| ma1 | 0.278 | 0.294 | 0.272 | 0.204 | 0.251 | 0.272 | 0.257 | 0.293 | 0.0 | -0.052 | -0.226 | -0.41 | -0.22 | -0.023 | 0.159 | -0.093 | -0.073 | 0.01 | -0.009 | 0.016 | -0.007 |
| ma2 | 0.273 | 0.238 | 0.202 | 0.223 | 0.256 | 0.243 | 0.242 | 0.219 | 0.576 | 0.0 | -0.154 | -0.313 | -0.305 | -0.153 | -0.103 | 0.061 | -0.15 | 0.185 | 0.053 | -0.038 | -0.014 |
| ma3 | 0.239 | 0.239 | 0.196 | 0.18 | 0.205 | 0.247 | 0.18 | 0.167 | 0.394 | 0.405 | 0.0 | -0.229 | -0.363 | -0.114 | -0.034 | -0.014 | 0.013 | 0.032 | 0.026 | -0.037 | 0.01 |
| ma4 | 0.073 | 0.219 | 0.235 | 0.177 | 0.147 | 0.255 | 0.241 | 0.208 | 0.504 | 0.508 | 0.424 | 0.0 | 0.147 | -0.289 | 0.032 | 0.022 | 0.087 | -0.135 | -0.068 | -0.02 | 0.083 |
| ma5 | 0.182 | 0.209 | 0.277 | 0.16 | 0.217 | 0.255 | 0.287 | 0.246 | 0.559 | 0.498 | 0.352 | 0.716 | 0.0 | -0.281 | 0.035 | 0.005 | 0.057 | -0.093 | -0.039 | 0.043 | -0.003 |
| ma6 | 0.188 | 0.188 | 0.252 | 0.173 | 0.269 | 0.239 | 0.136 | 0.087 | 0.575 | 0.496 | 0.414 | 0.502 | 0.492 | 0.0 | -0.096 | 0.017 | 0.063 | 0.012 | 0.044 | 0.047 | -0.086 |
| orgcmt1 | 0.232 | 0.266 | 0.281 | 0.255 | 0.215 | 0.256 | 0.261 | 0.226 | 0.371 | 0.271 | 0.275 | 0.394 | 0.348 | 0.258 | 0.0 | -0.237 | -0.366 | -0.356 | -0.103 | 0.025 | 0.074 |
| orgcmt2 | 0.215 | 0.201 | 0.219 | 0.282 | 0.259 | 0.292 | 0.281 | 0.215 | 0.307 | 0.376 | 0.318 | 0.431 | 0.374 | 0.343 | 0.495 | 0.0 | -0.341 | -0.389 | 0.015 | -0.022 | 0.006 |
| orgcmt3 | 0.182 | 0.128 | 0.174 | 0.246 | 0.279 | 0.219 | 0.191 | 0.174 | 0.362 | 0.342 | 0.369 | 0.502 | 0.44 | 0.404 | 0.474 | 0.528 | 0.0 | -0.309 | -0.061 | 0.082 | -0.02 |
| orgcmt7 | 0.288 | 0.297 | 0.216 | 0.317 | 0.288 | 0.277 | 0.223 | 0.243 | 0.328 | 0.418 | 0.322 | 0.343 | 0.313 | 0.323 | 0.362 | 0.39 | 0.455 | 0.0 | 0.141 | -0.083 | -0.055 |
| orgcmt5 | -0.039 | -0.114 | -0.162 | -0.201 | -0.075 | -0.166 | -0.16 | -0.14 | -0.214 | -0.178 | -0.179 | -0.352 | -0.328 | -0.147 | -0.369 | -0.321 | -0.393 | -0.185 | 0.0 | -0.437 | -0.533 |
| orgcmt6 | -0.016 | -0.088 | -0.071 | -0.018 | -0.004 | -0.061 | -0.017 | 0.015 | -0.14 | -0.155 | -0.157 | -0.258 | -0.22 | -0.086 | -0.151 | -0.163 | -0.157 | -0.137 | 0.379 | 0.0 | -0.529 |
| orgcmt8 | -0.203 | -0.154 | -0.205 | -0.205 | -0.25 | -0.269 | -0.156 | -0.173 | -0.255 | -0.245 | -0.22 | -0.341 | -0.357 | -0.242 | -0.3 | -0.327 | -0.381 | -0.272 | 0.42 | 0.322 | 0.0 |

The lower diagonal of this table shows the correlations among all indicators, whereas the upper diagonal shows the differences between the sample correlations and model-implied correlations.

**Correlations between indicators and components**

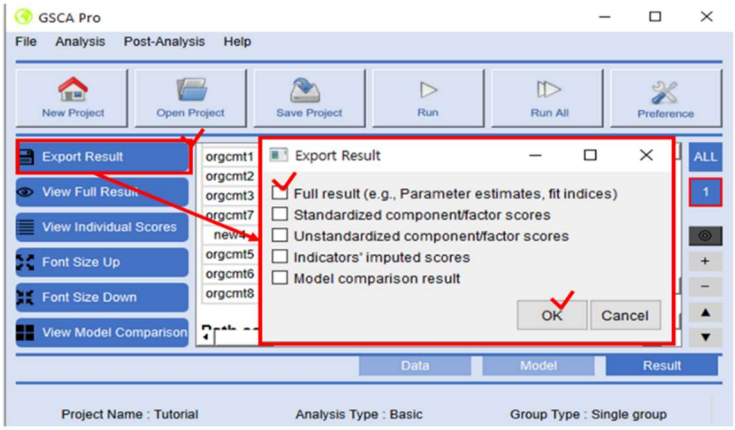
| | OP | OI | AC_Joy | AC_Love |
|---|---|---|---|---|
| cei1 | 0.781 | 0.262 | 0.295 | -0.119 |
| cei2 | 0.825 | 0.302 | 0.283 | -0.157 |
| cei3 | 0.77 | 0.314 | 0.286 | -0.196 |
| cei4 | 0.804 | 0.243 | 0.356 | -0.193 |
| cei5 | 0.801 | 0.288 | 0.34 | -0.152 |
| cei6 | 0.843 | 0.33 | 0.338 | -0.224 |
| cei7 | 0.776 | 0.299 | 0.309 | -0.152 |
| cei8 | 0.801 | 0.271 | 0.277 | -0.138 |
| ma1 | 0.332 | 0.787 | 0.445 | -0.27 |

| | | | | |
|---|---|---|---|---|
| ma2 | 0.296 | 0.758 | 0.457 | -0.255 |
| ma3 | 0.259 | 0.637 | 0.42 | -0.244 |
| ma4 | 0.244 | 0.823 | 0.548 | -0.419 |
| ma5 | 0.287 | 0.811 | 0.484 | -0.4 |
| ma6 | 0.241 | 0.743 | 0.436 | -0.213 |
| orgcmt1 | 0.311 | 0.425 | 0.748 | -0.365 |
| orgcmt2 | 0.307 | 0.473 | 0.79 | -0.361 |
| orgcmt3 | 0.249 | 0.533 | 0.82 | -0.416 |
| orgcmt7 | 0.335 | 0.446 | 0.707 | -0.264 |
| orgcmt5 | -0.165 | -0.316 | -0.417 | 0.796 |
| orgcmt6 | -0.041 | -0.229 | -0.198 | 0.71 |
| orgcmt8 | -0.253 | -0.369 | -0.42 | 0.781 |

This table shows the correlations between each indicator and all components. This information may be used for re-specifying the relationships between indicators and components (measurement model).

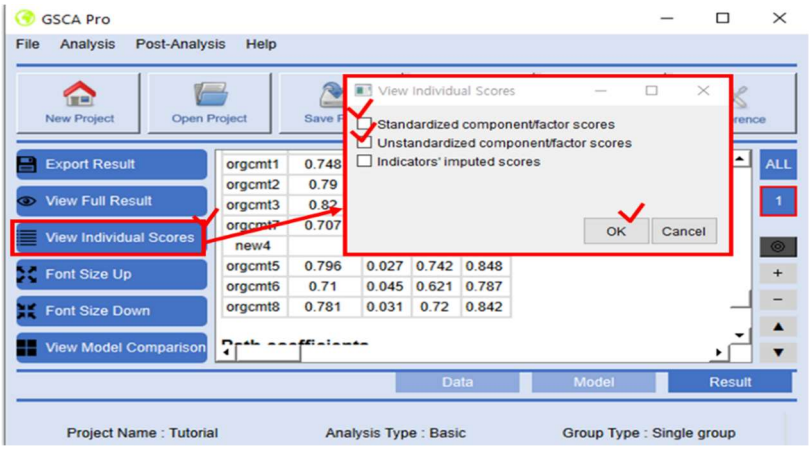
## 4. Export Results

- Users can export and store full results in csv format by clicking on [**Export Result**], checking the Full result box in the "Export Result" window, and clicking on [OK].




## 5. View Individual Scores

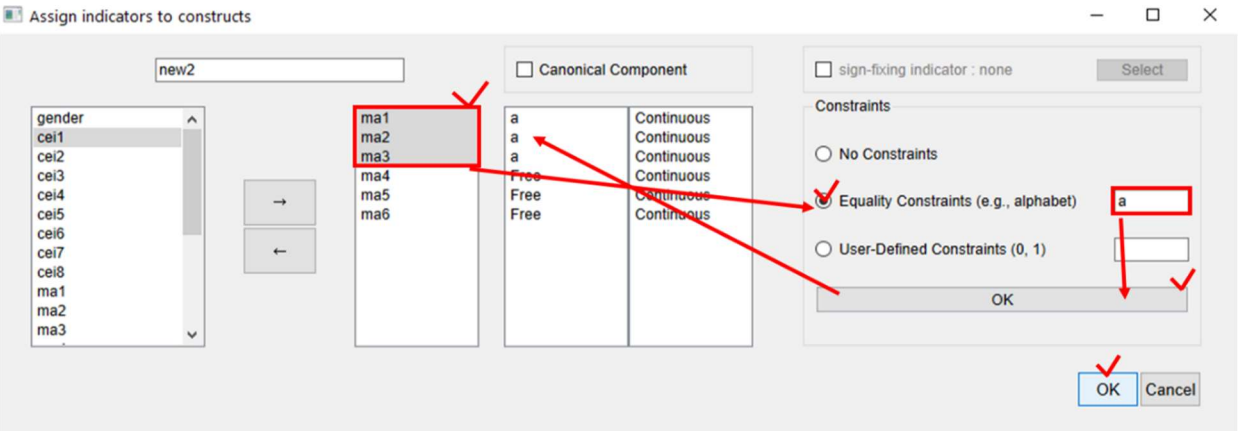
- Users can view individual scores (i.e., standardized construct scores, unstandardized construct scores, or indicator scores with missing values imputed) by clicking on [**View Individual Scores**].


