

Scientific Research Workshops - A Practical Perspective

Prepared by Dr. Mona Moustafa Elashry

Session 10





مجموعة جامعة
الجميع الذكية
للتعليم القابضة

MIDOCEAN
UNIVERSITY
BY EVERYONE'S SMART UNIVERSITY

“Statistical Analysis- Part 3”

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Session Outline

- Construct Validity
- Construct Reliability
- Hypotheses Testing

Construct Validity

(Convergent validity+ Discriminant validity)

1



Convergent Validity Factor Analysis (EFA+CFA)

Factor Analysis

What is factor analysis?

- ★ Factor analysis is a very useful and popular method of multivariate research technique, mostly used in social and behavioural sciences.
- ★ This technique is applicable when there is a systematic interdependence among a set of observed variables, and the researcher is interested in finding out something more fundamental which creates this commonness.
- ★ Factor analysis attempts to represent a set of observed variables $X_1, X_2, \dots, X_n$ in terms of a number of 'common' factors. The common factors (sometimes called latent variables) are hypothetical variables which explain why a number of variables are correlated with each other -- it is because they have one or more factors in common.

Contd..

Factor analysis seeks to resolve a large set of measured variables in terms of relatively few categories, known as factors. This technique allows the researcher to group variables into factors (based on correlation between variables), and the factors so derived may be treated as new variables (often termed as latent variables) and their value derived by summing the values of the original variables which have been grouped into the factor. The meaning and name of such variable is subjectively determined by the researcher.

Some concepts used in factor analysis

- **Factor**- It is an underlying dimension that accounts for several observed variables.
- **Factor loadings**- are those values which explain how closely the variables are related to each one of the factors discovered. It is the absolute size of the loadings that is important in the interpretation of a factor.
- **Communality** – shows how much of each variable is accounted for by the underlying factor taken together. A high value of communality means that not much of the variable is left over after whatever the factors represent is taken into consideration.
- **Eigenvalue (or latent root)** – sum of squared values of factor loadings relating to a factor. It indicates the relative importance of each factor in accounting for the particular set of variables analysed.
- **Rotation**- reveals different structures in the data and provides meaning to the results of factor analysis.

KEEPING THINGS SIMPLE

- ❑ Factor analysis (FA) is all about simplification.
- ❑ A method that allows us to understand large quantities of observable variables in terms of a smaller number of unobservable variables.
- ❑ FA and PCA (principal components analysis) are methods of data reduction

KEEPING THINGS SIMPLE

- ☐ Take many variables and explain them with a few “factors” or “components”
- ☐ Regardless of purpose, factor analysis is used in: the determination of a small number of factors based on a particular number of inter-related quantitative variables.
- ☐ In FA, correlated variables are grouped together and separated from other variables with low or no correlation

STEPS IN FACTOR ANALYSIS

Factor analysis usually proceeds in four steps:

- ❑ 1st Step: The correlation matrix for all variables is computed.
- ❑ 2nd Step: Factor extraction.
- ❑ 3rd Step: Factor rotation.
- ❑ 4th Step: Make final decisions about the number of underlying factors.

1st Step: the correlation matrix

- ❑ Generate a correlation matrix for all variables
- ❑ Identify variables not related to other variables
- ❑ If the correlation between variables are small, it is unlikely that they share common factors (variables must be related to each other for the factor model to be appropriate).
- ❑ Think of correlations in absolute value.
- ❑ Correlation coefficients greater than 0.4 in absolute value are indicative of acceptable correlations.
- ❑ Examine visually the appropriateness of the factor model.

1st Step: the correlation matrix

- **Example**

	X1	X2	X3	X4	X5	X6
X2	0.580					
X3	0.201	0.364				
X4	0.911	0.834	0.439			
X5	0.283	0.166	-0.704	0.163		
X6	0.287	0.261	-0.681	0.202	0.990	
X7	-0.533	-0.609	-0.649	-0.676	0.427	0.357

2nd Step: Factor extraction

- ❑ Initial decisions can be made here about the number of factors underlying a set of measured variables.
- ❑ Estimates of initial factors are obtained using Principal Components Analysis.
- ❑ The principal components analysis is the most commonly used extraction method . Other factor extraction methods include:
 - Maximum likelihood method
 - Principal axis factoring
 - Alpha method
 - Unweight least squares method
 - Generalized least squares method
 - Image factoring.

3rd Step: Factor rotation.

- ❑ Un-rotated factors are typically not very interpretable (most factors are correlated with many variables).
- ❑ Factors are rotated to make them more meaningful and easier to interpret (each variable is associated with a minimal number of factors).
- ❑ Different rotation methods may result in the identification of somewhat different factors. The most popular rotational method is Varimax rotations yielding uncorrelated factors

4th Step: Making final decisions

- ❑ The final decision about the number of factors to choose is the number of factors for the rotated solution that is most interpretable.
- ❑ To identify factors, group variables that have large loadings for the same factor.
- ❑ Interpret factors according to the meaning of the variables

STATISTICS ASSOCIATED WITH FACTOR ANALYSIS

- ❑ Bartlett's test of sphericity. Bartlett's test of sphericity is used to test the hypothesis that the variables are uncorrelated in the population (i.e., the population corr matrix is an identity matrix)
- ❑ Communality. Amount of variance a variable shares with all the other variables. This is the proportion of variance explained by the common factors.
- ❑ Eigenvalue. Represents the total variance explained by each factor.

The most common method
eigenvalue >1 approach

FACTOR LOADINGS

- ❑ If we had a factor loading of .80 it means 64% of variance in responses to that indicator is attributable to that variable.
- ❑ The remaining variance is due to either systematic or random sources of variation
- ❑ Factor loadings above .6 are desirable
- ❑ Factor loadings $> .4$ are acceptable
- ❑ Factor loadings $\leq .4$ are not desirable

- Based on Kaiser, (1960), factor loadings that are less than 0.5 were ignored and deleted from the construct
- the eigenvalue of 1 or greater than 1 indicates better variation that to be explained by a factor.
- In social science, the accepted cumulative variance is 60% (Hair, et al., 2006).
- The average communalities, based on the criterion of Kaiser that indicates when the sample size is greater than 250, the average communalities should be equal to or greater than 0.6. The extracted communalities average was calculated by dividing the sum of all communality values on the total number of items.

EXAMPLE 1

High Factor Loading

Variable	Factor1	Factor2	Factor3	Factor4	Factor5	Factor6	Communality
X1	-0.928	0.253	0.008	0.143	0.073	-0.220	1.000
X2	0.301	0.795	0.459	0.255	-0.027	0.030	1.000
X3	-0.936	0.131	0.105	0.093	0.252	0.153	1.000
X4	0.342	0.789	-0.453	0.203	0.113	0.043	1.000
X5	0.869	-0.351	0.119	0.023	0.317	0.085	1.000
X6	0.177	0.871	0.026	-0.453	-0.009	-0.060	1.000

Medium Factor Loading

Low Factor Loading

STATISTICS ASSOCIATED WITH FACTOR ANALYSIS

- ❑ Factor loadings. Correlations between the variables and the factors. (weights W)
- ❑ Factor matrix. A factor matrix contains the factor loadings of all the variables on all the factors
- ❑ Scree plot. A scree plot is a plot of the Eigenvalues against the number of factors in order of extraction.

TYPES OF FACTOR ANALYSIS

- ❖ *Exploratory analysis (EFA)* attempts to discover the nature of the constructs infusing a set of responses.
- ❖ *Confirmatory factor analysis (CFA)* tests whether a specified set of constructs is infusing responses in a predicted way

There are two types of factor analysis.

Exploratory

It is exploratory when you do not have a pre-defined idea of the structure or how many dimensions are in a set of variables.

Confirmatory.

It is confirmatory when you want to test specific hypothesis about the structure or the number of dimensions underlying a set of variables (i.e. in your data you may think there are two dimensions and you want to verify that).

Exploratory Factor Analysis (EFA) in SPSS



	AgeParticipant	Participant
1	37.00	
2	38.00	
3	.	
4	.	
5	36.00	
6	26.00	
7	37.00	
8	35.00	
9	37.00	
10	34.00	
11	25.00	
12	.	
13	36.00	
14	.	
15	27.00	
16	33.00	
17	.	
18	35.00	
19	40.00	
20	40.00	
21	29.00	
22	43.00	
23	29.00	
24	29.00	

- Reports
- Descriptive Statistics
- Bayesian Statistics
- Tables
- Compare Means
- General Linear Model
- Generalized Linear Models
- Mixed Models
- Correlate
- Regression
- Loglinear
- Neural Networks
- Classify
- Dimension Reduction
- Scale
- Nonparametric Tests
- Forecasting
- Survival
- Multiple Response
- Missing Value Analysis...
- Multiple Imputation
- Complex Samples
- Simulation...
- Quality Control
- ROC Curve...
- Spatial and Temporal Modeling...
- Direct Marketing



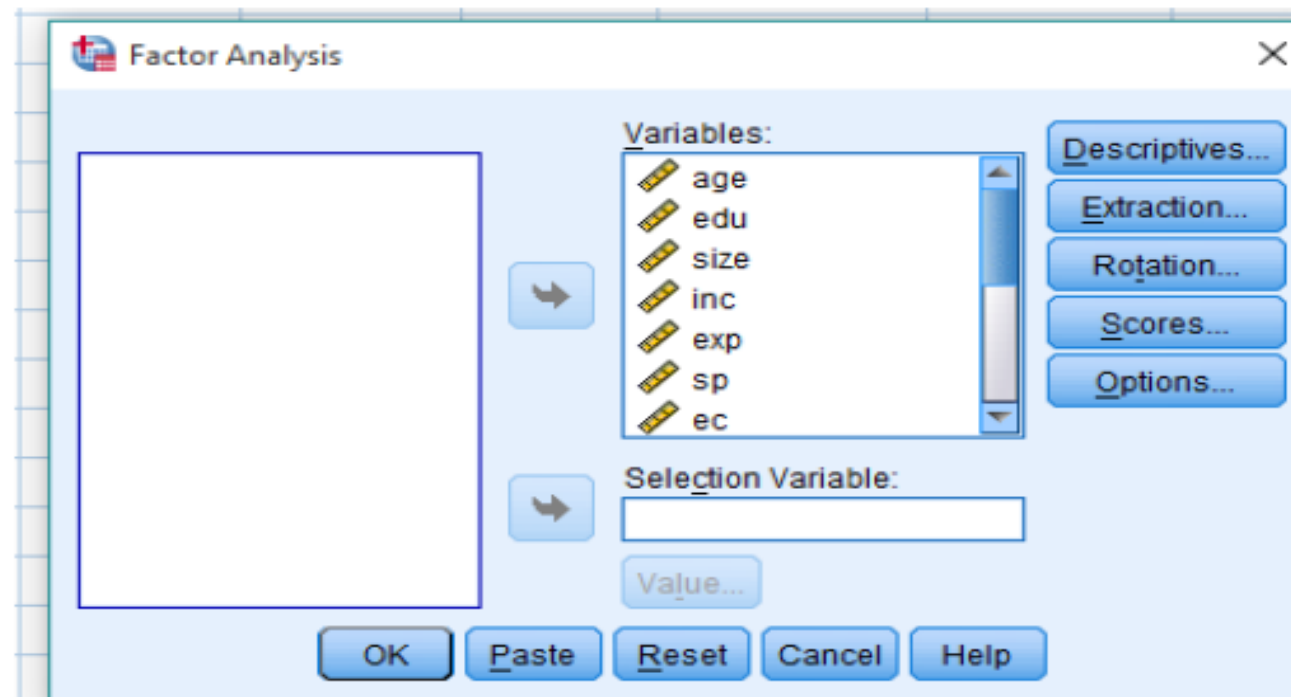
Income	AgeChild	Dx	SxSeverity	DxDate	Admissions
.00	2.00	6.00	14.00	3.00	1.00
.00	3.00	10.00	14.00	1.00	1.00
.00	.	2.00	14.00	1.00	2.00
.00	2.00	10.00	.	1.00	3.00
.00	.	.00	.	3.00	1.00
.00	.	6.00	.	3.00	.
.00	3.00	9.00	4.00	2.00	1.00
.00	4.00	6.00	11.00	3.00	2.00
.00	.	2.00	.	4.00	2.00
.00	.	.	4.00	1.00	.00
.00	.	.	11.00	2.00	1.00
.00	.	.	3.00	4.00	2.00
.00	2.00	2.00	2.00	1.00	1.00
.00	2.00	.	.	3.00	.
.00	.00	5.00	6.00	2.00	1.00
.00	1.00	6.00	.	3.00	.00
.00	2.00	2.50	10.00	3.00	.00
.00	5.00	4.00	.	.	2.00
.00	.	7.00	9.00	5.00	4.00
.00	.	.	8.00	4.00	1.00
.00	3.00	2.00	.	1.00	2.00
.00	3.00	7.50	5.00	2.00	2.00
.00	.00	2.00	.	1.00	1.00
.00	1.00	.	7.00	2.00	4.00

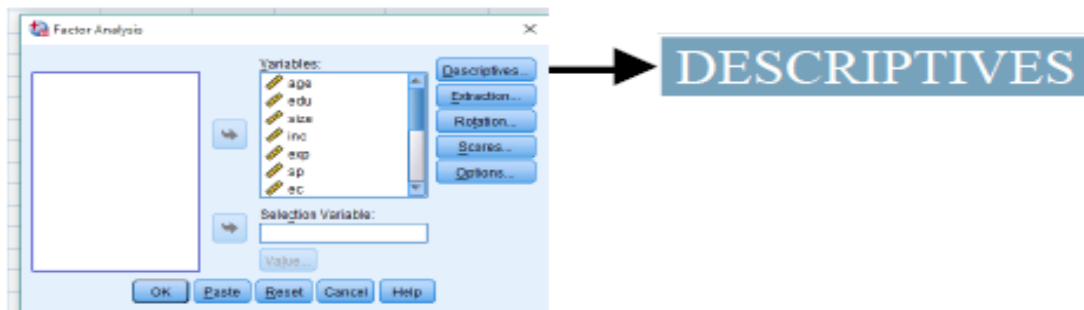
Visible: 103 of 103 Variables

- Factor...
- Correspondence Analysis...
- Optimal Scaling...

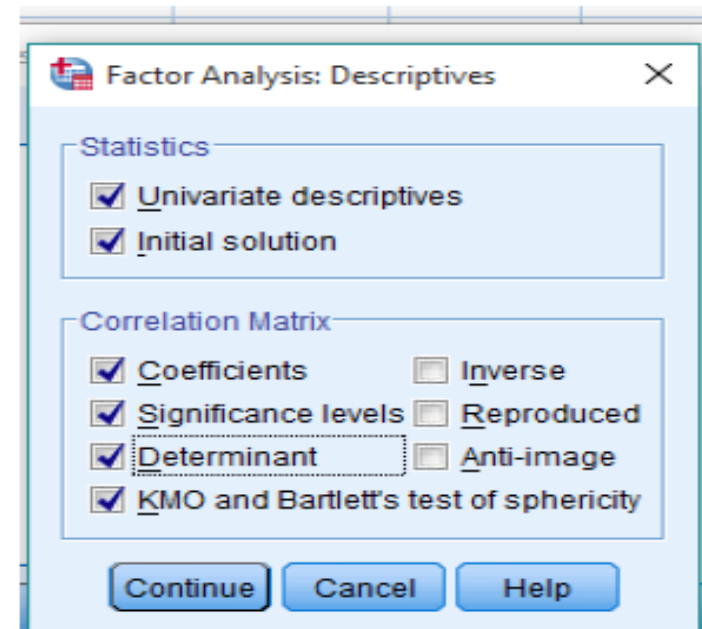
HOW TO CARRY OUT FACTOR ANALYSIS IN SPSS?

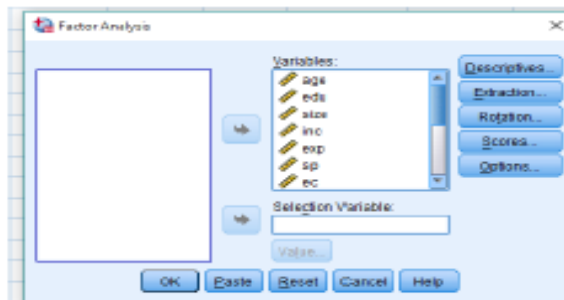
- Access the main dialog box by using the Analyze⇒Data Reduction⇒Factor menu path. Simply select the variables you want to include in the analysis and transfer them to the box labelled Variables by clicking on the button.





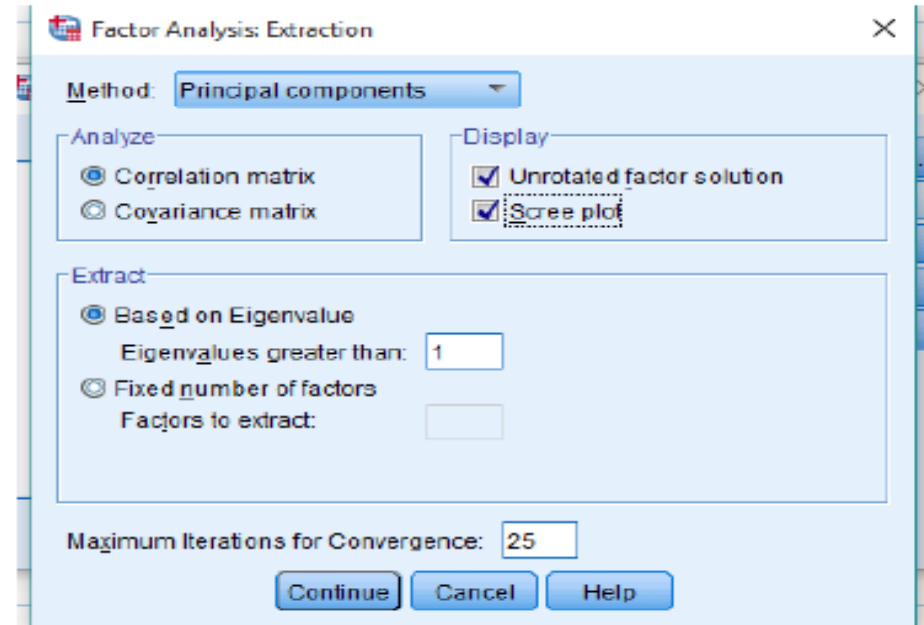
- The *Coefficients* option produces the R-matrix, and the *Significance levels* option will produce a matrix indicating the significance value of each correlation in the R-matrix. You can also ask for the *Determinant* of this matrix and this option is vital for testing for multicollinearity or singularity. *KMO and Bartlett's test* produces the Kaiser-Meyer-Olkin measure of sampling adequacy. The value of KMO should be greater than 0.5 if the sample is adequate.



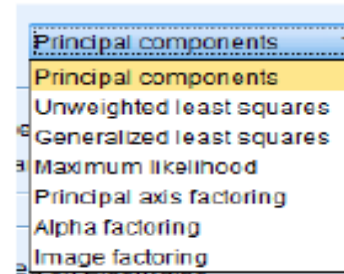


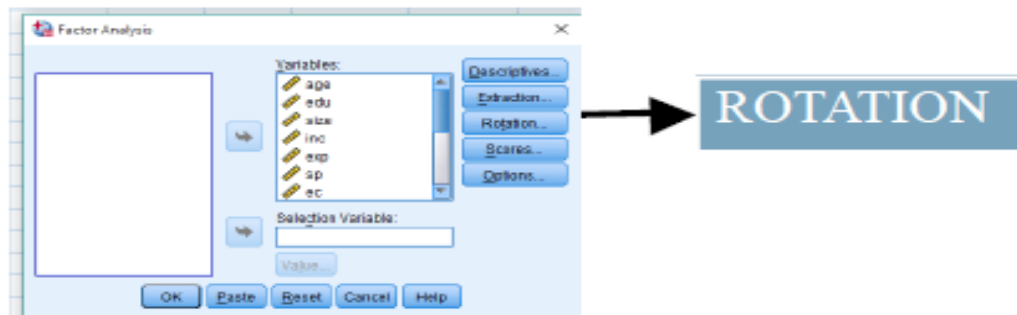
EXTRACTION

- There are several ways to conduct factor analysis.
- The **Display** box has two options: to display the *Unrotated factor solution* and a *Scree plot*. The scree plot is a useful way of establishing how many factors should be retained in an analysis. The unrotated factor solution is useful in assessing the improvement of interpretation due to rotation.
- The **Extract** box provides options pertaining to the retention of factors. You have the choice of either selecting factors with eigenvalues greater than a user-specified value or retaining a fixed number of factors. It is desirable to select factors for which eigenvalues greater than one.

