

Final Project-2

Lecture 6

L6- Statistical Analysis- P2

Prepared by
Dr. Mona Moustafa Elashry



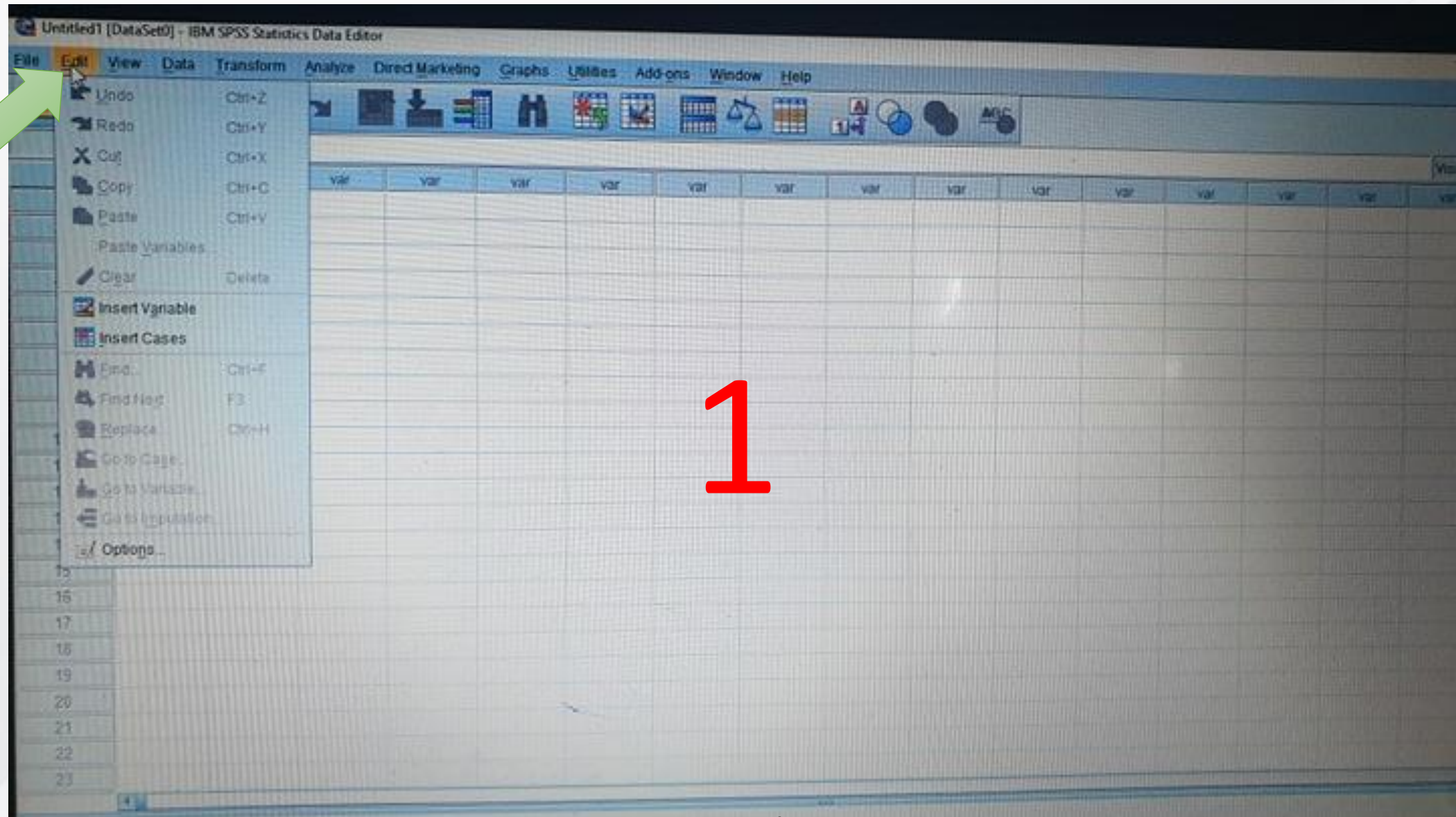
Session Outline

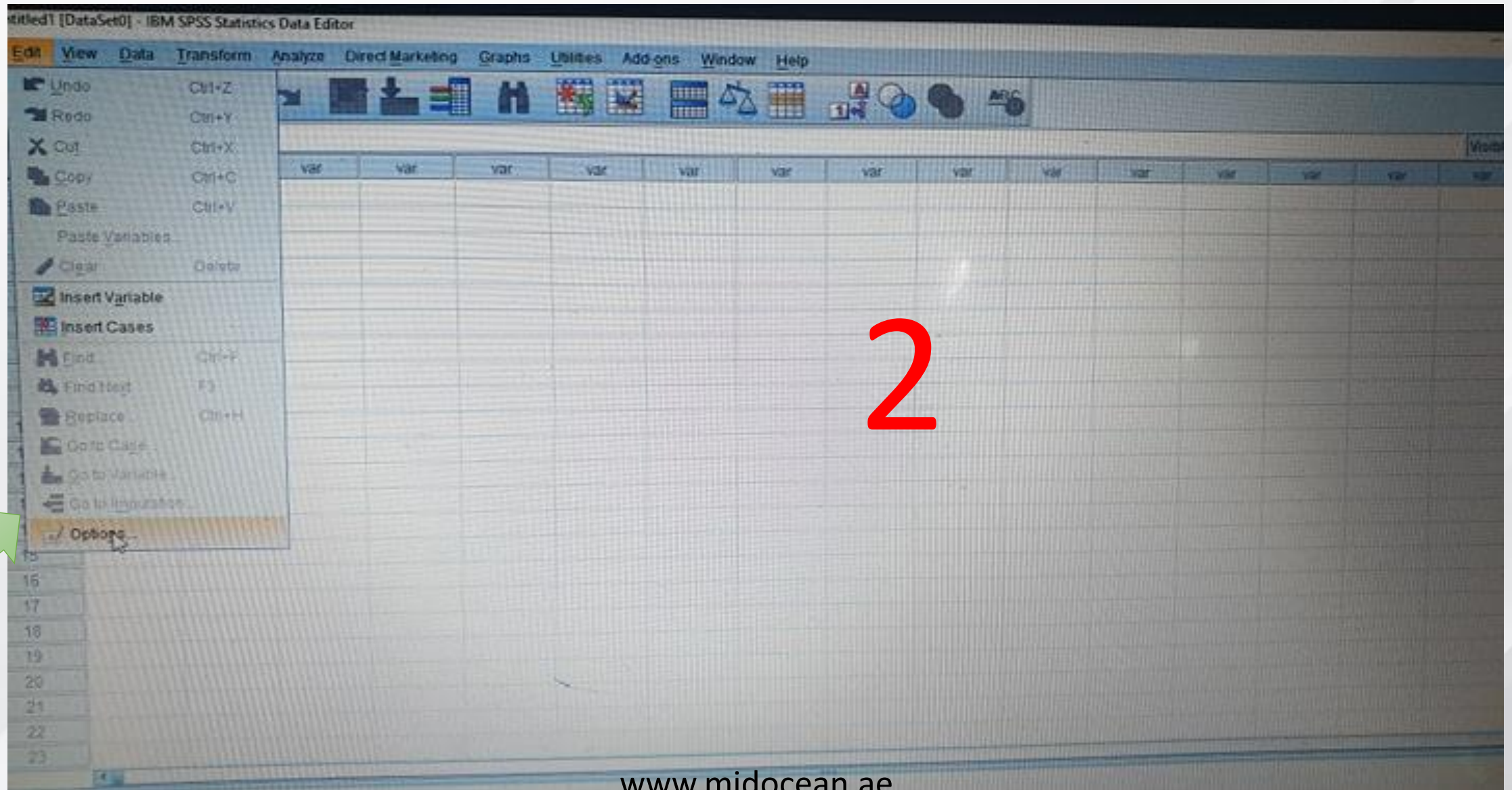
- Change SPSS Language
- How to import data file to SPSS
- How to label data in SPSS?
- How to compute a mean variables?
- Construct Validity
- Construct Reliability