GSCA Pro
File
Analysis
Post-Analysis
Help
New Project
Open Project
Export Result
View Full Result
View Individual Scores
Font Size Up
Font Size Down
View Model Comparison
View Individual Scores
Standardized component/factor scores
Unstandardized component/factor scores
Indicators' imputed scores
OK
Cancel
orgcmt1 0.748
orgcmt2 0.79
orgcmt3 0.82
new4
orgcmt5 0.796 0.027 0.742 0.848
orgcmt6 0.71 0.045 0.621 0.787
orgcmt8 0.781 0.031 0.72 0.842
ALL
1
Data
Model
Result
Project Name : Tutorial
Analysis Type : Basic
Group Type : Single group

# Analysis – Basic GSCA with Constrained Parameters

## 1. How to impose equality constraints on loadings

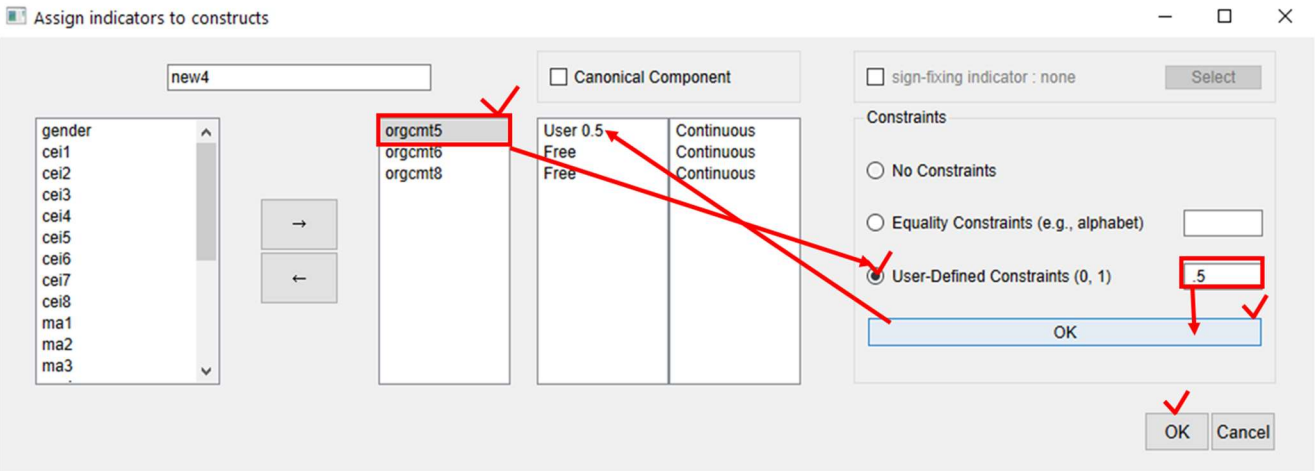
- In the "**Assign Indicators to Constructs**" window, select indicators whose loadings are constrained to be equal.
- Constrain the loadings of the selected indicators to be identical by inserting a label (e.g., an alphabet letter or number) in the "**Equality Constraints**" dialog box. Then, click on "**OK**".




* Note that any loadings with the same label will be constrained to be equal. In the above example, three indicators (ma1 – ma3) are chosen and labeled "a", indicating that the loadings for these indicators are constrained to be equal.

## 2. How to constrain loadings to user-defined values

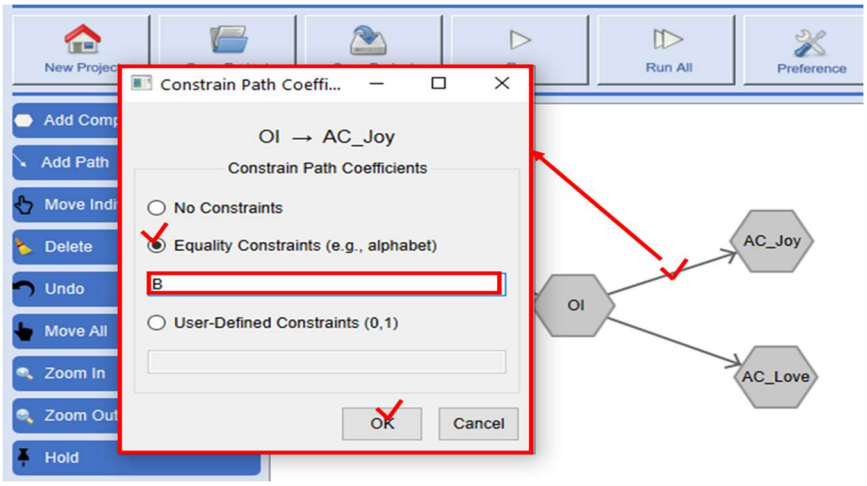
- In the "**Assign Indicators to Constructs**" window, select an indicator whose loading is to be fixed to a user-defined value.
- Constrain the loading of the selected indicator to a user-defined value by inserting that value in the "**User-Defined Constraints**" dialog box. Then, click on "**OK**".



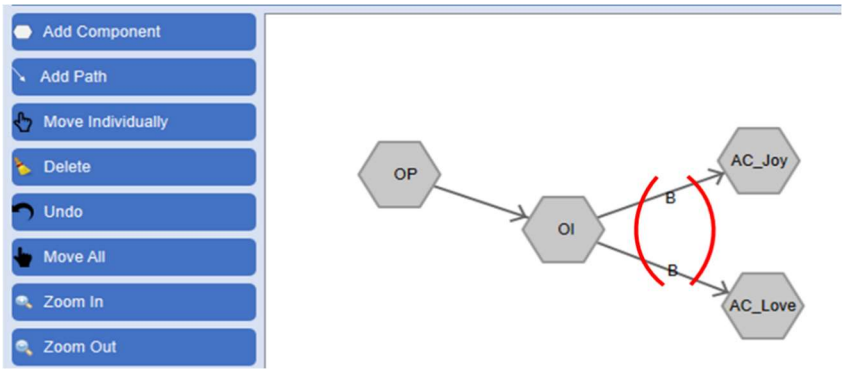
* Note that user-defined values should be between 0 and 1 (**exclusive**).

## 3. How to impose equality constraints on path coefficients

- Double-click on the middle point of an individual path to be constrained in the model.
- In the "**Constrain Path Coefficients**" window, constrain the selected path coefficient by inserting a label (alphabet or number) in the "**Equality Constraints**" dialog. Then, click on "**OK**".

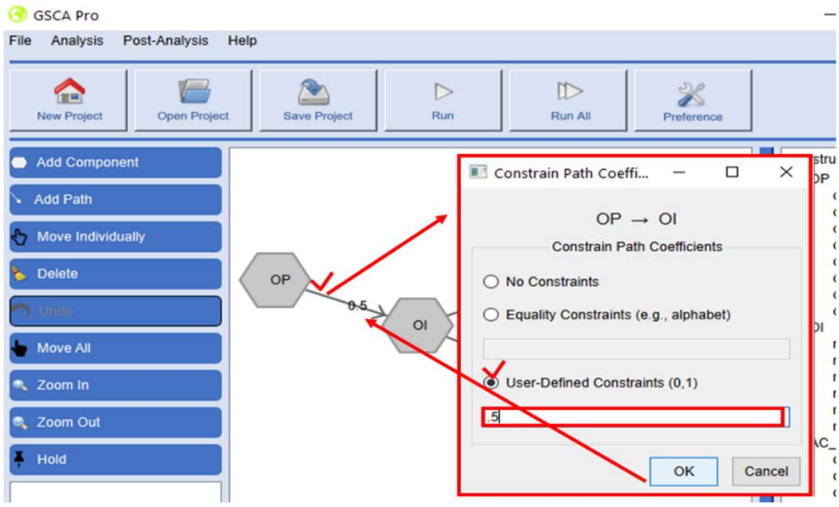



- Repeat the above step for other path coefficients that are to be held equal to the first path coefficient, using the same label.
- In the model, subsequently, users can see all chosen paths labeled the same ("B"), indicating that they are constrained to be equal.




## 4. How to impose a user-defined constraint on path coefficients

- Double-click on the middle point of an individual path to be constrained in the model.
- In the "**Constrain Path Coefficients**" window, constrain the selected path coefficient to a user-defined value (between 0 and 1) by inserting that value in the "**User-Defined Constraints**" dialog. Then, click on "**OK**".



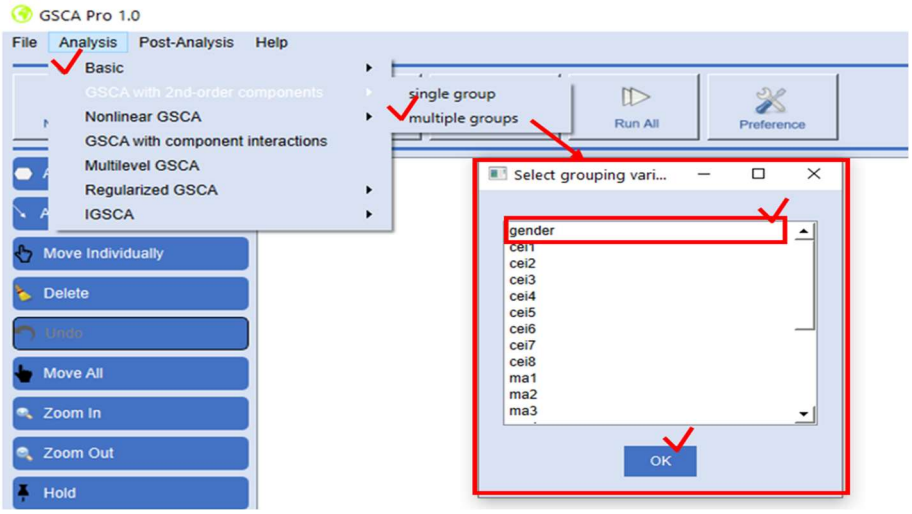

- In the model, subsequently, users can see the path fixed to the defined value.
- Note that user-defined values should be between 0 and 1 (**exclusive**).