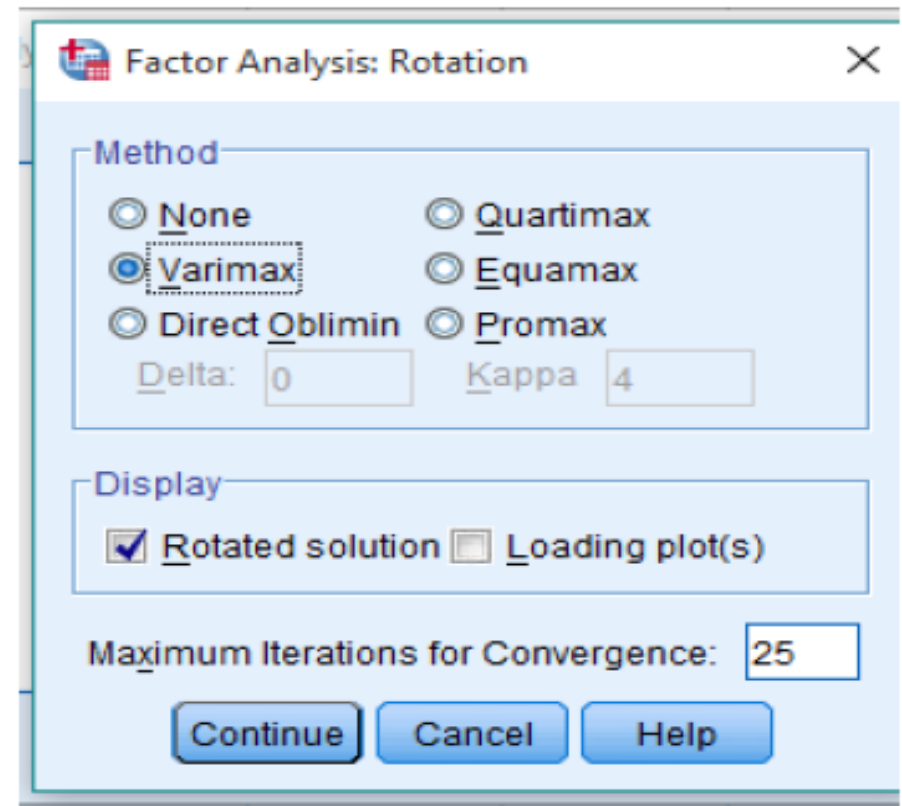


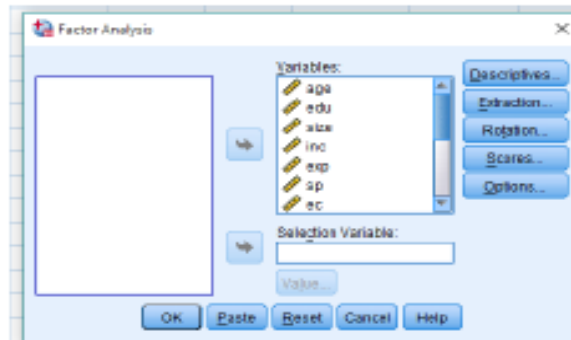
Analysis: Extraction





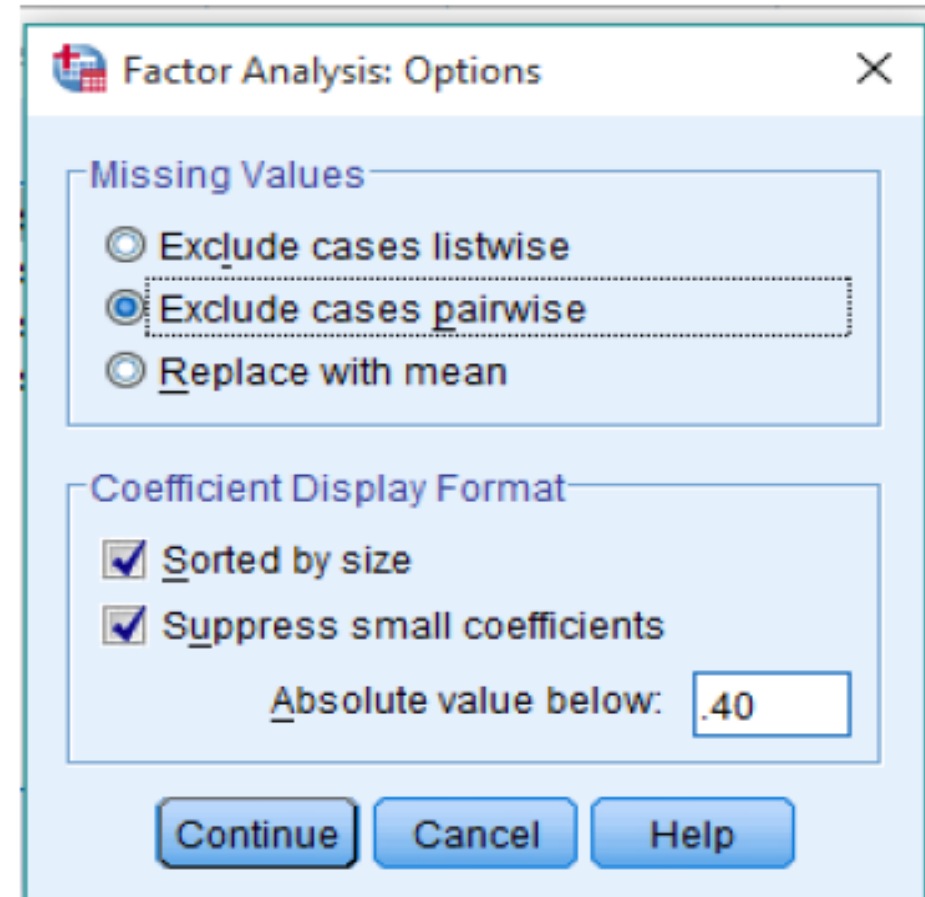
- The interpretability of factors can be improved through rotation. Rotation maximizes the loading of each variable on one of the extracted factors whilst minimizing the loading on all other factors.
- Varimax, quartimax and equamax are orthogonal rotations whereas direct oblimin and promax are oblique rotations. The exact choice of rotation depends largely on whether or not you think that the underlying factors should be related.





OPTIONS

- By selecting Sorted by size, SPSS will order the variables by their factor loadings. There is also the option to Suppress absolute values less than a specified value (by default 0.1). This option ensures that factor loadings within ± 0.1 are not displayed in the output.



Interpretation of output from SPSS

- OUTPUT 1: Scan the correlation coefficients and look for any greater than 0.9. If any are found then you should be aware that a problem could arise because of singularity in the data.

Correlation Matrix^a

	age	edu	size	inc	exp	sp	ec	so	mo	em	isb	rta	cosmp	mmp	envi
Correlation	age	edu	size	inc	exp	sp	ec	so	mo	em	isb	rta	cosmp	mmp	envi
	1.000	-.309	-.339	-.388	.674	-.382	-.236	-.302	-.156	-.251	-.353	-.201	-.186	-.243	-.359
	edu	1.000	.094	.056	-.099	.232	.199	.166	.220	.188	.221	.142	.158	.273	.284
	size	-.339	.094	1.000	.506	-.211	.415	.143	.197	.192	.100	.193	.103	.555	.273
	inc	-.388	.056	.506	1.000	-.398	.183	.111	.298	.082	.159	.241	.009	.427	.129
	exp	.674	-.099	-.211	-.398	1.000	-.152	-.080	-.255	-.088	-.154	-.301	-.132	-.072	-.029
	sp	-.382	.232	.415	.183	-.152	1.000	.611	.236	.533	.346	.300	.363	.584	.595
	ec	-.236	.199	.143	.111	-.080	.611	1.000	.394	.618	.339	.414	.333	.539	.606
	so	-.302	.166	.197	.298	-.255	.236	.394	1.000	.499	.554	.379	.278	.339	.329
	mo	-.156	.220	.192	.082	-.088	.533	.618	.499	1.000	.551	.543	.525	.457	.620
	em	-.251	.188	.100	.159	-.154	.346	.339	.554	.551	1.000	.328	.418	.219	.380
	isb	-.353	.221	.193	.241	-.301	.300	.414	.379	.543	.328	1.000	.316	.448	.420
	rta	-.201	.142	.103	.009	-.132	.363	.333	.278	.525	.418	.316	1.000	.290	.395
	cosmp	-.186	.158	.555	.427	-.072	.584	.539	.457	.219	.448	.290	1.000	.565	.565
	mmp	-.243	.273	.273	.129	-.029	.595	.606	.329	.620	.380	.420	.395	1.000	.682
	envi	-.359	.284	.238	.263	-.281	.443	.463	.368	.554	.263	.557	.324	.495	1.000
Sig. (1-tailed)	age		.000	.000	.000	.000	.005	.000	.045	.003	.000	.014	.021	.004	.000
	edu	.000		.153	.273	.142	.005	.014	.035	.008	.020	.008	.061	.043	.001
	size	.000	.153		.000	.010	.000	.059	.016	.018	.140	.017	.131	.000	.001
	inc	.000	.273	.000		.000	.023	.114	.186	.042	.004	.482	.000	.080	.000
	exp	.000	.142	.010	.000		.048	.193	.002	.229	.047	.000	.075	.219	.376
	sp	.000	.005	.000	.023	.048		.000	.005	.000	.000	.000	.000	.000	.000
	ec	.005	.014	.059	.114	.193	.000		.000	.000	.000	.000	.000	.000	.000
	so	.000	.035	.016	.000	.002	.005	.000		.000	.000	.000	.001	.000	.000
	mo	.045	.008	.018	.186	.229	.000	.000	.000		.000	.000	.000	.000	.000
	em	.003	.020	.140	.042	.047	.000	.000	.000	.000		.000	.000	.000	.000
	isb	.000	.008	.017	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	rta	.014	.061	.131	.000	.000	.000	.001	.000	.000	.000	.000		.001	.000

Double-click to activate

- OUTPUT 2: Kaiser and Bartlett test- The KMO statistic varies between 0 and 1. The value of 0 indicates that factor analysis is likely to be inappropriate for the data. Kaiser (recommends accepting values greater than 0.5. Furthermore, values between 0.5 and 0.7 are mediocre, values between 0.7 and 0.8 are good, values between 0.8 and 0.9 are great and values above 0.9 are superb.
- Bartlett's measure tests the null hypothesis that the original correlation matrix is an identity matrix. We want this test to be significant (i.e. have a significance value less than 0.05).

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.806
Bartlett's Test of Sphericity	Approx. Chi-Square	902.985
	df	120
	Sig.	.000

- **OUTPUT 3:** lists the eigenvalues associated with each linear component (factor) before extraction, after extraction and after rotation.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5.695	37.965	37.965	5.695	37.965	37.965	3.732	24.879	24.879
2	1.913	12.753	50.718	1.913	12.753	50.718	2.393	15.950	40.829
3	1.385	9.234	59.952	1.385	9.234	59.952	1.988	13.255	54.084
4	1.058	7.051	67.004	1.058	7.051	67.004	1.938	12.919	67.004
5	.845	5.630	72.634						
6	.822	5.483	78.117						
7	.674	4.492	82.608						
8	.512	3.413	86.022						
9	.458	3.056	89.078						
10	.422	2.812	91.890						
11	.316	2.105	93.995						
12	.283	1.884	95.879						
13	.254	1.694	97.573						
14	.196	1.310	98.883						
15	.168	1.117	100.000						

Extraction Method: Principal Component Analysis

■ OUTPUT 4 : Communalities and Component matrix.

Communalities

	Initial	Extraction
age	1.000	.792
edu	1.000	.548
size	1.000	.718
inc	1.000	.730
exp	1.000	.766
sp	1.000	.639
ec	1.000	.621
so	1.000	.670
mo	1.000	.784
em	1.000	.692
isb	1.000	.481
rta	1.000	.444
cosmp	1.000	.805
mmp	1.000	.742
envi	1.000	.620

Extraction Method: Principal Component Analysis

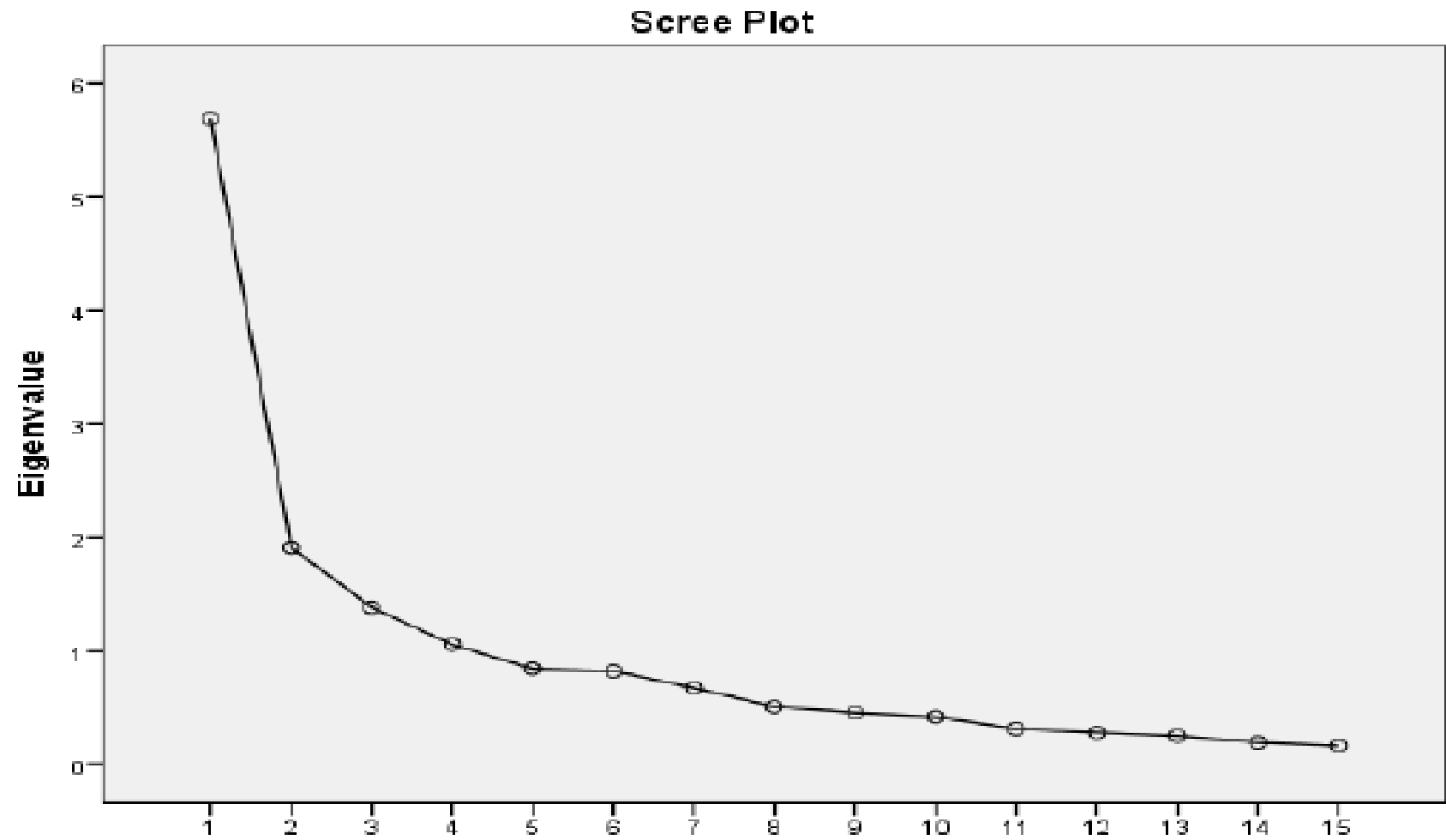
Component Matrix^a

	Component			
	1	2	3	4
mo	.774			
mmp	.767			
envi	.747			
sp	.727			
cosmp	.719		.527	
ec	.715			
isb	.672			
so	.610			.441
em	.580		-.420	
rta	.542			
exp		.690		
inc	.410	-.651		
age	-.534	.596		
size	.469	-.442	.531	
edu				-.611

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

■ OUTPUT 5. Scree plot



■ OUTPUT 6: Rotated component matrix

Rotated Component Matrix^a

	Component			
	1	2	3	4
mmp	.819			
sp	.732			
ec	.709			
envi	.672			
cosmp	.652			.596
mo	.633	.619		
isb	.447	.400		
em		.805		
so		.755		
rta		.533		
age			-.831	
exp			-.812	
edu	.475		.491	
size				.789
inc				.777

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 15 iterations.

Component Matrix^a

	Component			
	1	2	3	4
mo	.774			
mmp	.767			
envi	.747			
sp	.727			
cosmp	.719		.527	
ec	.715			
isb	.672			
so	.610			.441
em	.580		-.420	
rta	.542			
exp		.690		
inc	.410	-.651		
age	-.534	.596		
size	.469	-.442	.531	
edu				-.611

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Confirmatory Factor Analysis (CFA)

CONFIRMATORY FACTOR ANALYSIS (CFA)

- ❖ Used to study how well a hypothesized factor model fits a new sample from the same population or a sample from a different population characterized by allowing restrictions on the parameters of the model
- ❖ CFA has strong links to structural equation modeling, a relatively nonstandard area of statistics.
- ❖ Much more difficult to perform a CFA than it is to perform an EFA.

- A CFA requires a larger sample size than an EFA, because the CFA produces inferential statistics
- CFA can be performed in SAS using *proc calis*, but cannot be performed in SPSS.
- However, SPSS does produce another software package called AMOS which will perform CFA.
- CFA are also commonly analyzed using LISREL.
- The exact sample size necessary will vary heavily with the number of measures and factors in the model, but you can expect to require around 200 subjects for a standard model.



CFA USING AMOS

	Interface Properties...	Ctrl+I
	Analysis Properties...	Ctrl+A
	Object Properties...	Ctrl+O
	Variables in Model...	Ctrl+Shift+M
	Variables in Dataset...	Ctrl+Shift+D
	Parameters...	Ctrl+Shift+P
	Matrix Representation...	Ctrl+Shift+R
	Text Output	F10
	Full Screen	F11

Unstandardized estimates
Standardized estimates


Interface Properties
?
×

Page Layout

Formats

Colors

Typefaces

Pen Width

Misc

Accessibility

Margins

Top

1

Bottom

1

Left

1

Right

1

Paper Size

Portrait - Letter

Portrait - A6

Portrait - Legal

Portrait - Letter

Landscape - A4

Landscape - A6

Landscape - Legal

Landscape - Letter

☒ Inches

☐ Centimeters

Apply

Cancel

Margins

Top

1

Bottom

1

Left

1

Right

1

Paper Size

Landscape - A4

Height

8.26771653

Width

11.6929133

☒ Inches☐ Centimeters

Apply

Cancel

Data Files

Group Name	File	Variable	Value	N
Group number 1 <working>				

File Name

Working File

Help

View Data

Grouping Variable

Group Value

OK

Cancel

☐ Allow non-numeric data

☐ Assign cases to groups

Open



« Dissertation-2020 » Doctorate files »

Search Doctorate files



Organize ▾

New folder



▾ This PC

> 3D Objects

> Desktop

> Documents

> Downloads

> Music

> Pictures

> Videos

> Local Disk (C:)

> New Volume (D:)

> System Reserved

> Local Disk (F:)

Name

Date modified

Type

Perfect FIT

6/17/2020 8:17 PM

File folder

Extracted item OA-Untitled2.sav

6/14/2020 9:40 PM

SPSS Statistics Dat...