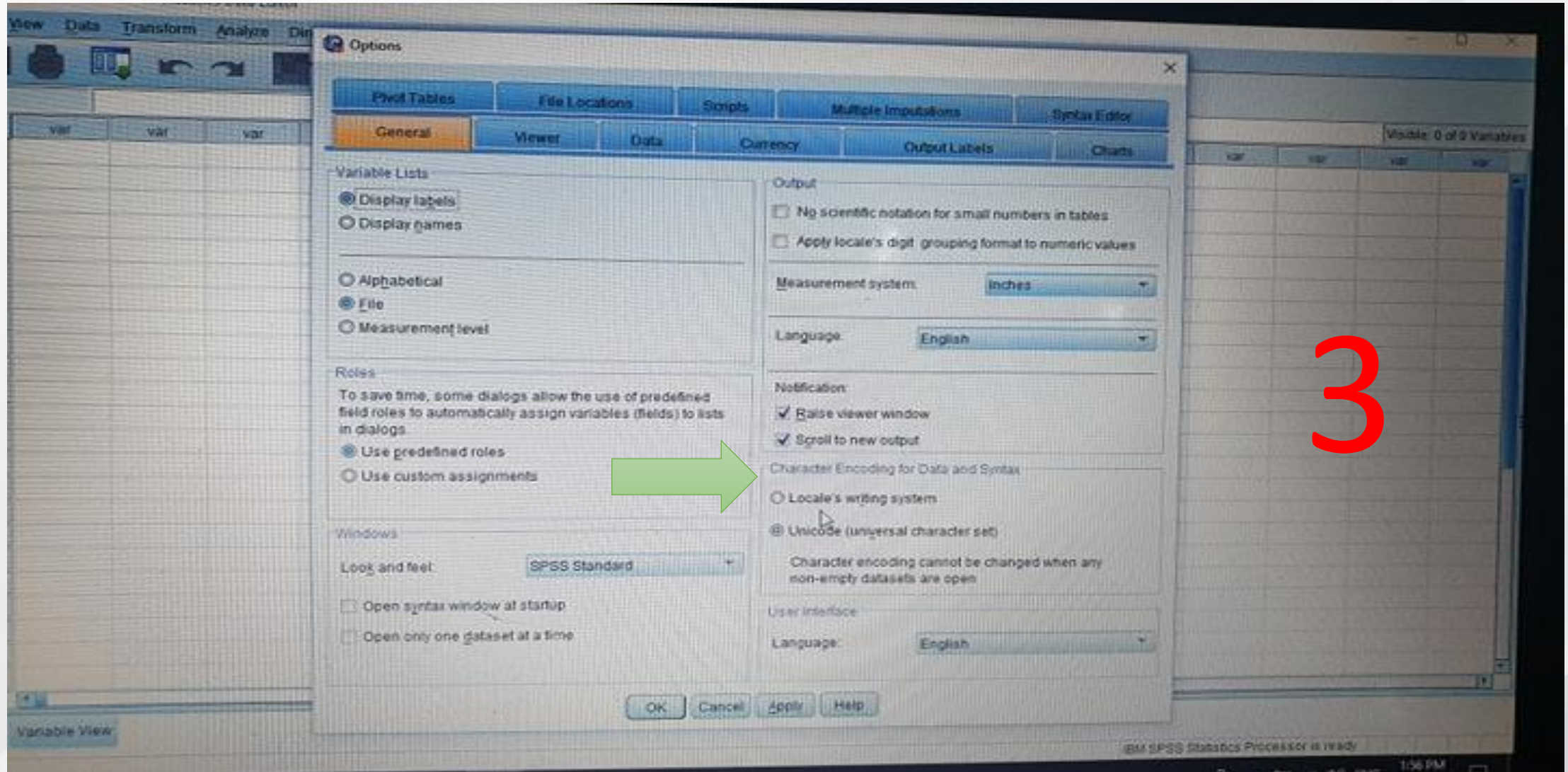
Change SPSS Language

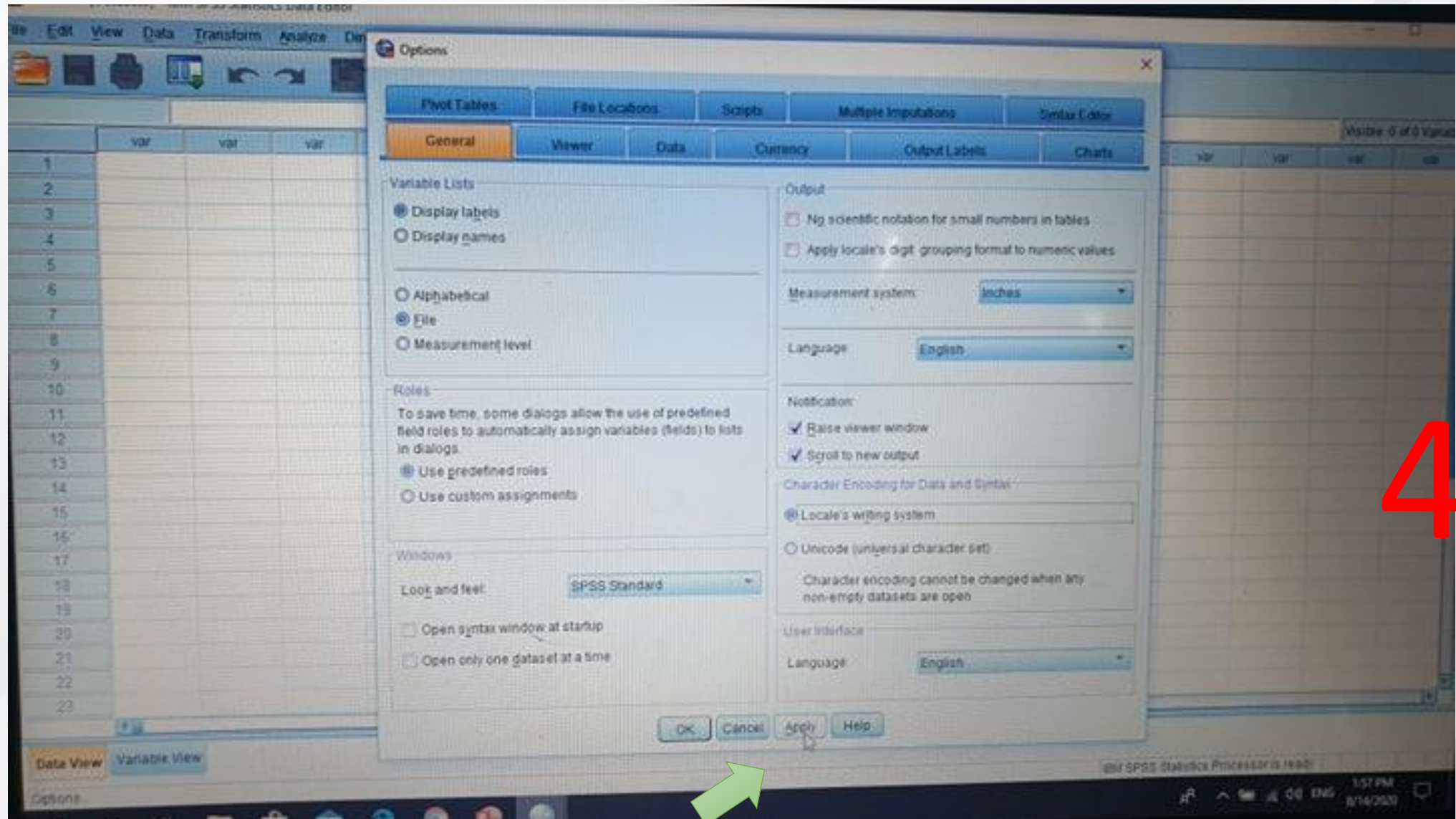