# Analysis – Basic GSCA: Multigroup Analysis

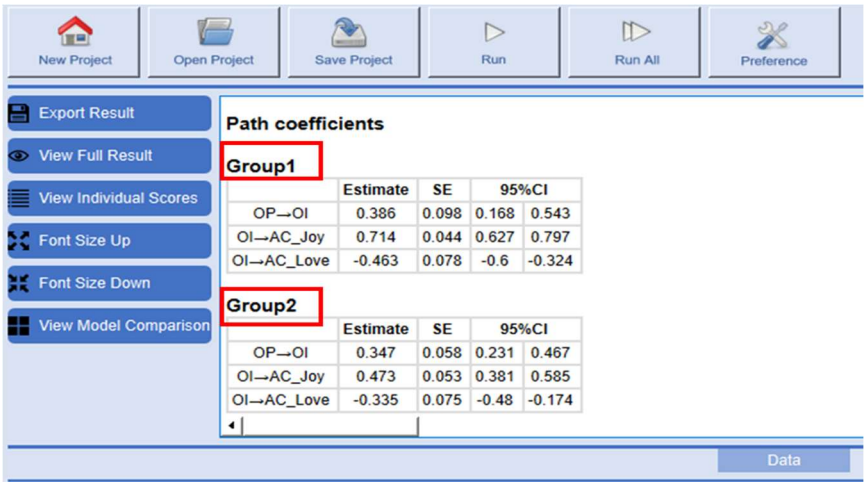
* Note: To conduct a multiple-group analysis, users must include a categorical, grouping variable in the data, which indicates group memberships of cases. Group memberships must be denoted by integers (e.g., sex: 1 = male & 2 = female), not by non-numeric characters.

## 1. How to conduct a multi-group analysis without cross-group equality constraints

- To begin, select "**Analysis → Basic GSCA → multiple groups**" under the [**Analysis**] menu.
- Select a grouping variable in the list of indicators in a dialog box. Then, click on "**OK**". In this example, "gender" was chosen.

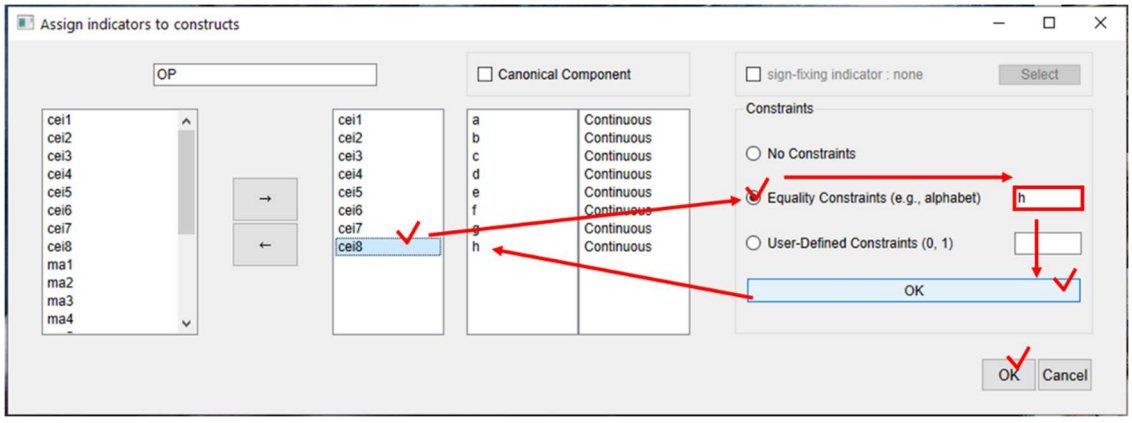



- Users then specify their measurement and structural models in the same way as described for a basic, single group analysis.
- Once the above steps are complete, users can run *GSCA Pro* for fitting the specified model to multiple groups simultaneously. This is done by clicking on the **[Run]** shortcut.
- As shown below, all multi-group analysis results are displayed in the "**Results**" window. In this example, the same model was applied to two groups (males and females) at the same time. Thus, all parameter estimates are provided for each of the two groups labeled Group 1 and Group 2.

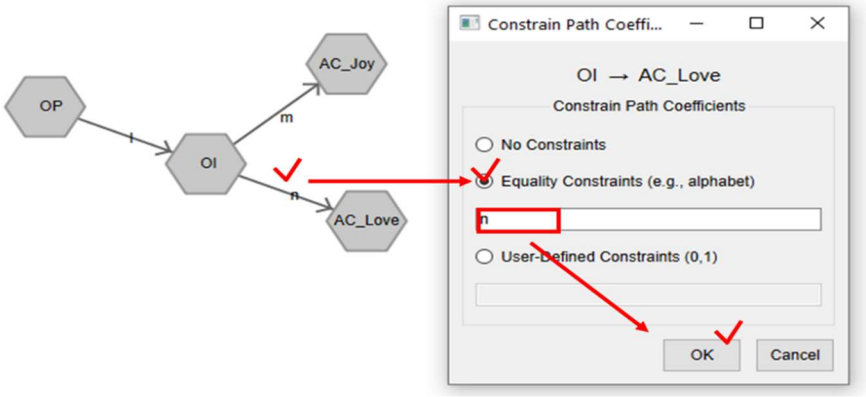



## 2. How to conduct a multi-group analysis with cross-group equality constraints

- To impose cross-group equality constraints on loadings, select indicators whose loadings are constrained to be equal across groups in the "**Assign Indicators to Constructs**" window. Then, constrain the loadings of the selected indicators to be identical across groups by inserting a label (alphabet or number) in the "**Equality Constraints**" dialog box. Then, click on "**OK**".




- To impose cross-group equality constraints on path coefficients, clicking on the middle point of a path in the model. Then, constrain the selected path coefficient to be identical across groups by inserting a label in the "**Equality Constraints**" dialog box. Then, click on "**OK**".

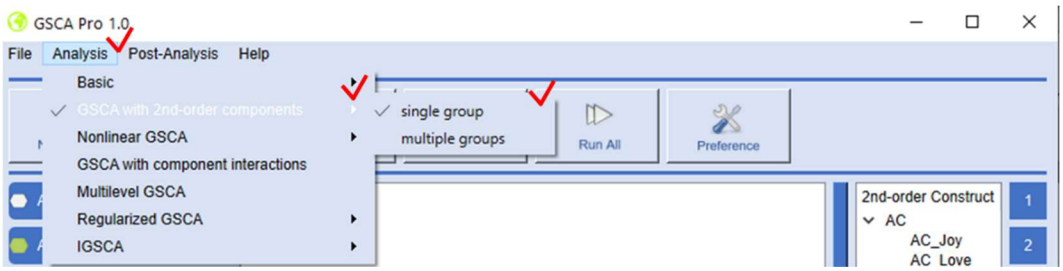



- Note that any loadings and path coefficients with the same label will be constrained to be equal across groups.

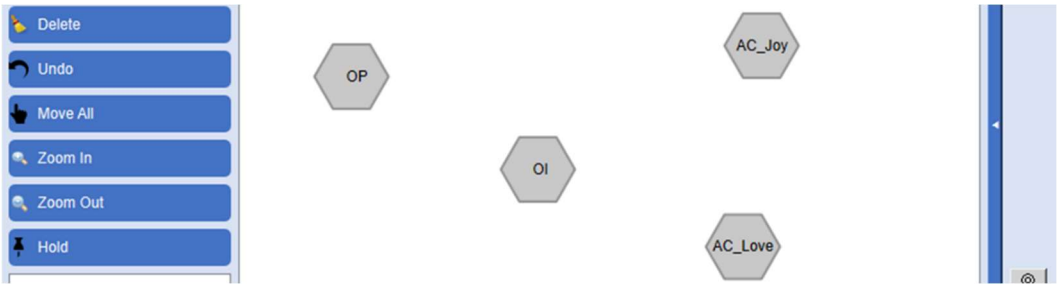
# Analysis – GSCA with 2nd-order Components

Users can specify and examine a model that involves second-order components (Hwang & Takane, 2014, Chapter 3).

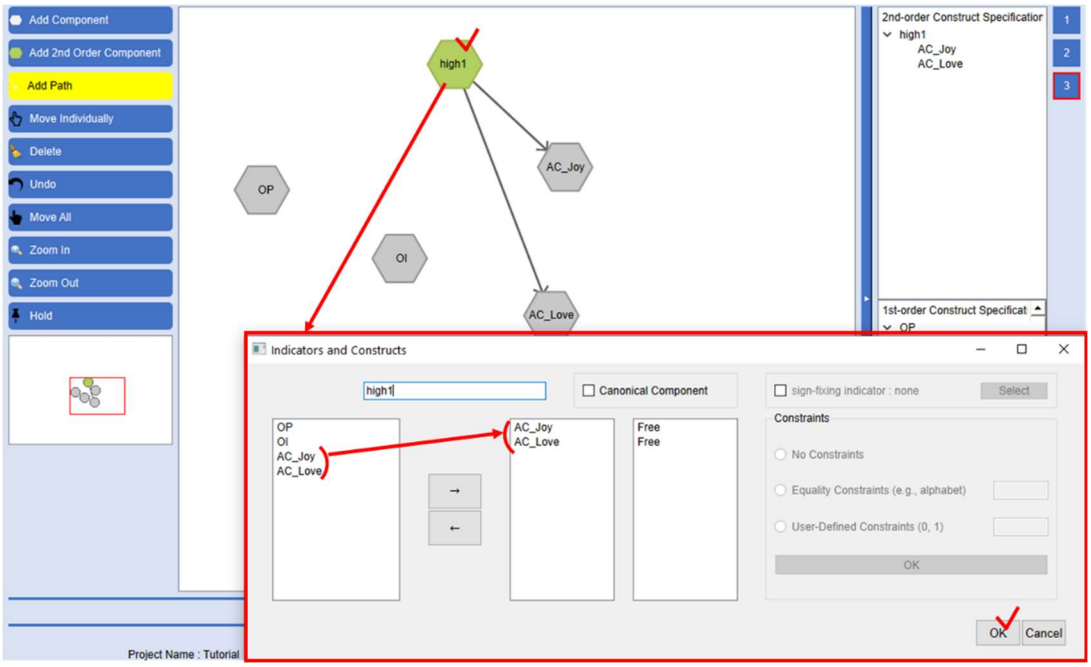
- To begin, select "**Analysis → GSCA with 2nd-order Components → single group or multiple groups**" under the [**Analysis**] menu.




- Users specify (first-order) components as described earlier.