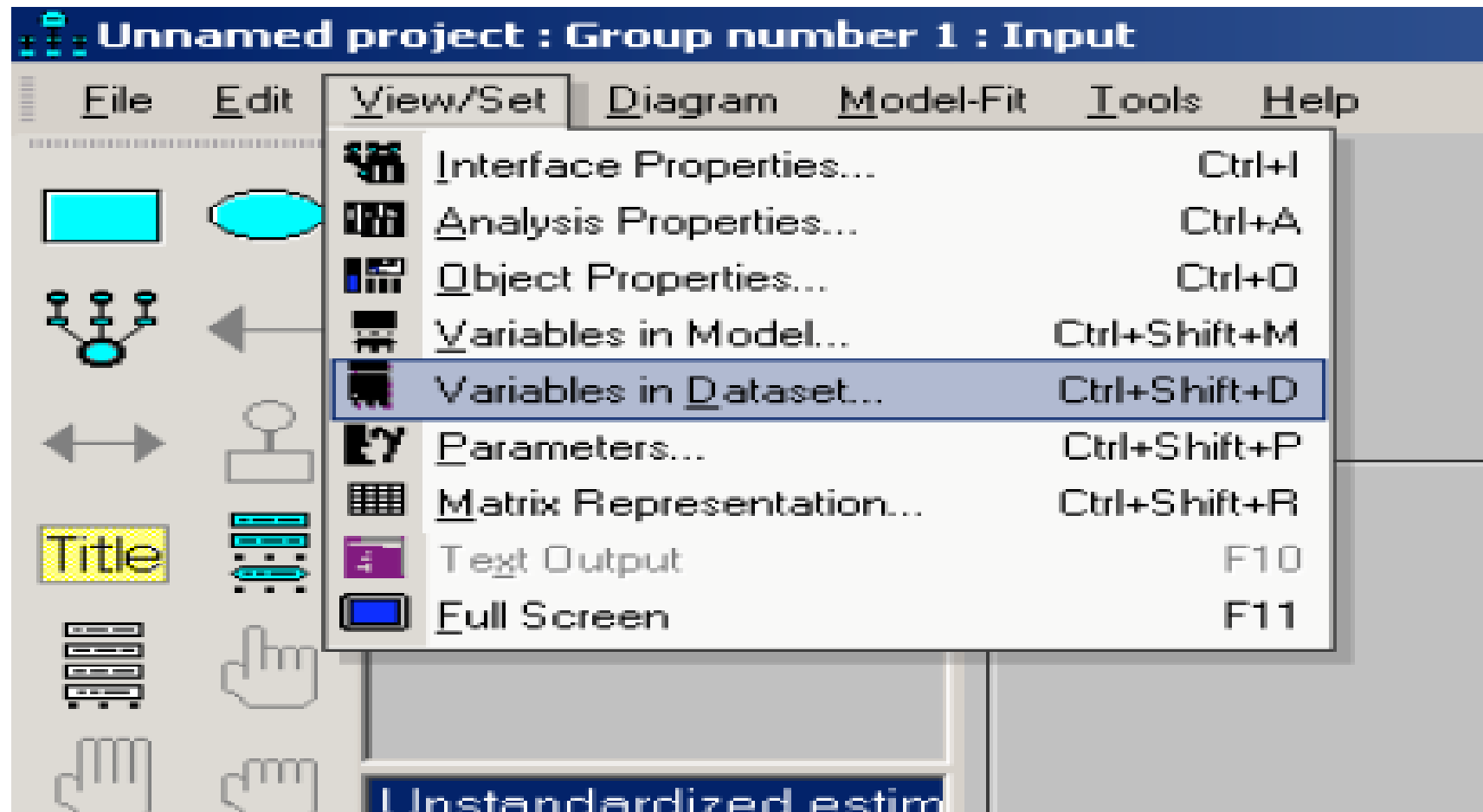
File name:

IBM SPSS Statistics (*.sav)

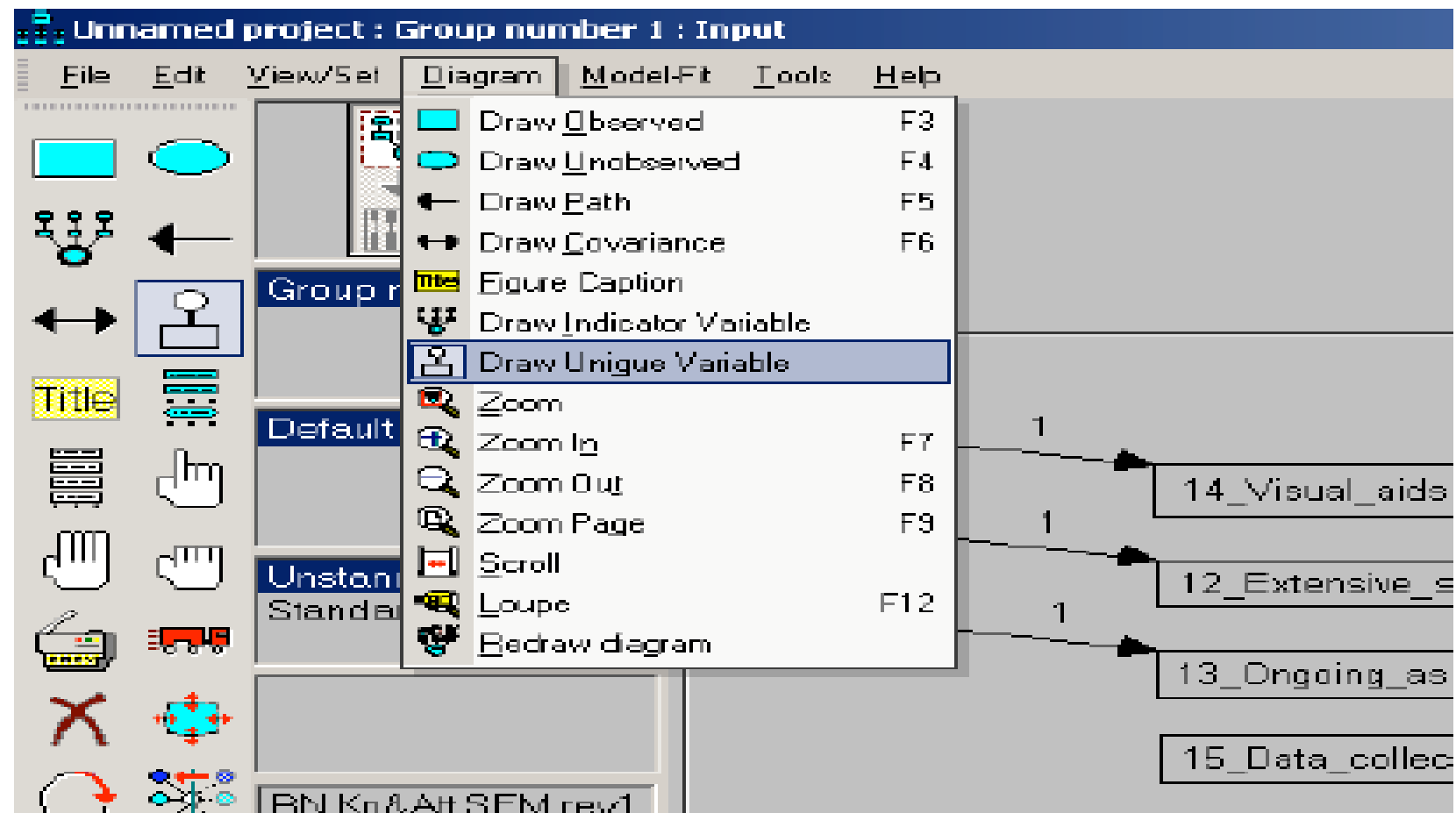
Open

Cancel

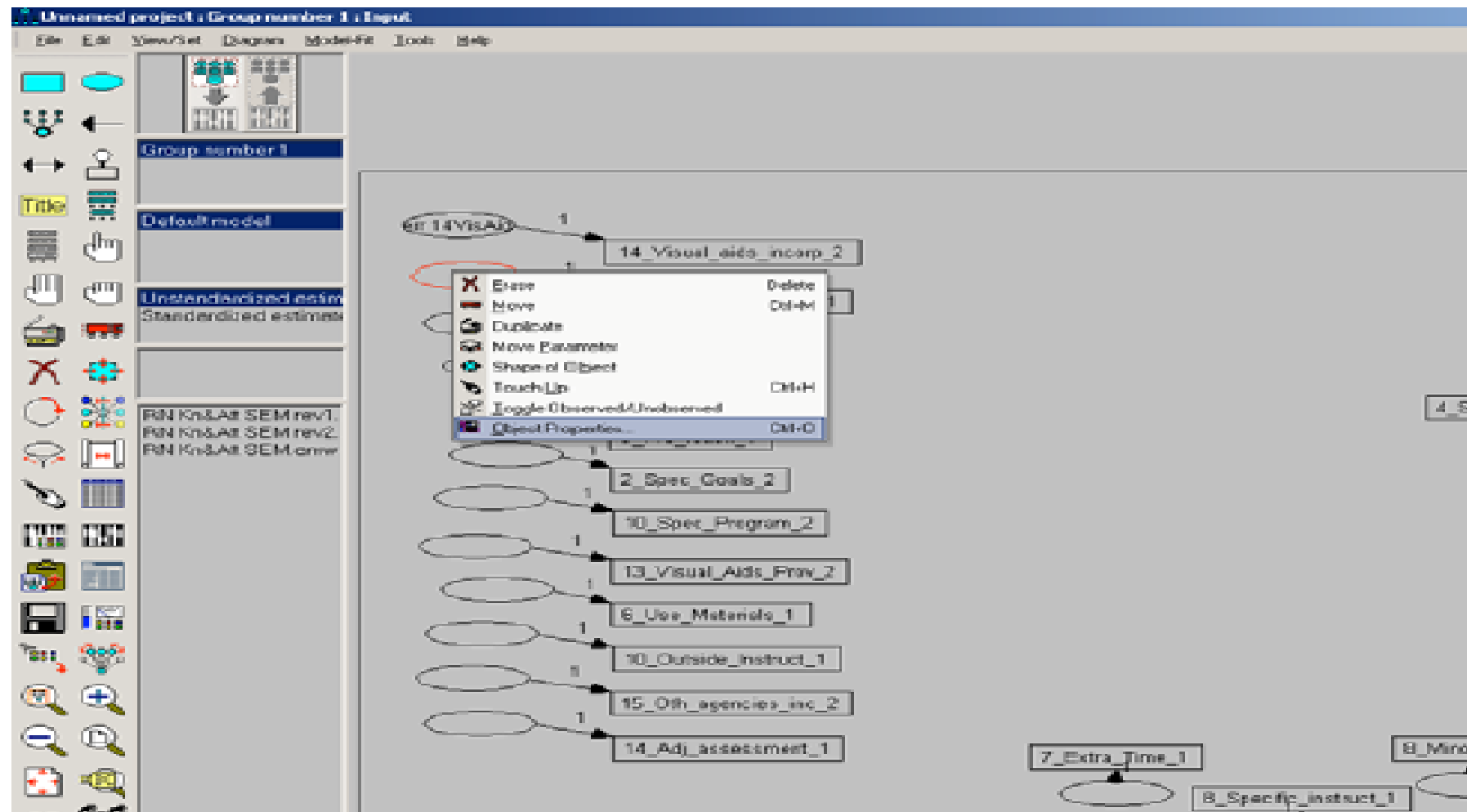
Select variables in dataset from view/set menu



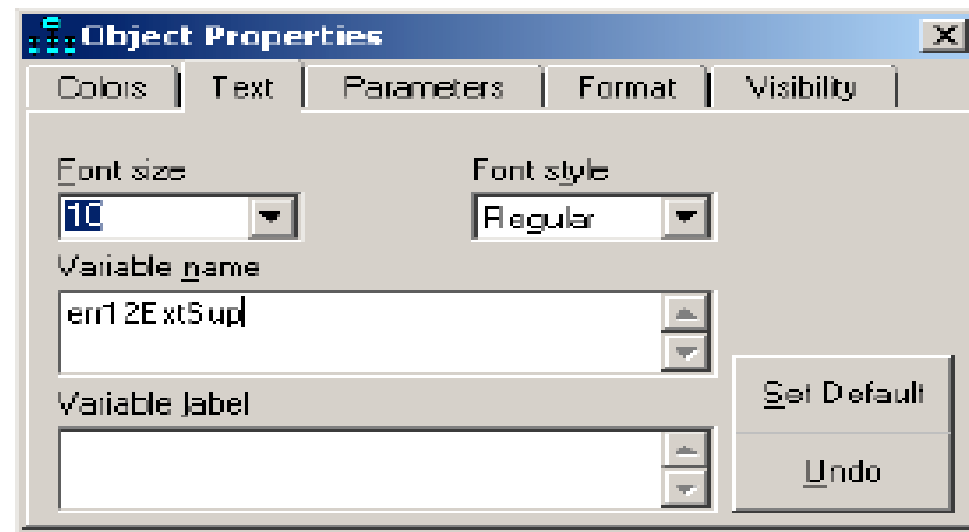
Add error terms via diagram menu



Can adjust object properties (font size, variance) for measured (rectangular) and latent (semi-circular) boxes (left-click for Windows or control click for Apple Macs)



Here adjusting font size for labels and numbers to 10



Here adjusting analysis properties to take account of missing values

Analysis Properties

Bootstrap Permutations Random # Title

Estimation Numerical Bias Output

Discrepancy

☒ Maximum likelihood

☐ Generalized least squares

☐ Unweighted least squares

☐ Scale-free least squares

☐ Asymptotically distribution-free

☒ Estimate means and intercepts

☐ Emulate B

☐ Chicago

For the purpose of computing fit measures with incomplete data:

☒ Fit the saturated and independence models

☐ Fit the saturated model only

☐ Fit neither model

Here selecting analytic output of interest

Analysis Properties

Bootstrap	Permutations	Random #	Title
Estimation	Numerical	Bias	Output

☐ Minimization history

☒ Standardized estimates

☒ Squared multiple correlations

☐ Sample moments

☐ Implied moments

☐ All implied moments

☐ Residual moments

☐ Modification indices

☐ Indirect, direct & total effects

☐ Factor score weights

☐ Covariances of estimates

☐ Correlations of estimates

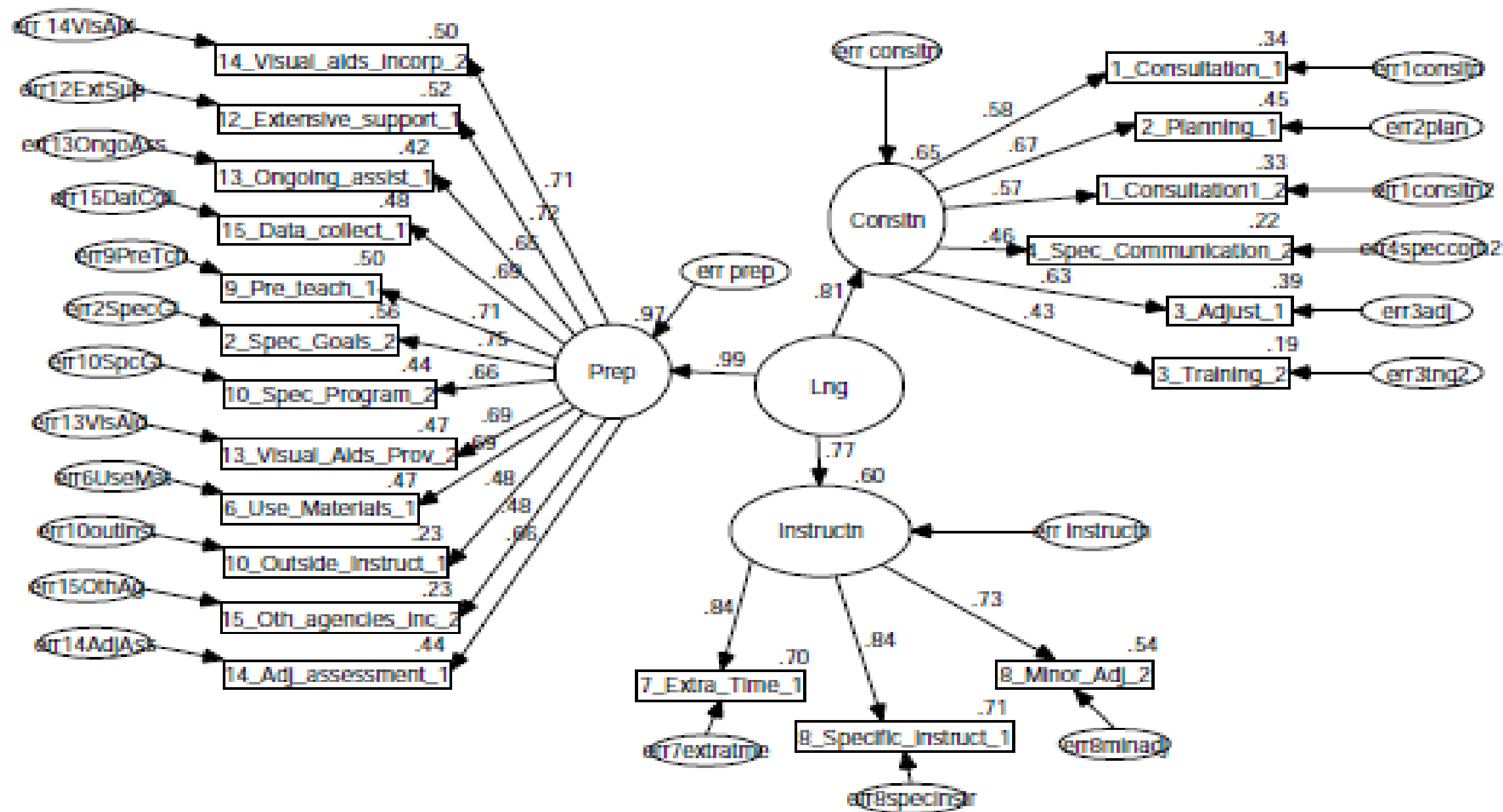
☐ Critical ratios for differences

☐ Tests for normality and outliers

☐ Observed information matrix

Threshold for modification indices

Resulting Confirmatory factor analysis



Correlations: (Group number 1 - Default model)

	Estimate
Consltn <--> Prep	.724
Consltn <--> Instructn	.613
Prep <--> Instructn	.764

Models

Default model (Default model)

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments: 252

Number of distinct parameters to be estimated: 66

Degrees of freedom (252 - 66): 186

Result (Default model)

Minimum was achieved

Chi-square = 1478.445

Degrees of freedom = 186

Probability level = .000

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
Prep <--- Lng	5.987	3.470	1.725	.084	
Consltn <--- Lng	1.368	.093	14.725	***	
Instructn <--- Lng	1.219	.068	17.794	***	
V33 <--- Prep	.088	.050	1.771	.077	
V13 <--- Prep	.090	.051	1.771	.077	
V14 <--- Prep	.054	.030	1.769	.077	
V16 <--- Prep	.097	.055	1.771	.077	
V10 <--- Prep	.103	.058	1.770	.077	
V21 <--- Prep	.099	.056	1.771	.077	
V29 <--- Prep	.092	.052	1.769	.077	
V32 <--- Prep	.095	.054	1.770	.077	
V7 <--- Prep	.120	.068	1.769	.077	
V11 <--- Prep	.077	.043	1.764	.078	
V34 <--- Prep	.068	.039	1.762	.078	
V15 <--- Prep	.091	.052	1.770	.077	
V8 <--- Instructn	.313	.012	25.828	***	

Standardized Regression Weights: (Group number 1 - Default model)

	Estimate
Prep <--- Lng	.986
Consltn <--- Lng	.807
Instructn <--- Lng	.773
V33 <--- Prep	.706
V13 <--- Prep	.720
V14 <--- Prep	.650
V16 <--- Prep	.694
V10 <--- Prep	.708
V21 <--- Prep	.749

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
Consltn	.652
Instructn	.598
Prep	.973
V20	.328
V23	.216
V2	.340
V3	.450
V4	.394
V22	.187
V27	.520

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	66	1478.445	186	.000	7.949
Saturated model	252	.000	0		
Independence model	21	9875.940	231	.000	42.753

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.850	.814	.867	.834	.866
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.805	.685	.697
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	1292.445	1173.676	1418.654
Saturated model	.000	.000	.000
Independence model	9644.940	9323.106	9973.101

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	.945	.826	.750	.907
Saturated model	.000	.000	.000	.000
Independence model	6.315	6.167	5.961	6.377

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.067	.064	.070	.000
Independence model	.163	.161	.166	.000

Type	Fit Index	Description	Cut-off Value
Absolute Fit Indices	Chi-Square (X ²)	Assessing the overall fit of the model by comparing the differences between the sample covariance matrix and the fitted covariance matrix	$p > 0.05$
	Normed-Chi-Square (X ² /df)	Evaluates the model fit after reducing the impact of large sample sizes on the model Chi-Square (X ²)	$1 < X^2/df < 3$
	RMSEA	Evaluates the degree to which the study model fits the covariance matrix of the population	< 0.08
	GFI	Evaluates the degree to which the model can replicate the covariance matrix	> 0.90
	AGFI	Similar to GFI with adjustments made based on the degrees of freedom (df)	> 0.90
	RMR	The square root of the difference between the residuals of the sample covariance matrix and the hypothesised covariance model	< 0.08
	SRMR	Similar to RMR but easier to interpret when the study questionnaire comprises different types of scales (e.g. scales that range from 1 to 5 and others that range from 1 to 7)	< 0.08
Incremental Fit Indices	NFI	Assesses the model by comparing X ² of the study model to that of a null model	> 0.90
	NNFI	Similar to NNFI but provides better interpretations for models that are simple	> 0.90
	CFI	A revised version of NFI that works better when sample sizes are small	> 0.90
Parsimony Fit Indices	PGFI	An index that is based on GFI while accounting for loss of degrees of freedom. It does not work well when the model is complex.	> 0.50
	PNFI	An index that is based on NFI while accounting for loss of degrees of freedom. It does not work well when the model is complex	> 0.50

Source: Relied on Hooper, et al. (2008)

Discriminant Validity using AVE value

- Discriminant validity refers to the items of different constructs are not related to each other (Cooper and Schindler, 2003)
- AVE (Average Variance Extracted) method is used to measure convergent validity. However, the root of AVE is used to measure discriminant validity.