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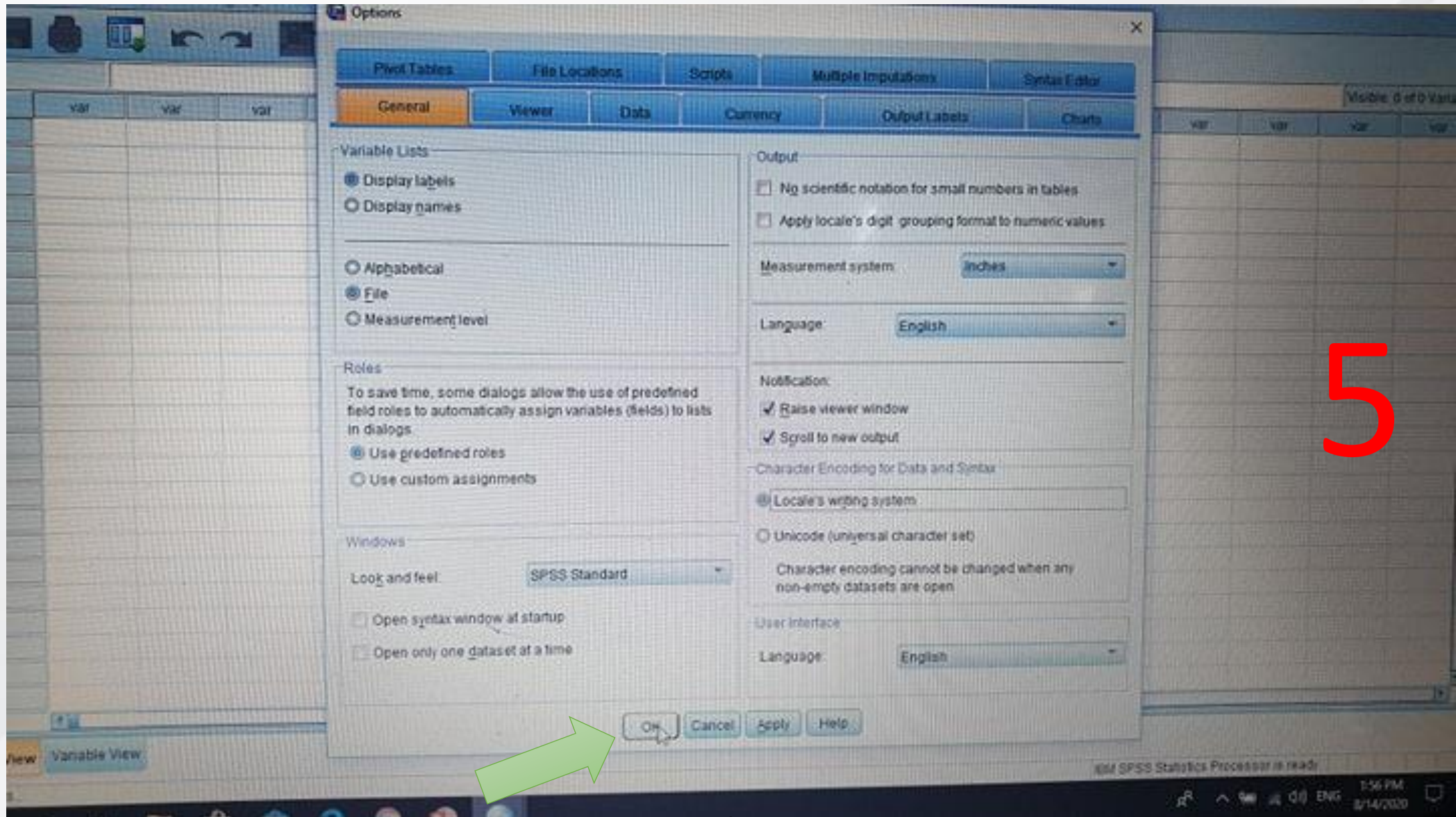








