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# Structural Equation Modeling with AMOS

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## *Chapter-1*

### *The Basic Concepts of Structural Equation Modeling*

#### **1.1. Introduction**

SEM is an extension of the general linear model (GLM) that enables a researcher to test a set of regression equations simultaneously. In other words, the purpose of SEM is to examine a set of relationships between one or more exogenous Variables (independent variables) and one or more endogenous variables (dependent variables). SEM software can test traditional models, but it also permits examination of more complex relationships and models, such as confirmatory factor analysis and time series analysis. Moreover, through SEMs the structural relations can be modeled graphically to enable a clear understanding of the theory under study.

#### **1.2. Benefits of using SEM**

With compared to old multivariate procedures, there are several advantages can be seen in using SEM.

- It conducts a confirmatory rather than exploratory approach to the data analysis (exploratory approach also can be conducted through SEM).
- SEM estimates error variance parameters but traditional multivariate procedures are incapable of estimating the measurement error.
- SEM can incorporate both observed and latent variables, whereas former methods are based on observed measurements only.
- Researcher can get a unifying framework that fit numerous linear models by using SME.
- SEM programs provide overall tests of model fit and individual parameter estimate tests simultaneously.
- Regression coefficients, means, and variances may be compared simultaneously, even across different groups

- Longitudinal data, databases with auto correlated error structures (time series analysis), databases with non-normally distributed variables and incomplete data can be handled.

Because of these advantages of SEM, it has become a popular methodology in non experimental research.

### **1.3. Common terms in SEM**

- Observed and latent variables

Especially in behavioral and social sciences, researchers are often interested in studying two types of theoretical constructs, namely observed (manifest) and latent variables. Observed variables can be observed directly (e.g. income, blood sugar etc.). But researchers very often have to deal with latent variables that cannot be directly measured such as personality, perception, buying behavior etc. Researchers use observed variables to measure the latent variables. The observation may include, for example, self report responses to attitudinal scale, coded responses to an interview questions and the like. These measured scores or in other words observed or manifest variables are used to measure the latent variables.

- Exogenous and endogenous latent variables

Exogenous latent variables are synonymous with independent variables and endogenous latent variables are synonymous with dependent variables. Endogenous variables are influenced by exogenous variables directly or indirectly.

- Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA)

Factor analysis is conducted to investigate the relations between sets of observed and latent variables. If the links between the observed and latent variables are unknown or uncertain, exploratory factor analysis is conducted. Exploratory factor analysis is conducted to determine how, and to what extent, the observed variables are linked to their underline factors. Confirmatory factor analysis is appropriate, when the researcher has some understanding (through theory, empirical research or both) of the latent variable structure.

- The path diagram

Path diagram is a visual representation of relations among variables which are assumed to hold in the study. Basically four geometric symbols are used in the path diagrams; circles or ellipses (  $\bigcirc$  ) represent unobserved latent variables, squares or rectangles represent (  $\square$  ) observed variables, single-headed arrows (  $\longrightarrow$  ) represent the effect of one variable on another variable, and double-headed arrows (  $\longleftrightarrow$  ) represent covariance or correlation between two variables. Figure 1.1, is the simple model used to explain the meanings of the symbols of a path diagram.

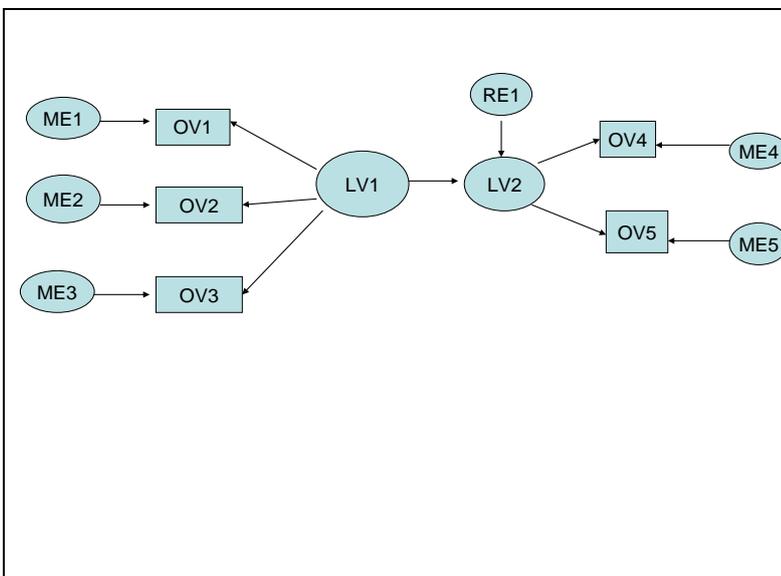


Figure 1.1- Simple path diagram

ME- Measurement Error

RE- Residual Error

OV- Observed Variable

LV- Latent Variable

In the above model (Figure 1.1), there are two latent variables (LV1 is the exogenous variable and LV2 is the endogenous variable) and five observed variables; three are used to measure LV1 and two are used to measure LV2. In addition, there are five measurement errors (ME 1- ME5); associated with each observed variables and one residual error associated with the factor being predicted (LV2).

There is an important distinction between measurement error and residual error. Error in measuring the underline factor or latent variable through observed variable is reflected by measurement error. Residual error represents error in the prediction of endogenous factor from exogenous factor. For example, the residual error shown in figure 1.1 (RE1) represents error in the prediction of endogenous factor (LV2) from exogenous factor (LV1)

The general SEM can be divided in to two sub models; measurement models and structural models. The measurement model shows the relationship between observed and latent variables. In other words it represents the CFA model specifying the pattern by which each measure loads on a particular factor. But structural model shows the relationship between latent variables. There are two measurement models and one structural model in the Figure 1.1 discussed earlier. Figure 1.2 shows an example for a measurement model and Figure 1.3 shows an example model for a structural model and both models are sub models derived from the model given in Figure 1.1

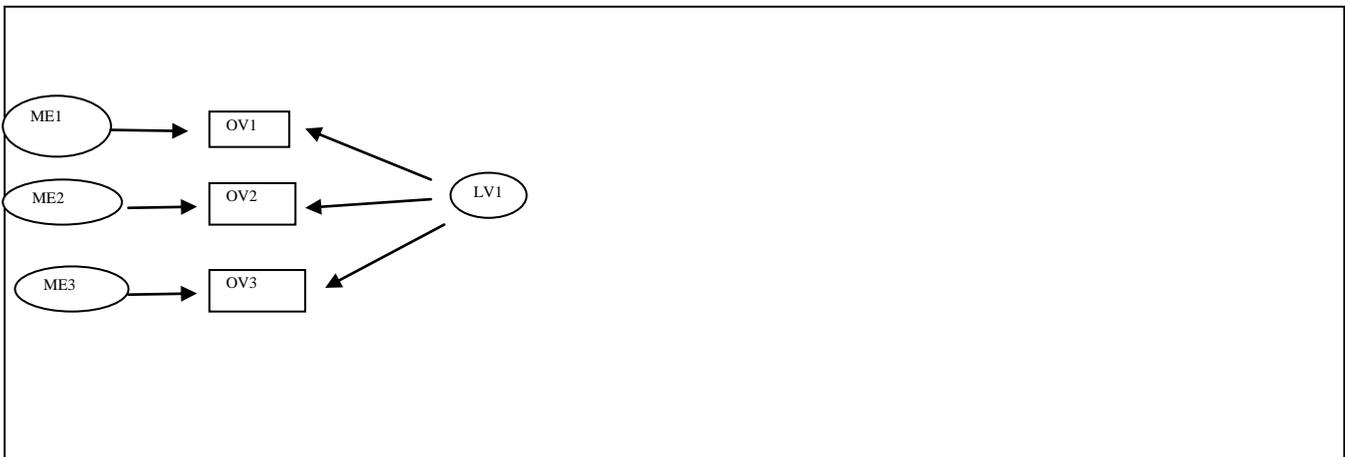


Figure 1.2 – Measurement model

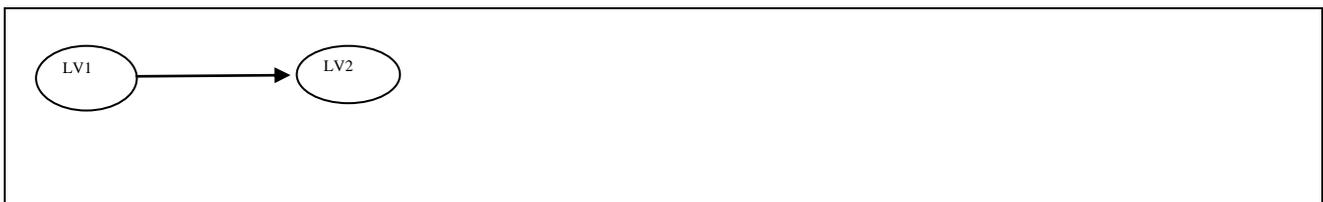


Figure 1.3- Structural model

## **1.4. Chapter Summery**

SEM can test complex set of regression equations simultaneously. Further, in addition to the text outputs, SEM can model the relationships graphically. By using SEM, a researcher can conduct confirmatory approach in data analysis. As well as it estimates error variance parameters. Further, SEM can incorporate both observed and latent variables, whereas former methods are based on observed measurements only. In addition to the above advantages, researcher can get a unifying framework that fit numerous linear models by using SME. It provides overall tests of model fit and individual parameter estimate tests simultaneously, even across different groups.

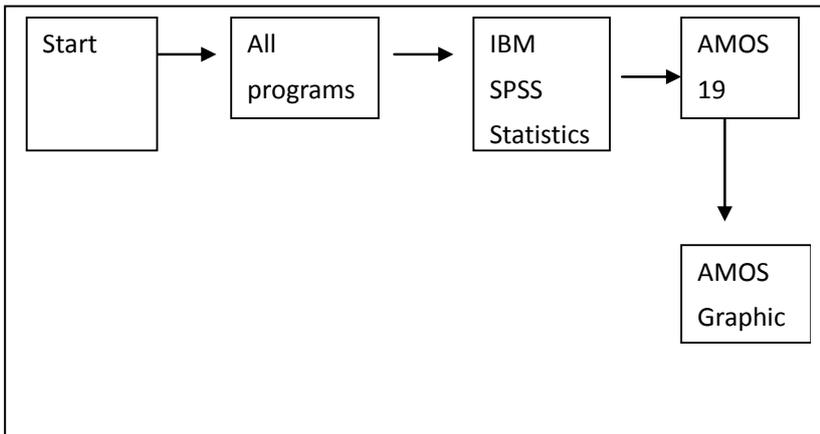
The general SEM can be divided in to two sub models; measurement models and structural models. The measurement model shows the relationship between observed and latent variables. The structural model shows the relationship between latent variables.

## *Chapter Two*

### *Introduction to AMOS program*

#### **2.1. Starting AMOS graphics**

To start AMOS graphics, it is needed to follow the usual steps as follows:



Once you finish these steps, you can see the AMOS graphic screen given in Figure 2.1 below. You can use the tools in the screen to draw the path diagram in the empty space of the screen.

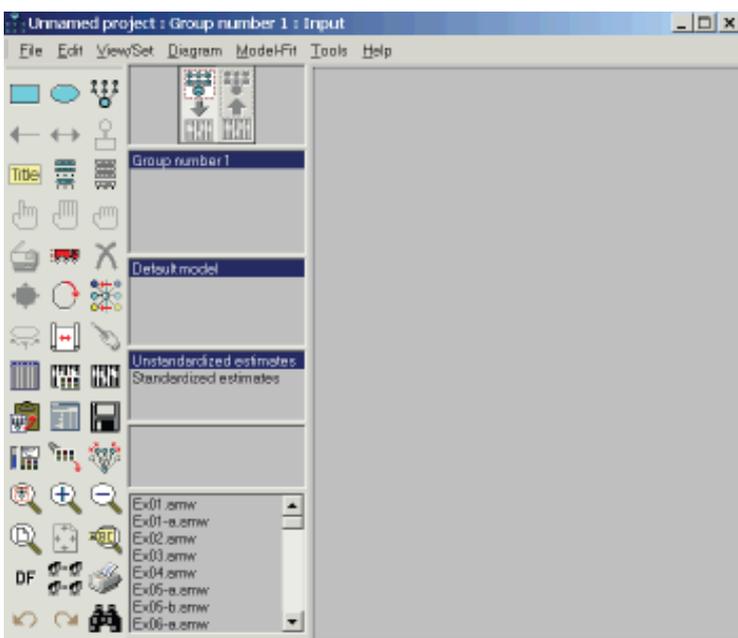


Figure 2.1- AMOS graphic screen

In order to start the drawing, first of all it is needed to select the data file. The Data Files dialog allows you to specify the database file (or files) to be analyzed. To select the database file click on “*File*” shown at the top of the graphic screen and then select “*Data Files*”.