- The method for measuring the discriminant validity is the average variance extracted (AVE), which was computed from the sum of the squared multiple correlations of items divided by the number of these items (Hair et al., 2010).

$$\text{Root of [the sum of squared multiple correlations/ n]} = \text{AVE}$$

- However, the construct discriminant validity can be assessed through various methods, either by identifying the correlation between the constructs, or by comparing “the root of average variance extracted (AVE) scores for any two different constructs with the estimate of the squared correlation between them” (Hair et al., 2006, p. 778).

- The discriminant validity of the constructs was measured through comparing the square roots of the AVE scores with the correlations among the latent constructs.
- The discriminant validity is supported if the square roots of the AVE values are exceeding the highest squared correlation

Table 35: Results of Discriminant Validity among the whole constructs

Constructs	HPWSs	KMSs	OA
HPWSs	0.72		
KMSs	0.672	0.92	
OA	0.609	0.592	0.84

Reliability

(Cronbach`s alpha+ Composite reliability)

2



- There are two ways to estimate reliability, the value of both of them should ≥ 0.7 (Hair et al., 2010).
- Composite reliability (CR) differs from Cronbach's alpha. As, when calculating reliability of the constructs, CR relies on using measurement error.
- Thus, Composite Reliability (CR) and Cronbach's Alpha were extracted and calculated to measure the internal consistency of the constructs which were adopted for the purpose of the current study.

Cronbach's Alpha

Cronbach's alpha

- the most common measure of internal consistency ("reliability").
- It is most commonly used when you have multiple Likert questions in a survey/questionnaire that form a scale and you wish to determine if the scale is reliable.
- expressed as a number between 0 and 1.

- describes the extent to which **all the items in a test measure the same concept or construct** and hence it is connected to the inter-relatedness of the items within the test
- For example, if a test has a reliability of **0.80**, there is **0.36** error variance (**random error**) in the scores
($0.80 \times 0.80 = 0.64$; $1.00 - 0.64 = 0.36$)
- acceptable values of alpha, ranging from 0.70 to 0.95

Example of reporting

- In Table
(Cronbach's $\alpha = .80$; $m = 3.34$)

Cronbach's alpha	Internal consistency
$\alpha \geq 0.9$	Excellent (High-Stakes testing)
$0.7 \leq \alpha < 0.9$	Good (Low-Stakes testing)
$0.6 \leq \alpha < 0.7$	Acceptable
$0.5 \leq \alpha < 0.6$	Poor
$\alpha < 0.5$	Unacceptable

Cronbach's alpha.sav [DataSet5] - IBM SPSS Statistics Data Editor

File Edit View Data Transform **Analyze** Graphs Utilities Add-ons Window Help

31: Qu1 5

	Qu1	Qu2
1	3	
2	6	
3	5	
4	4	
5	4	
6	6	
7	6	
8	5	
9	6	
10	6	
11	5	
12	6	
13	6	
14	6	
15	5	
16	4	
17	6	6
18	6	3

Reports
Descriptive Statistics
Compare Means
General Linear Model
Generalized Linear Models
Mixed Models
Correlate
Regression
Loglinear
Classify
Dimension Reduction
Scale
Nonparametric Tests
Forecasting
Survival
Multiple Response
Simulation...
Quality Control
ROC Curve...

Qu5 Qu6 Qu7 Qu8

4	4	4	4
2	3	3	3
3	3	2	3
5	6	5	6
5	6	5	6
3	3	2	3
2	3	4	4
3	4	4	5
3	2	3	2
3	3	2	3
2	3	4	4
3	4	4	5
4	5	4	4
3	3	2	3
2	3	4	4

Reliability Analysis...
Multidimensional Scaling (ALSCAL)...

Reliability Analysis

Items:

Qu1
Qu2
Qu3
Qu4
Qu5
Qu6
Qu7
Qu8
Qu9

Model: Alpha

Scale label:

OK Paste Reset Cancel Help

Statistics...

Reliability Analysis

Items:

- Qu1
- Qu2
- Qu3
- Qu4
- Qu5
- Qu6
- Qu7
- Qu8
- Qu9

Model: Alpha

Scale label:

OK Paste Reset Cancel Help

Statistics...

Reliability Analysis: Statistics

Descriptives for

- ☒ Item
- ☒ Scale
- ☒ Scale if item deleted

Inter-Item

- ☒ Correlations
- ☐ Covariances

Summaries

- ☐ Means
- ☐ Variances
- ☐ Covariances
- ☐ Correlations

ANOVA Table

- ☒ None
- ☐ F test
- ☐ Friedman chi-square
- ☐ Cochran chi-square

☐ Hotelling's T-square

☐ Intraclass correlation coefficient

☐ Tukey's test of additivity

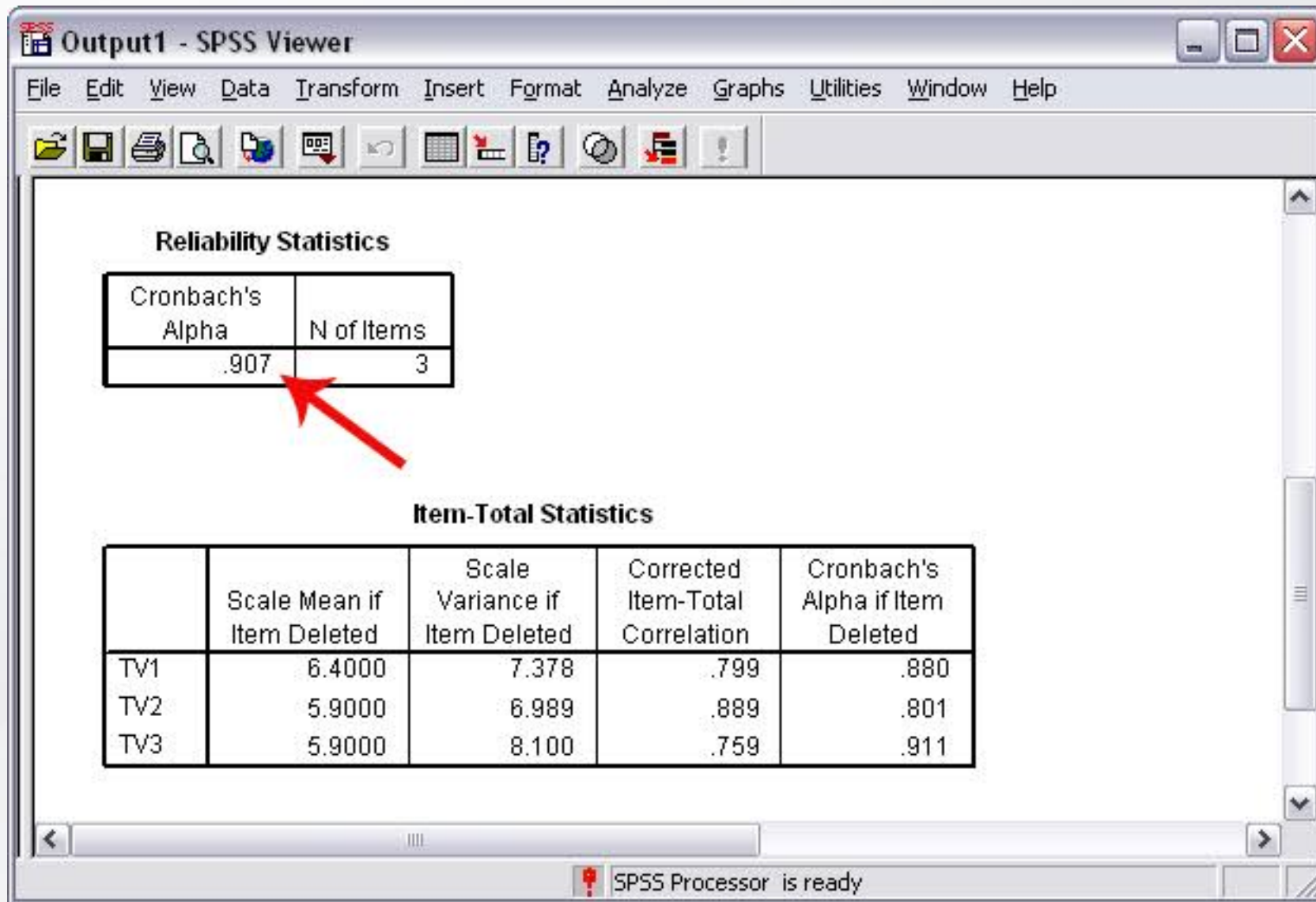
Model: Two-Way Mixed

Type: Consistency

Confidence interval: 95 %

Test value: 0

Continue Cancel Help



The first important table is the **Reliability Statistics** table that provides the actual value for **Cronbach's alpha**

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.805	.796	9

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"Cronbach's Alpha if Item Deleted"

- We can see that removal of any question, except question 8, would result in lower Cronbach's alpha. Therefore, we would not want to remove these questions. Removal of question 8 would lead to a small improvement in Cronbach's alpha, and we can also see that the "**Corrected Item-Total Correlation**" value was low (0.128) for this item. This might lead us to consider whether we should remove this item.

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Qu1	24.20	45.029	.633	.588	.767
Qu2	23.93	47.352	.520	.651	.783
Qu3	24.07	46.638	.654	.899	.767
Qu4	23.40	47.114	.551	.823	.779
Qu5	23.60	51.257	.389	.573	.799
Qu6	24.47	50.695	.372	.693	.802
Qu7	24.07	45.210	.615	.777	.770
Qu8	24.20	56.457	.128	.791	.823
Qu9	24.07	45.210	.589	.610	.774

- A low value of alpha could be due to a low number of questions, poor interrelatedness between items or heterogeneous constructs.
- For example if a low alpha is due to poor correlation between items then some should be revised or discarded.
- items with low correlations (approaching zero) are deleted.

- A reliability of .5 means that about half of the variance of the observed score is attributable to truth and half is attributable to error.
- Low Cronbach's alpha also means that a group of people did not respond to that set of items consistently

Composite Reliability

- $CR = \{(\text{sum of standardized loadings})^2\} / \{(\text{sum of standardized loadings})^2 + (\text{sum of indicator measurement errors})\}$

$$CR = (\text{sum Estimates})^2 / ((\text{sum estimates})^2 + \text{sum } (1 - \text{estimate square}))$$

Hypotheses Testing

3



SIMPLE AND MULTIPLE LINEAR REGRESSION

INTRODUCTION TO REGRESSION ANALYSIS

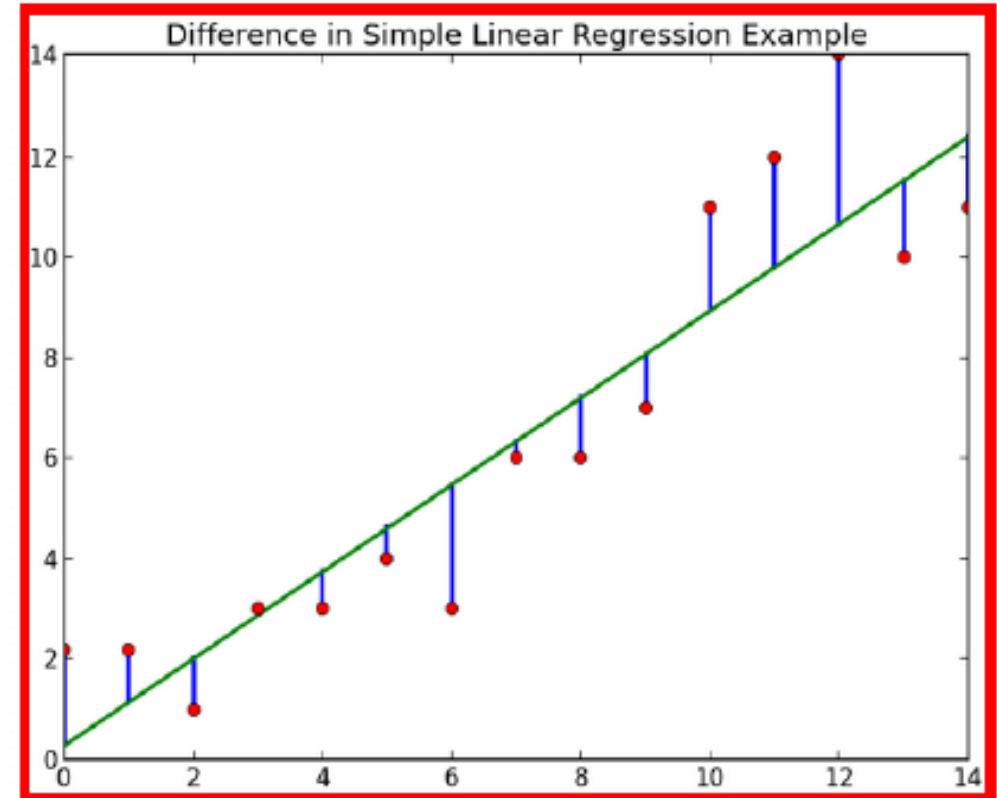
- ▶ **Regression analysis** is used to:
 - ▶ Predict the value of a dependent variable based on the value of at least one independent variable
 - ▶ Explain the impact of changes in an independent variable on the dependent variable

Dependent variable: the variable we wish to predict or explain. **(Usually Y)**

Independent variable: the variable used to predictor explain the dependent variable. **(Usually X)**

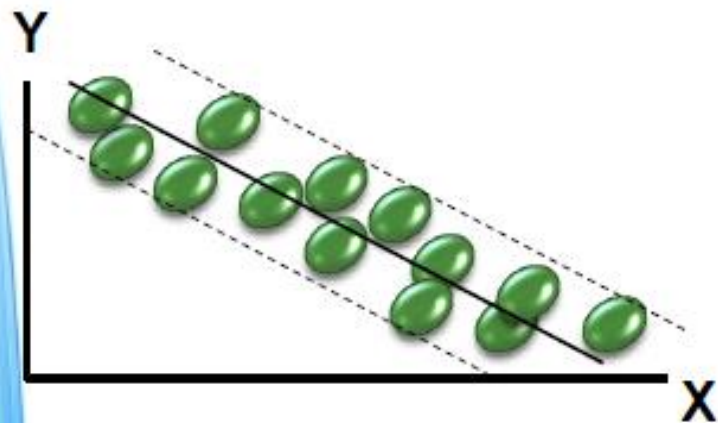
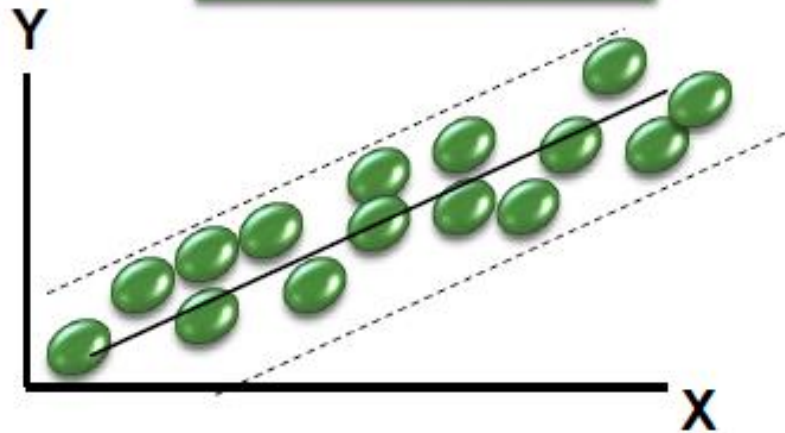
SIMPLE LINEAR REGRESSION MODEL

- ▶ Only **one independent variable**, X .
- ▶ Relationship between X and Y is described by a linear function.
- ▶ Changes in Y are assumed to be related to changes in X .

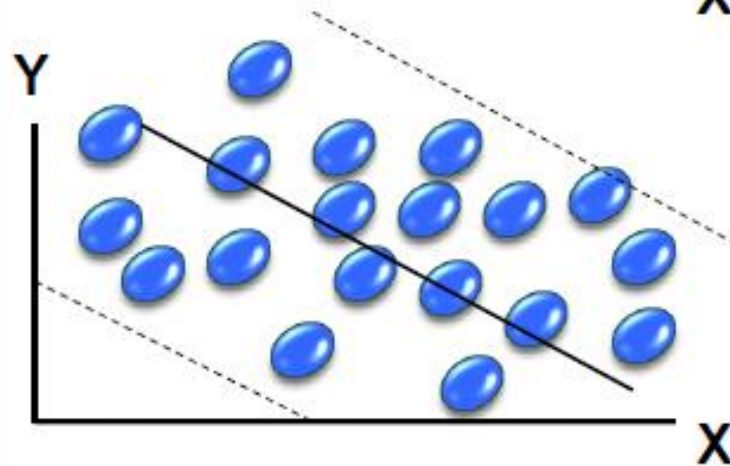
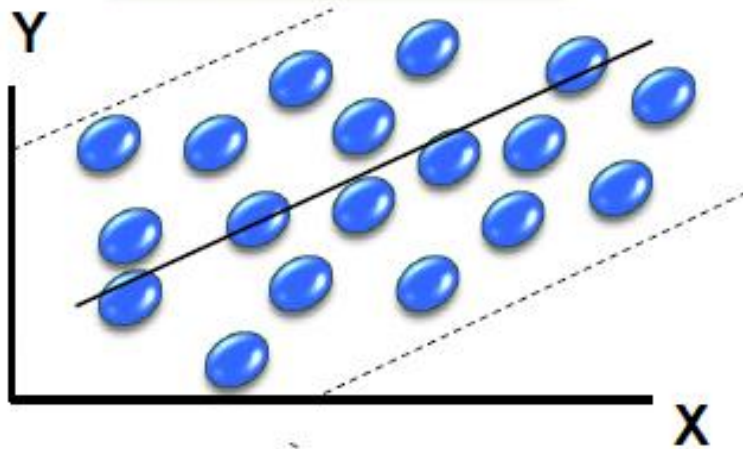


TYPES OF RELATIONSHIPS

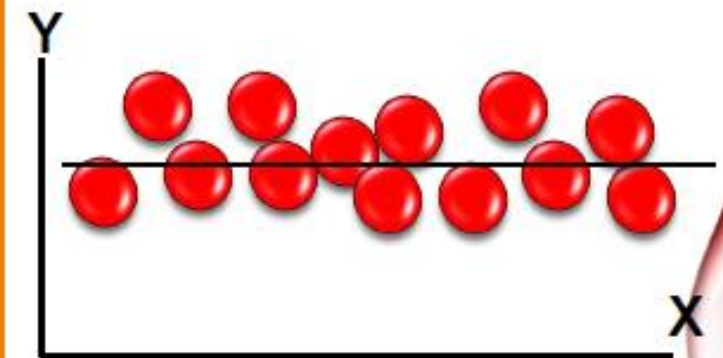
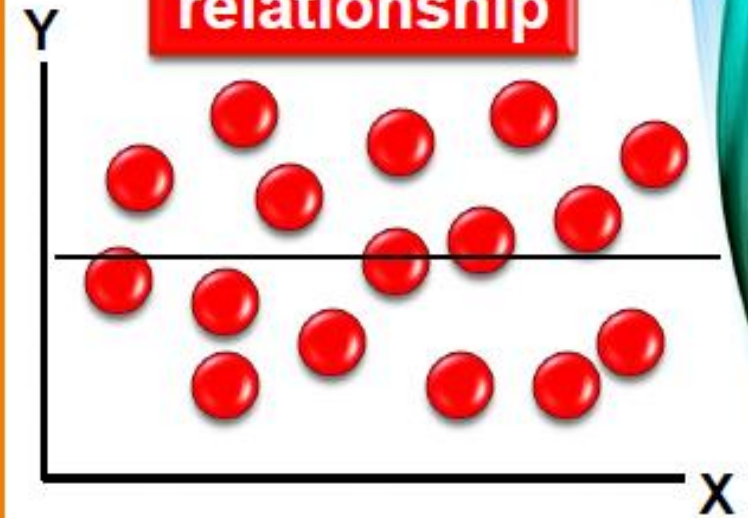
**Strong
relationships**



**Weak
relationships**



**No
relationship**



SIMPLE LINEAR REGRESSION MODEL

The diagram illustrates the Simple Linear Regression Model equation, $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$, which is displayed in a green rectangular box. The equation is annotated with labels and arrows pointing to its components:

- Dependent Variable**: Points to Y_i .
- Population Y intercept**: Points to β_0 .
- Population Slope Coefficient**: Points to β_1 .
- Independent Variable**: Points to X_i .
- Random Error term**: Points to ϵ_i .