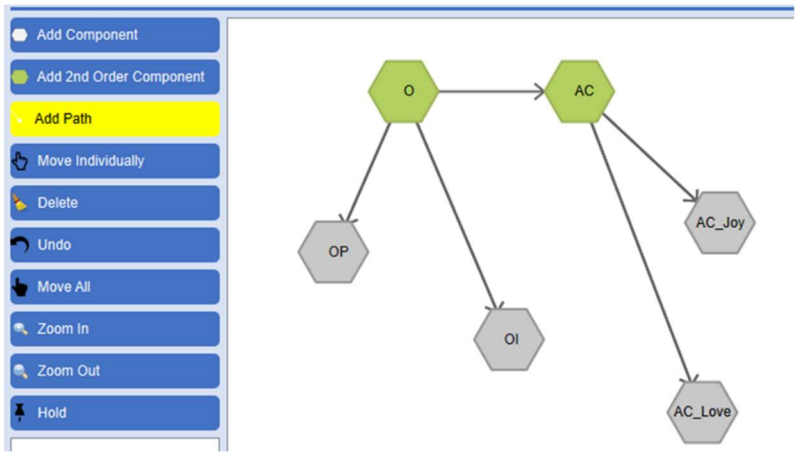



- Subsequently, users specify second-order components as follows:
  - Click once on **[Add 2nd-Order Component]** in the Tool Panel. Click the left mouse button with the cursor placed in the Main Window as many times as the number of second-order components, which appear as green hexagons. In the example below, a second-order component, labeled *high1*, is assumed to be linked to *AC_Joy* and *AC_Love*.
  - After drawing all second-order components, double-click on an individual second-order component.




- In the "**Assign Indicators to Constructs**" window,
  - Users can rename the second-order component by typing a new name.
  - User select the (first-order) components in the list and move them to the right-hand dialog window ("Free" means a free loading to be estimated).
  - Then, arrows connecting second-order components to their first-order components will appear in the model.
  - Optionally,
    - ✓ Users can specify the second-order component as a canonical component, which does not involve loadings. In this case, the second-order component is connected to its first-order component by a straight line.
    - ✓ If users want to align the sign of each first-order component's weight with the correlation of a certain first-order component (a sign-fixing indicator) with the second-order component, they can indicate which first-order component is used as the sign-fixing indicator.
    - ✓ Users can impose constraints on loadings for 2nd-order components. This can be done in the "**Constrain Path Coefficients**" window. Users can access this window by double-clicking on the middle point of an individual arrow from a 2nd order component to (first-order) components.
  - Click on OK.
- Repeat the above steps for the remaining second-order components.

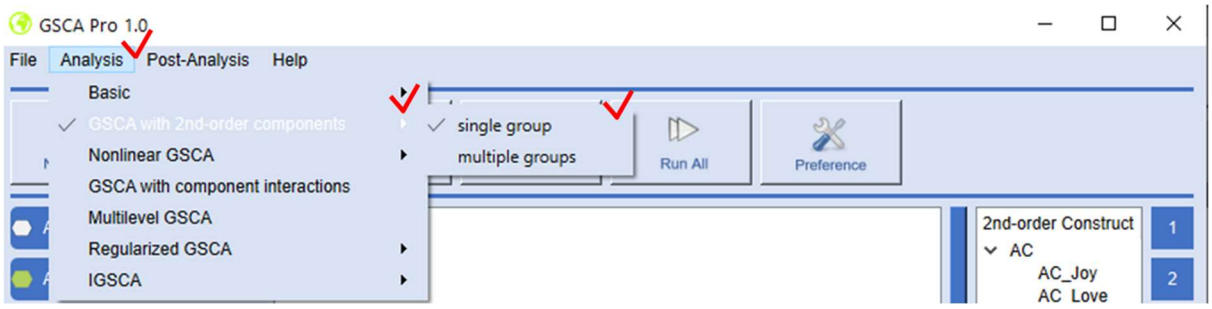
- Users draw path coefficients to complete their structural model.


Add Component
Add 2nd Order Component
Add Path
Move Individually
Delete
Undo
Move All
Zoom In
Zoom Out
Hold
O
AC
OP
OI
AC_Joy
AC_Love

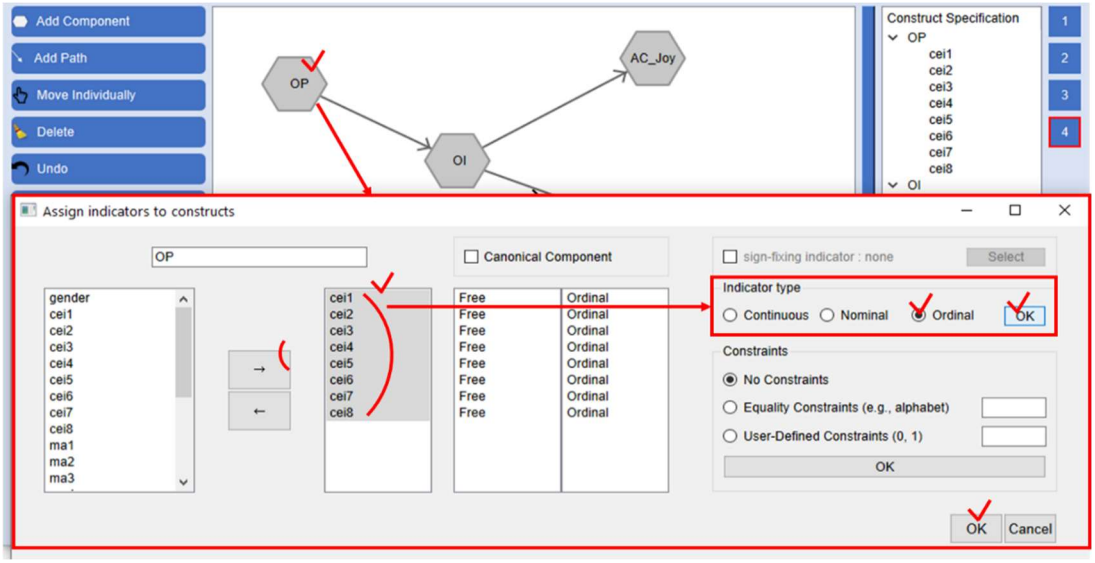
# Analysis – Nonlinear GSCA

Users can apply nonlinear GSCA when indicators are not continuous (i.e., nominal or ordinal) (Hwang & Takane, 2014, Chapter 5).

- To begin, select "**Analysis → Nonlinear GSCA → single group or multiple groups**" under the [**Analysis**] menu.



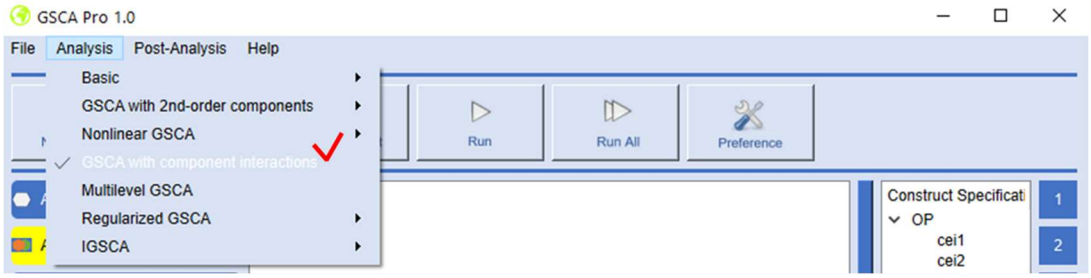

- Users then specify their measurement and structural models as in a basic analysis, as described earlier.
- Double-click on an individual component (a hexagon). Then, the "**Assign Indicators to Constructs**" window will appear.
- In the "**Assign Indicators to Constructs**" window, users select an indicator and then choose the indicator's type in a right-hand dialog box called "**Indicator Type**" and click on "OK" in the box.



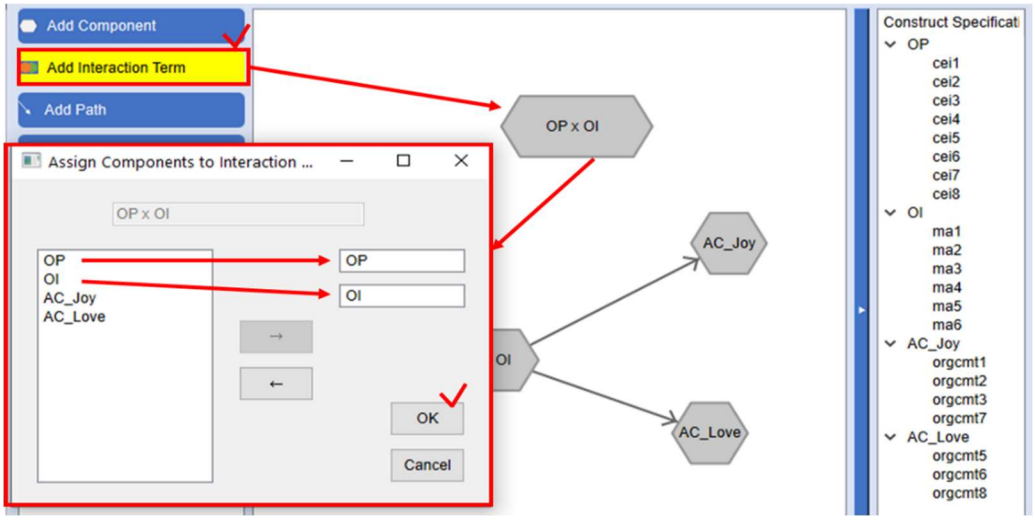
# Analysis – GSCA with Component Interactions

Users can specify and examine interaction terms of components (Hwang et al., 2021; Hwang, Ho, & Lee, 2010; Hwang & Takane, 2014, Chapter 6).

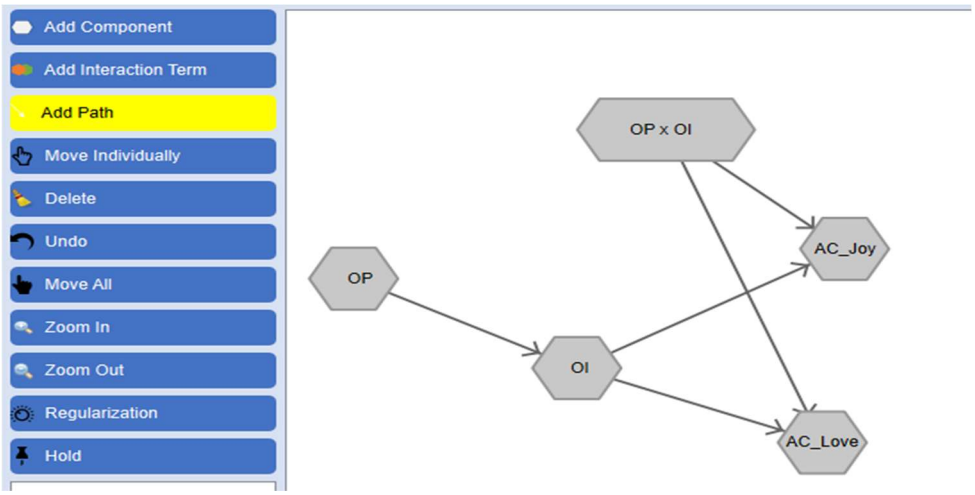
- To begin, select "**Analysis → Component Interaction**" under the [**Analysis**] menu.