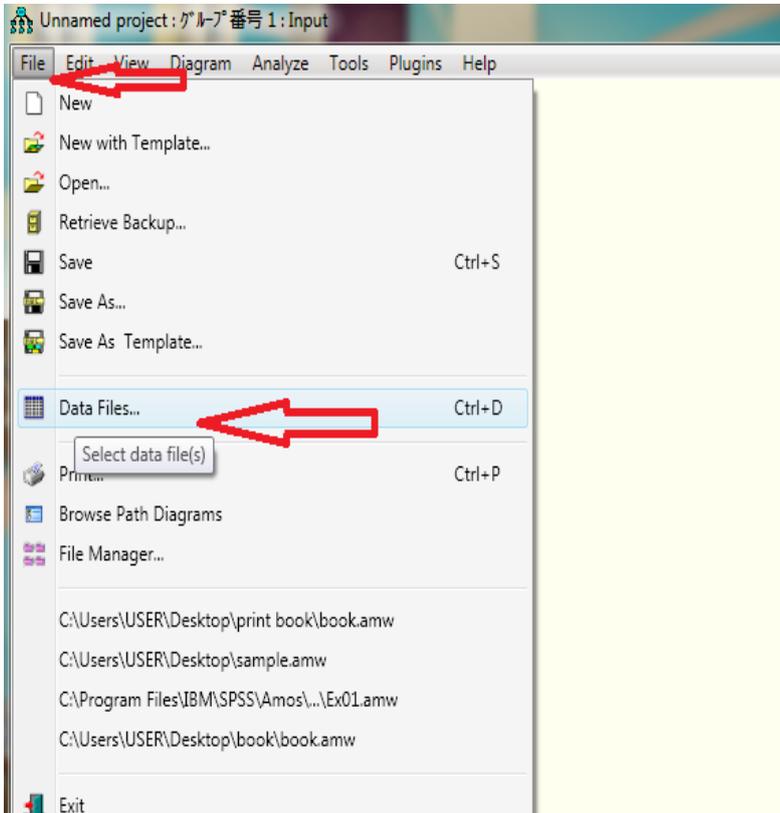


Figure 2.2- Selecting a data file (step 1)

Then click on “*File Name*” and select the relevant database file and click on “*OK*”.

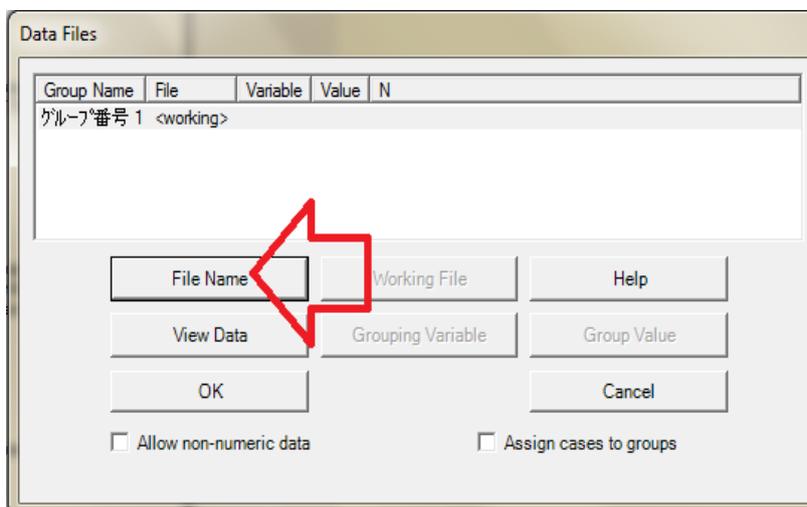


Figure 2.3- Selecting a data file (step 2)

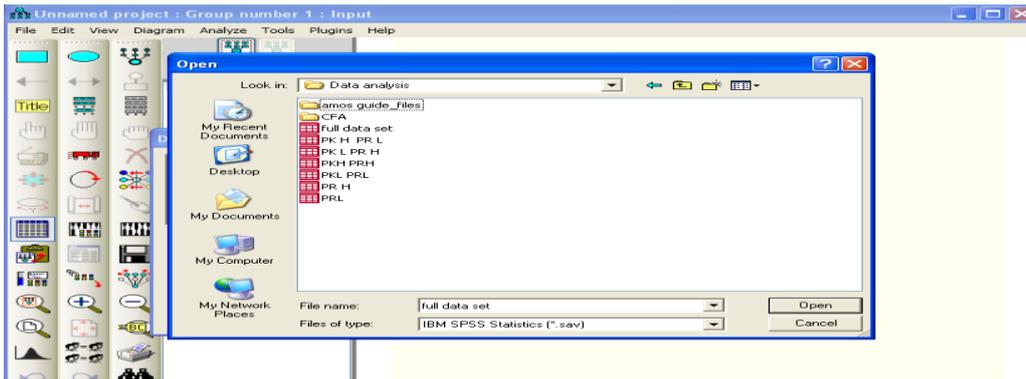


Figure 2.4- Selecting a data file (step 3)

In the above Figure 2.4, the SPSS saved files are indicated, but data files in other programs also can be accessed. By clicking the “view data” in the AMOS dialogue box given in Figure2.3, it is possible to see the data file selected.

## 2.2 Drawing the path Diagram

Now you can start the drawing of your path diagram. You can use the drawing tools at the left side of the screen to draw the path diagram. You are required to click the relevant tool to activate it. Then click in the blank drawing space while holding down the left mouse button and dragging it slightly, you will be able to create the relevant picture. You can use either the tools of rectangle , ellipse , arrows to draw the diagram or the tool  to draw a latent variable or add an indicator to a latent variable.

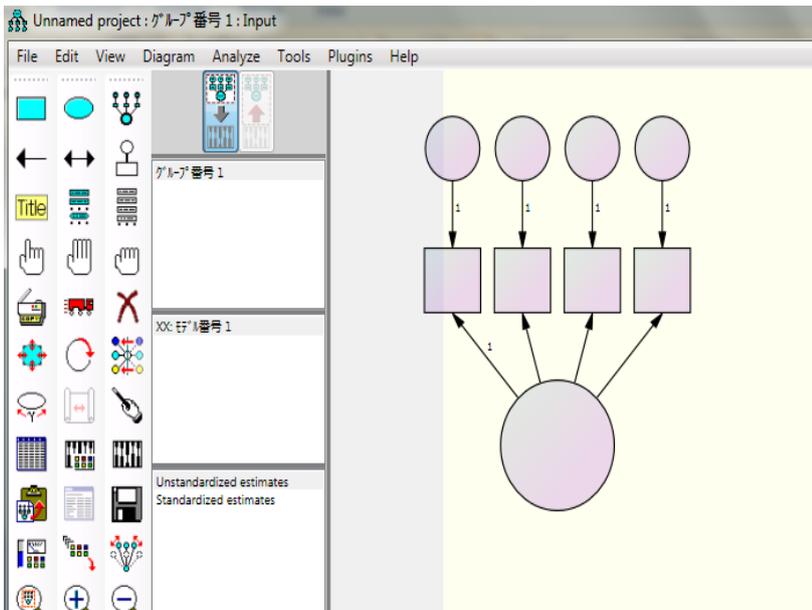


Figure 2.5- Drawing the path Diagram

### 2.3. Naming the Variables

In order to name the variables, right click the rectangle/ellipse and choose “object properties” from the pop up menu. Then, type the variable name and close the pop up menu. The same method should be applied to name the other variables and error terms.

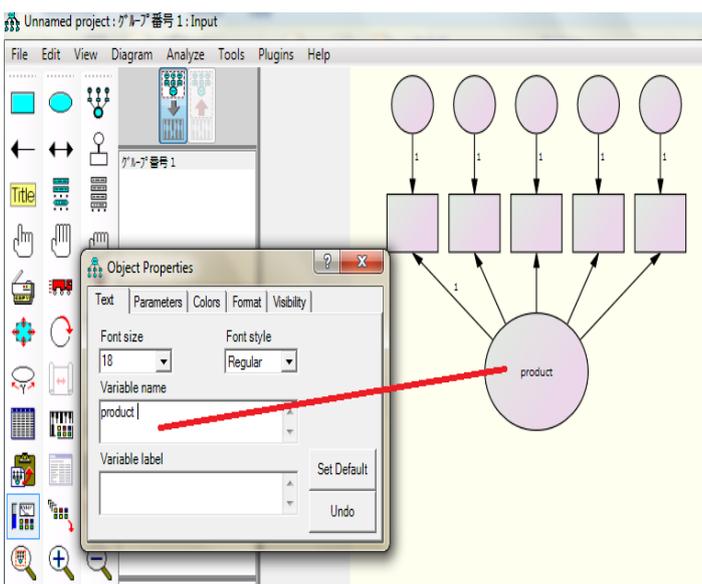


Figure 2.6- Naming the Variables

Observed variables can be directly taken from your data set easily without naming them as discussed above. Use the “List Variables in Dataset” button on the left-hand side to see the variables in your dataset

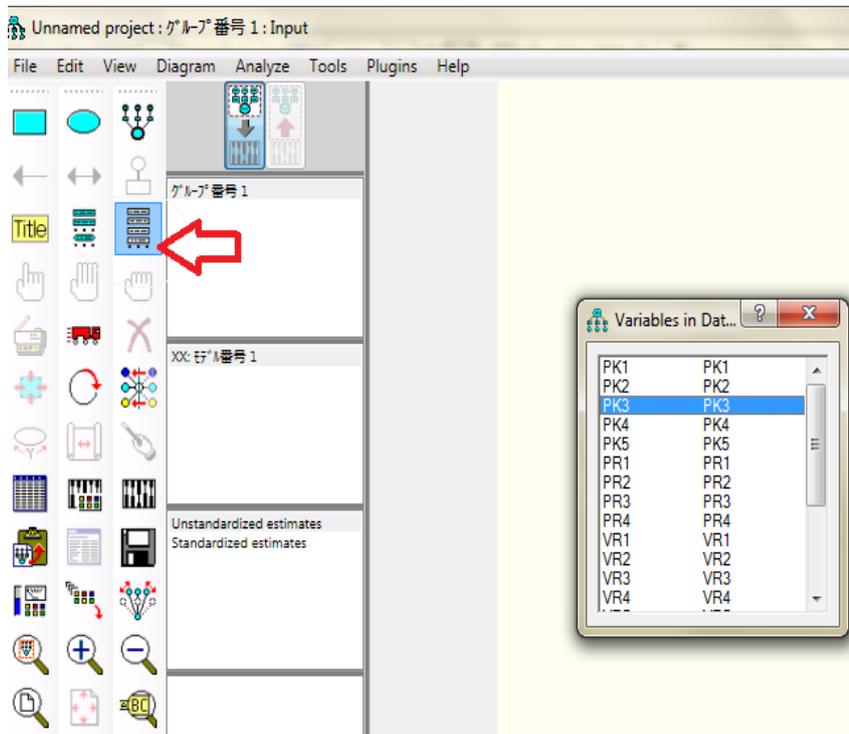


Figure 2.7- Naming Observed Variables Directly

Drag and drop the observed variables that you want to include in your model onto the gray workspace as shown in Figure 2.8 below.

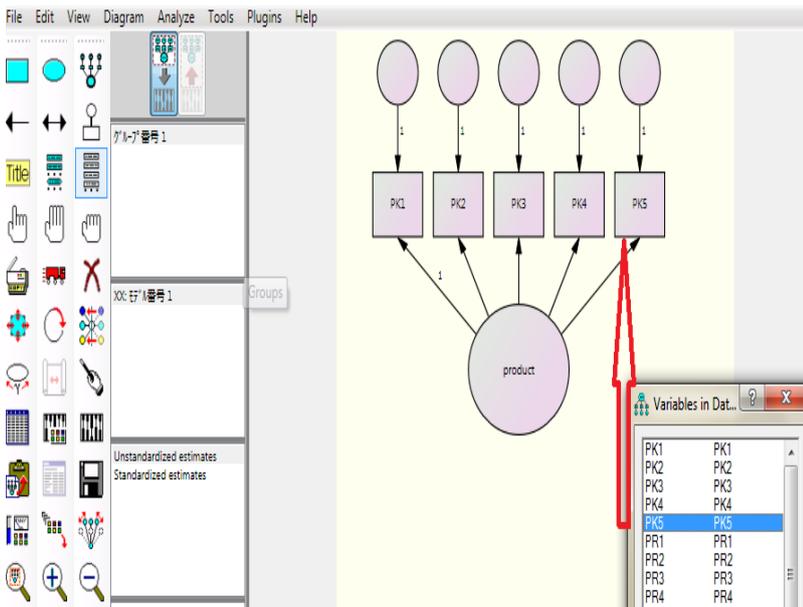


Figure 2.8- Dragging Observed Variables to the Path Diagram

Similarly the path diagram can be rotate using the rotate button in the left hand side.

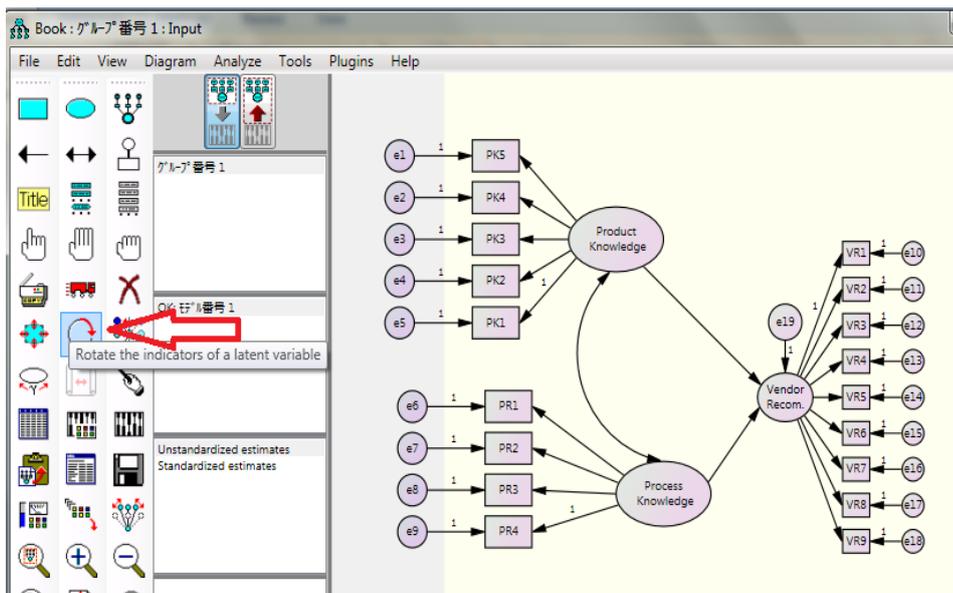


Figure 2.9- Rotate Button

In the above Figure 2.9, there are two latent exogenous variables, product knowledge and process knowledge. In addition to that, there is a latent endogenous variable; vendor recommendations. Single headed arrows pointing towards endogenous variable (vendor recommendations), predicted as a linear combination of the other two exogenous variables, product knowledge and process knowledge. Error is an

unobserved variable and therefore, used an ellipse to draw the variable. Double headed arrow shows the correlation between product and process knowledge.