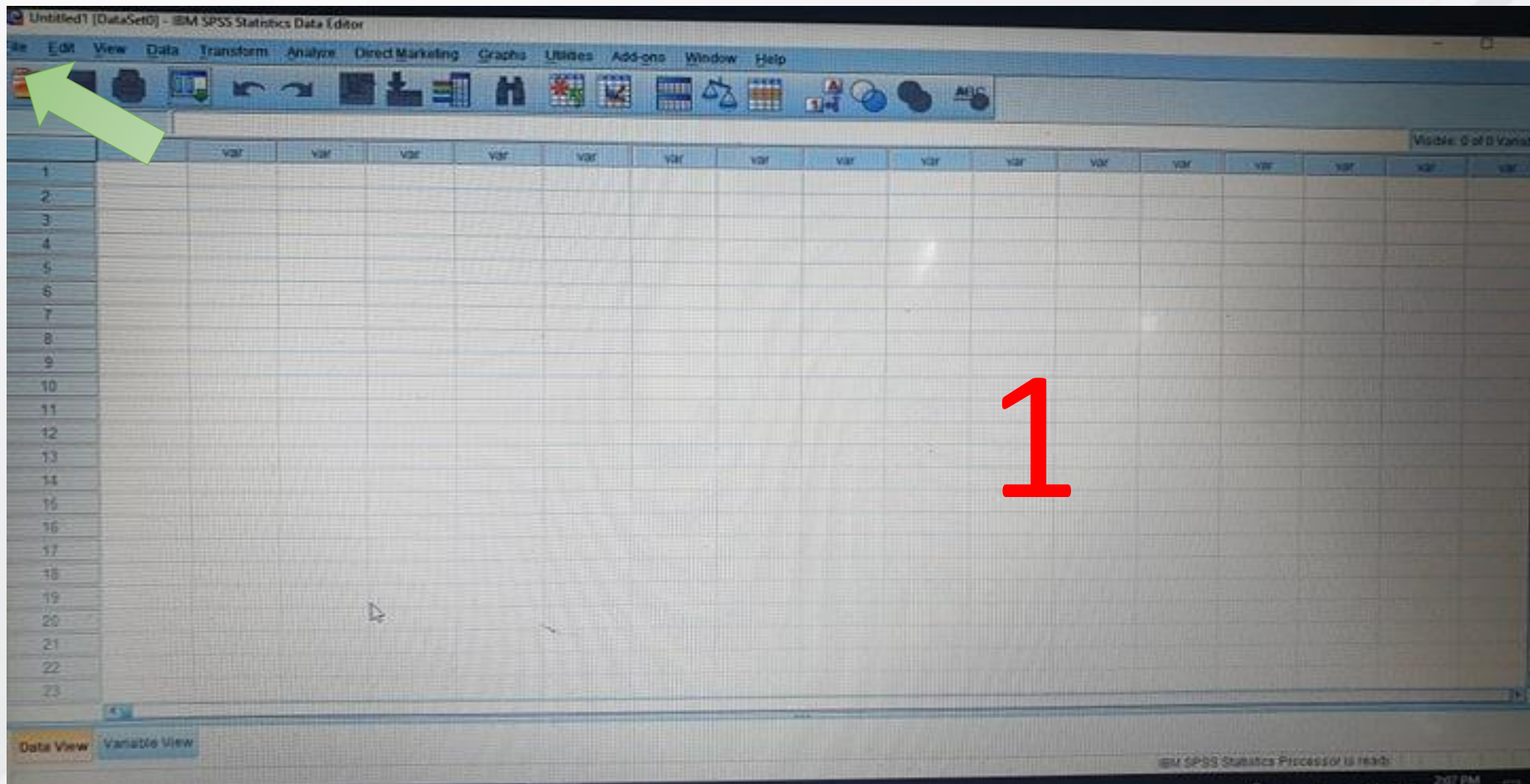
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