Below the equation, two yellow brackets group the terms:

- Linear components**: A bracket under $\beta_0 + \beta_1 X_i$.
- Random Error component**: A bracket under ϵ_i .

SIMPLE LINEAR REGRESSION EQUATION (PREDICTION LINE)

The simple linear regression equation provides an estimate of the population regression line

Estimated (or
predicted) Y value for
observation i

Estimate of the
regression
intercept

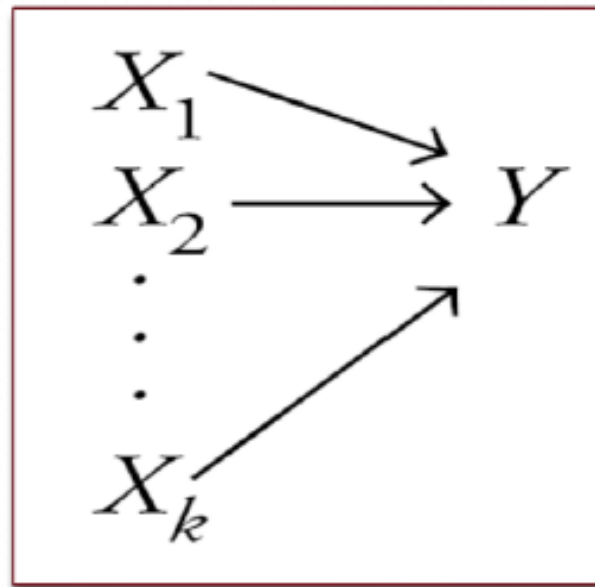
Estimate of the
regression slope

Value of X for
observation i

$$\hat{Y}_i = b_0 + b_1 X_i$$

MULTIPLE LINEAR REGRESSION MODEL

Multiple regression simultaneously considers the influence of multiple explanatory variables on a response variable Y



The intention is to look at the independent effect of each variable while “adjusting out” for other variables

THE MULTIPLE REGRESSION MODEL

Relationship between one dependent & 2 or more independent variables is a linear function

Population Y-intercept Population slopes Random error

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

Linear components Random Error component

The diagram shows the multiple regression equation $Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i$ on a green background. Arrows point from labels above to specific parts of the equation: 'Population Y-intercept' points to β_0 , 'Population slopes' points to the β coefficients, and 'Random error' points to ε_i . A yellow bracket under the first four terms is labeled 'Linear components', and another yellow bracket under ε_i is labeled 'Random Error component'.

Y is the dependent (Response) variable

$X_1, X_2, \dots, X_k$ are the independent (Explanatory) variables

R square estimate

- R-squared is a statistical measure of how close the data are to the fitted regression line. It is also known as the coefficient of determination, or the coefficient of multiple determination for multiple regression.
- R-squared is always between 0 and 100%:
- 0% indicates that the model explains none of the variability of the response data around its mean.
- 100% indicates that the model explains all the variability of the response data around its mean.
- In general, the higher the R-squared, the better the model fits your data.

P value

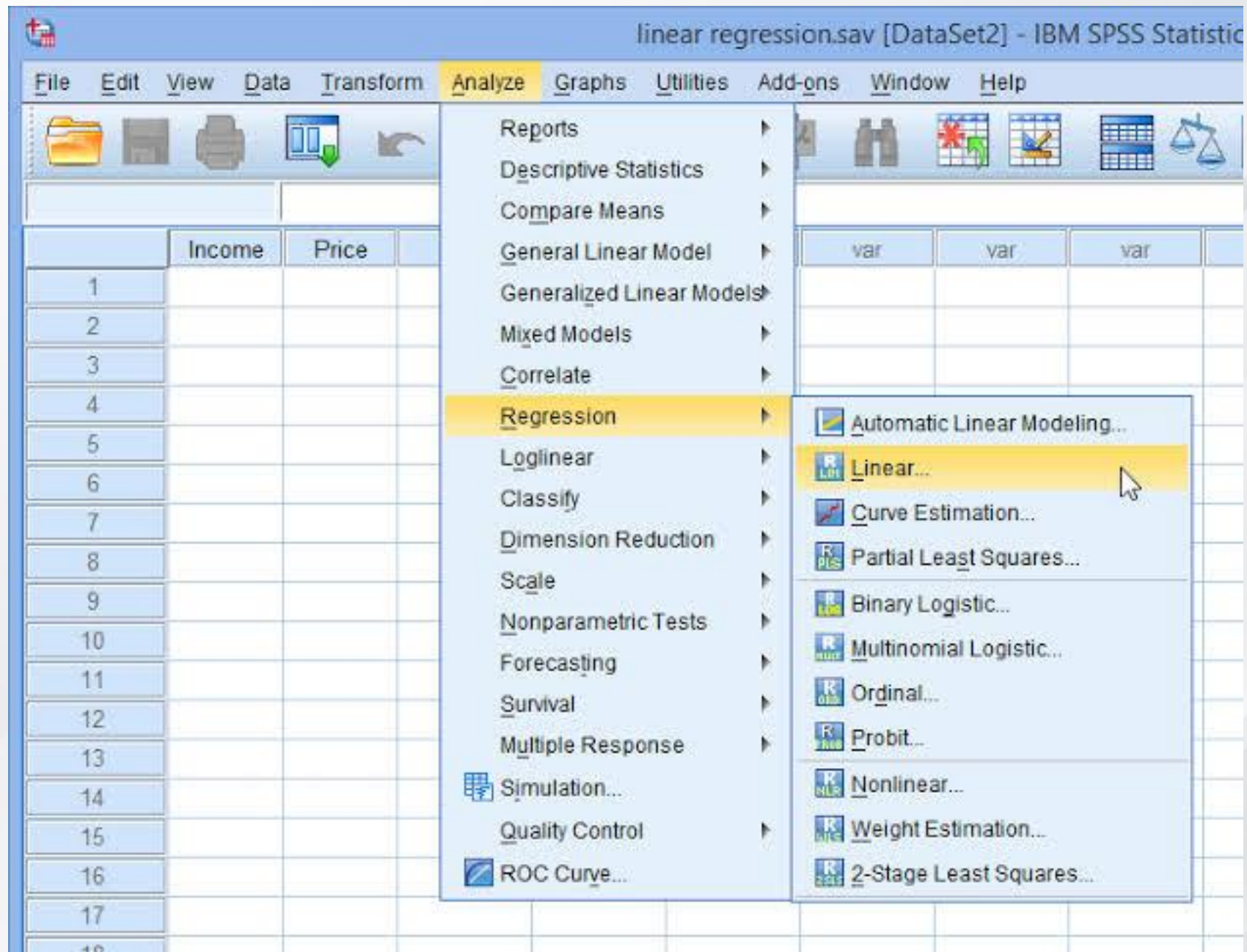
- The p-value for each term tests the null hypothesis that the coefficient is equal to zero (no effect). A low p-value (< 0.05) indicates that you can reject the null hypothesis. In other words, a predictor that has a low p-value is likely to be a meaningful addition to your model because changes in the predictor's value are related to changes in the response variable.
- Conversely, a larger (insignificant) p-value suggests that changes in the predictor are not associated with changes in the response.

Beta coefficient

A standardized beta coefficient compares the strength of the effect of each individual independent variable to the dependent variable. The higher the absolute value of the beta coefficient, the stronger the effect.

SPSS

Regression in SPSS



Linear Regression

Income

Dependent: Price

Block 1 of 1

Previous Next

Independent(s): Income

Method: Enter

Selection Variable:

Case Labels:

WLS Weight:

OK Paste Reset Cancel Help

Statistics... Plots... Save... Options...

SPSS Statistics File Edit View Data Transform Insert Format Analyze Direct Marketing Graphs Utilities Add-ons Window Help Sat 7:50 AM David L

Multiple Linear Regression .sav [DataSet2] - IBM SPSS Statistics Data Editor

Output3 [Document3] - IBM SPSS Statistics Viewer

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Output

- Log
- Regression
 - Title
 - Notes
 - Active Dataset
 - Variables Entered/Removed
 - Model Summary
 - ANOVA
 - Coefficients

[DataSet2] /Users/davidlongstreet/Documents/SPSS Examples/Multiple Linear Regression .sav

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Study_Time, IQ ^b		Enter

a. Dependent Variable: GPA
b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Sd. Error of the Estimate
1	.954 ^a	.910	.890	.2654

a. Predictors: (Constant), Study_Time, IQ

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.389	2	3.194	45.353	.000 ^b
	Residual	.634	9	.070		
	Total	7.023	11			

a. Dependent Variable: GPA
b. Predictors: (Constant), Study_Time, IQ

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Sd. Error	Beta		
1					

IBM SPSS Statistics Processor is ready

IBM SPSS Statistics Processor is ready

Testing Mediation Effect via SPSS

There are two methods in testing indirect effect (mediation):

- 1– Baron and Kenny method
- 2- Hayes method (macro- process)

Baron & Kenny method

Baron and Kenny mediation steps

- The above steps of mediation is based on the four step mediation analysis test proposed by Baron and Kenny (1986), Judd and Kenny (1981), and James and Brett (1984).
- Thus, to indicate mediation four steps are to be analyzed-

Step 1: Show that the causal variable is correlated with the outcome. Use Y as the criterion variable in a regression equation and X as a predictor (estimate and test path c in the above figure). This step establishes that there is an effect that may be mediated.

Step 2: Show that the causal variable is correlated with the mediator. Use M as the criterion variable in the regression equation and X as a predictor (estimate and test path a). This step essentially involves treating the mediator as if it were an outcome variable.

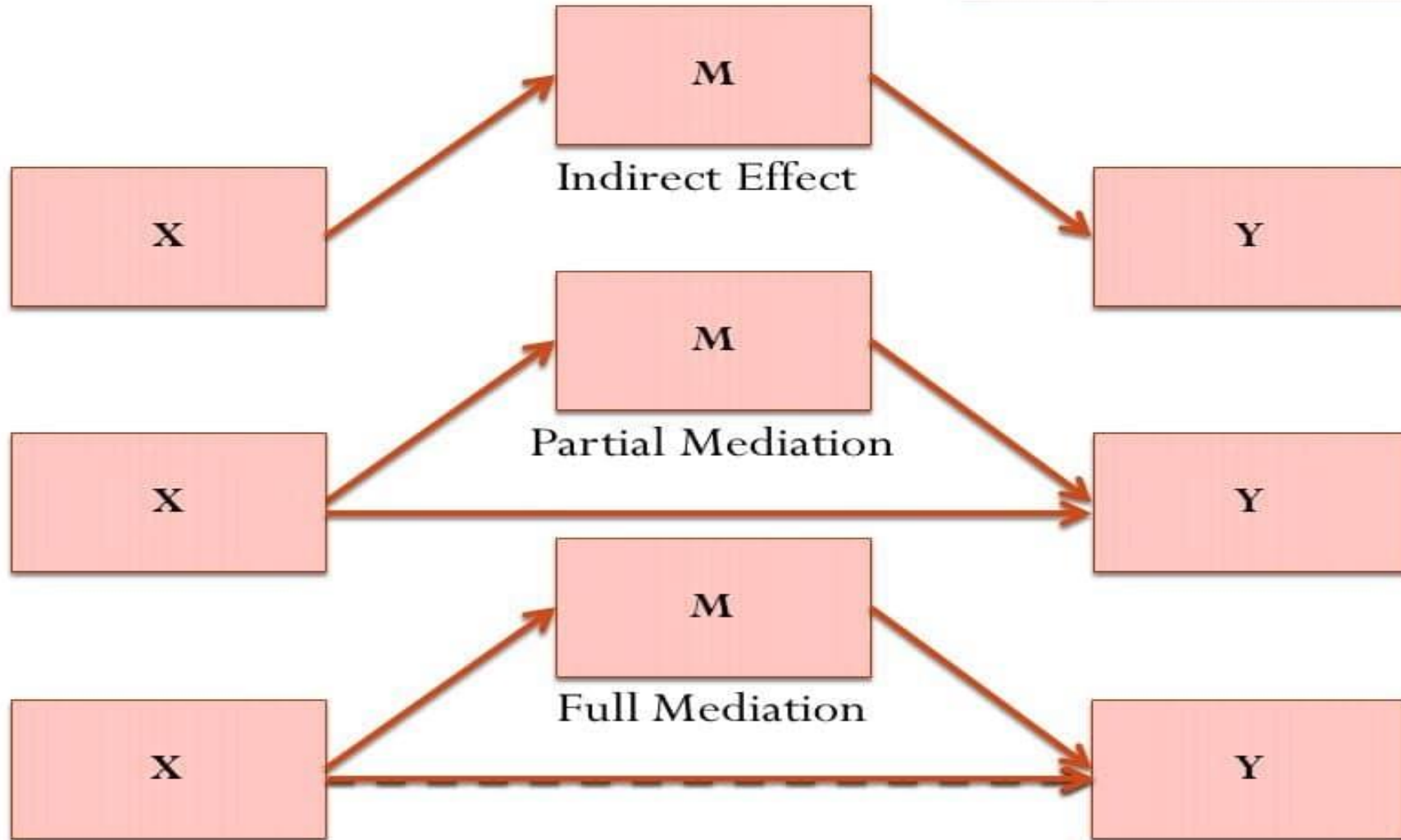
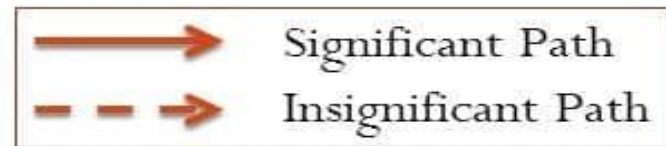
Step 3: Show that the mediator affects the outcome variable. Use Y as the criterion variable in a regression equation and X and M as predictors (estimate and test path b). It is not sufficient just to correlate the mediator with the outcome because the mediator and the outcome may be correlated because they are both caused by the causal variable X . Thus, the causal variable must be controlled in establishing the effect of the mediator on the outcome.

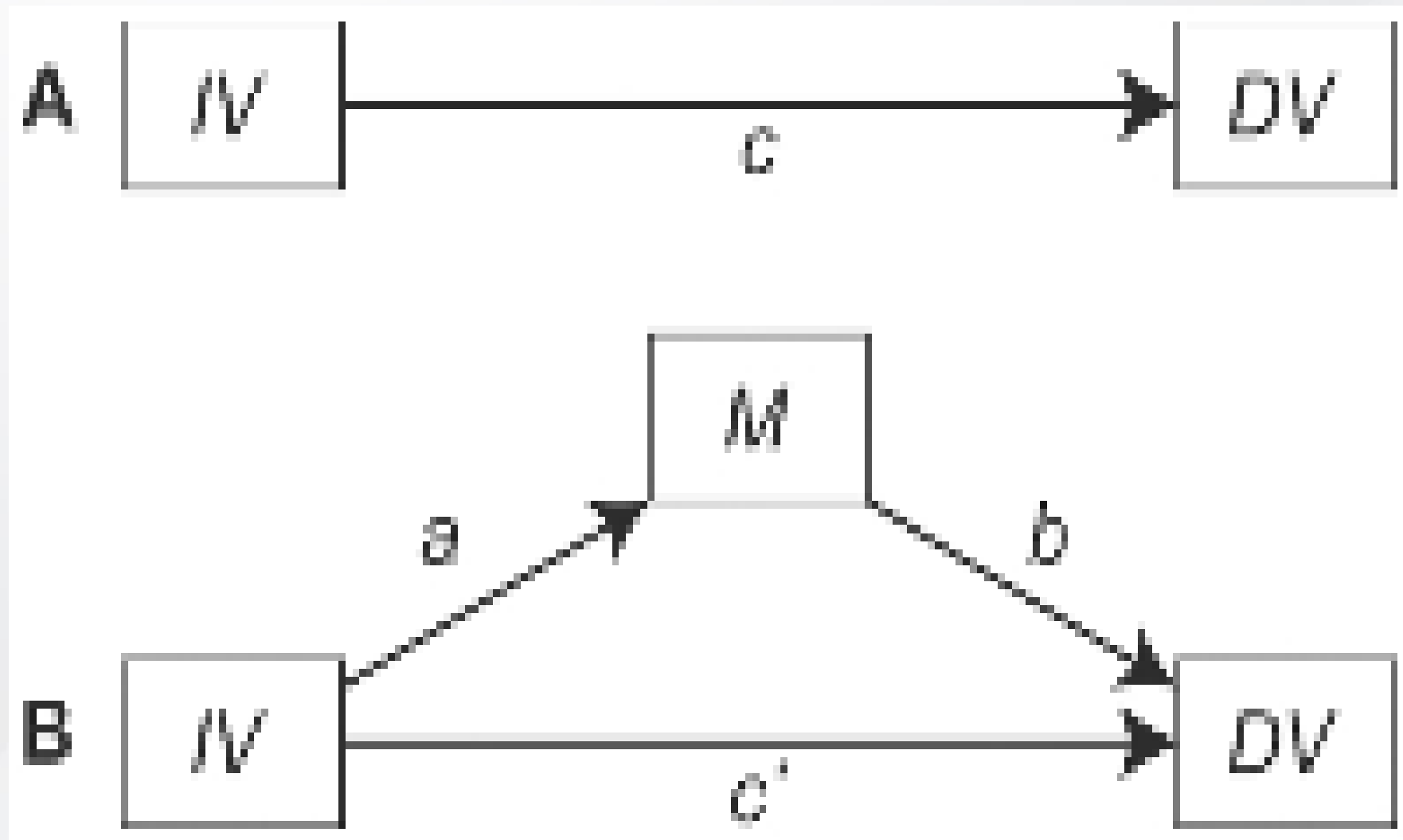
Step 4: To establish that M completely mediates the X - Y relationship, the effect of X on Y controlling for M (path c') should be zero (see discussion below on significance testing). The effects in both Steps 3 and 4 are estimated in the same equation.