In other words, effects are represented by single-headed arrows in the path diagram while correlations and covariance are represented by bidirectional arrows, which represent relationships without an explicitly defined causal direction. In the above diagram there is an association or relationship between product knowledge and process knowledge. But, a claim cannot be made about product knowledge affect process knowledge or vice versa.

Since effects are represented by single-headed arrows in the path diagrams, in the above path diagram, we can claim that *product knowledge* affect the scores observed on the measured variables *p1* and *p2 etc.*

## **2.4. Chapter Summery**

This chapter discussed the different tools of Amos that can be used in drawing path diagrams. Rectangles are used to draw latent variables and ellipses are used to draw observed variables. Single headed arrows shows the linear combination of two variables, while double headed arrows show the correlation between variables. Further, variables should be named using the relevant tools in AMOS and rotation also possible in AMOS to draw the path diagram in a proper manner.

## Chapter-3

### *Running the Model and Interpreting the Results*

#### 3.1. Saving the File

After the model is drawn, be sure to save it by choosing the **File** menu, and then selecting **Save As**. When you save the model, AMOS automatically creates two back-up model files in the same directory in which you have your original diagram. The back-up files will have the extensions **.bk1** and **.bk2**, respectively.

#### 3.2. AMOS Output

In AMOS, it is not required to do different test at different times since AMOS provide all the required output by conducting analysis of the properties once. The output required to show after the analysis is optional in Amos. In other words, we can decide the output required at the end of the analysis. With the aim of selecting output options, select “**view**” at the top of the window and then choose “Analysis Properties” as shown in the Figure 3.1 below.

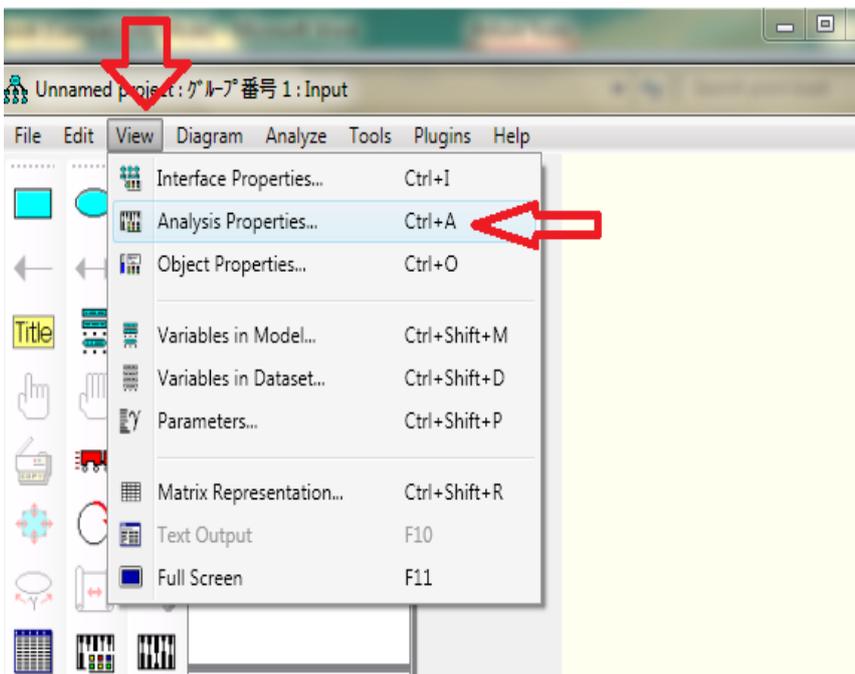


Figure 3.1- selecting output required (step-1)

Then, select the output in the analysis properties dialog box. The following dialog box will appear to select the outputs you required. For this example, Minimization history, Standardized estimates, and Squared multiple correlations are checked.

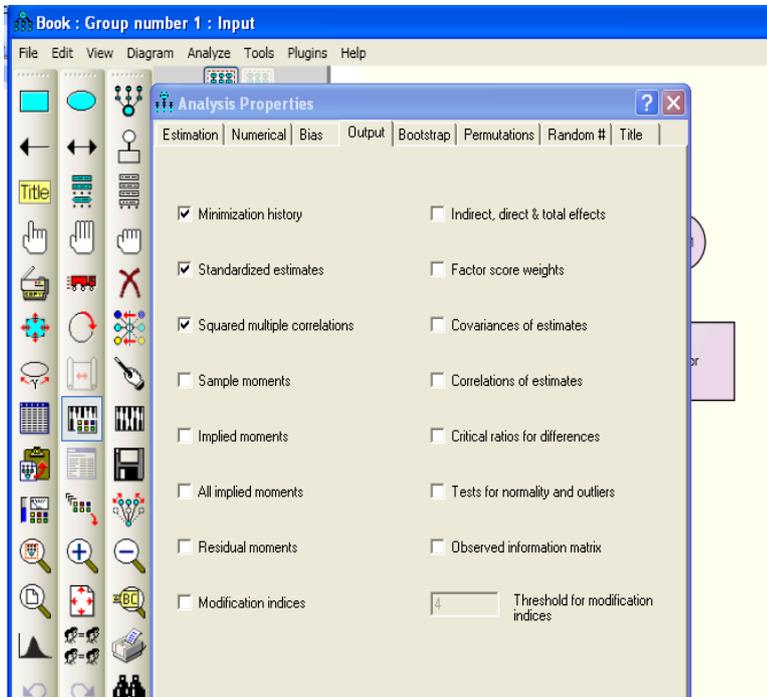


Figure 3.2- selecting output required (step-2)

Next, examine the **Estimation** tab. This tab provides a check box that allows you to estimate means and intercepts if your database has any cases with incomplete data. AMOS will require you to estimate means and intercepts, if your database has any missing data on observed variables included in your model. Because this model's database does not contain any missing data and we are not interested in means at present, we leave the **Estimation** tab settings at their default values. Before you run the model, be sure to save it by choosing **Save As** from the **File** menu and saving a copy of the model file to an appropriate location on your computer's disk drive. To run the model, close the **Analysis Properties** window and click on the **Calculate Estimates** tool icon. It resembles an abacus:



In order to view the output path diagram, click the relevant icon shown in Figure 3.3.

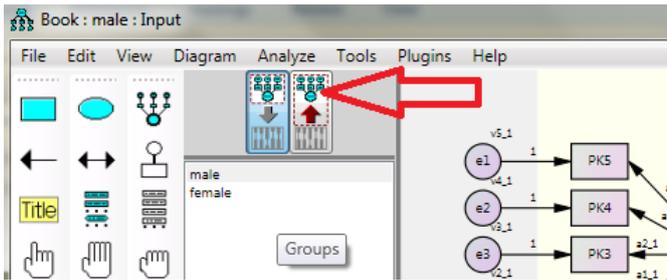


Figure 3.3- “View the Output Path Diagram” Icon

Then, AMOS will provide both standardized and un-standardized coefficients.

### 3.3. Standardized vs. Un-standardized coefficients

The standardized coefficients are sample specific and not stable across different samples. The un-standardized coefficients permit an examination of change across different samples. The coefficient values can be taken by clicking the required type of coefficient as shown in Figure 3.4 below.

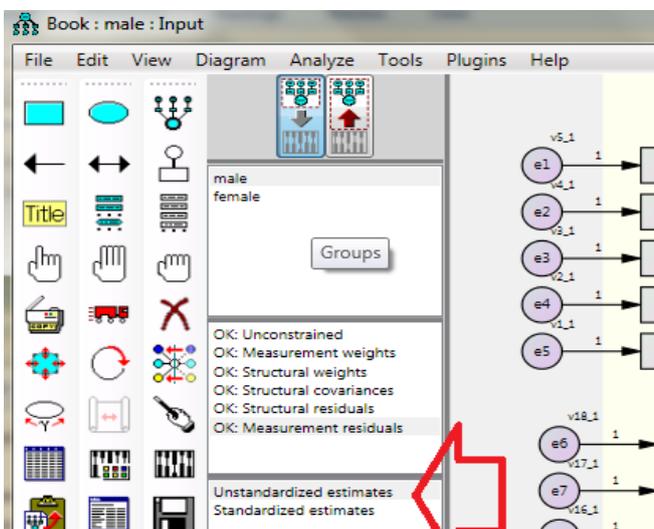


Figure 3.4- standardized and un-standardized estimates

Under standardized and un-standardized estimates the researcher is highly interested in to see the correlation coefficients and regression coefficients between variables.

### 3.4. Correlation Coefficient

The Pearson correlation coefficient provides the basis for point estimation (test of significance) and explain the variance accounted for in a dependent variable by an independent variable. In order to do a prediction, of a dependent variable from an independent variable, it is required to conduct a linear regression analysis. In addition to that partial and part correlations provide identification of specific bivariate relationship between variables showing unique variance shared by two variables while controlling the influence of other variables.

Different types of correlation coefficients are used to check the correlation between variables depending on the properties of scales of measurement.

Table 1-Types of correlation coefficients

Correlation coefficient	Level of measurement
Pearson product moment	Both variables interval
Spearman's Rank Correlation and Kendall Rank Correlation	Both variables ordinal
Phi, Contingency	Both variables nominal
Point- Biserial	One variable interval and one variable dichotomous
Rank-Biserial	One variable ordinal and one variable nominal
Biserial	Interval data against ordinal data, but ordinal data with an underlying continuity but measured

	discretely as two values (dichotomous).
Polyserial	One variable interval and one variable ordinal with underline continuity
Tetrachoric	both variables are dichotomous
polychoric	Both variables ordinal with underline continuity

Source: “A Beginner's Guide to Structural Equation Modeling”, Randall E. Schumacker, 3rd Edition, 2010

Though, this chapter so far discussed the procedure of running the model, there are several steps in SEM analyses; model specification, model identification, model testing, and model modification.

### **3.5. Model specification**

In model specification, researcher specifies the model determining every relationship among variables relevant to the researcher’s interest. For this purpose researcher should conduct an extensive literature review. Otherwise, there may be a difference between true model and the implied model either having irrelevant variables in the model or not including important variables into the model.

### **3.6. Model identification**

SEM programs require an adequate number of known correlations or covariances as inputs in order to generate a sensible set of results. Identification refers to the idea that there is at least one unique solution for each parameter estimate in a SEM model. Models in which there is only one possible solution for each parameter estimate are

said to be *just-identified*. Models for which there are an infinite number of possible parameter estimate values are said to be *underidentified*. Finally, models that have more than one possible solution (but one best or optimal solution) for each parameter estimate are considered *overidentified*.

Model is considered as identified if the model is either just- or overidentified. If a model is identified only, the parameter estimates can be trusted. If the model is unidentified, the degrees of freedom for the model are zero or negative. However, such a model may become identified if additional constraints are imposed, that is, the degrees of freedom equal 1 or greater.

### **3.7. Model Testing**

In SEM modeling researcher can use three main approaches to test whether the data fit the model.

1. *Confirmatory approach*-Researcher develops the model based on literature review and test whether the data fit the model. If model fit criteria is acceptable, the model can be accepted.
2. *Alternative model approach*- Based on literature review, researcher can developed several models and select the model the data fit best. If the same data set is used to test the models, it is called as nested models.
3. *Model generating approach*- If data does not fit with the model generated by the researcher, model modification is done to receive a final best model. Amos generates alternative models by specifying optional and/or required paths in a model. Hence, in AMOS, researcher needs not to generate and delete paths to find out the best model.

### 3.8. Types of Model Fit Criteria

In order to test the model fit, different criterion can be checked. Some of the recognized and popular criteria are given in Table 3.2 below.

Table 3.2- model Fit Criterion

Model fit criterion	Acceptable level	Interpretation
Chi- square	Tabled $\chi^2$ value	Compares obtained $\chi^2$ value with tabled value for given $df$
Goodness- of- Fit (GFI)	0 (no fit) to 1 (perfect fit)	Value close to .95 reflects a good fit
Adjusted GFI (AGFI)	0 (no fit) to 1 (perfect fit)	Value adjusted for $df$ . With .95 a good model fit.
Root- Mean- Square Residual (RMR)	Researcher defines level	Indicate the closeness of to $S$ matrix
Root – Mean – Square Error of Approximation (RMSEA)	< 0.5	Value less than 0.05 indicates a good model fit
Tucker- Lewis Index	0 (no fit) to 1 (perfect fit)	Value close to .95 reflects a good model fit

	fit)	
Normed Fit Index	0 (no fit) to 1 (perfect fit)	Value close to .95 reflects a good model fit
Normed Chi-Square	1.0-5.0	Less than 1.0 is a poor model fit; more than 5.0 reflects a need for improvement.
Parsimonious Fit Index	0 (no fit) to 1 (perfect fit)	Compare values in alternative models.
Akaike Information Criterion	0 (perfect fit) to negative value (poor fit)	Compares values in alternative models

Source: “A Beginner's Guide to Structural Equation Modeling”, Randall E. Schumacker, 3rd Edition, 2010

Relating to the Chi- Square test, model is considered as fit to the data if the  $\chi^2$  value is low relative to degree of freedom with an **insignificant p value ( $p > 0.05$ )**.

Consider the following example.

In the following path diagram in Figure 3.5, the first latent variable, i.e. product knowledge has been measured using five observed variables and the second latent

variable i.e. process knowledge has been measured using four observed variables. As well as vendor recommendation has been measured using nine observed variables.