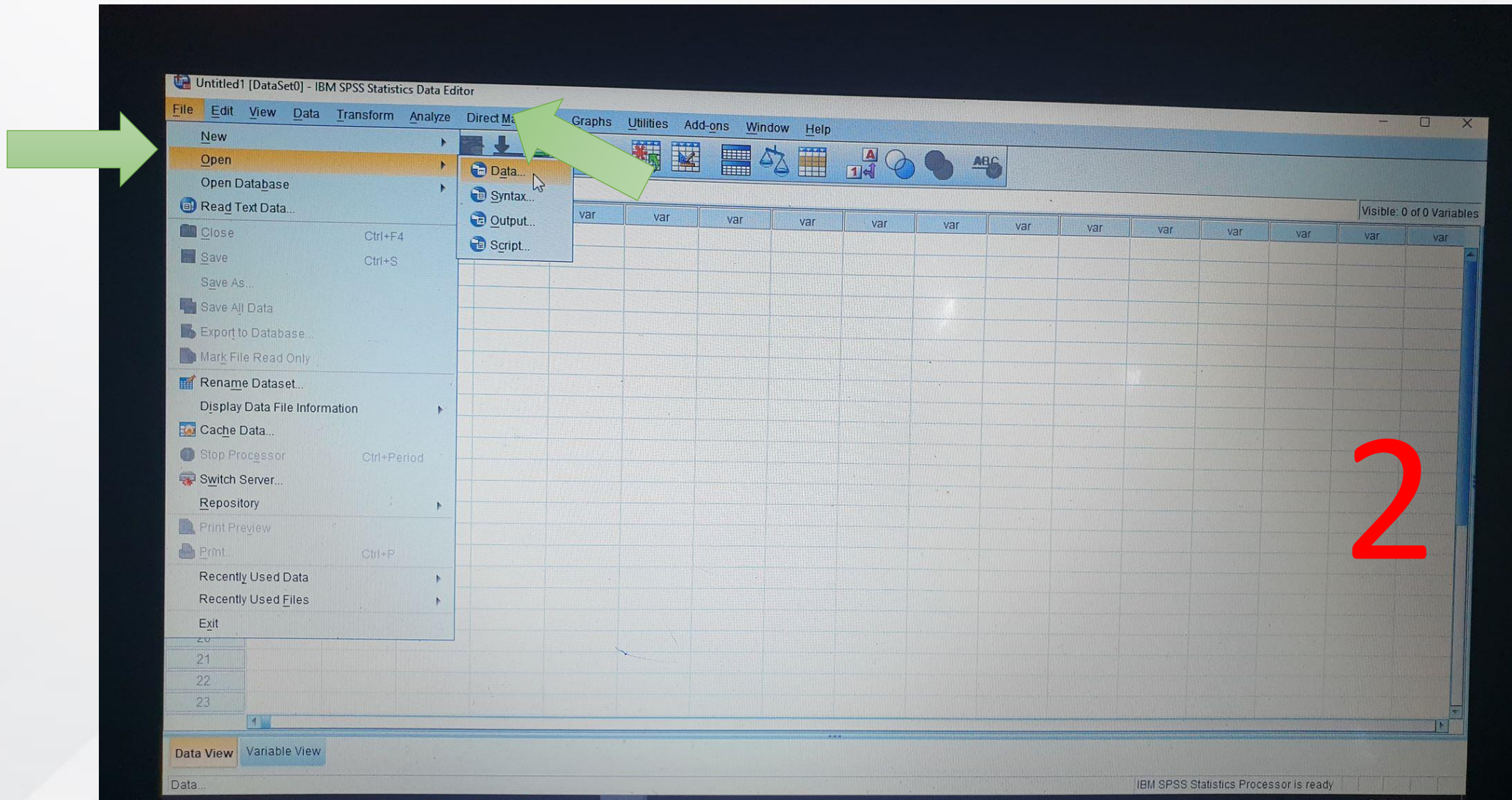