Final mediation decision

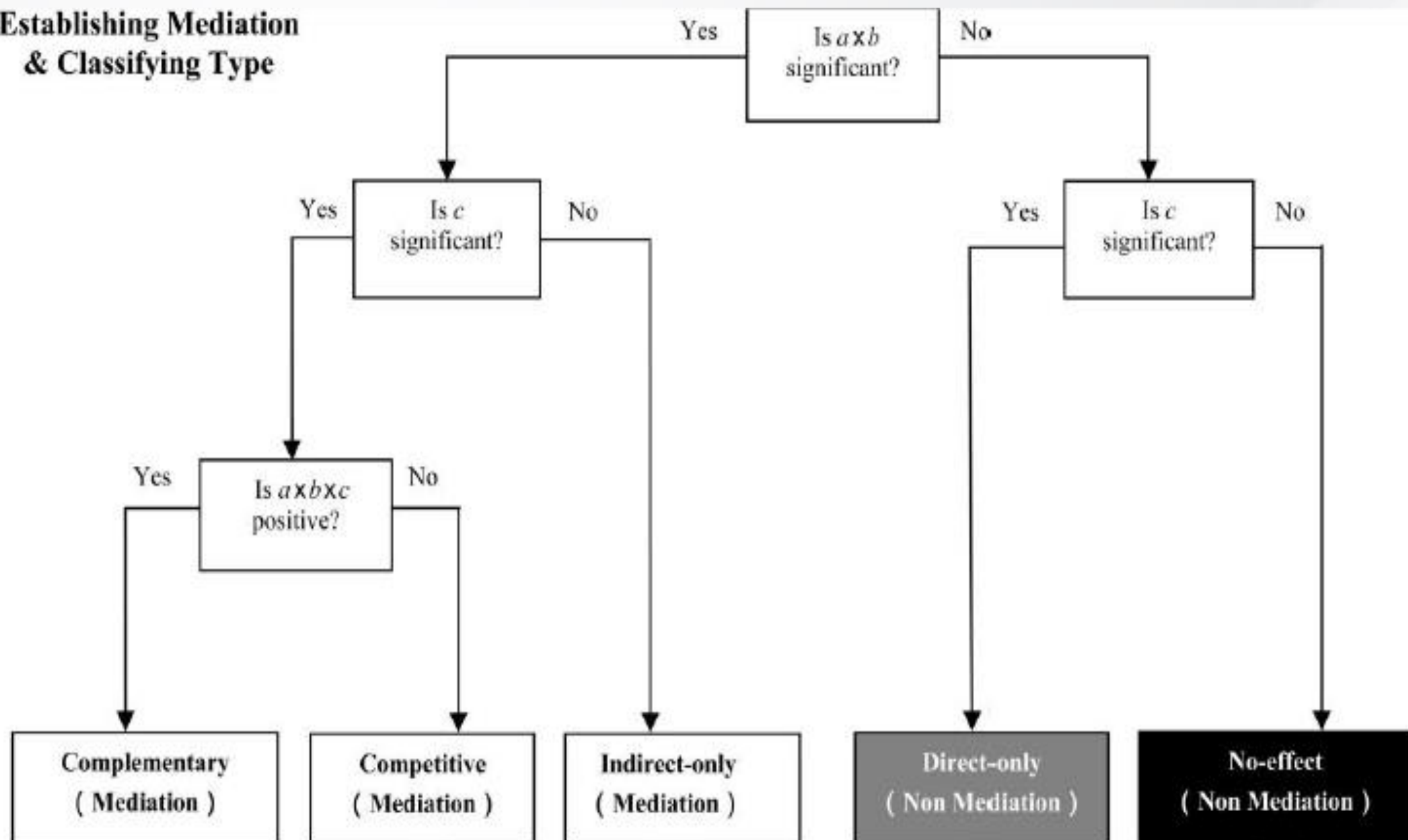
- If all four of these steps are met, then the data are consistent with the hypothesis that variable *M* *completely* mediates the X-Y relationship, and if the first three steps are met but the Step 4 is not, then *partial* mediation is indicated. Meeting these steps does not, however, conclusively establish that mediation has occurred because there are other (perhaps less plausible) models that are consistent with the data. Some of these models are considered later in the [Specification Error](#) section.

Types of Mediation





Establishing Mediation & Classifying Type



References:

Hayes, A.F., 2009. Beyond Baron and Kenny: Statistical mediation analysis in the new millennium. *Communication monographs*, 76(4), pp.408-420.

Shrout, P.E. and Bolger, N., 2002. Mediation in experimental and nonexperimental studies: new procedures and recommendations. *Psychological methods*, 7(4), p.422.

Zhao, X., Lynch Jr, J.G. and Chen, Q., (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of consumer research*, 37(2), pp.197-206.

Linear Regression

Dependent: OA

Block 1 of 1

Previous Next

Independent(s): HPWS, KMS

Method: Enter

Selection Variable: Rule...

Case Labels:

WLS Weight:

SVQ4, SVQ5, OA1, OA2, OA3, OA4, OA5, OA6, OA7, OA8, Ability, Motivation, Opportunity, SQ, IQ, SVQ, KMS, HPWS

Statistics..., Plots..., Save..., Options..., Bootstrap...

OK, Paste, Reset, Cancel, Help

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.665 ^a	.442	.404	.698

a. Predictors: (Constant), KMS, HPWS

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.561	2	5.780	11.862	.000 ^b
	Residual	14.619	30	.487		
	Total	26.180	32			

a. Dependent Variable: OA

b. Predictors: (Constant), KMS, HPWS

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.115	.709		2.984	.006
	HPWS	.188	.162	.180	1.158	.256
	KMS	.823	.228	.560	3.610	.001

a. Dependent Variable: OA

Hayes Method Macro- PROCESS

- Macro- PROCESS method is originated by Hayes, (2012), as it is most flexible and effective tool in testing the indirect effect (the mediation effect) (MacKinnon, Fairchild, and Fritz, 2007; Hayes, 2009).
- The advantage with using PROCESS tests that the mediation effect is assessed with the aid of bootstrapping.
- Indirect effect to be tested, bootstrapping steps (n= 5000 resample) and confidence interval at 95%.
- The mediation effect can be considered statistically significant only when (zero) doesn't exist between their range of confidence intervals, namely: BootLLCI "Bootstrap Lower Limit Confidence Interval" and BootULCI "Bootstrap Upper Limit Confidence Interval" (Hayes, 2012; Vinod, et al., 2015).

In Macro- PROCESS, select the number of the model as follows:

- Model 4 for mediation
- Model 1 for moderation
- Model 5 for mediation/ moderation



--	--

A1	A2
4	
4	
3	
1	
2	
3	
2	
2	
5	
4	
5	
5	
5	
4	
3	
2	
4	
4	
1	

- Reports ▶
- Descriptive Statistics ▶
- Tables ▶
- Compare Means ▶
- General Linear Model ▶
- Generalized Linear Models ▶
- Mixed Models ▶
- Correlate ▶
- Regression ▶
- Loglinear ▶
- Neural Networks ▶
- Classify ▶
- Dimension Reduction ▶
- Scale ▶
- Nonparametric Tests ▶
- Forecasting ▶
- Survival ▶
- Multiple Response ▶
-  Missing Value Analysis... ▶
- Multiple Imputation ▶
- Complex Samples ▶
- Quality Control ▶

M2	M3	M4	M5	O1	O2	O3	O4
4	3	4	2	3	3	4	3
3	2	4	3	3	3	4	4
2	2	4	2	3	3	4	3
1	1	4	1	1	1	1	2
			2	1	2	2	2
			2	2	4	4	4
			1	1	1	1	1
			1	1	1	3	2
			4	4	4	2	2
			1	3	3	4	3
			3	2	2	2	1
			3	3	3	4	4
			5	5	2	2	2
			2	3	2	3	2
			2	2	3	4	4
			1	1	2	2	2
			2	1	3	5	3
			2	4	4	5	3
			2	2	3	4	4
			3	3	4	3	3

	A3	M
4	3	
4	3	
2	3	
3	2	
2	2	
4	4	
3	4	
3	4	
5	5	
3	2	
4	5	
5	4	
5	5	
5	4	
2	3	
2	2	
2	1	
4	4	
4	3	
4	4	
5	4	
4	4	

Variables:

- A1
- A2
- A3
- M1
- M2
- M3
- M4
- M5
- O1
- O2
- O3
- O4
- SQ1
- SQ2

Model number:

4

Confidence intervals

95

Number of bootstrap samples

5000

☐ Save bootstrap estimates☐ Bootstrap inference for model coefficients

Y variable:

OA

X variable:

HPWS

Mediator(s) M:

KMS

Covariate(s):

Moderator variable W:

Moderator variable Z:

Do not use PASTE button

About

Options

Multicategorical

Long variable names

OK

Paste

Reset

Cancel

Help

O4

SQ1

3

4

4

4

3

5

2

3

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2

PROCESS options

- ☐ Show covariance matrix of regression coefficients
- ☐ Generate code for visualizing interactions
- ☒ Show total effect model (only models 4, 6, 80, 81, 82)
- ☐ Pairwise contrasts of indirect effects
- ☒ Effect size (mediation-only models)
- ☒ Standardized coefficients (mediation-only models)
- ☐ Test for X by M interaction(s)
- ☐ Residual correlations

Many options available in PROCESS through command syntax are not available through this dialog box. See Appendices A and B of <http://www.guilford.com/p/hayes3>

Heteroscedasticity-consistent inference

None

Decimal places in output

4

Mean center for construction of products

- ☒ No centering
- ☐ All variables that define products
- ☐ Only continuous variables that define products

Moderation and conditioning

Probe interactions...

if $p \leq .10$

Conditioning values

- ☒ 16th, 50th, 84th percentiles
- ☐ -1SD, Mean, +1SD

☐ Johnson-Neyman output

Continue

Cancel

OK

Paste

Reset

Cancel

Help

- Matrix
- Title
- Notes
- Active Dataset
- Text Output
- Log
- Matrix
- Title
- Notes
- Active Dataset
- Text Output

KMS

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4760	.2265	.3027	9.0796	1.0000	31.0000	.0051

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.2740	.3810	5.9679	.0000	1.4968	3.0511
HPWS	.3390	.1125	3.0132	.0051	.1096	.5685

Standardized coefficients

	coeff
HPWS	.4760

OUTCOME VARIABLE:

OA

Model Summary

R	R-sq	MSE	F	df1	df2	p
.6645	.4416	.4873	11.8616	2.0000	30.0000	.0002

Model

	coeff	se	t	p	LLCI	ULCI
constant	2.1145	.7087	2.9837	.0056	.6672	3.5619
HPWS	.1880	.1623	1.1580	.2560	-.1435	.5195
KMS	.8225	.2279	3.6095	.0011	.3571	1.2879

OUTCOME VARIABLE:

OA

Model Summary

R	R-sq	MSE	F	df1	df2	p
.4462	.1991	.6764	7.7047	1.0000	31.0000	.0093

Model

	coeff	se	t	p	LLCI	ULCI
constant	3.9849	.5696	6.9964	.0000	2.8233	5.1466
HPWS	.4668	.1682	2.7757	.0093	.1238	.8099

Standardized coefficients

	coeff
HPWS	.4462

***** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y *****

Total effect of X on Y

Effect	se	t	p	LLCI	ULCI	c_ps	c_cs
.4668	.1682	2.7757	.0093	.1238	.8099	.5161	.4462

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI	c'_ps	c'_cs
.1880	.1623	1.1580	.2560	-.1435	.5195	.2078	.1796

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
KMS	.2789	.1012	.0966	.4982

Moderation Effect via SPSS

Terminology

- Criterion Variable (dependant variable)
- Predictor Variable (Independent variable)

$$y = a + b_1x$$

y = criterion
variable

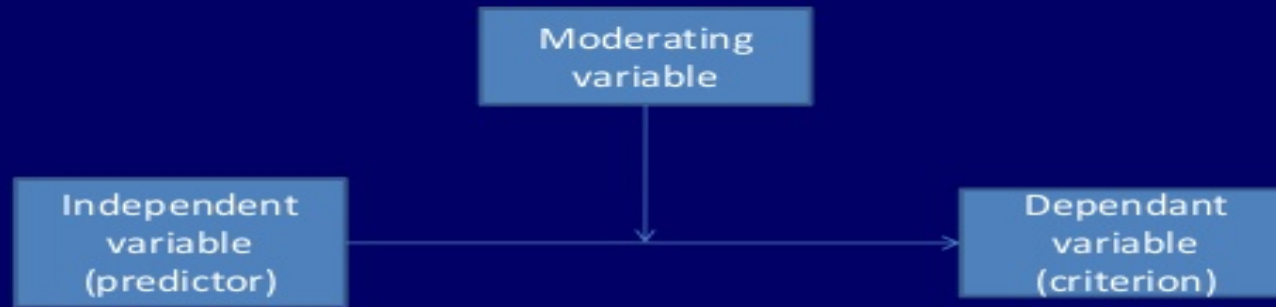
x = predictor
variable

Moderation

- A third variable changes the relationship between two related variable

In other words

- Relationship between two variables changes with the level of another variable of construct



Worshop on Research Methods at GUDMS

Moderator v/s Mediation

- Mediator variable is consequent of predictor variable.



Moderator v/s Mediation

- Moderator variable is at same level as predictor variable.



Aiken and West Approach

- Step1 : Regress on dependant variable the independent variable and moderator variable
- Step2: Center all the continuous variables
- Step3: Multiply the independent and moderator variable and create interaction variable
- Step 4: Regress on dependant variable the independent variable ,moderator variable and Interaction variable

Aiken, L. S., & West, S. G. (1991). *Multiple regression: Testing and interpreting interactions*. Sage.

Workshop on Research Methods at GUDMS

Aiken and West Approach

- Step 5: Check whether interaction variable is significant else no Moderation
- Step 6: ΔR^2
- Step 7 : If moderator is continuous variable classify into meaning full groups or classify the same based at $\pm \geq 1 \sigma$ level
- Step 8: Plot Graphs and interpret the same with significant slopes

Independent Variable	Moderation Variable	Interaction Variable	Moderation Effect
Significant	Significant	Significant	Yes
Significant	Significant	Not Significant	No
Significant	Not Significant	Not Significant	No
Not Significant	Significant	Significant	Yes



Reports

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Compare Means

General Linear Model

Generalized Linear Models

Mixed Models

Correlate

Regression

Loglinear

Neural Networks

Classify

Dimension Reduction

Scale

Nonparametric Tests

Forecasting

Survival

Multiple Response

Missing Value Analysis...

Multiple Imputation

Complex Samples

123 Frequencies...

P Descriptives...

Explore...

Crosstabs...

1/2 Ratio...

P-P Plots...

Q-Q Plots...

M4

M5

O1

O2

O3

O4

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Descriptives

Variable(s):

OA7
OA8
Ability
Motivation
Opportunity
OA
SQ
IQ
SVQ

KMS
HPWS

☒ Save standardized values as variables

OK Paste Reset Cancel Help

Options...
Bootstrap...

KMS	HPWS	ZKMS	ZHPWS	var	var	var	var	var
4	3	.99831	.06427					
4	3	.99831	.16067					
4	3	1.77164	-.61055					
3	2	-.70303	-1.96017					
3	2	-.70303	-1.67097					
4	4	.99831	.35347					
3	2	-.93503	-1.57456					
3	2	-.54837	-1.38176					
3	4	-.62570	.73908					
3	3	-.62570	-.22494					
3	3	-.70303	-.03213					
3	4	.07030	.35347					
2	4	-1.78570	1.12469					
3	4	-.70303	.35347					
3	3	-.93503	-.03213					
3	2	-.70303	-1.47816					
4	3	.30230	-.32134					
4	4	1.30764	.64268					
2	3	-.70303	-.61055					



- Compute Variable...
- Count Values within Cases...
- Shift Values...
- Recode into Same Variables...
- Recode into Different Variables...
- Automatic Recode...
- Visual Binning...
- Optimal Binning...
- Prepare Data for Modeling
- Rank Cases...
- Date and Time Wizard...
- Create Time Series...
- Replace Missing Values...
- Random Number Generators...
- Run Pending Transforms



	SVQ
1	4
2	4
3	4
4	3
5	3
6	4
7	3
8	4
9	3
10	3
11	3
12	4
13	3

	ZHPWS	var	var	v
831	.06427			
831	.16067			
164	-.61055			
303	-1.96017			
303	-1.67097			
831	.35347			
503	-1.57456			
837	-1.38176			
570	.73908			
570	-.22494			
303	-.03213			
030	.35347			
570	1.12469			

Compute Variable

Target Variable:

Type & Label...

- OA1
- OA2
- OA3
- OA4
- OA5
- OA6
- OA7
- OA8
- Ability
- Motivation
- Opportunity
- OA
- SQ
- IQ
- SVQ
- KMS
- HPWS
- Zscore(KMS) [ZK...
- Zscore(HPWS) [Z...

Numeric Expression:

ZKMS * ZHPWS

+	<	>	7	8	9
-	<=	>=	4	5	6
*	=	~=	1	2	3
/	&		0	.	
**	~	()	Delete		

Function group:

- All
- Arithmetic
- CDF & Noncentral CDF
- Conversion
- Current Date/Time
- Date Arithmetic
- Date Creation

Functions and Special Variables:

Compute Variable

Target Variable:

moderator

=

Numeric Expression:

ZKMS * ZHPWS

Type & Label...

- OA1
- OA2
- OA3
- OA4
- OA5
- OA6
- OA7
- OA8
- Ability
- Motivation
- Opportunity
- OA
- SQ
- IQ
- SVQ
- KMS
- HPWS
- Zscore(KMS) [ZK...
- Zscore(HPWS) [Z...



+	<	>	7	8	9
-	<=	>=	4	5	6
*	=	~=	1	2	3
/	&		0	.	
**	~	()	Delete		

Function group:

- All
- Arithmetic
- CDF & Noncentral CDF
- Conversion
- Current Date/Time
- Date Arithmetic
- Date Creation

Functions and Special Variables:

If (optional case selection condition)

	KMS	HPWS	ZKMS	ZHPWS	moderator	var	var	var	va
4	4	3	.99831	.06427	.06				
4	4	3	.99831	.16067	.16				
4	4	3	1.77164	-.61055	-1.08				
3	3	2	-.70303	-1.96017	1.38				
3	3	2	-.70303	-1.67097	1.17				
4	4	4	.99831	.35347	.35				
3	3	2	-.93503	-1.57456	1.47				
4	3	2	-.54837	-1.38176	.76				
3	3	4	-.62570	.73908	-.46				
3	3	3	-.62570	-.22494	.14				
3	3	3	-.70303	-.03213	.02				
4	3	4	.07030	.35347	.02				
3	2	4	-1.78570	1.12469	-2.01				
3	3	4	-.70303	.35347	-.25				
3	3	3	-.93503	-.03213	.03				
3	3	2	-.70303	-1.47816	1.04				
4	4	3	.30230	-.32134	-.10				
4	4	4	1.30764	.64268	.84				
3	3	3	-.70303	-.61055	.43				
3	4	4	.53431	.25707	.14				

View Data Transform **Analyze** Direct Marketing Graphs Utilities Add-ons Window Help



SVQ KMS

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- Reports
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- Generalized Linear Models
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- Correlate
- Regression**
- Loglinear
- Neural Networks
- Classify
- Dimension Reduction
- Scale
- Nonparametric Tests
- Forecasting
- Survival
- Multiple Response
- Missing Value Analysis...



	ZHPWS	moderator	var	var	var	var
9831	.06427	.06				
9831	.16067	.16				
7164	-.61055	-1.08				
0303	-1.96017	1.38				

- Automatic Linear Modeling...
- Linear...**
- Curve Estimation...
- Partial Least Squares...
- PROCESS v3.5 by Andrew F. Hayes
- Binary Logistic...
- Multinomial Logistic...
- Ordinal...
- Probit...
- Nonlinear...

Linear Regression

Dependent: OA

Block 1 of 1

Independent(s): Zscore(HPWS) [ZHPWS], Zscore(KMS) [ZKMS], Moderator

Method: Enter

Selection Variable:

Case Labels:

WLS Weight:

OK Paste Reset Cancel Help

	ZHPWS	Moderator	var
.06427	.06		
.16057	.16		
-.61055	-1.08		
-1.96017	1.38		
-1.67097	1.17		
.35347	.35		
-1.57456	1.47		
-1.38176	.76		
.73908	-.45		
-.22494	.14		
-.03213	.02		
.35347	.02		
1.12469	2.01		
.35347	-.25		
-.03213	.03		
-1.47816	1.04		
-.32134	.18		
.64268	.84		
-.61055	.43		
.25707	.14		
1.51039	-.59		
.44368	.10		
1.78310	4.47		

(KMS)

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.771	3	3.924	7.898	.001 ^b
	Residual	14.408	29	.497		
	Total	26.180	32			

a. Dependent Variable: OA

b. Predictors: (Constant), Moderator, Zscore(HPWS), Zscore(KMS)

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	5.554	.136		40.782	.000
	Zscore(HPWS)	.130 ^{**}	.150	.144	.867	.393
	Zscore(KMS)	.550	.156	.608	3.514	.001
	Moderator	-.083	.128	-.100	-.652	.520

a. Dependent Variable: OA

SEM via AMOS

SEM – GRAPHICAL SOFTWARE

Structural Equation Modeling (SEM) is an extension of the general linear model. It is used to test a set of regression equations simultaneously. The advantages of SEM Analysis are as follows:

- SEM provides overall tests of model fit and individual parameter estimate tests simultaneously.
- Regression coefficients, means and variances may be compared simultaneously.
- It is the graphical interface software.

Website: www.statswork.com

Contact: 8754446690

What is SEM?

SEM represents the relationship between dependent (unobserved) variable and independent (observed) variables using path diagrams.