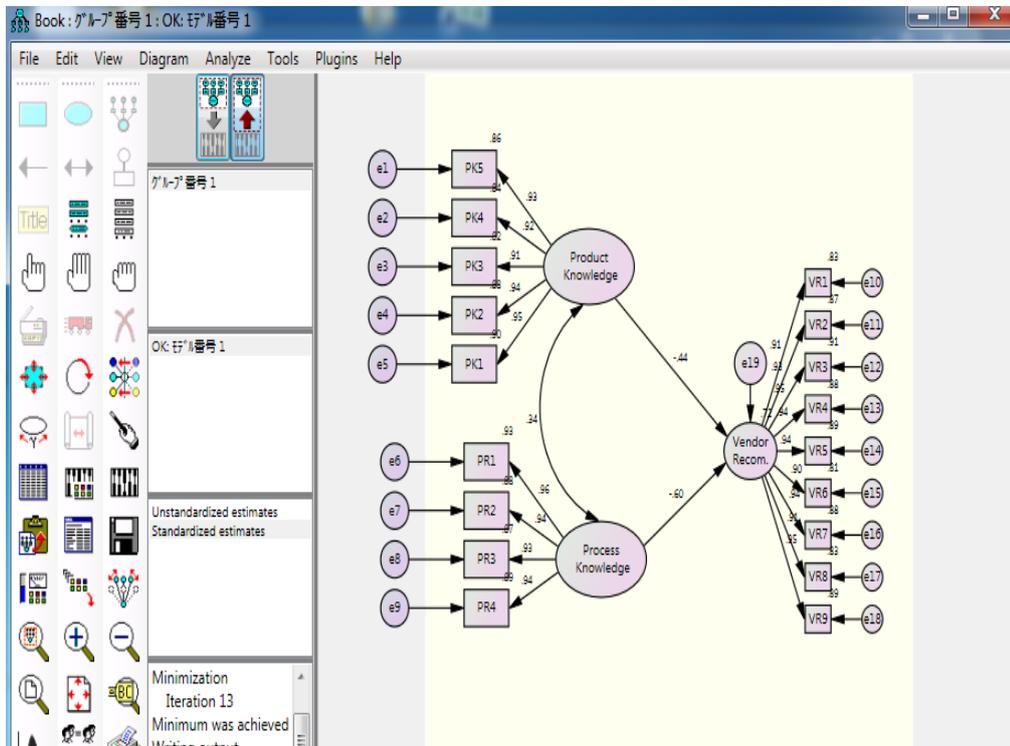


Figure 3.5- Graphical output of AMOS

In order to see the graphical output click  and you can see standardized and unstandardized estimates by clicking relevant estimate.

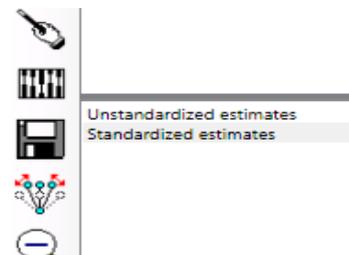


Figure 3.6- standardized vs. Unstandardized estimates

The text output can be viewed by using the icon of .

The table that appears contains a list of output categories on the left side of the window and an open space on the right. When you select a particular subset of output

for display, it appears in the right-hand space. Consider the “Notes for Model” section of the text output.

The notes for model of the text output of the above diagram (Figure 3.5) is as follows

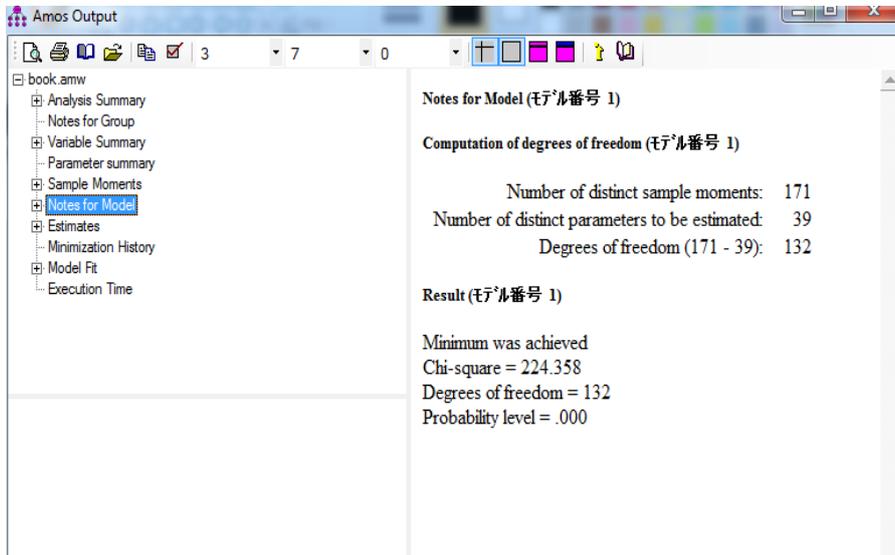


Figure 3.7 – Notes for Model

In this section, AMOS will display most errors and warnings in this section of the output. In the output shown above (Figure 3.7), AMOS reports that the minimum was achieved with no errors or warnings. If errors or warnings are not reported in this section of the output means that it is safe for you to proceed to the next output section of interest.

### 3.9. Absolute Model Fit

The chi-square test of overall model fit value of the model given in Figure 3.6 is 224.358 with 132 degrees of freedom. Since the probability value of the chi-square test is smaller than the .05 level used by convention, you would reject the null hypothesis that the model fits the data. This conclusion is not good news for the researcher who hopes to fit this model to the dataset.

Absolute model fit determines the degree to which the sample data fit the structural

equation model. Absolute model fit criteria commonly used are chi-square ( $\chi^2$ ), the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), and the root-mean-square residual (RMR) and the Root Mean Square Error of Approximation (*RMSEA*). **Absolute fit indices do not use an alternative model as a base for comparison.**

### 3.9.1. Chi-Square

A significant  $\chi^2$  value relative to the degrees of freedom indicates that the suggested model does not supported by the observed data. Hence researchers are interested in obtaining a non significant  $\chi^2$  value which proved the model fit to the data collected. But researcher solely cannot depend on the chi-square value since the  $\chi^2$  model fit criterion is sensitive to sample size because as sample size increases (generally above 200), the  $\chi^2$  statistic has a tendency to indicate a significant probability level. In contrast, as sample size decreases (generally below 100), the  $\chi^2$  statistic indicates non-significant probability levels. In addition to that  $\chi^2$  statistic is also sensitive to departures from multivariate normality of the observed variables. Hence, a researcher should not only depend on the chi-square analysis in testing the model fit.

### 3.9.2. Goodness-of-Fit Index (GFI) and Adjusted Goodness-of-Fit Index (AGFI)

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
モデル番号 1	.080	.884	.850	.683
Saturated model	.000	1.000		
Independence model	1.478	.114	.009	.102

Figure 3.8- GFI and AGFI values

◇ モデル番号 is a Japanese word and its meaning is “Model Number” in English

The **goodness of fit** of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question.

([http:// en. wikipedia.org/wik/Goodness\\_of\\_fit](http://en.wikipedia.org/wiki/Goodness_of_fit)). The GFI index in Figure 3.8, is 0.884; and the AGFI index is 0.850 indicate a good model fit since it is close to 1.

In the Figure 3.8, the first row is labeled as モデル番号1 (Model Number 1) is the *Default model*, contains the fit statistics for the model you specified in your AMOS Graphics diagram. The next two row, labeled *Saturated* and *Independence* refer to two baseline or comparison models automatically fitted by AMOS as part of every analysis. The *Saturated* model contains as many parameter estimates as there are available degrees of freedom or inputs into the analysis. The *Saturated* model is thus the least restricted model possible that can be fit by AMOS. By contrast, the *Independence* model is one of the most restrictive models that can be fit: it contains estimates of the variances of the observed variables only. In other words, the Independence model assumes all relationships between the observed variables are zero.

### **3.9.3. The root mean squared error approximation (RMSEA)**

Chi-square statistics is a way of evaluating fit of data to the model (Rasch, 1980, p. 25). However, large sample sizes have always posed problems for significance tests based on chi-square statistics. The issue is that, the larger the sample, the greater the power, and so ever smaller differences are reported as indicating statistically significant misfit between the data and the model. Thus very large sample sizes can detect miniscule differences, and with such samples there is almost no need to undertake a chi-square test since that it will be significant (P. Martin-Löf (1974). But, "On the whole we should not overlook that since a model is never true, but only more or less adequate, deficiencies are bound to show, given sufficient data" (Rasch, 1980, p. 92). One possible mechanism to handle large sample sizes may be to use the Root

Mean Square Error of Approximation (RMSEA) (Steiger and Lind, 1980). The RMSEA is widely used in Structural Equation Modeling to provide a mechanism to adjust the sample size where chi-square statistics are used.

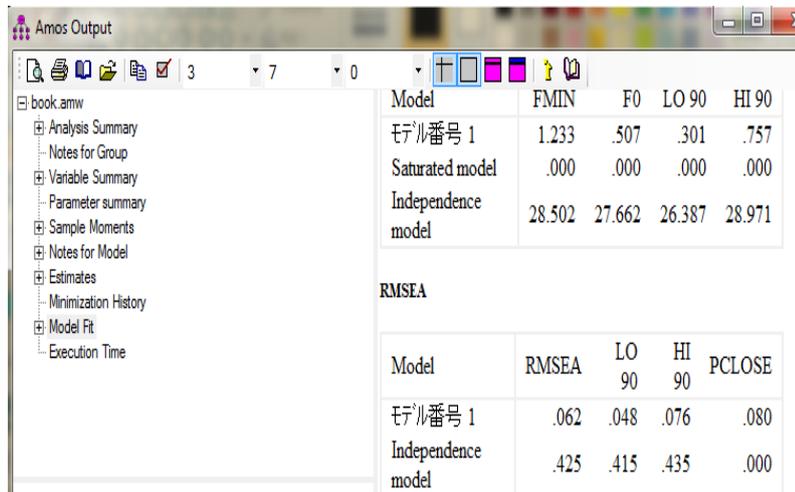


Figure 3.9- RMSEA

According to the Figure 3.9, since the RMSEA value is 0.062 which is higher than 0.05, the model does not fit.

### 3.9.4. Root mean square residual (RMR) and standardised root mean square residual (SRMR)

The RMR and the SRMR are the square root of the difference between the residuals of the sample covariance matrix and the hypothesized covariance model. The SRMR is much more meaningful when varying level of questions are included in the questionnaire since the range of the RMR is calculated based upon the scales of each indicator. As an example if there are both five point likert scale questions and seven point likert scale questions, SRMR is a better option to the researcher. RMR becomes difficult to interpret when there are varying level of items in the questionnaire (Kline, 2005). Values for the SRMR range from zero to 1.0 with well fitting models obtaining values less than .05 (Byrne, 1998; Diamantopoulos and Siguaw, 2000),

however values as high as 0.08 are deemed acceptable (Hu and Bentler, 1999). An SRMR of 0 indicates perfect fit but it must be noted that SRMR will be lower when there is a high number of parameters in the model and in models based on large sample sizes.

The screenshot shows the Amos Output window with a tree view on the left and a table of fit indices on the right. The table is divided into two sections: CMIN and RMR, GFI.

CMIN					
Model	NPAR	CMIN	DF	P	CMIN/D
モデル番号 1	39	224.358	132	.000	1.70
Saturated model	171	.000	0		
Independence model	18	5187.451	153	.000	33.90

RMR, GFI				
Model	RMR	GFI	AGFI	PGFI
モデル番号 1	.080	.884	.850	.683
Saturated model	.000	1.000		
Independence model	1.478	.114	.009	.102

Figure 3.10- RMR & SRMR

In order to get SRMR in AMOS, select Analyze, Calculate Estimates as usual. Then Select Plug ins, Standardized RMR: this brings up a blank Standardized RMR dialog. Then re-select Analyze, Calculate Estimates, and the Standardized RMR dialog will display SRMR.

**In the Figure 3.10, RMR is not close to 1.0, and RMSEA also >0.05 (Figure 3.8), as well as  $\chi^2$  (Figure 3.7), also significant. Therefore, the given model does not fit with the data.**

### 3.10. Tests of Relative Fit

By using absolute fit, a model may be rejected, yet a researcher may still claim that a given model out performs some other baseline model by a substantial amount. Put another way, the argument researchers make in this context is that their chosen model

is substantially less false than a baseline model, typically the independence model. A model may not fit to the data, and yet performs well in comparison to other models may be of substantive interest. For example, the Tucker-Lewis Index (*TLI*) and the Comparative Fit Index (*CFI*) compare the absolute fit of your specified model to the absolute fit of the Independence model.

Tucker Lewis index (*TLI*) is named as Non-Normed Fit Index (*NNFI*) as well. This index is called as “non-normed” because, there may be occasions, the value of the index can be larger than 1 or slightly below 0. In order to compare the default model with baseline model following Incremental fit indices can be used. Incremental fit indices, also known as comparative (or relative fit indices are a group of indices that do not use the chi-square in its raw form but compare the chi-square value to a baseline model.