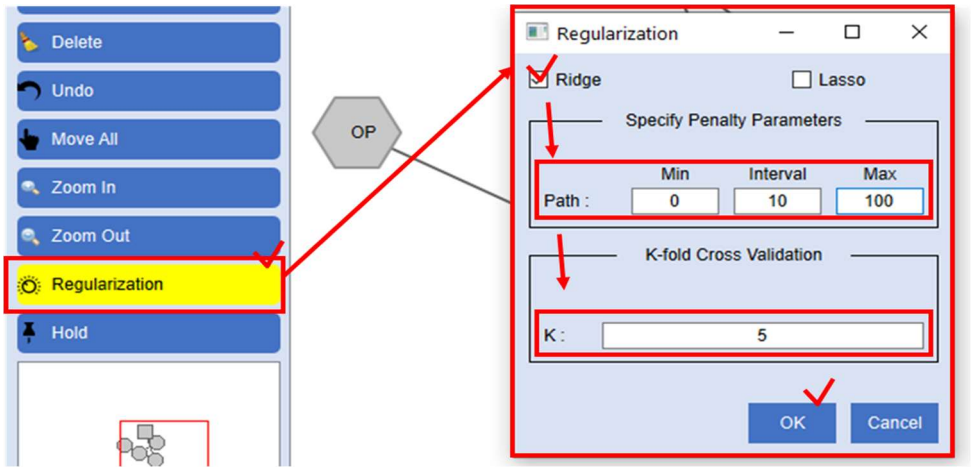

- Users then specify their measurement and structural models without component interaction terms as in a basic analysis, as described earlier.
- To add component interaction terms, click once on **[Add Component Interaction]** in the Tool Panel.
- Click the left mouse button with the cursor placed in the Main Window as many times as the number of component terms. In the present example, one interaction term between OP and OI is specified.
- Double-click on a component interaction term. Then, in the "**Assign Components to Interaction Terms**" window, move each component of the interaction term and click on "OK."




- Repeat the above step for remaining interaction terms.
- Add the paths of the interaction terms.



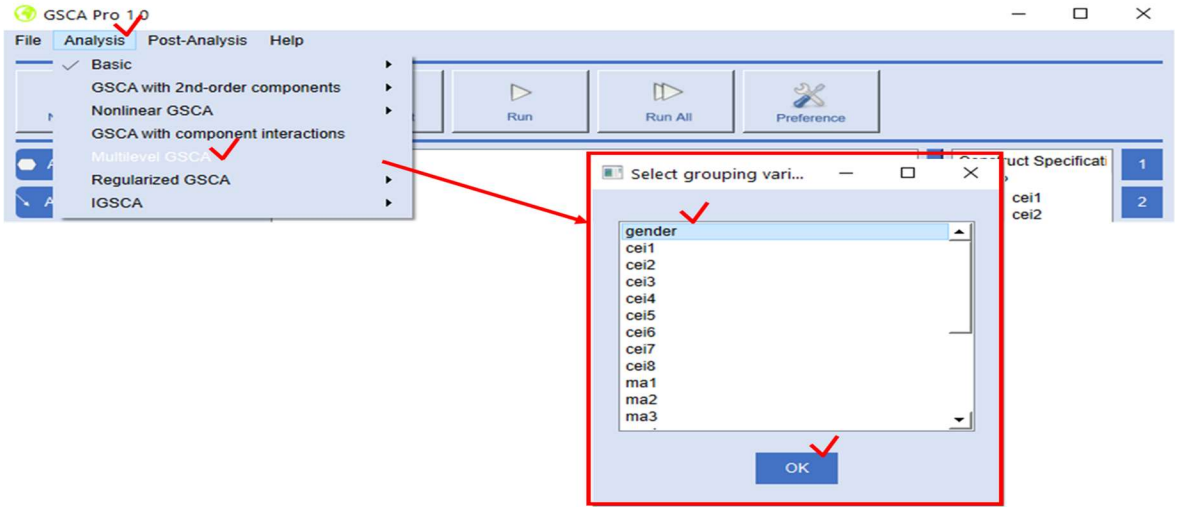

- Optionally, users can conduct **regularized** estimation of path coefficients to avoid potential multicollinearity in the structural model. Such multicollinearity may occur because component interaction terms tend to be highly correlated with their components.
    - To apply regularization, click once on **[Regularization]** in the Tool Panel.
    - In the "**Regularization**" window, users can choose either ridge or lasso regularization. Also, they can choose the range of candidate penalty parameters and the number of data splits for cross validation (i.e., K).



# Analysis – Multilevel GSCA

Note: To apply multilevel GSCA, users must include a categorical, grouping variable in the data, which indicates second-level units. GSCA Pro currently provides a two-level analysis only (Hwang & Takane, 2014, Chapter 7; Hwang, Takane, & Malhotra, 2007).

- To begin, select "**Analysis → Multilevel GSCA**" under the [**Analysis**] menu.
- Select a second-level variable in the list of indicators in the data file in a dialog box. Then, click on "**OK**".

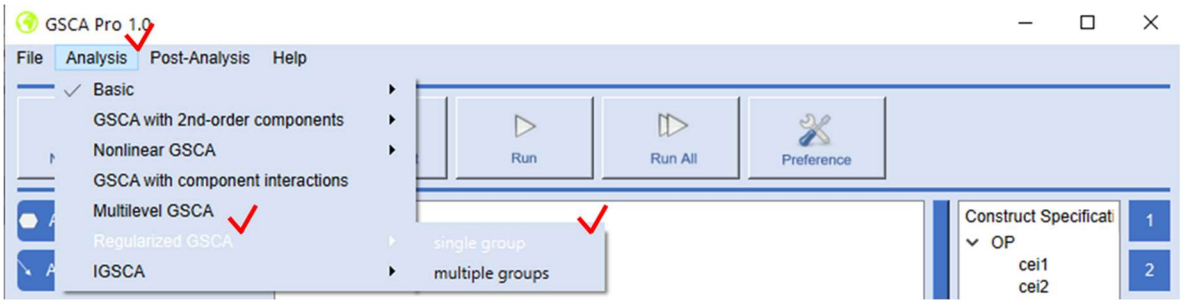



- Then, specify both measurement and structural models as described earlier.

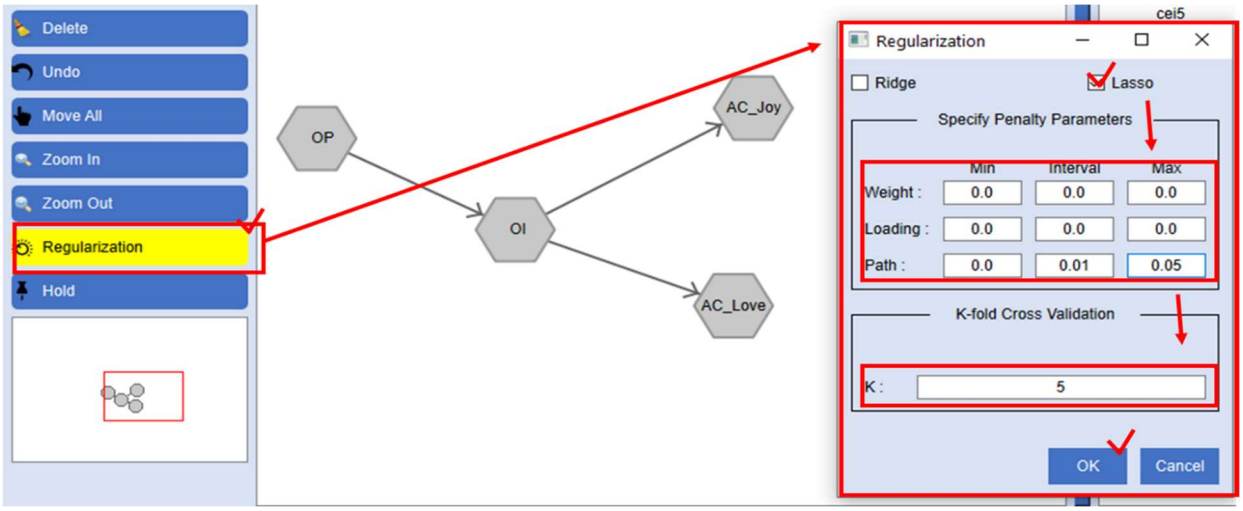
# Analysis – Regularized GSCA

Users can obtained regularized parameter estimates for addressing multicollinearity or selecting variables (Hwang, 2009; Hwang & Takane, 2014, Chapters 8, 9).

- To begin, select "**Analysis → Regularized GSCA → single group or multiple groups**" under the [**Analysis**] menu.



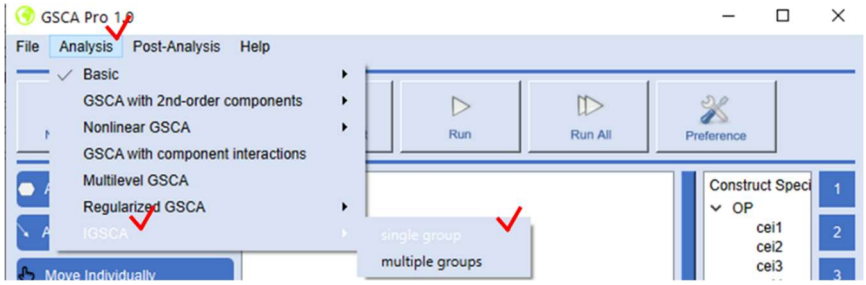

- Specify both measurement and structural models.
- Then, click once on **[Regularization]** in the Tool Panel.
- In the "**Regularization**" window, users can choose either ridge or lasso regularization. Also, they can choose the range of candidate parameters of each penalty term for each parameter set (weight, loading, and path coefficient) and the number of data splits for cross validation (i.e., K).