- ❖ In this analysis, ovals or circles represent dependent variable.
- ❖ Rectangles or squares represent independent variable.
- ❖ Residuals (error term) variables also represent by ovals or circles, because they are always unobserved.

Website: www.statswork.com

Contact: 8754446690

What are the values extracted from the Test?

If the hypothesized model has a good fit, the statistical test values should be in the following manner.

- Chi-square value should be less than 5
- P value should be greater than 0.05
- GFI, AGFI and CFI values should be greater than 0.90
- RMR & RMSEA values should be less than 0.08

Website: www.statswork.com

Contact: 8754446690

Steps of SEM

- 1- Draw Confirmatory factor analysis CFA for the model
- 2- Draw path analysis for the model
- 3- Draw SEM model from step 1+ step 2

Step 1: CFA for the model

Analysis Properties

Title

Estimation

Numerical

Bias

Output

Bootstrap

Permutations

Random #

☒ Minimization history

☐ Indirect, direct & total effects

☒ Standardized estimates

☐ Factor score weights

☒ Squared multiple correlations

☒ Covariances of estimates

☐ Sample moments

☒ Correlations of estimates

☐ Implied moments

☐ Critical ratios for differences

☐ All implied moments

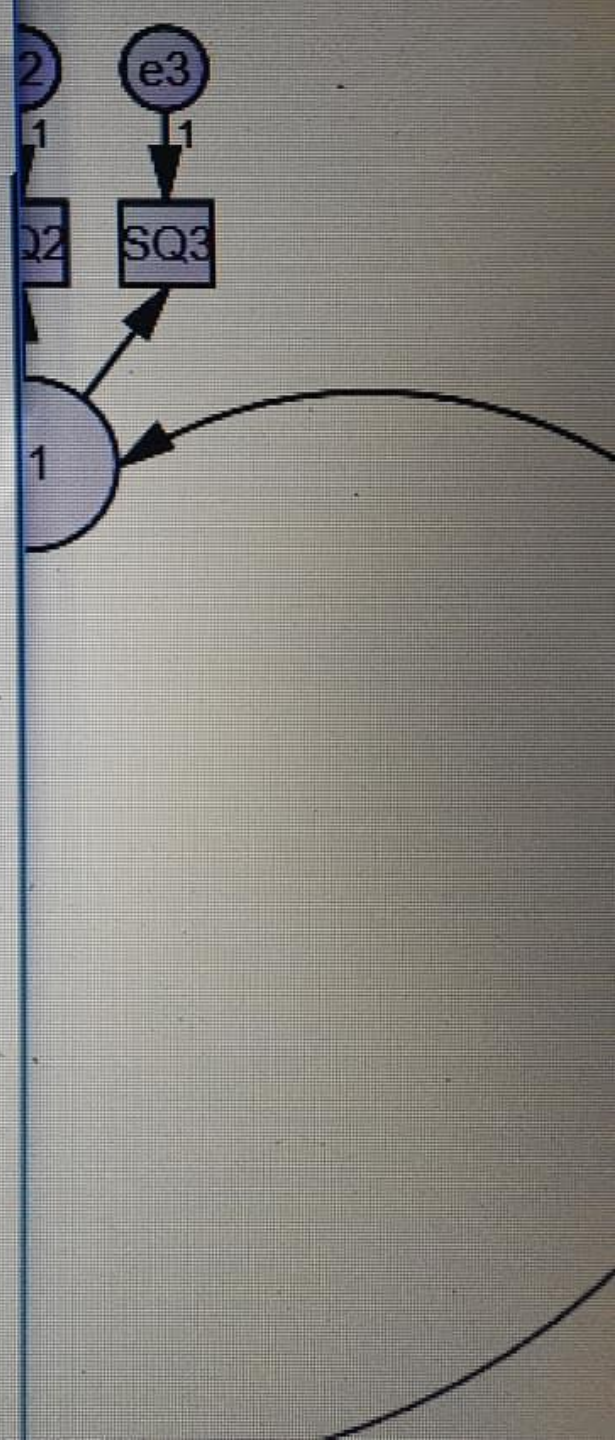
☐ Tests for normality and outliers

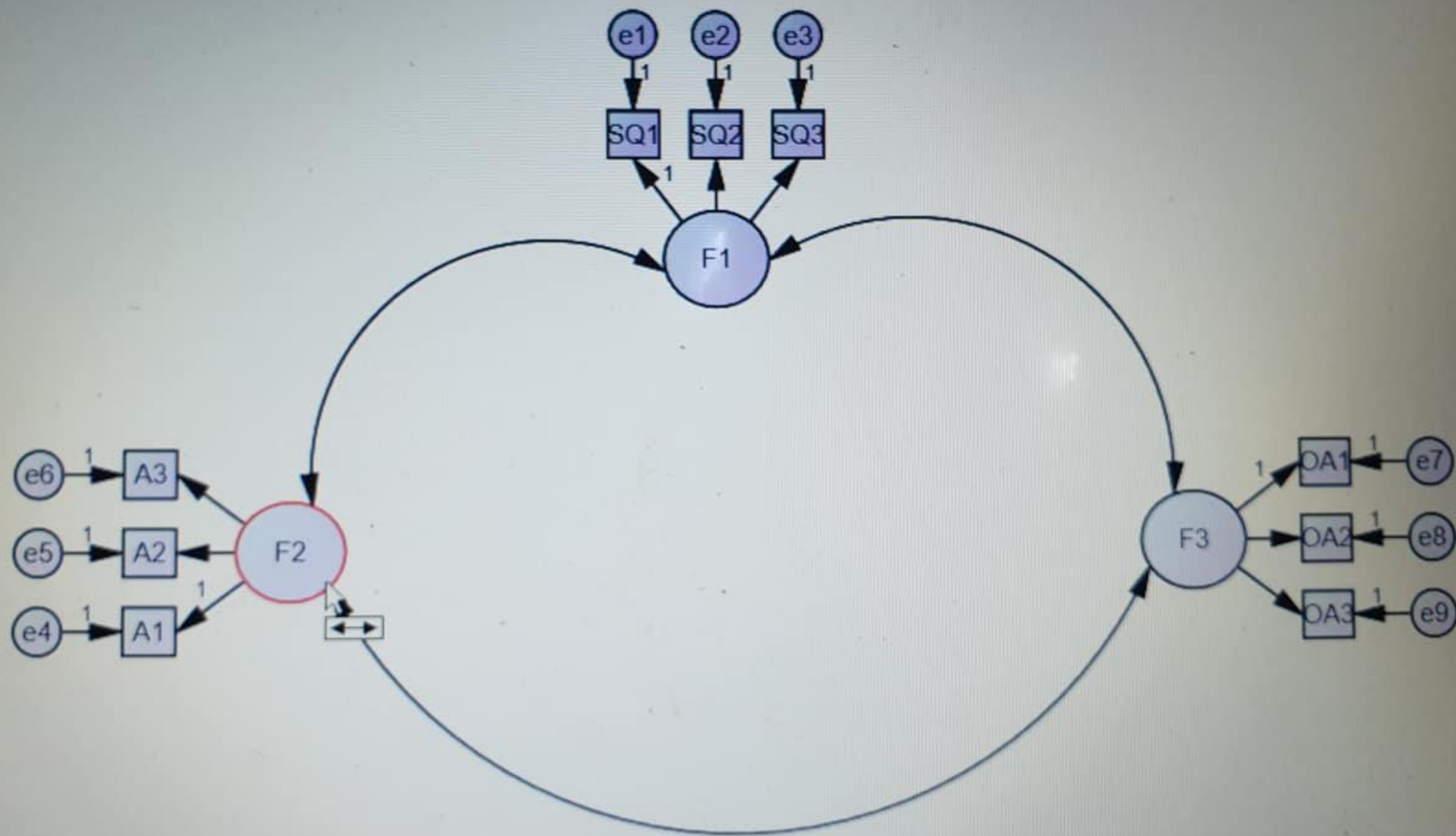
☐ Residual moments

☐ Observed information matrix

☐ Modification indices

Threshold for modification indices





Step 2: Path Analysis



Group number 1

Default model

Unstandardized estimates
Standardized estimates

ability
b
ghgjh
v



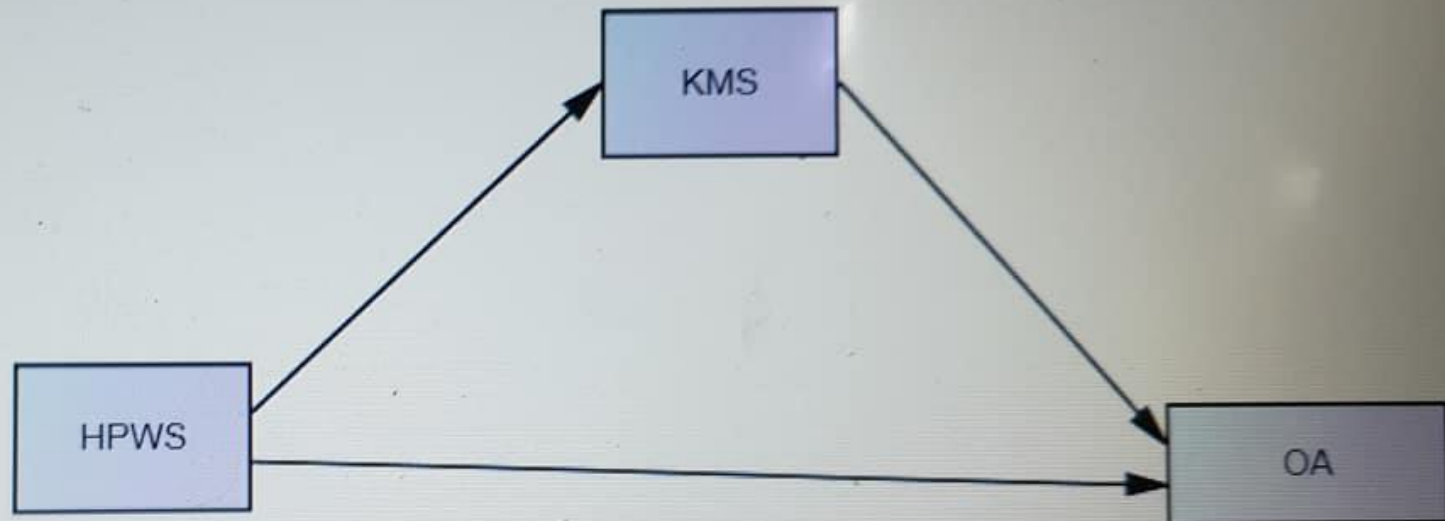
Group number 1

Default model

Reflect the indicators of a latent variable

Unstandardized estimates
Standardized estimates

ability
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ghgjh
v



Project: Group number 1: Input

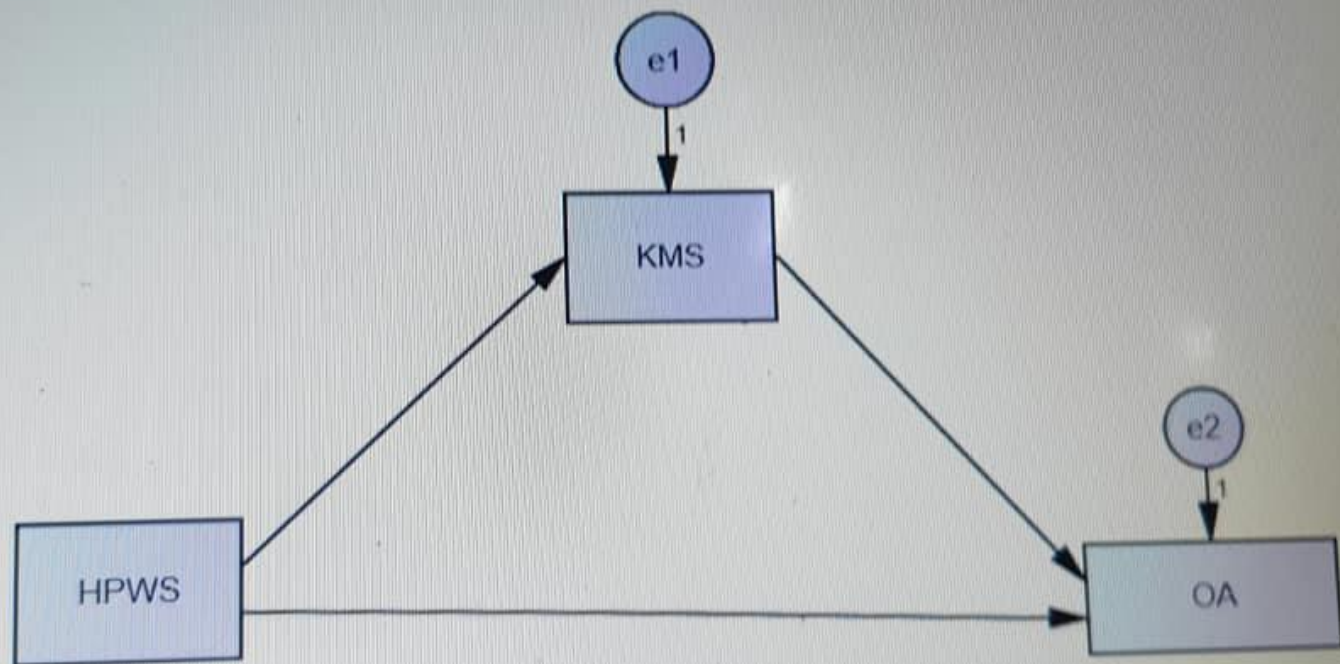
Diagram Analyze Tools Plugins Help



Group number 1

Default model

Unstandardized estimates
Standardized estimates



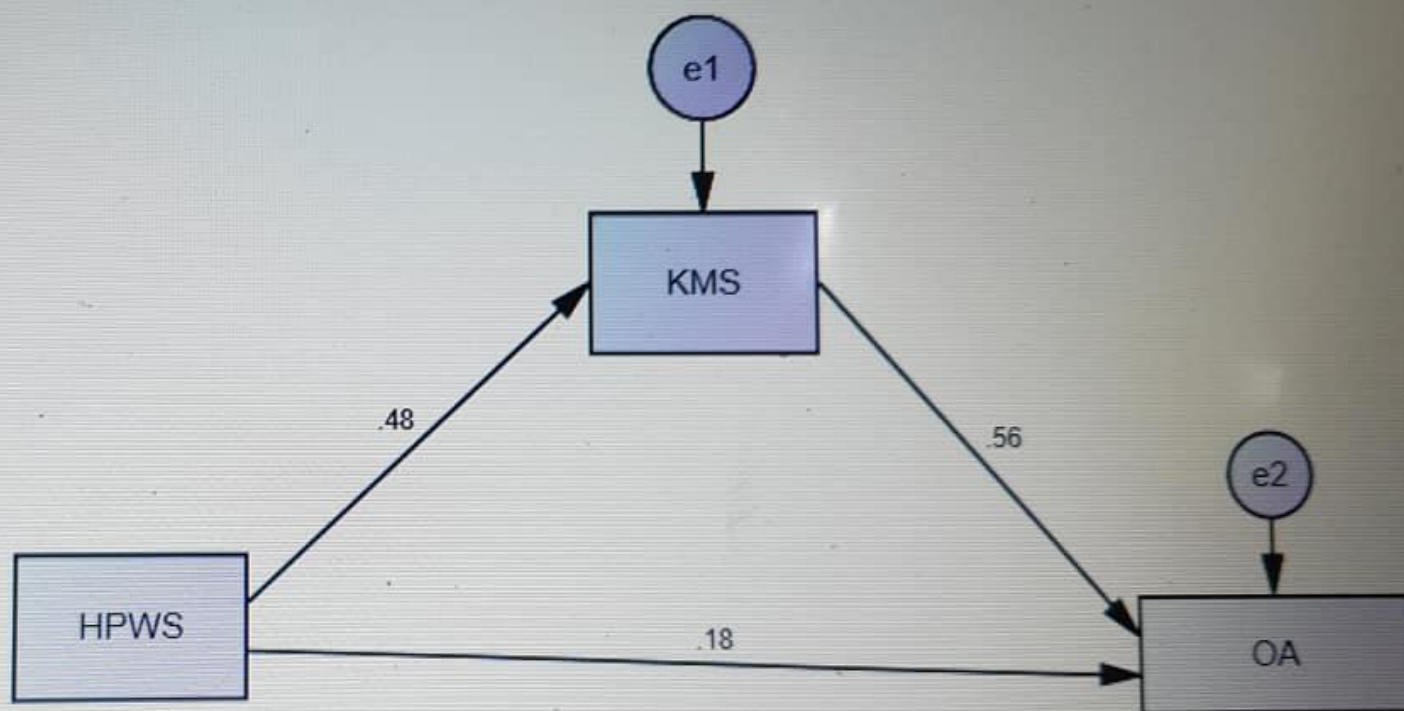
Group number 1

OK: Default model

Unstandardized estimates
Standardized estimates

Scanning SPSS Original
Default model
Minimization
Iteration 7
Minimum was achieved
Writing output
Chi-square = 0.0, df = 0

ability



Step 3: SEM

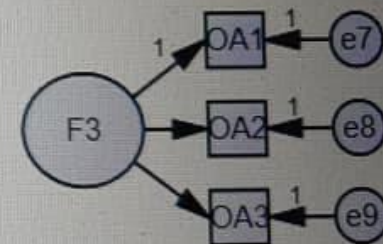
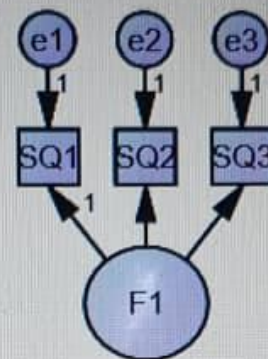
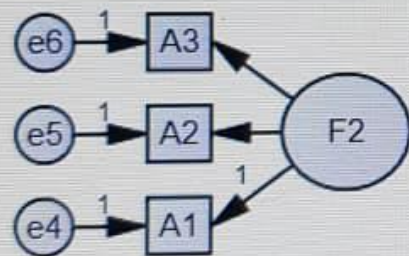
Group number 1