Table 3.3- Incremental/ comparative indices and the levels of acceptance

<b>Incremental indices/ comparative indices</b>			
NFI (better use CFI)	Normed Fit Index	between [0;1]	A: 0=poor fit close to 1=good fit B: NFI>0.90, 0.95: good fit
RFI	Relative Fit Index	Usually between [0;1]	0=poor fit close to 1=very good fit
			B: RFI >

			0.95: guter Fit
IFI	Incremental Fit Index		0=poor fit close to 1=very good fit
TLI =rho_2 =NNFI	Tucker-Lewis Index rho_2 oder Non-Normed Fit Index	[0;1]	0=poor fit close to 1=very good fit
			B: TLI>0.95: guter Fit
CFI =RNI	Comparative Fit Index, Relative Noncentrality Index	between [0;1]	A: 0=poor fit close to 1=very good fit B: CFI >.95: good fit

### 3.11. Parsimonious Fit Indices

Theoretical fit of a model is high when compared to a complex model. To overcome this problem, Mulaik et al (1989) have developed two types of parsimony fit indices. These fit indices are relative fit indices that make adjustments to most of the indices discussed earlier in this book. The adjustments are to penalize models that are less parsimonious. The Parsimony Goodness-of-Fit Index (PGFI) and the Parsimonious Normed Fit Index (PNFI) are good examples for adjusted indices. The PGFI is based

upon the GFI by adjusting for loss of degrees of freedom. The PNFI also adjusts for degrees of freedom however it is based on the NFI (Mulaik et al 1989). Both of these indices seriously penalize for model complexity which results in parsimony fit index values that are considerably lower than other goodness of fit indices. Although many researchers believe that parsimony adjustments are important, there is some debate about whether or not they are appropriate.

Another form of parsimony fit indices is known as ‘information criteria’ indices. The widely used of these indices is the Akaike Information Criterion (AIC) or the Consistent Version of AIC (CAIC) which adjusts for sample size (Akaike, 1974). These indices select the most parsimonious model by comparing non-nested or non-hierarchical models using the same data. Smaller values suggest a good fitting of models. The model that produces the lowest value is the most superior. In addition to that, it is important to keep in mind that the ‘information criteria’ indices need a sample size of 200 to make their use reliable (Diamantopoulos and Siguaw, 2000).

### **3.12. Misconception relating to SEM**

Many researches use the term “effect” in structural equation modeling. But, it does not mean that a Structural Equation Model is a causal model (Nachtigall et.al. 2003). “Although under specific circumstances, SEM can represent causal relationships, a well-fitting SEM does not necessarily have to contain any information on causal dependencies at all. Hence, testing the fit of a SEM is not a test of causality” (Nachtigall et.al. 2003).

### **3.13. Chapter Summary**

There are several steps in SEM analyses; model specification, model identification, model testing, and model modification.

In model specification, researcher specifies the model determining every relationship among variables relevant to the researcher’s interest.

SEM programs require an adequate number of known correlations or covariances as inputs in order to generate a sensible set of results. Identification refers to the idea that there is at least one unique solution for each parameter estimate in a SEM model. Models in which there is only one possible solution for each parameter estimate are said to be *just-identified*. Models for which there are an infinite number of possible parameter estimate values are said to be *underidentified*. Finally, models that have more than one possible solution (but one best or optimal solution) for each parameter estimate are considered *overidentified*. Model is considered as identified if the model is either just- or overidentified. If a model is identified only, the parameter estimates can be trusted.

In SEM modeling researcher can use three main approaches to test whether the data fit the model; *Confirmatory approach*, *Alternative model approach*, and *Model generating approach*

If data does not fit with the model generated by the researcher, model modification is done to receive a final best model. Amos generates alternative models by specifying optional and/or required paths in a model. Hence, in AMOS, researcher needs not to generate and delete paths to find out the best model. In order to test the model fit, absolute model fit, test of relative fit, Parsimonious Fit Indices can be used. Absolute model fit criteria commonly used are chi-square ( $\chi^2$ ), the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI), and the root-mean-square residual (RMR) and the Root Mean Square Error of Approximation (*RMSEA*). Tucker-Lewis Index (*TLI*) and the Comparative Fit Index (*CFI*) compare the absolute fit of your specified model to the absolute fit of the Independence model and used as the criteria to test the relative fit. The Parsimony Goodness-of-Fit Index (PGFI) and the Parsimonious Normed Fit Index (PNFI) are good examples to test the Parsimonious Fit.

## *Chapter-4*

### *Confirmatory factor models*

#### **4.1. Validity & Reliability**

Validity of a measurement can be explained as “The extent to which a measurement represents characteristics that exist in the phenomenon under investigation” (Malhotra & Dash 2010).

Reliability of a measurement is “the extent to which a measurement reproduces consistent results if the process of measurement were to be repeated” (Malhotra & Dash 2010).

Traditionally, validity and reliability was checked by examining the validity and reliability scores on instrument used in a particular context. Given an acceptable level of score validity and reliability, is ensured. The traditional statistical analysis does not consider the measurement error of variables. But it is found that the impact of measurement error have serious consequences. Since structural equation modeling software was developed which can accounts for the measurement error of variables.

##### **4.1.1. Construct Validity**

Construct validity can be tested using factor analysis. Factor analysis attempts to determine which sets of observed variables share common variance-covariance characteristics that define theoretical constructs or factors (latent variables). Factor analysis presumes that some factors, which are smaller in number than the number of observed variables, are responsible for the shared variance-covariance among the observed variables. Once data is collected on observed variables, factor analysis is used, to either *confirm* that a set of variables defines those constructs or factors or *explore* which variables relate to factors.

A **confirmatory factor analysis** assumes that you enter the factor analysis with a firm idea about the number of factors you will encounter, and about which variables will most likely load onto each **factor**.

Your expectations are usually based on published findings of a **factor analysis**.

As an example, consider the fatigue scale that has previously been validated. You would like to make sure that the variables in your sample load onto the factors the same way they did in the original research.

In other words, you have very clear expectations about what you will find in your own sample. This means that you know the number of factors that you will encounter and which variables will load onto the factors.

The criteria for variable inclusion are much more stringent in a confirmatory factor analysis than in an exploratory factor analysis. A rule of thumb is that variables that have factor loadings  $<|0.7|$  are dropped.

An **exploratory factor analysis** aims at exploring the relationships among the variables and does not have an a priori fixed number of factors. You may have a general idea about what you think you will find, but you have not yet settled on a specific hypothesis. Or you may have formulated a research question based on your theoretical understanding, and are now testing it.

Of course, in an exploratory factor analysis, the final number of factors is determined by your data and your interpretation of the factors. Cut-offs of factor loadings can be much lower for exploratory factor analyses.

When you are developing scales, you can use an exploratory factor analysis to test a new scale, and then move on to confirmatory factor analysis to validate the factor structure in a new sample.

In exploratory factor model approaches, the researcher tries to find a model that fits the data. Hence, in practice, researchers develop different alternative models, expecting to find a model that fits the data and has theoretical support. This is the

primary rationale for exploratory factor analysis (EFA). In confirmatory factor model approaches, researchers statistically test the significance of a hypothesized factor model, that is, whether the sample data confirm the model. Additional samples of data that fit the model further confirm the validity of the hypothesized model. This is the primary reason for conducting confirmatory factor analysis (CFA). Following Figure 4.1 and Figure 4.2, shows the factor loadings/standardized regression weights of observed variables that determine the latent variables.

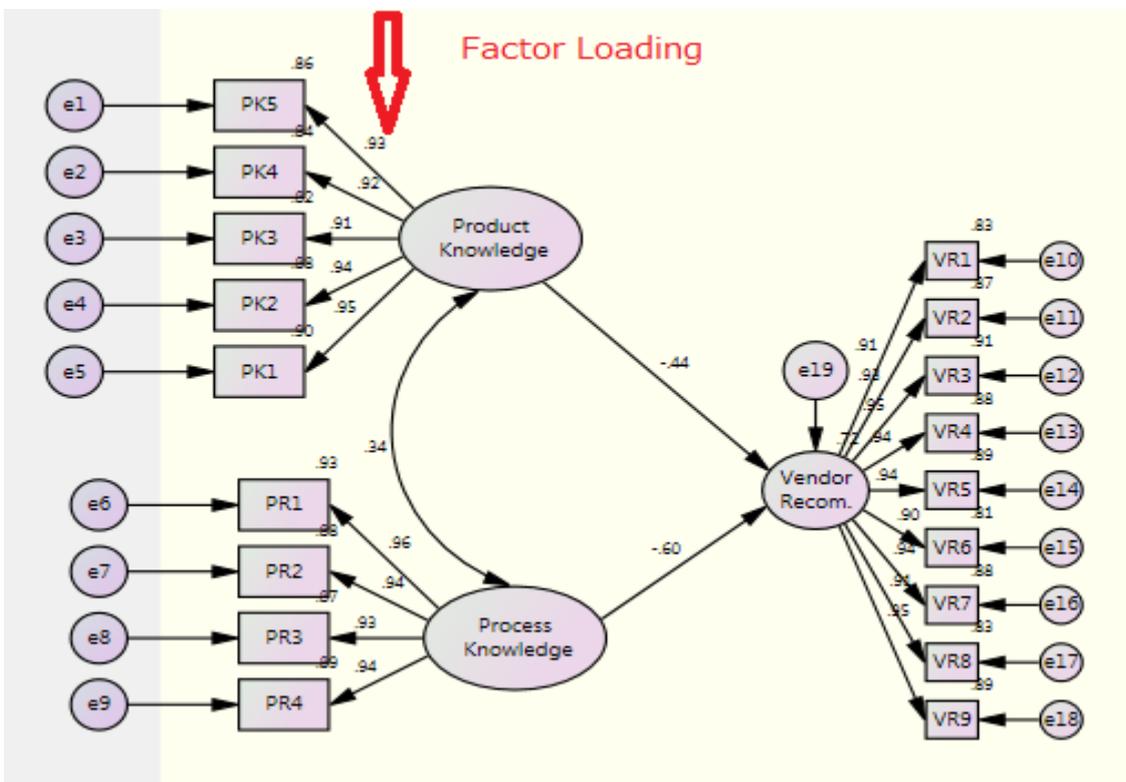


Figure 4.1- Factor Loading of Observed Variables

**Standardized Regression Weights:**

	Estimate
VR <--- PK	-.438
VR <--- PR	-.595
PK1 <--- PK	.948
PK2 <--- PK	.937
PK3 <--- PK	.906
PK4 <--- PK	.917
PK5 <--- PK	.927
VR1 <--- VR	.913
VR2 <--- VR	.932
VR3 <--- VR	.952
VR4 <--- VR	.938
VR5 <--- VR	.942
VR6 <--- VR	.902
VR7 <--- VR	.936
VR8 <--- VR	.914
VR9 <--- VR	.946
PR4 <--- PR	.944
PR3 <--- PR	.933
PR2 <--- PR	.937
PR1 <--- PR	.963

**Figure 4.2 -Text output of Factor loading values**

In order to obtain a confirmatory factor model, the model fits should be checked as discussed in chapter three.

## **4.2. Chapter Summary**

In addition to the exploratory factor analysis, AMOS has the ability to estimate the confirmatory factor analysis as well. Under exploratory factor analysis, you will explore the factors. But in confirmatory factor analysis, you confirm the factors which are already developed by other researchers.

## Chapter Five

### Managing Multiple Groups

#### 5.1. Selecting Data Set

Amos has a facility of analyzing multiple groups at the same time. For this purpose select the data file as discussed earlier in this book by using;

File → Data File or using .

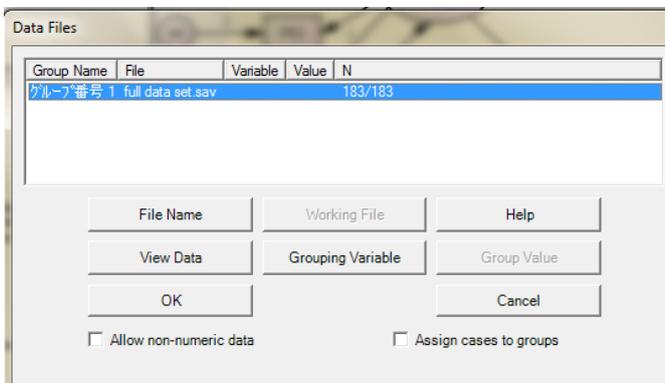


Figure 5.1- Data Files window

Now in order to subset the data into girls and boys, click on Grouping Variable and then choose “gender” and click OK.

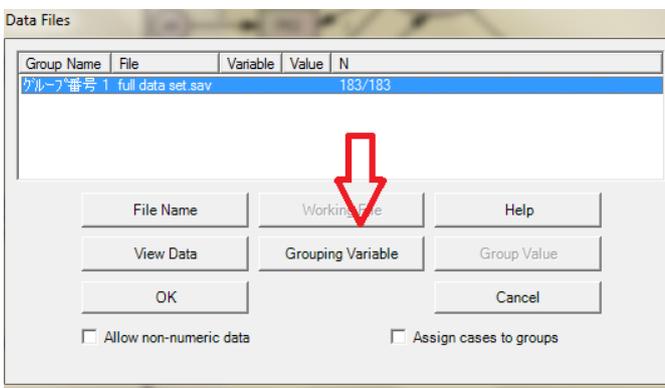


Figure 5.2- Grouping Variable

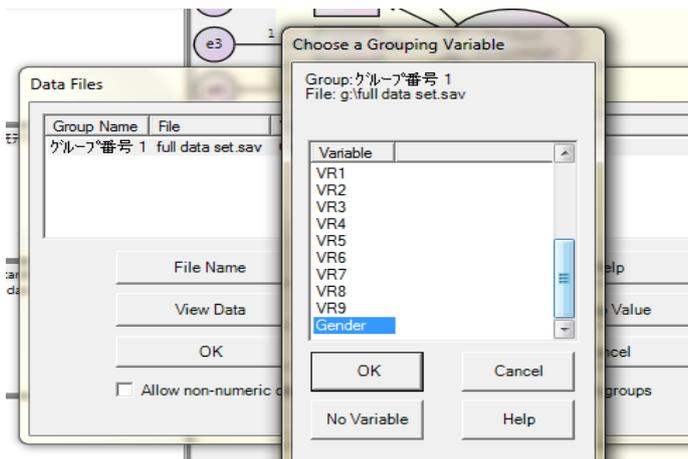


Figure 5.3- Choosing Grouping

## Variable

You can carry on if you have already given grouping values in the data set. Otherwise you can use “Group value” to give the values to nominal variables.