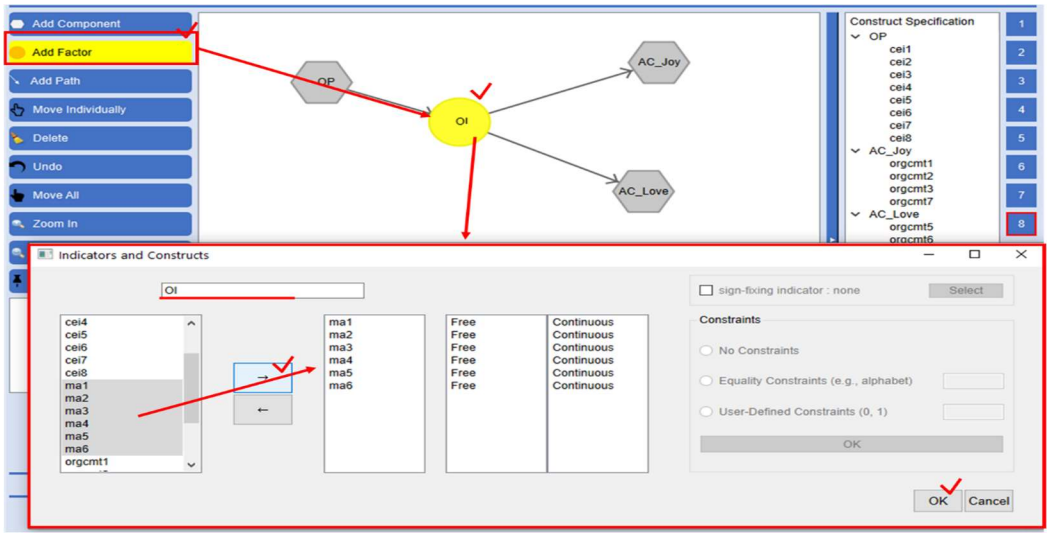
# Analysis – IGSCA

Users can apply Integrated GSCA (IGSCA) for estimating a model that contains both common factors and components (Hwang et al., 2020)

- To begin, select "**Analysis → IGSCA → single group or multiple groups**" under the [**Analysis**] menu.




- Users can add components as described earlier.
- To add factors, click once on **[Add Factor]** in the Tool Panel. Click the left mouse button with the cursor placed in the Main Window as many times as the number of factors. Each factor is displayed by a circle.
- Then, assign indicators to each factor.




- Specify the structural model.

# Post-Analysis – Model Comparison

Users can compare competing models (e.g., constrained and unconstrained models) after fitting the models to the same data (Cho et al., 2019; Hwang & Takane, 2014, Chapter 3).

- Specify a model or open an existing model from a project.
- Users can specify as many competing models as they want by clicking on the [+] box in the Model Bar.
- In the "**Add Model**" window, click on "New Model" and then a new blank page appears in the Main Window for specifying another model (refer to Figure (1)).
- In the "**Add Model**" window, users can also copy and paste an existing model by clicking on the "copy" dialog box. Then, the model appears on a new page in the Main Window and users can modify it (refer to Figure (2)).

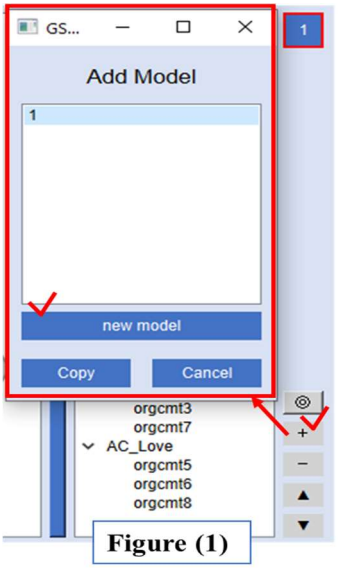


Figure (1)

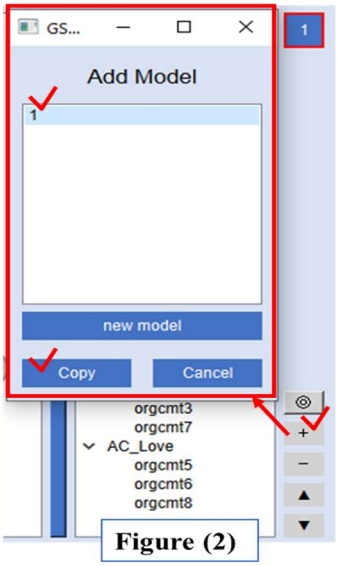
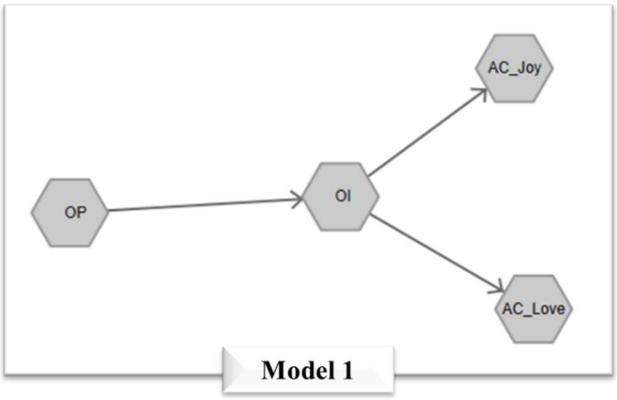
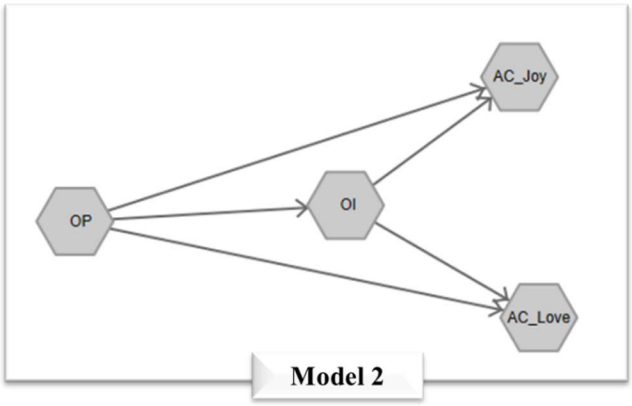


Figure (2)

- Likewise, users can delete any model by clicking on the [-] box in the Model Bar.
  - In the present example, we specified the following competing models.

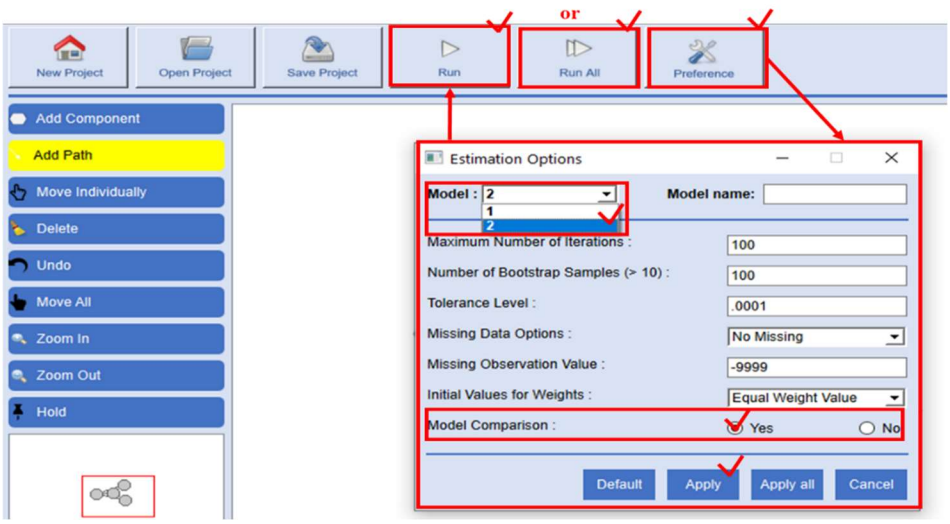


Model 1

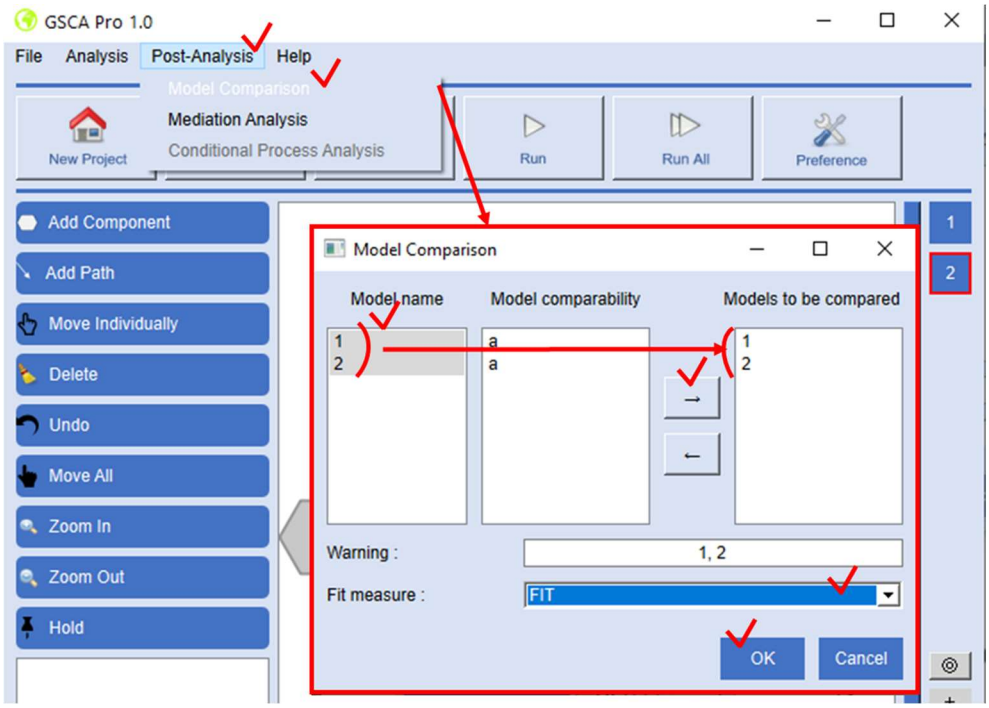


Model 2

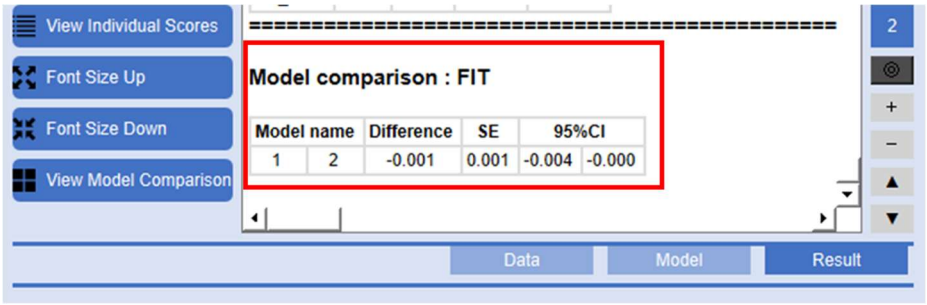
- Users can fit specified models individually by clicking on the [**Run**] shortcut for each model or fit all models simultaneously by clicking on the [**Run All**] shortcut.
  - **IMPORTANT:** Before fitting models, users should indicate which models they plan to compare. To do this, select the [**Preference**] shortcut and select "Yes" in the bottom option of **Model Comparison** per model and click on "**Apply**". If you click on "**Apply all**", all the preference options that you set up for a model will also be applied to the other models.