Model: Default model

Standardized estimates
Standardized estimates

Default model
Minimization
Iteration 13
Minimum was achieved
Writing output
Chi-square = 41.2, df =

ity
ijh



File Edit View Diagram Analyze Tools Plugins Help

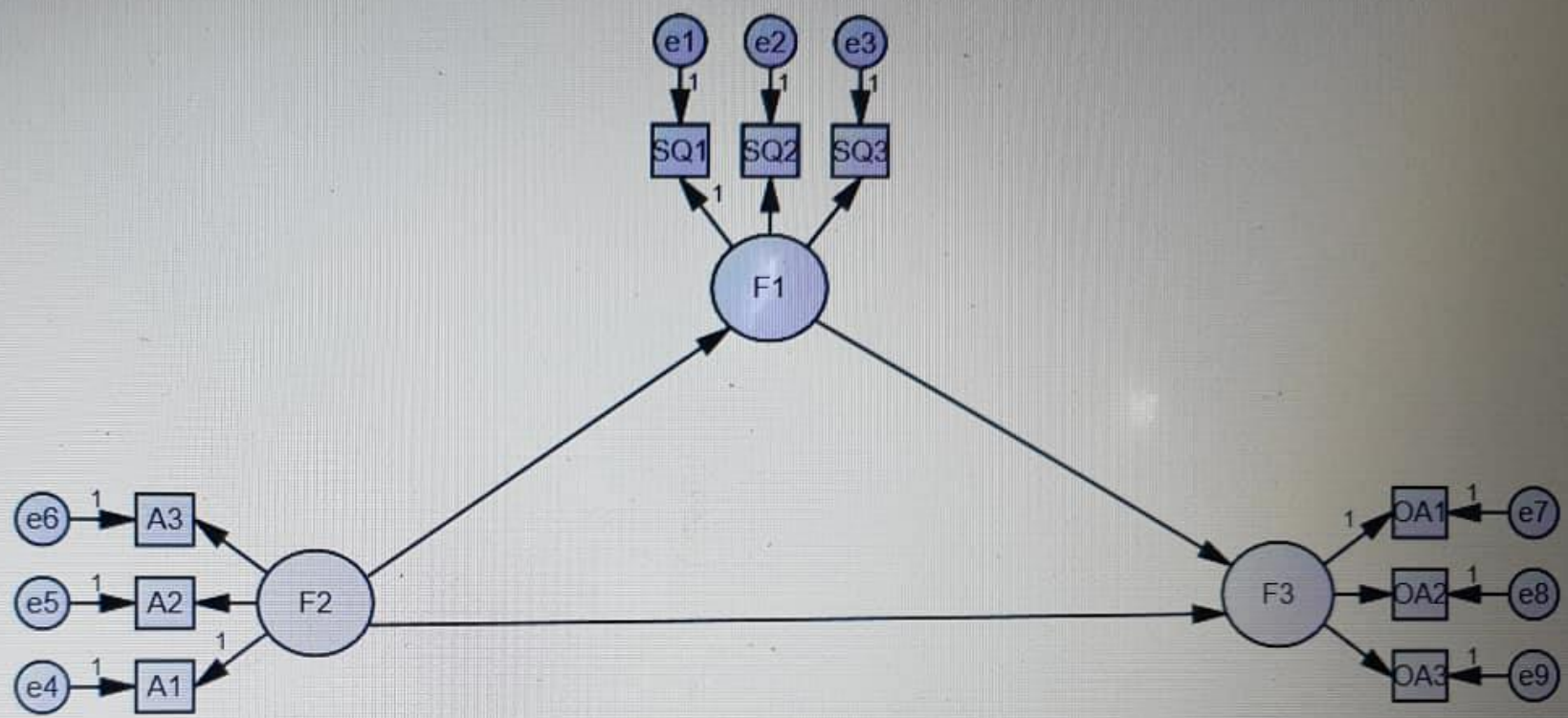
Group number 1

XX: Default model

Unstandardized estimates
Standardized estimates

Default model
Minimization
Iteration 13
Minimum was achieved
Writing output
Chi-square = 41.2, df =

ability
ghqjh
v



B : Group number 1 : Input

File Edit View Diagram Analyze Tools Plugins Help

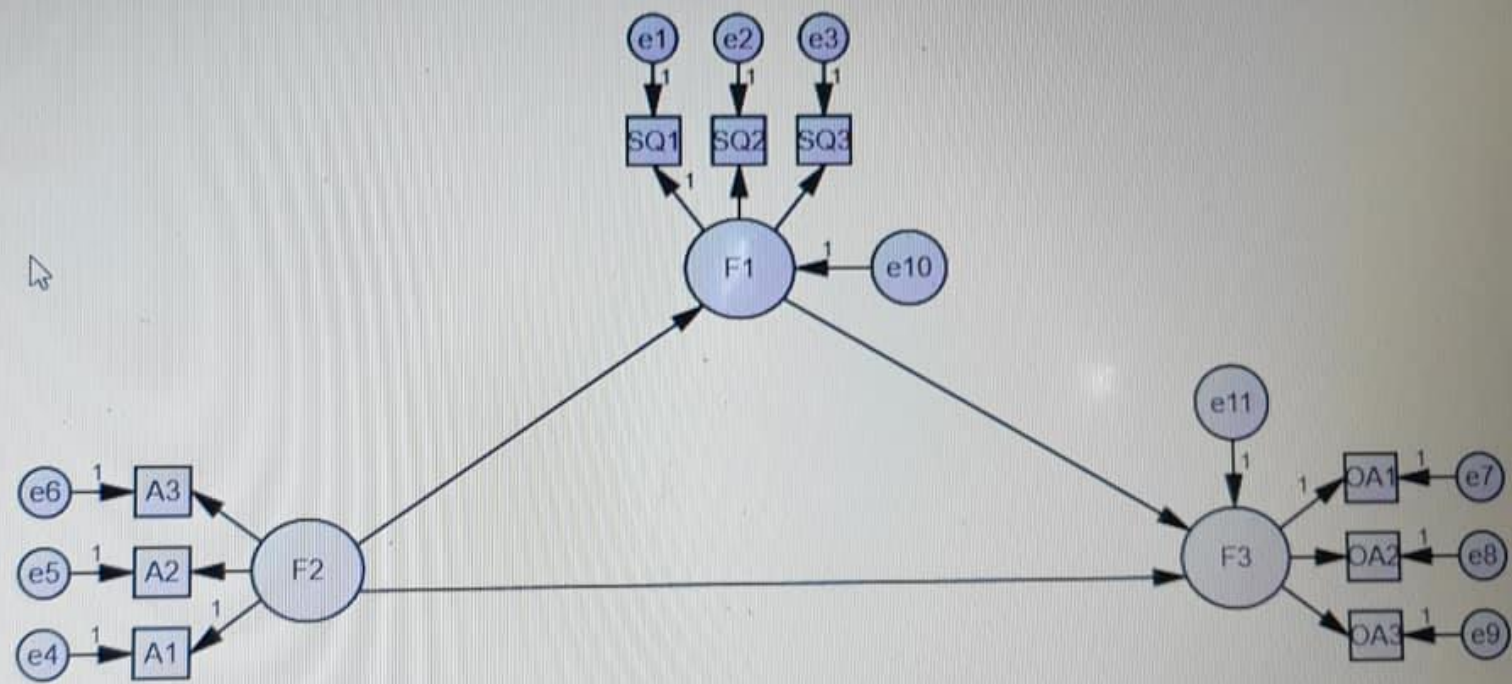
Group number 1

XX: Default model

Unstandardized estimates
Standardized estimates

Default model
Minimization
Iteration 13
Minimum was achieved
Writing output
Chi-square = 41.2, df =

ability
ghgjh
v



OK: Default model

Diagram Analyze Tools Plugins Help



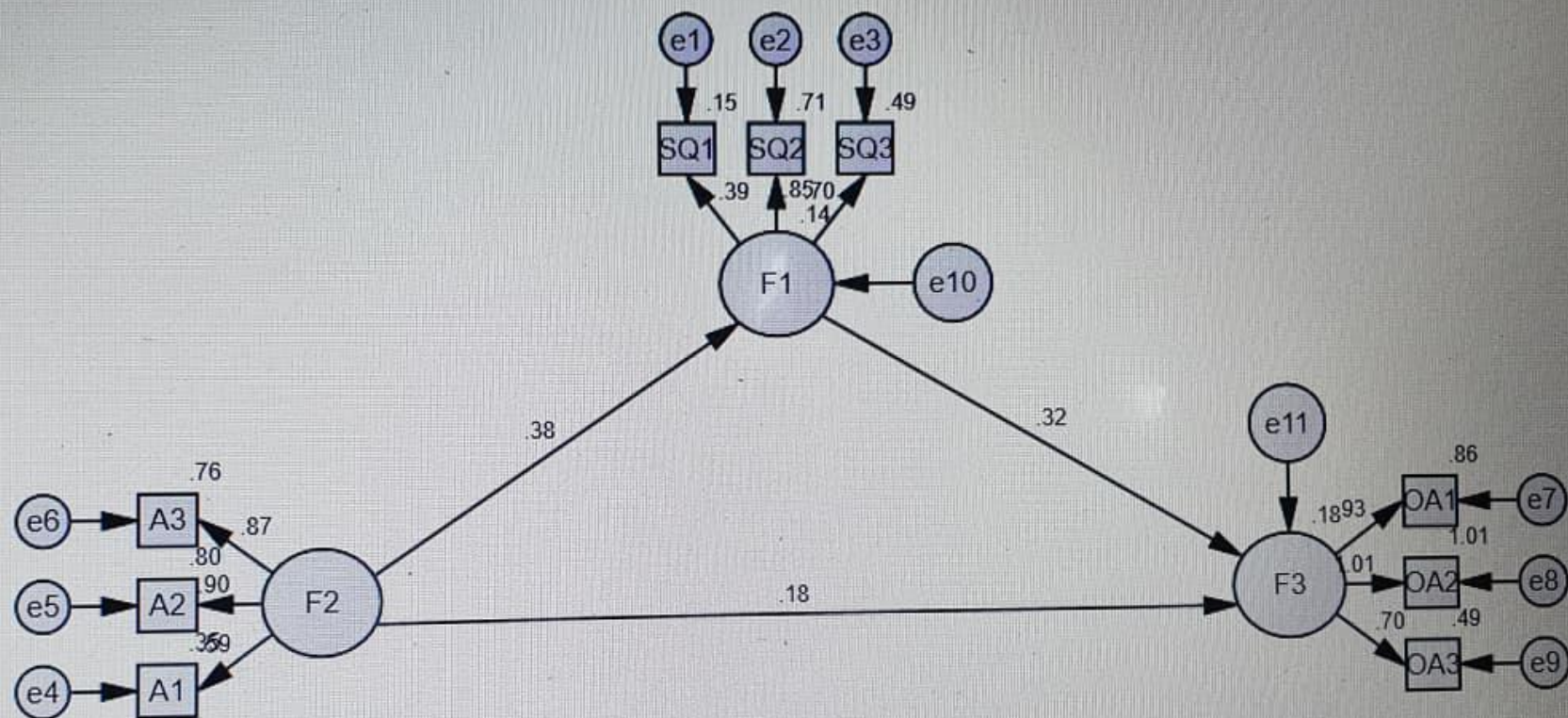
Group number 1

OK: Default model

Unstandardized estimates
Standardized estimates

Scanning SPSS Original
Default model
Minimization
Iteration 15
Minimum was achieved
Writing output
Chi-square = 41.2, df = 24

ability
ghgjh

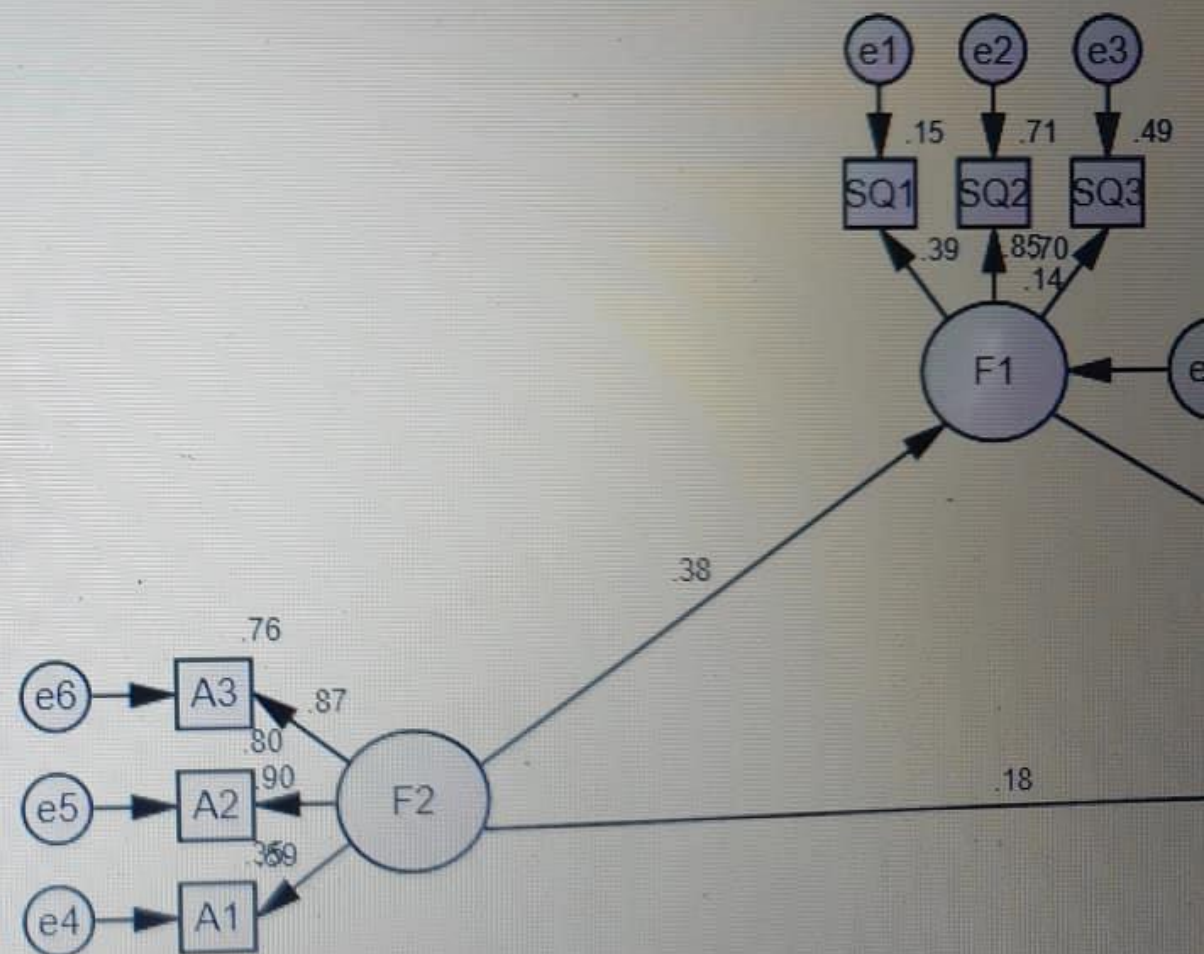


B : Group number 1 : OK: Default model

File Edit View Diagram Analyze Tools Plugins Help

	Interface Properties...	Ctrl+I
	Analysis Properties...	Ctrl+A
	Object Properties...	Ctrl+O
	Variables in Model...	Ctrl+Shift+M
	Variables in Dataset...	Ctrl+Shift+D
	Parameters...	Ctrl+Shift+P
	Matrix Representation...	Ctrl+Shift+R
	Text Output	F10
	Full Screen	F11

View Text



Correlations: (Group number 1 - Default model)

	Estimate
Consltn <--> Prep	.724
Consltn <--> Instructn	.613
Prep <--> Instructn	.764

Models

Default model (Default model)

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments: 252

Number of distinct parameters to be estimated: 66

Degrees of freedom (252 - 66): 186

Result (Default model)

Minimum was achieved

Chi-square = 1478.445

Degrees of freedom = 186

Probability level = .000

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label
Prep <--- Lng	5.987	3.470	1.725	.084	
Consltn <--- Lng	1.368	.093	14.725	***	
Instructn <--- Lng	1.219	.068	17.794	***	
V33 <--- Prep	.088	.050	1.771	.077	
V13 <--- Prep	.090	.051	1.771	.077	
V14 <--- Prep	.054	.030	1.769	.077	
V16 <--- Prep	.097	.055	1.771	.077	
V10 <--- Prep	.103	.058	1.770	.077	
V21 <--- Prep	.099	.056	1.771	.077	
V29 <--- Prep	.092	.052	1.769	.077	
V32 <--- Prep	.095	.054	1.770	.077	
V7 <--- Prep	.120	.068	1.769	.077	
V11 <--- Prep	.077	.043	1.764	.078	
V34 <--- Prep	.068	.039	1.762	.078	
V15 <--- Prep	.091	.052	1.770	.077	
V8 <--- Instructn	.313	.012	25.828	***	

Standardized Regression Weights: (Group number 1 - Default model)

	Estimate
Prep <--- Lng	.986
Consltn <--- Lng	.807
Instructn <--- Lng	.773
V33 <--- Prep	.706
V13 <--- Prep	.720
V14 <--- Prep	.650
V16 <--- Prep	.694
V10 <--- Prep	.708
V21 <--- Prep	.749

Squared Multiple Correlations: (Group number 1 - Default model)

	Estimate
Consltn	.652
Instructn	.598
Prep	.973
V20	.328
V23	.216
V2	.340
V3	.450
V4	.394
V22	.187
V27	.520

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	66	1478.445	186	.000	7.949
Saturated model	252	.000	0		
Independence model	21	9875.940	231	.000	42.753

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.850	.814	.867	.834	.866
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.805	.685	.697
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

NCP

Model	NCP	LO 90	HI 90
Default model	1292.445	1173.676	1418.654
Saturated model	.000	.000	.000
Independence model	9644.940	9323.106	9973.101

FMIN

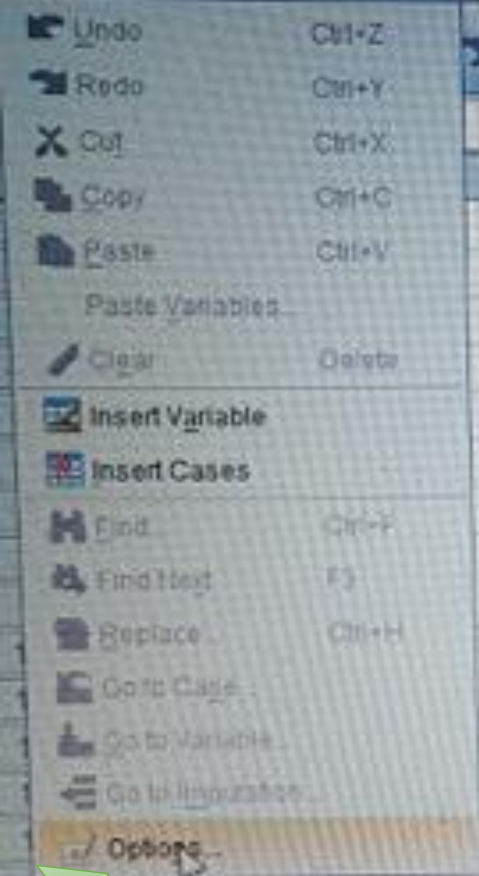
Model	FMIN	F0	LO 90	HI 90
Default model	.945	.826	.750	.907
Saturated model	.000	.000	.000	.000
Independence model	6.315	6.167	5.961	6.377

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.067	.064	.070	.000
Independence model	.163	.161	.166	.000

Type	Fit Index	Description	Cut-off Value
Absolute Fit Indices	Chi-Square (X ²)	Assessing the overall fit of the model by comparing the differences between the sample covariance matrix and the fitted covariance matrix	$p > 0.05$
	Normed-Chi-Square (X ² /df)	Evaluates the model fit after reducing the impact of large sample sizes on the model Chi-Square (X ²)	$1 < X^2/df < 3$
	RMSEA	Evaluates the degree to which the study model fits the covariance matrix of the population	< 0.08
	GFI	Evaluates the degree to which the model can replicate the covariance matrix	> 0.90
	AGFI	Similar to GFI with adjustments made based on the degrees of freedom (df)	> 0.90
	RMR	The square root of the difference between the residuals of the sample covariance matrix and the hypothesised covariance model	< 0.08
	SRMR	Similar to RMR but easier to interpret when the study questionnaire comprises different types of scales (e.g. scales that range from 1 to 5 and others that range from 1 to 7)	< 0.08
Incremental Fit Indices	NFI	Assesses the model by comparing X ² of the study model to that of a null model	> 0.90
	NNFI	Similar to NNFI but provides better interpretations for models that are simple	> 0.90
	CFI	A revised version of NFI that works better when sample sizes are small	> 0.90
Parsimony Fit Indices	PGFI	An index that is based on GFI while accounting for loss of degrees of freedom. It does not work well when the model is complex.	> 0.50
	PNFI	An index that is based on NFI while accounting for loss of degrees of freedom. It does not work well when the model is complex	> 0.50

Source: Relied on Hooper, et al. (2008)

[illegible]

2



File Edit View Data Transform Analyze Data Editor

	var	var	var
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Data View Variable View

Options

Pivot Tables File Locations Scripts Multiple Imputations Syntax Editor

General Viewer Data Currency Output Labels Charts

Variable Lists

- ☒ Display labels
- ☐ Display names

Alphabetical

- ☐ Alphabetical
- ☒ File
- ☐ Measurement level

Roles

To save time, some dialogs allow the use of predefined field roles to automatically assign variables (fields) to lists in dialogs.

- ☒ Use predefined roles
- ☐ Use custom assignments

Windows

Look and feel: SPSS Standard

- ☐ Open syntax window at startup
- ☐ Open only one dataset at a time

Output

- ☐ Ng scientific notation for small numbers in tables
- ☐ Apply locale's digit grouping format to numeric values

Measurement system: inches

Language: English

Notification

- ☒ Raise viewer window
- ☒ Scroll to new output

Character Encoding for Data and Syntax

- ☒ Locale's writing system
- ☐ Unicode (universal character set)

Character encoding cannot be changed when any non-empty datasets are open

User Interface

Language: English

OK Cancel Apply Help

4

Options

Pivot Tables File Locations Scripts Multiple Imputations Syntax Editor

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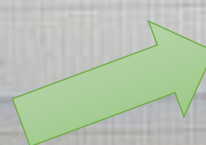
Character encoding cannot be changed when any non-empty datasets are open

User Interface

Language: English

OK Cancel Apply Help

5



Variable View

IBM SPSS Statistics Processor is ready

Course Evaluation





رأيك يهمني
أكتب أسمك + تقييمك لدورة البحث العلمي

<https://padlet.com/monaashry77/padlet-xr709opfeqfrbh7t>



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Thank You