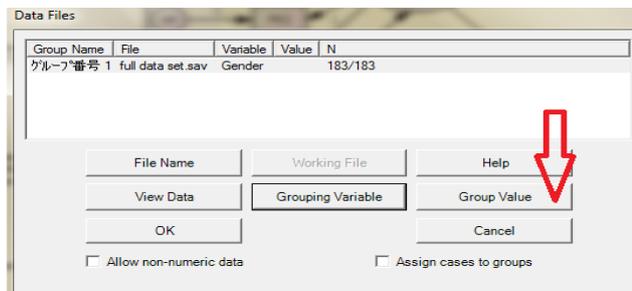


Figure 5.4- Group Value

## 5.2. Multi Group Comparison

Now we can test whether the measurement model of boys is different than the measurement model for the girls. For that purpose, we should include the two groups using,

Analyze → Manage Groups

You will see that the window that pops up says “Group number 1”. That is the current name of the “males” group. To change this name just type over it “males” in the window. Then click NEW and you’ll see it says “Group number 2”. Change this name to say “female” and then click Close.

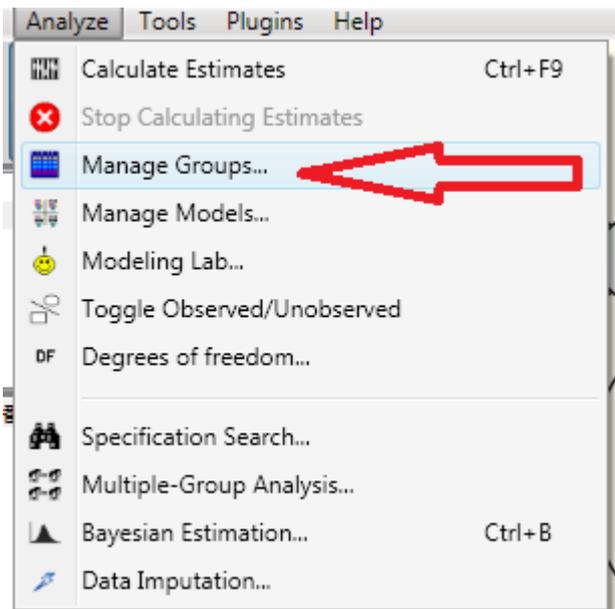


Figure 5.5- Multi Group Comparison (Step 1)

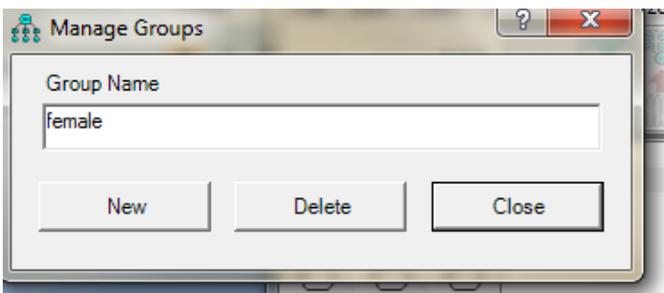


Figure 5.6- Manage Groups window

Now you can see in the left side of the AMOS window “male” and “female” listed.

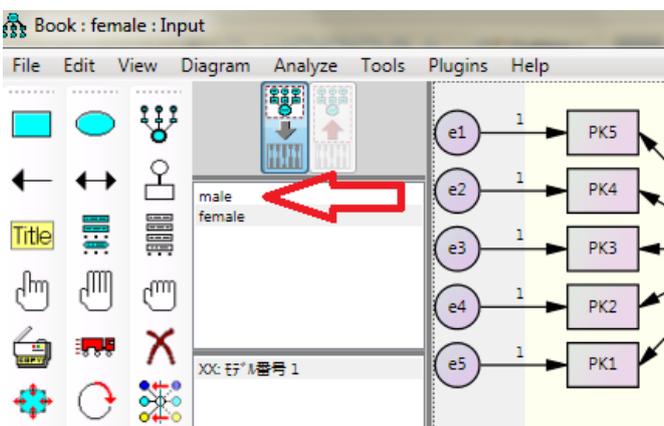


Figure 5.7- Groups in Amos Window

Now we need to attach the separate data sets according to the groups. For this purpose,;

File → Data files (now you should see both “male” and “female” listed under group name but you’ll notice that there are no files under each category.

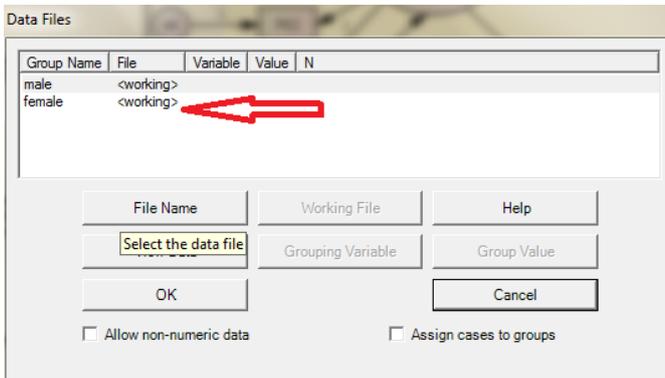


Figure 5.8- working files

Therefore, click on male then File Name and find the data again. Then data set appear in front of male. Then it is required to click the “Grouping variable” and select “gender” and click ok. Next, under “Group Value”, select “1” and click Ok. You should do the same to the second group; female. If you have done it correctly, it will be shown as follows:

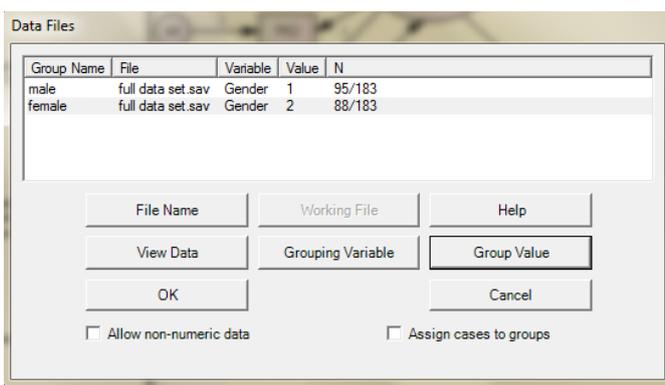


Figure 5.9- Data Files

Now, you can draw your model and named the variables as discussed earlier in this book. Then in order to do the group comparison,

Analyze → Multiple- Group Analyze or use the icon of

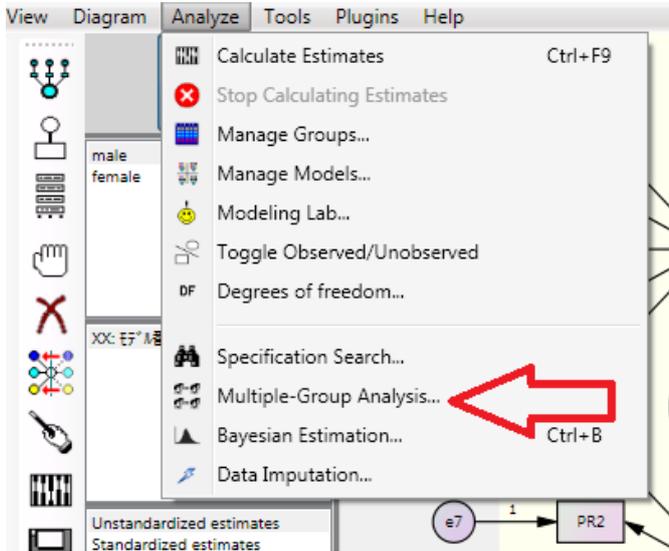


Figure 5.10- Selecting Multiple Group Analysis icon

A window will pop up listing the different models which will be considered, each one is constraining additional parameters to be equal across the two groups (male and females).

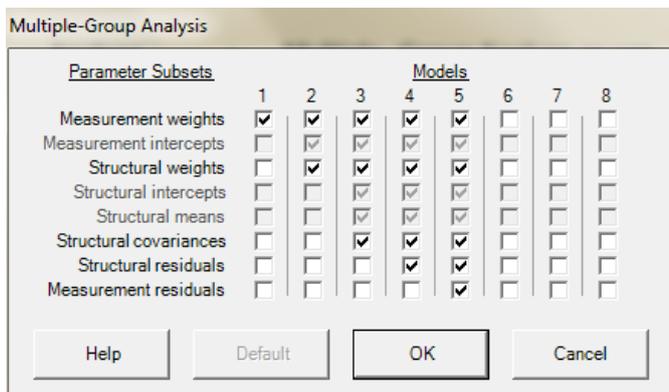


Figure 5.11- Multiple Group Analysis Window

Click Ok and there should now different models listed in the left side of the Amos window.

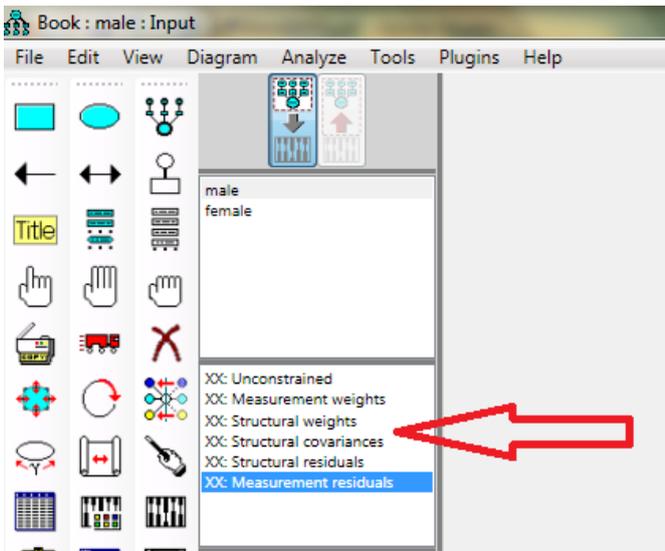


Figure 5.12- Amos window with different models

The “measurement weights” model is fixing only the factor loadings, the “structural covariances” is additionally fixing the variance of the factor to be the same across groups and the “measurement residuals” is fixing the covariances and variances of the errors to be the same. You can double click on each model to see what it is constraining.

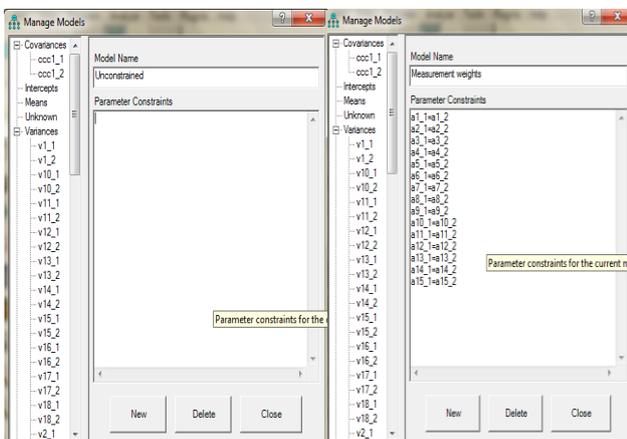


Figure 5.13- parameter names of models

You will be able to see that AMOS has placed parameter names on the model and that it uses a different naming root for different kinds of parameters.

Click the abacus  to run the models. If they all worked correctly, each should say OK rather than XX.

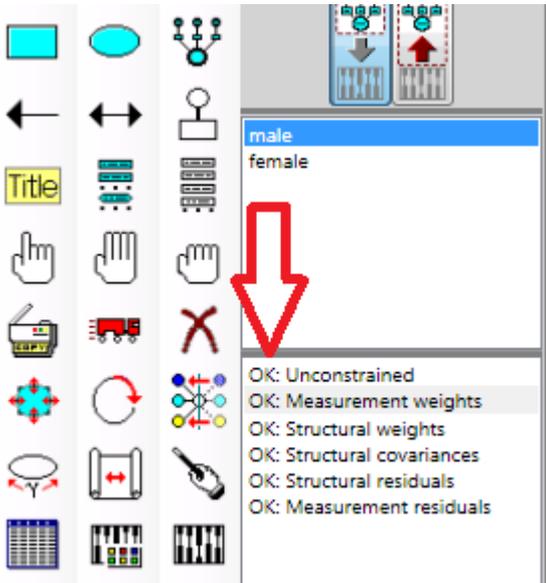


Figure 5.14- Models which ran correctly



To look at the results, click  and, click on the AMOS output window and click on Model Fit and Model Comparison. The values for the different models can be seen there by clicking relevant group.

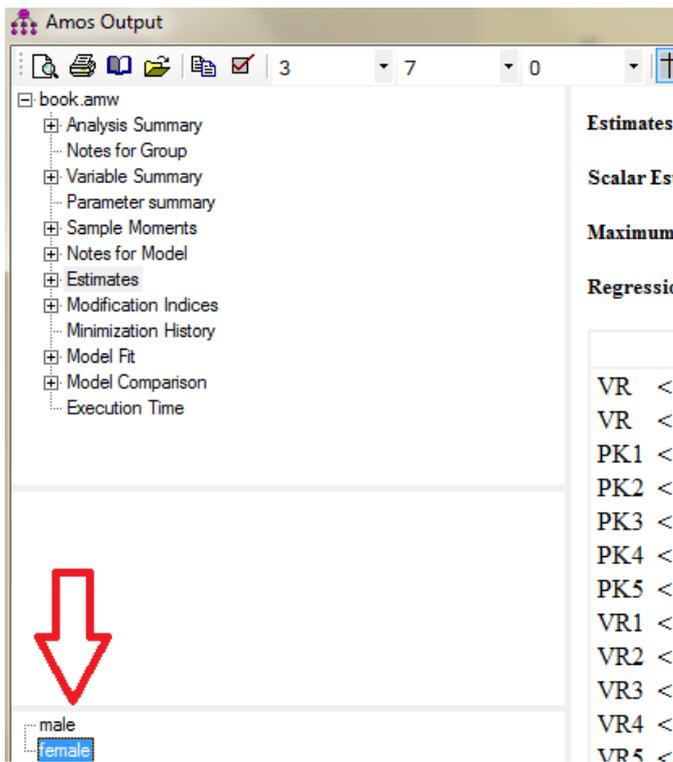


Figure 5.15- Amos output for multi groups

### 5.3. Chapter Summary

This chapter discussed the steps of multi group comparisons using Amos. The interpretations of findings are discussed in chapter-6.