- After fitting all models, select "**Post-Analysis → Model Comparison**" under the [**Analysis**] menu.
- In the left-hand "**Model Name"** dialog box of the [**Model Comparison**] window, move all the models that users want to compare to the right-hand "**Models to be compared**" dialog box. Note that the middle "**Model comparability"** dialog box shows which models are directly comparable. Only the models with the same label can be compared in a pair-wise manner.
- Users can choose which model fit index(es) they will use for comparing models in the bottom dialog box "**Fit measures**."

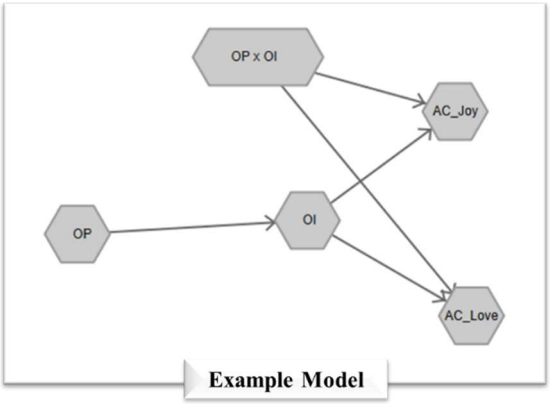


- In the "**Result**" window, each pair of the selected competing models is compared based on each fit index. For example, if the FIT difference between two models is statistically significant (i.e., its 95% confidence interval does not contain a zero), the model with the larger FIT value may be preferred in terms of explanation power of the sample at hand. If the OPE difference between two models is statistically significant, the model with the smaller OPE may be preferred in terms of prediction power of unseen samples.

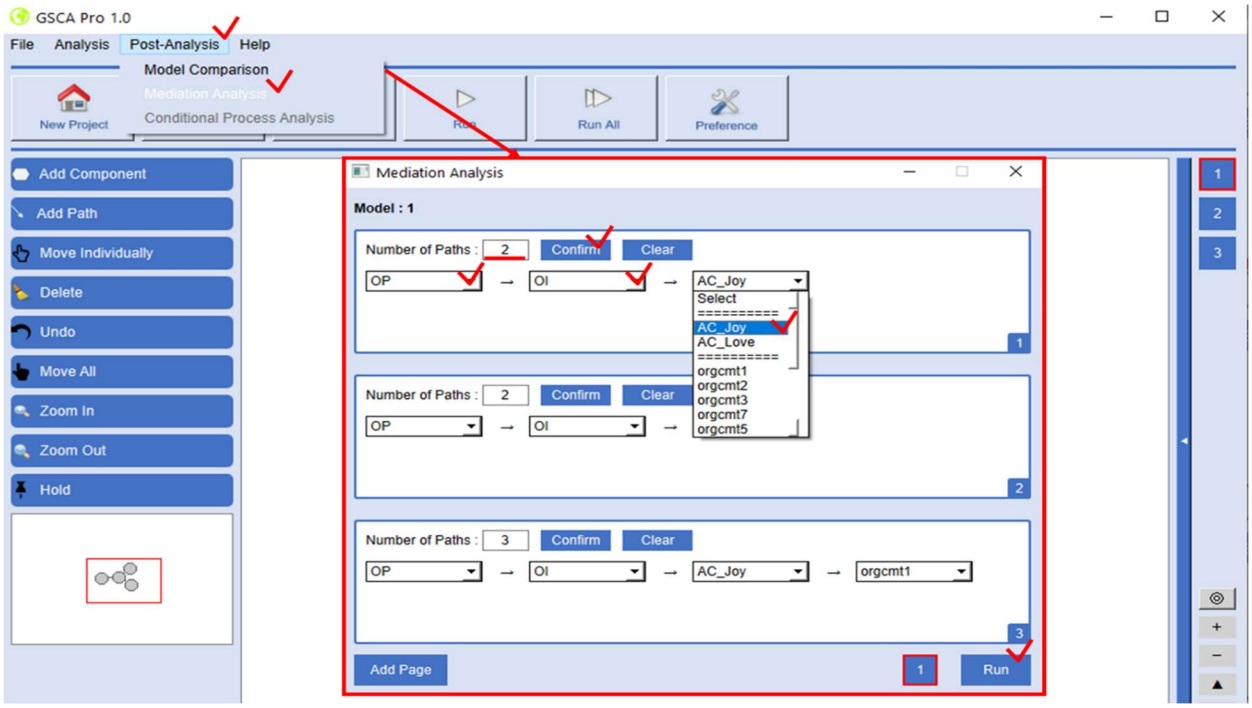


# Post-Analysis – Mediation Analysis

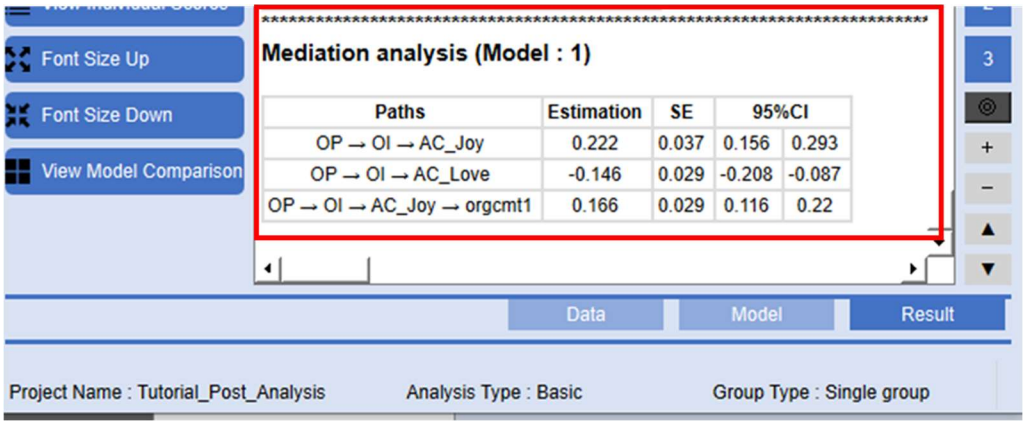
After fitting a model, users can calculate an indirect effect of a variable (component or indicator) and examine its statistical significance (Hwang & Takane, 2014, Chapter 3).




- After fitting a model, select "**Post-Analysis → Mediation Analysis**" under the menu of [**Analysis**].
- In the "**Mediation Analysis**" window, indicate how many paths are involved in an indirect effect of interest in the "**Number of Paths**" box and click on "**Confirm**."
  - In the present example, if users want to test the indirect effect of OP on AC_Joy through OI, there are two paths involved (i.e., OP → OI and OI → AC_Joy). Thus, they can put 2 in the Number of Paths box.
- Then, assign a variable (component or indicator) to each of the small boxes and click on "**Run**" in the bottom.
  - In the present example, if users want to test the indirect effect of OP on AC_Joy through OI, they assign OP to the first box, OI to the second, and AC_Joy to the third box.
- Users can test a maximum of three indirect effects per page. If they want to test more indirect effects, they can add an extra page by clicking on "**Add Page**" in the bottom.



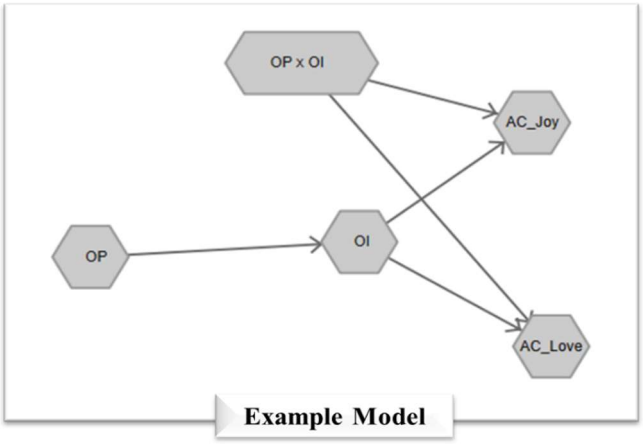
- In the "**Result**" window, users can view each indirect effect's estimate and its standard error and 95% confidence interval.



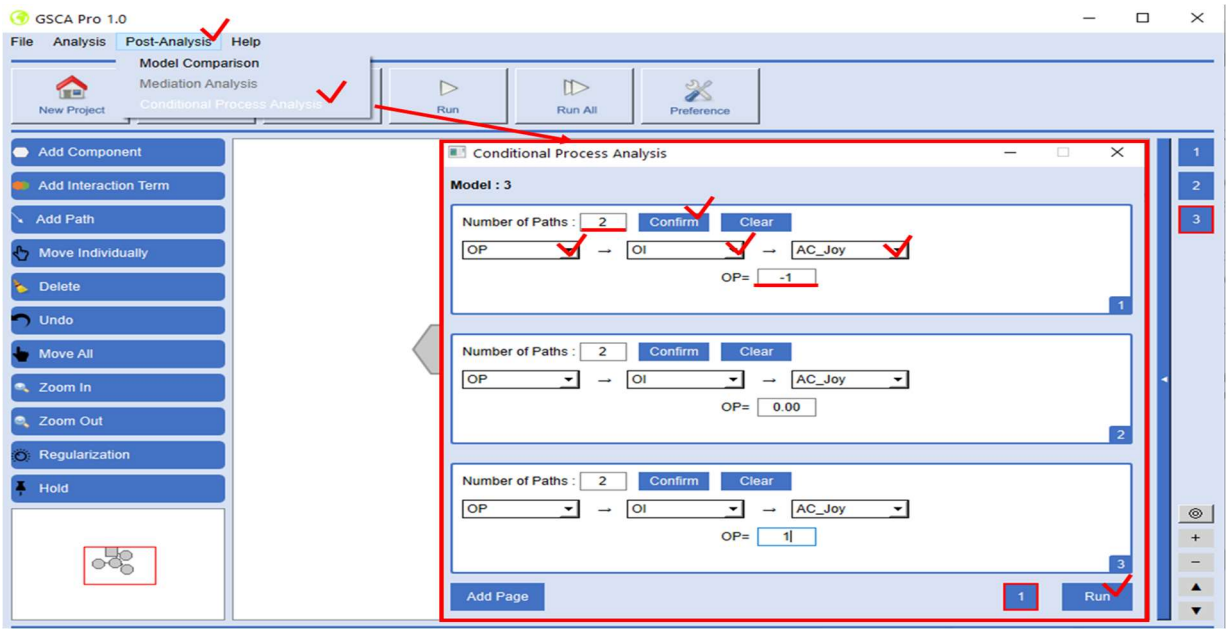
## Post-Analysis – Conditional Process Analysis

Conditional process analsyis refers to an analytic approach that encompasess mediation, moderation, moderated mediaton, and mediated moderation analyses (Hayes, 2013; Hayes & Preacher, 2013). *GSCA Pro* enables users to conduct a conditional process analysis that involves components or indicators. Before conducting this analysis, users first specify and fit a model with component interaction terms. Hwang et al. (2021) provides an example of a conditional process analysis in GSCA.