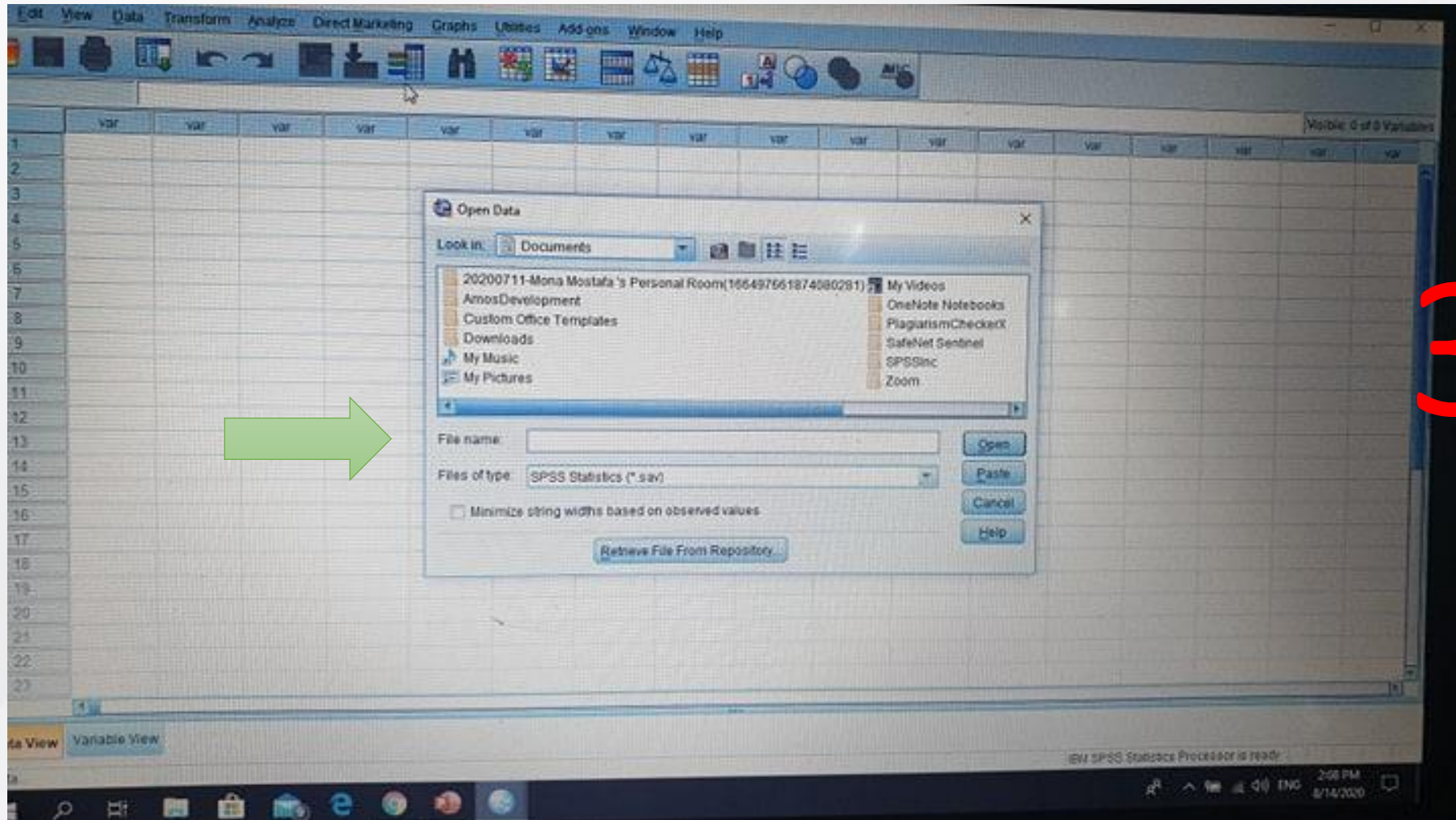
How to import data file to SPSS

2

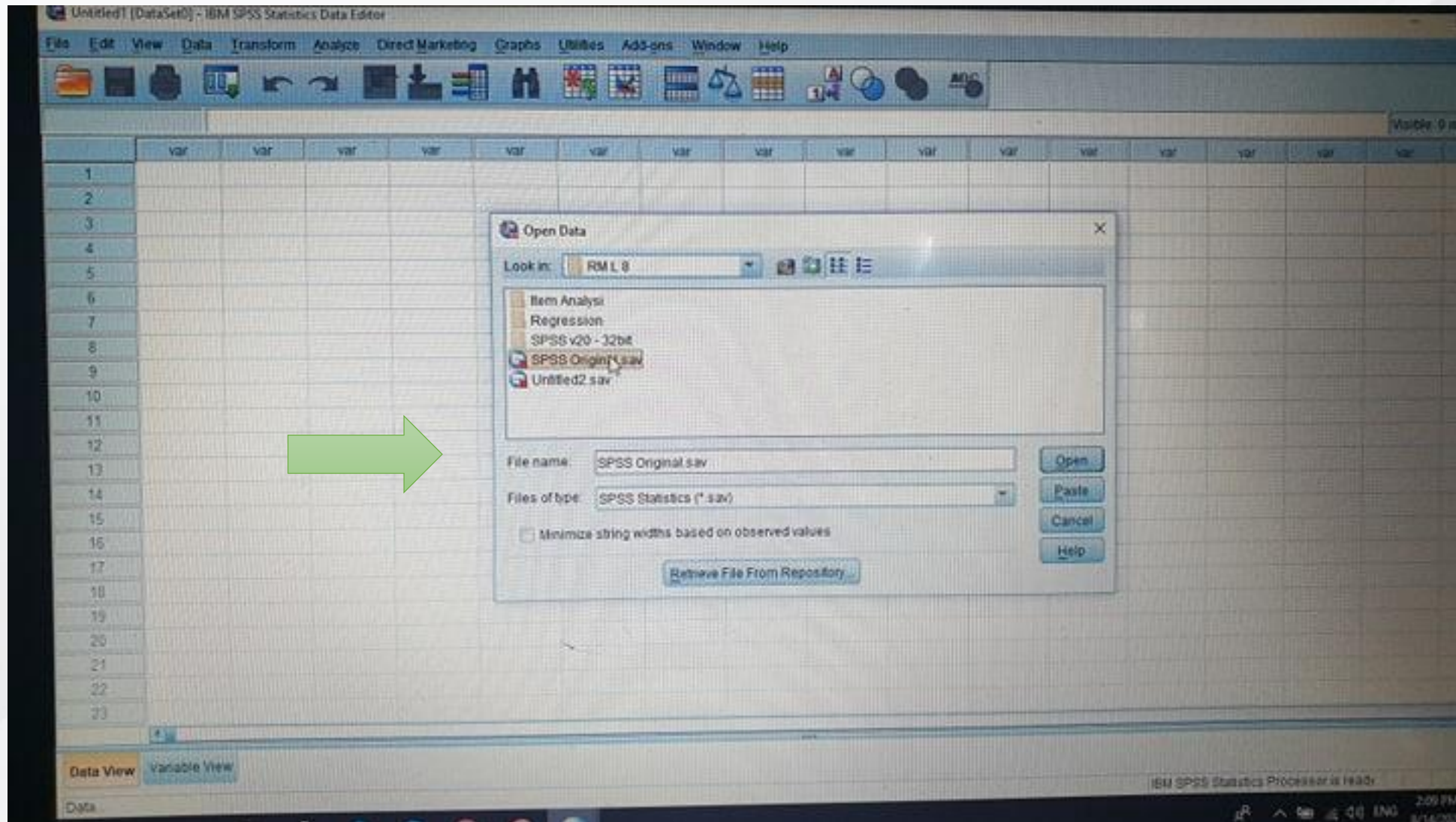








3



4

SPSS Original.sav [DataSet1] - IBM SPSS Statistics Data Editor

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