## Chapter-6

### Interpretation of the Results and Modifying the Model

Interpretation of the results is difficult for a researcher after the analysis. Hence an example of interpretation of results is given below using a hypothetical model given in Figure 5.1.

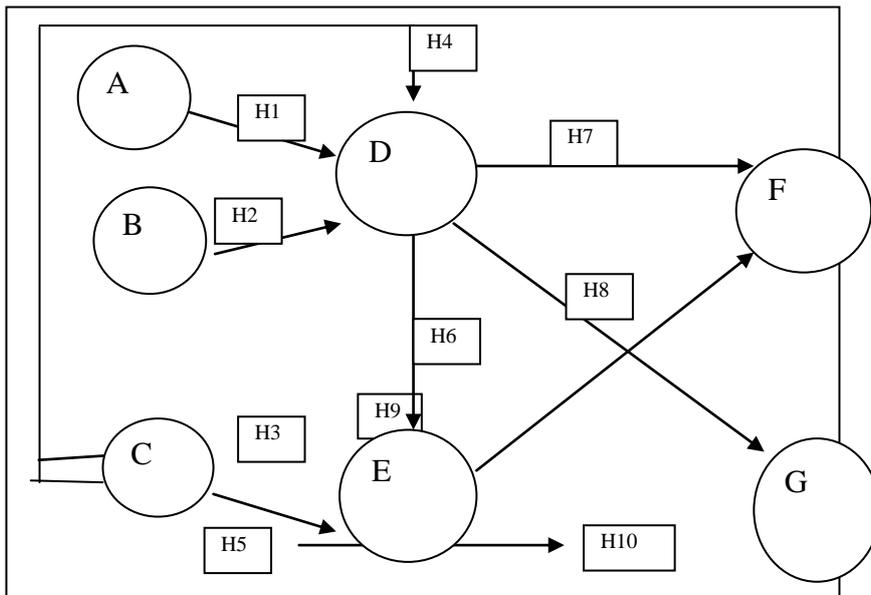


Figure 6.1- sample Model

Relevant hypotheses of the above model (Figure 6.1) are as follows

- H1.* Customer perceptions about “A” directly and positively influence “D”
- .
- H2.* Customer perceptions about”B” directly and positively influence “D”
- .
- H3.* Customer perceptions about the ”C”, directly and positively influence “D”.
- .
- H4.* “B” directly and positively influence “E”
- .
- H5.* Customer perceptions about the “C” directly and positively influence “E”
- .
- H6.* “D” positively influences “E”.
- .
- H7.* “D” directly and positively influences “F”.
- .
- H8.* “D” directly and positively influences “G”.
- .
- H9.* “E” directly and positively influences “F”

*H10.* “E” directly and positively influences “G”

*H11.* The type of organization moderates the effects of the dimensions of the Exogenous variables on endogenous variables

*H11a.* Customer perceptions about the “A” have a stronger positive effect on “D” for “X” type of organizations’ customers than “Y” type of organizations’ customers.

*H11b.* “B” have a stronger positive effect on “D” for “Y” type of organizations’ customers than “X” type of organizations’ customers.

*H11c.* “B” have a stronger positive effect on “E” for “Y” type of organizations’ customers than “X” type of organizations’ customers.

*H11d.* Customer perceptions about the “C” have a stronger positive effect on “D” for “X” type of organizations’ customers than “Y” type of organizations’ customers.

*H11e.* Customer perceptions about the “C” have a stronger positive effect on “E” for “X” type of organizations’ customers than “Y” type of organizations’ customers.

## **6.1. Interpretation of Validity & Reliability**

Before proceeding to the test of the conceptual model in each of the X and Y organizations’ samples, the psychometric properties of the scales were tested to ensure that the model properly fitted the data. For this purpose, the authors implemented first-order confirmatory factor analyses. The results are presented in Tables 6-1 and 6-2. The results confirmed that the chi-square was significant in the X type of companies ((380) 652.59, p 0.01) and Y type of companies’ samples ((380) 1562.21, p 0.01), which may indicate a poor fit of the model to the collected data. However, this result may be because of the large sample size of both samples (over 200 cases), which has been shown to potentially affect the chi-square test. Consequently, this indicator was complemented with an analysis of the comparative fit indexes – normed fit index (NFI), non-normed fit index (NNFI), confirmatory fit index (CFI) and incremental fit index (IFI). In all cases, these measures exceeded the minimum recommended value of 0.90, thus, confirming the goodness of fit of the

proposed model in the X type of organizations' (NFI 0.94; NNFI 0.97; CFI 0.97; IFI 0.97) and Y type of organizations' samples (NFI 0.93; NNFI 0.97; CFI 0.98; IFI 0.98). In addition, the root mean square error of approximation (RMSEA) index was below the minimum recommended value of 0.08 (RMSEA 0.03 in both samples). The reliability of the measurement scales was evaluated by means of the Cronbach's alpha ( $\alpha$ ) and the average variance extracted index, and in all the cases, these indicators were over the recommended values of 0.7 and 0.5, respectively. The convergent validity of the scales was also contrasted, as all the items were significant to a confidence level of 95 per cent and their standardized lambda coefficients ( $\lambda$ ) were higher than 0.5 (Table 6-1). For the purpose of testing the discriminant validity, the confidence intervals for the correlation between pairs of latent factors were estimated and compared with the unit.

It was observed that in none of the cases the proposed intervals contained the value 1 (Table 6-2).

Table 6.1- Internal consistency and convergent validity for two groups

Latent factors	Items	$\lambda$ X	$\lambda$ Y	R <sup>2</sup> X	R <sup>2</sup> Y	$\alpha$	AVE
A	1	0.73	0.71	0.53	0.51	0.89 (x)	0.56 (x)
	2	0.73	0.70	0.54	0.49		
	3	0.75	0.70	0.56	0.50	0.88 (Y)	0.56 (Y)
	4	0.79	0.84	0.62	0.71		
	5	0.80	0.82	0.64	0.67		
	6	0.70	0.70	0.49	0.48		
B	1	0.74	0.70	0.55	0.49	0.85 (x)	0.53 (x)
	2	0.79	0.75	0.62	0.57		
	3	0.71	0.72	0.51	0.51	0.84 (Y)	0.51 (Y)
	4	0.66	0.73	0.43	0.53		
	5	0.74	0.66	0.55	0.44		

C	1	0.75	0.74	0.56	0.54	0.87	0.61
	2	0.82	0.81	0.66	0.66	(x)	(x)
	3	0.82	0.82	0.66	0.67	0.87	0.57
	4	0.80	0.76	0.64	0.57	(Y)	(Y)
	5	0.71	0.63	0.50	0.40		
D	1	0.82	0.83	0.68	0.68	0.93(x)	0.70(x)
	2	0.86	0.85	0.74	0.72	0.93(Y)	0.70(Y)
	3	0.85	0.84	0.72	0.70		
	4	0.86	0.87	0.73	0.75		
	5	0.86	0.85	0.74	0.72		
	6	0.78	0.79	0.61	0.63		
E	1	0.85	0.80	0.73	0.64	0.92(x)	0.74(x)
	2	0.80	0.77	0.65	0.59	0.88(Y)	0.66(Y)
	3	0.89	0.85	0.79	0.71		
	4	0.89	0.82	0.79	0.68		
F	1	0.93	0.90	0.87	0.80	0.91(x)	0.84(x)
	2	0.90	0.94	0.81	0.88	0.92(Y)	0.85(Y)
G	1	0.85	0.89	0.72	0.80	0.88(X)	0.78(X)
	2	0.92	0.91	0.85	0.83	0.90(Y)	0.81(Y)

Notes: x- x type of organizations, Y- Y type of organizations,

x type of organizations-  $\chi^2(380)= 652.59$  ( $p<0.01$ ), NFI=0.94, NNFI=0.97, CFI=0.97, IFI=0.97, RMSEA=0.03

Y type of organizations-  $\chi^2(380)= 562.21$  ( $p<0.01$ ), NFI=0.93, NNFI=0.97, CFI=0.98, IFI=0.98, RMSEA=0.03

Table 6.2- Discriminant validity for the two samples

Latent Factors	A	B	C	D	E	F	G

A	-	0.59- 0.75	0.54- 0.70	0.37- 0.53	0.34- 0.50	0.37- 0.53	0.20- 0.40
B	0.40- 0.60	--	0.45- 0.65	0.43- 0.59	0.50- 0.66	0.44- 0.60	0.34- 0.54
C	0.54- 0.70	0.52- 0.72	-	0.25- 0.41	0.29- 0.45	0.27- 0.43	0.23- 0.43
D	0.23- 0.43	0.37- 0.57	0.27- 0.47	-	0.65- 0.77	0.65- 0.77	0.45- 0.61
E	0.26- 0.46	0.44- 0.64	0.30- 0.50	0.68- 0.80	-	0.74- 0.82	0.71- 0.83
F	0.27- 0.47	0.41- 0.61	0.25- 0.45	0.67- 0.79	- 0.72- 0.84	-	0.69- 0.81
G	0.13- 0.33	0.31- 0.51	0.20- 0.40	0.35- 0.55	0.61- 0.77	0.59- 0.75	-

## 6.2. Interpretation of the Findings

Once the validity of the measurement scales was successfully tested, the causal relationships in Figure 6-1 were estimated in the X type of organizations and Y type of organizations' samples. The results of both studies were compared using multi-group structural equation modeling (SEM).

### 6.2.1. Test of the conceptual model among X type of organizations' customers

The results for X type of organizations' customers are shown in Figure 6-2.

According to the Figure 6-2, "D" was significantly and positively influenced by "A" ( $\beta = 0.24, p < 0.05$ ) and "B" ( $\beta = 0.38, p < 0.05$ ) but "D" is not significantly influenced by "C" ( $\beta = 0.04, p > 0.05$ ). Thus, *H1* and *H2* are supported, whereas the *H4* is not.

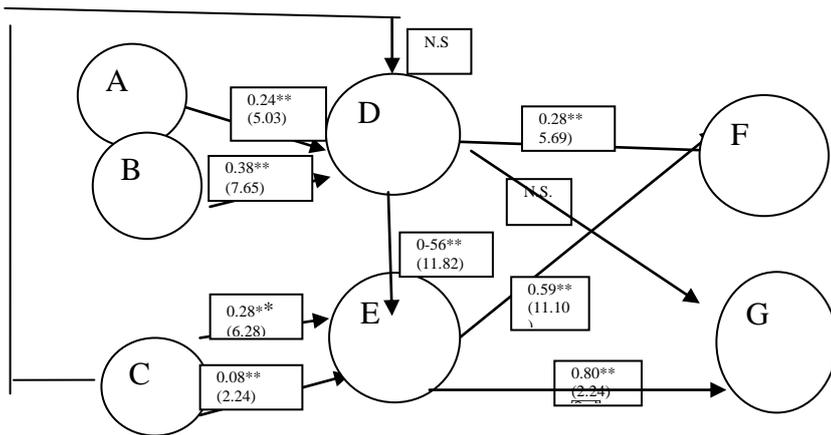


Figure 6-2- Structural model estimation in the X type of organizations

“B” also significantly and positively impacted “E” ( $\beta=0.28, p < 0.05$ ), as well as “C” ( $\beta= 0.08, p < 0.05$ ). Based on these results, *H3* and *H5* are supported. “D” also significantly and positively influenced “E” ( $\beta= 0.56, p < 0.05$ ) and “F” ( $\beta=0.28, p < 0.05$ ). However, it did not significantly influence “G” ( $\beta= 0.05, p > 0.05$ ). Thus, *H6* and *H7* are supported, whereas *H8* is not. Finally, “E” significantly and positively affected “F” ( $\beta= 0.59, p < 0.05$ ) and “G” ( $\beta=0.80, p < 0.05$ ). Based on these results, *H9* and *H10* are supported.

### 6.2.2. Test of the conceptual model among “Y” type of organization’ customers

The results of the analysis implemented with the data of the “y” type of organizations’ sample are shown in Figure 6-3.

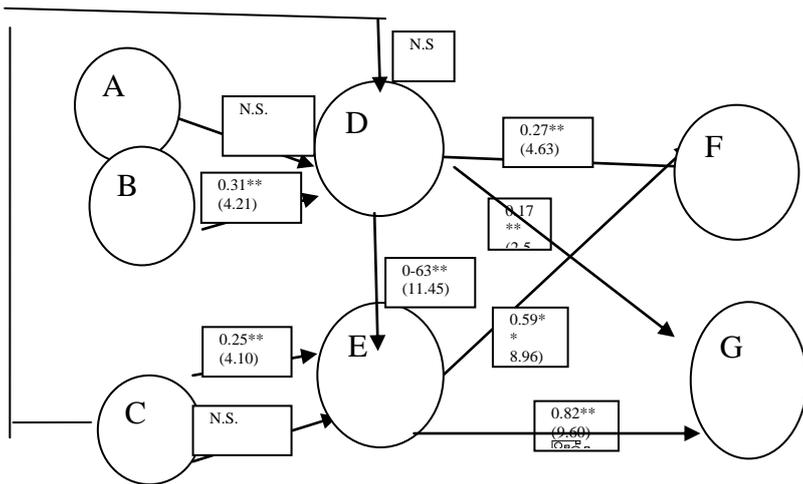


Figure 6.3- Structural model estimation in the “y” type of organization’s sample  
 First, “D” was significantly and positively influenced by “B” customers ( $\beta=0.31, p < 0.05$ ) but not “A” ( $\beta= 0.08, p > 0.05$ ) or “C” ( $\beta= 0.06, p > 0.05$ ). Thus, *H2* is supported, whereas *H1* and *H3* are not. “B” also significantly and positively impacted “E” ( $\beta= 0.25, p < 0.05$ ), but, again, “C” did not significantly affect “E” ( $\beta= 0.06, p < 0.05$ ). Based on these results, *H4* is supported, whereas *H5* is not. “D” identification also significantly and positively influenced “E” ( $\beta= 0.63, p < 0.05$ ), “F” ( $\beta= 0.27, p < 0.05$ ) and “G” ( $\beta= 0.17, p < 0.05$ ). Thus, *H6* to *H8* are supported. Finally, “E” significantly and positively affected “F”( $\beta=0.59, p < 0.05$ ) and “H” ( $\beta=0.82, p < 0.05$ ). Based on these results, *H9* and *H10* are supported.