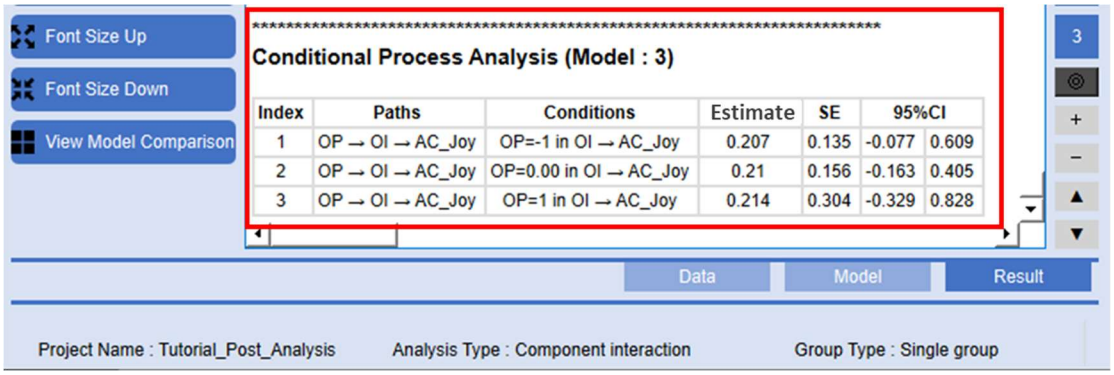
Below, we explain how to compute and test the indirect effect of a variable (component or indicator) at user-defined, specific values of moderators. For illustration, we consider the following model.




- After fitting a model, select "**Post-Analysis → Conditional Process Analysis**" under the **[Analysis]** menu.
- In the "**Conditional Process Analysis**" window, indicate how many paths are involved in a (conditional) direct or indirect effect of interest in the "**Number of Paths**" box and click on "**Confirm**."
    - In the present example, if users want to test the indirect effect of OP on AC_Joy mediated through OI at a certain value of OP, there are two paths involved (i.e., OP → OI and OI → AC_Joy). Thus, they can put 2 in the Number of Paths box.
- Then, assign a variable (component or indicator) to each of the small boxes. Then, *GSCA Pro* automatically searches moderators that are involved in a mediating pathway of interest and ask users to add the values of the moderators. Then, click on "**Run**" in the bottom.
    - In the example, if users want to test the indirect effect of OP on AC_Joy through OI at OP = -1, they assign OP to the first box, OI to the second, and AC_Joy to the third box. Then, they add -1 to the box appearing below the second path.

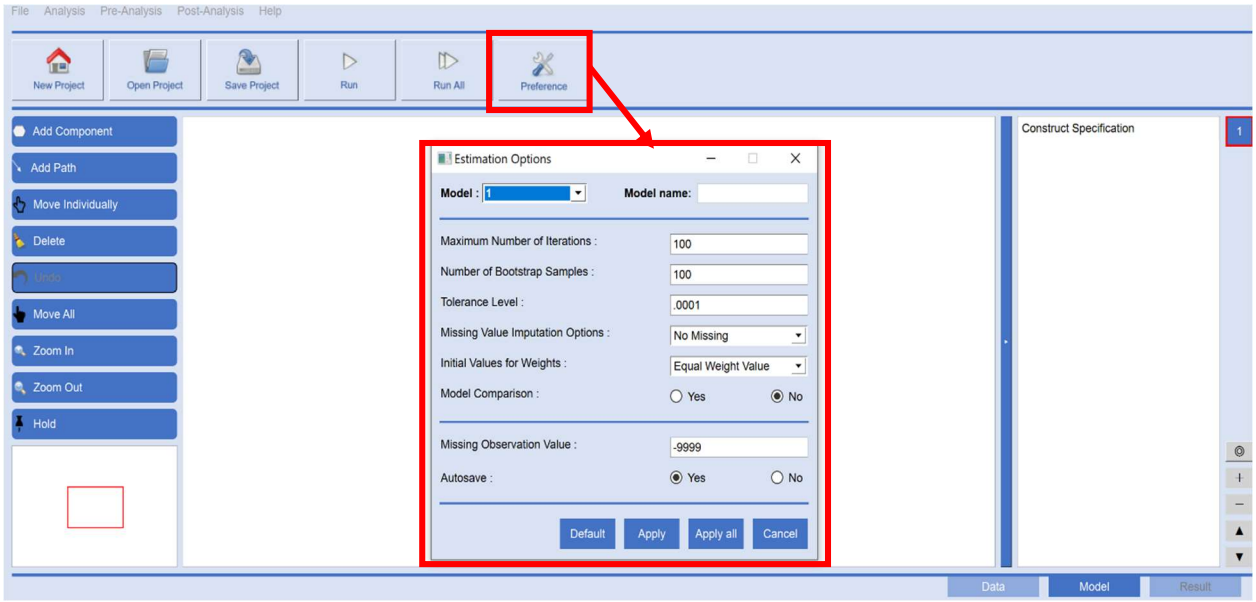



- Users can test three indirect effects per page. If they want to test more effects, they can add an extra page by clicking on "**Add Page**" in the bottom.
- In the "**Result**" window, users can view each effect's estimate and its standard error and 95% confidence interval.



## Preference – Estimation Options

- Users can set up their own estimation options. This can be done by clicking on the [**Preference]** shortcut.




- As GSCA utilizes an iterative algorithm for parameter estimation, users need to decide on the maximum number of iterations, a tolerance level (of the optimization function difference between two consecutive iterations), and initial values for weights. By default, the maximum number of iterations = 100, tolerance level = .0001, and equal initial values are used for weights. Users can change the maximum number of iterations and tolerance level and assign random initial values to weights.
- As GSCA uses the bootstrap method (Efron, 1982) to obtain the standard errors and 95% confidence intervals of parameter estimates, users need to prescribe the number of bootstrap samples. The default number of bootstrap samples is 100.
- *GSCA Pro* currently provides three options for handling missing values: (1) listwise deletion, (2) mean substitution, and (3) least-squares imputation (Hwang & Takane, 2014, Chapter 3). If the uploaded data contain missing observations, users choose one of the options and specify which numeric value indicates missing observations. The default value indicating missing observations is -9999. Users can change it to a user-defined value in the box of **[Missing Observation Value]**.
- If users consider comparing a group of models, they should select "Yes" in the [Model Comparison] option for each model in the comparison group. Then, *GSCA Pro* will save all necessary information on each fitted model for a post-analysis of model comparison. This option may have *GSCA Pro* use a high amount of RAM, tending to decrease computational speed particularly when sample size and/or the number of models to be compared is large.

- Users can set up their preference options for each model separately by clicking on the **[Apply]** button per model number. Also, they can apply the same preference options to all models at one by clicking on the **[Apply all]** button.
- The option **Autosave** (default = Yes) is available that automatically saves the current changes or progress in the program.

# References


Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management*, 57 (2), 103168. https://doi.org/10.1016/j.im.2019.05.003.

Bergami, M., & Bagozzi, R. P. (2000). Self-categorization, affective commitment and group self-esteem as distinct aspects of social identity in the organization. *British Journal of Social Psychology*, 39, 555–577. https://doi.org/10.1348/014466600164633

Cho, G., Hwang, H., Sarstedt, M., & Ringle, C. M. (2020). Cutoff criteria for overall model fit indexes in generalized structured component analysis. *Journal of Marketing Analytics*, *8*, 189–202. https://doi.org/10.1057/s41270-020-00089-1

Cho, G., Jung, K., & Hwang, H. (2019). Out-of-bag prediction error: A cross validation index for generalized structured component analysis. *Multivariate Behavioral Research*, *54*(4), 505–513. https://doi.org/10.1080/00273171.2018.1540340

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillside, NJ: Lawrence Erlbaum Associates.

Efron, B. (1982). *The jackknife, the bootstrap and other resampling plans*. Philadelphia, PA: SIAM. https://doi.org/10.1137/1.9781611970319

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Hair, J., Ringle, C., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19, 139-151. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach.* New York, NY: Guilford Press.

Hayes, A. F., & Preacher, K. J. (2013). Conditional process modeling: Using structural equation modeling to examine contingent causal processes. In *Quantitative Methods in Education and the Behavioral Sciences: Issues, Research, and Teaching. Structural equation modeling: A second course, 2nd ed.* (pp. 219–266). Charlotte, NC, US: IAP Information Age Publishing.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hwang, H. (2009). Regularized generalized structured component analysis. *Psychometrika*, *74*(3), 517–530. https://doi.org/10.1007/S11336-009-9119-Y

Hwang, H., Cho, G., Jin, M. J., Ryoo, J. H., Choi, Y., & Lee, S. H. (2021). A knowledge-based multivariate statistical method for examining gene-brain-behavioral/cognitive relationships: Imaging genetics generalized structured component analysis. *PloS One*, *16*(3), e0247592. https://doi.org/10.1371/journal.pone.0247592

Hwang, H., Cho, G., Jung, K., Falk, C., Flake, J., & Jin, M. (2020). An approach to structural equation modeling with both factors and components: Integrated generalized structured

component analysis. *Psychological Methods*, (Advance online publication). https://doi.org/10.1037/met0000336.
Hwang, H., Ho, M.-H. R., & Lee, J. (2010). Generalized Structured Component Analysis with Latent Interactions. *Psychometrika*, *75*(2), 228–242. https://doi.org/10.1007/s11336-010-9157-5
Hwang, H., & Takane, Y. (2014). *Generalized structured component analysis: A component-based approach to structural equation modeling*. New York, NY: Chapman and Hall/CRC Press.
Hwang, H., Takane, Y., & Malhotra, N. (2007). Multilevel generalized structural component analysis. *Behaviormetrika*, *34*(2), 95–109. https://doi.org/10.2333/bhmk.34.95
Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of The Royal Society A Mathematical Physical and Engineering Sciences.* doi: 10.1098/rsta.2015.0202.
Myers, R. H. (1990) *Classical and modern regression with applications*. PWS-Kent Publishing, Boston.
Rönkkö, M., & Cho, E. (2020). An updated guideline for assessing discriminant validity. *Organizational Research Methods*. Published online. https://doi.org/10.1177/1094428120968614