### 6.2.3. Multi-group comparison

With the aim of statistically examining the differences between both samples, a comparison of the intensity of each of the relationships for “X” and “Y” type of customers was carried out by applying a multi-group SEM analysis. The suitability of the analysis was tested with the Lagrange multiplier test. To confirm that the type of organization was a moderator of the relationships under scrutiny, it was necessary that the  $\chi^2$  differences were significant because this meant that differences existed in the intensity of the relationships between the samples. The results of this analysis are shown in Table 6-3, and they demonstrate that several relationships in the conceptual model were different among “X” and “Y” type of organizations’ customers. Thus,

the type of company is a moderator of the effects of the dimensions of the Exogenous variables on endogenous variables in the industry (Difference (Dif.) $\chi^2(33) = 131.52$ ,  $p < 0.01$ ). Based on these results, *H11* is supported. Although “A” positively influenced the “D” in the “X” type of organizations’ sample ( $\beta = 0.24$ ,  $p < 0.05$ ), it did not affect the “D” of “Y” type of organizations’ customers ( $\beta=0.08$ ,  $p>0.05$ ) (Dif.  $\chi^2=2.51$ ,  $p <0.01$ ). This result supports

*H11a*. The same trend was perceived in the relationship between “C” and “E” ( $\beta_x= 0.08$ ,  $p < 0.05$ ;  $\beta_y= 0.06$ ,  $p > 0.05$ ; Dif.  $\chi^2=1.49$ ,  $p < 0.01$ ). Thus, *H11e* is also supported.

Table 6.3- Multi Group Comparison

Relationship	Standardized Loadings		Dif
	X	Y	$\chi^2(1)$
A → D	0.24	n.s.	2.51*
B → D	0.38	0.31	0.31
B → E	0.28	0.25	0.18
C → D	n.s.	n.s.	0.99
C → E	0.08	n.s.	1.49*
D → E	0.56	0.63	5.29*
D → F	0.28	0.27	1.03
D → G	n.s	0.17	76.47*
E → F	0.59	0.59	0.33
E → G	0.80	0.80	26.42*

Notes: \* p- value<0.01; Goodness-of-fit index:  $\chi^2(815)=2162.81$  ( $p<0.01$ ); NFI=0.88; NNFI=0.92; CFI=0.93; IFI=0.93; RMSEA=0.04; Dif. $\chi^2(33)=131.52$ ( $p<0.01$ )

However, none of the other effects between the samples of two groups can be seen (Dif.  $\chi^2 < 1.04$ ,  $p > 0.1$ ). Based on these findings, *H11b* to *H11d* are not supported.

Some additional differences were observed in the effects of “D” on customer “E” ( $\beta_x = 0.56, p < 0.05$ ;  $\beta_y = 0.63, p < 0.05$ ; Dif.  $\chi^2 = 5.29, p < 0.01$ ) and “G” ( $\beta_x = 0.05, p > 0.05$ ;  $\beta_y = 0.17, p < 0.05$ ; Dif.  $\chi^2 = 76.47, p < 0.01$ ), as well as in the effect of “E” on “G” ( $\beta_x = 0.80, p < 0.05$ ;  $\beta_y = 0.82, p > 0.05$ ; Dif.  $\chi^2 = 26.42, p < 0.01$ ). In the three cases, the effects of “D” and “E” were stronger among “Y” type of organization’s customers.

### 6.3. Modifying the Model

It is difficult to find a model fit at the first time. In a situation where the researcher cannot get a fitted model to the data model modification may be required to obtain a better-fitting model. *Modification indices* in Amos facilitate the researcher to generate the expected model fit by reducing the overall chi-square by showing each possible path that can be added to the model. To request modification index output, select the **Modification Indices** check box in the **Output tab** in the **Analysis Properties** window which you can see under **View/Set**.

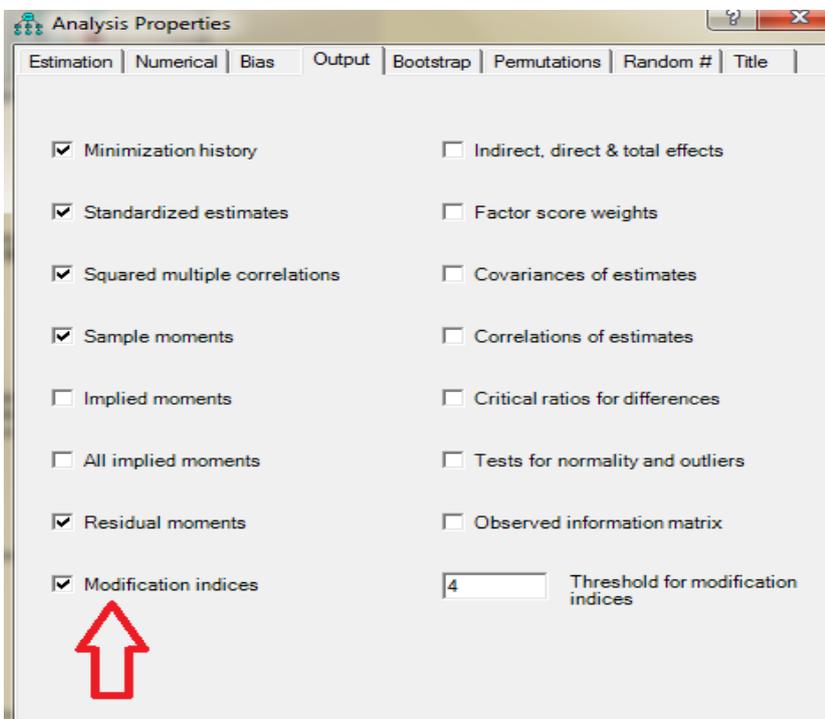


Figure 6.4- Analysis properties window

The **Threshold for Modification Indices** facilitate the researcher by specifying the level of chi-square change is required for a path to be included in the modification index output. The default value is 4.00 because it slightly exceeds the tabled critical value of a chi-square distribution with one degree of freedom: 3.84. Any additional parameter estimated by AMOS should result in an expected reduction in the model chi-square of at least 3.84.

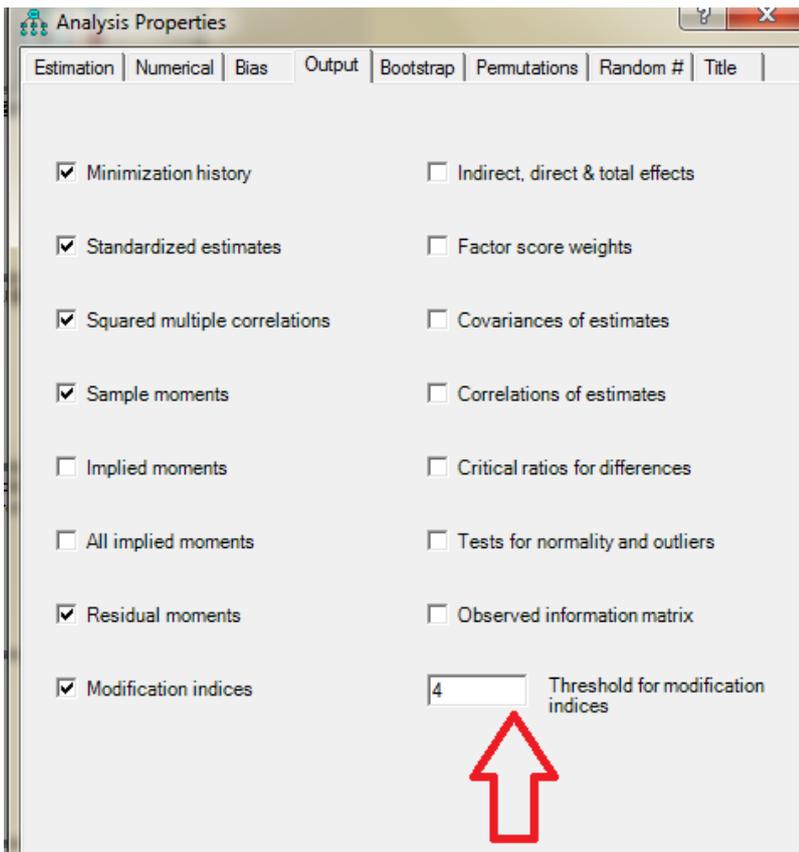


Figure 6.5- Threshold for modification indices The modification index results appear below in figure 6.6. But you should keep in mind that AMOS provides modification index output only when the complete data are available. In other words, you cannot obtain modification index information when you use missing data with AMOS.

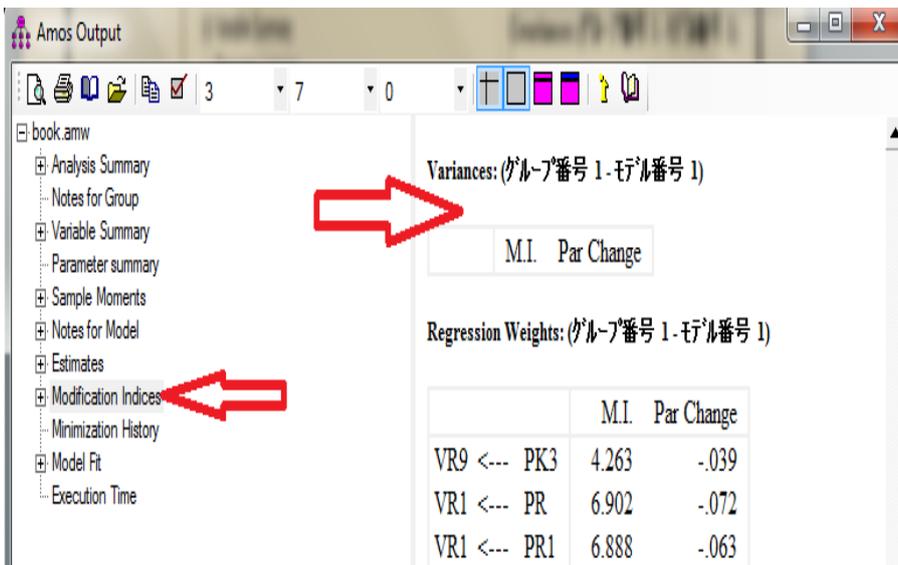


Figure 6.6- Modification Indices

All possible variances were estimate in the model. Hence, there are no variances that could be considered to improve the existing model. Thus, the *Variances* section contains no model modification information in the Figure 6.6.

There are, however, possible regression weights and covariances that can be used in the modified model (Figure 6.7).

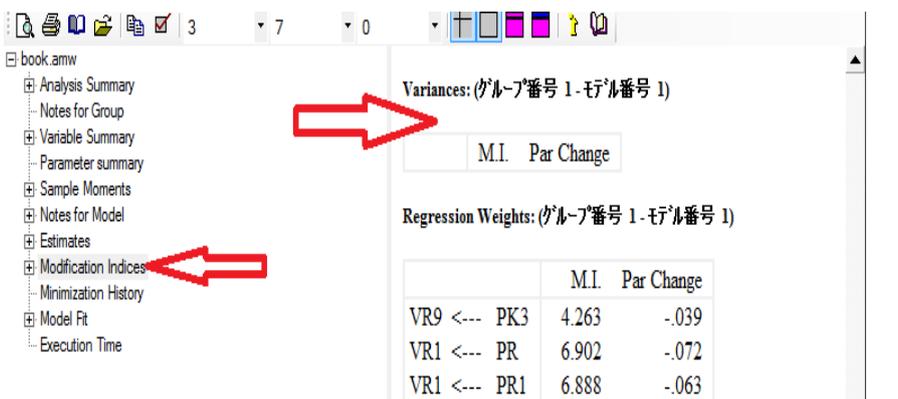


Figure 6.7- possible regression weights and covariances of the modified model

If the modification index values are high, you can do the suggested changes and check the model fit. But in the above Figure 6.7, the modification index values are not that much significant to do the modifications to the current model. But if the values are high, for example, the covariance of  $e15$  with  $e17$  is expected to be 0.901, you can re-specify the model with that covariance added and then refit the model. It is worth to keep in mind that the researcher should reconsider the conceptual implications before modifying the existing model.

#### 6.4. Modifying the appearance of the model

1. AMOS prints the  $R^2$  values for each dependent or mediating variable above the variable. But, sometimes the value cannot be seen clearly. To move a parameter on the output diagram, use the **Move Parameter** tool.



Select the tool and click your mouse pointer over the required variable until it is highlighted in red. Then pull the mouse in a direction where you want the value to appear.

#### 6.5. Chapter Summary

How to interpret the output of AMOS is discussed in this chapter using a hypothetical model. Results and its interpretation is given for individual groups and the interpretation of results are given for multi group comparison as well using two set of samples. Further, the steps for model modification has also discussed in this chapter.

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