Visible: 10 of 50 Variables

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Data View Variable View

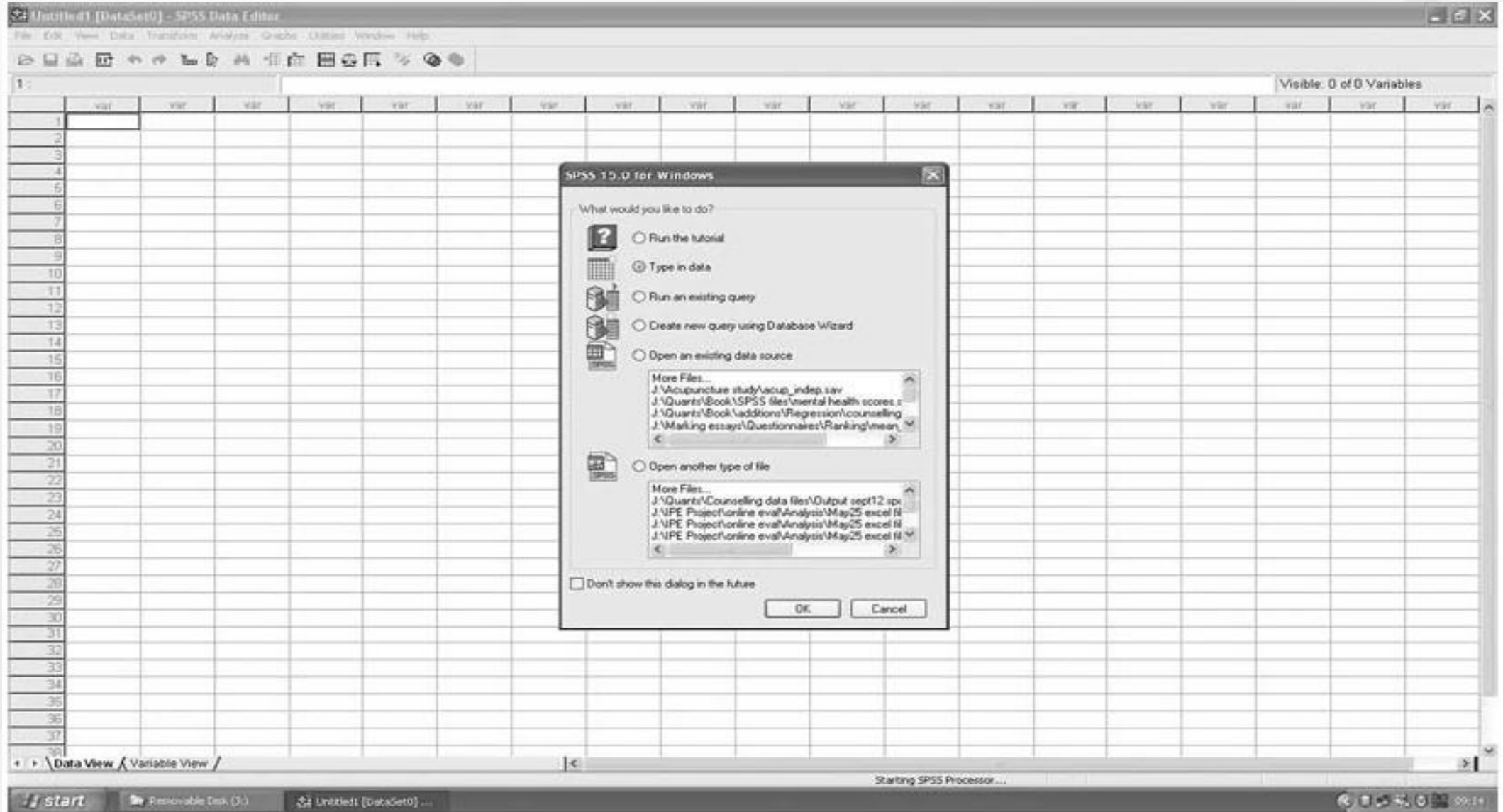
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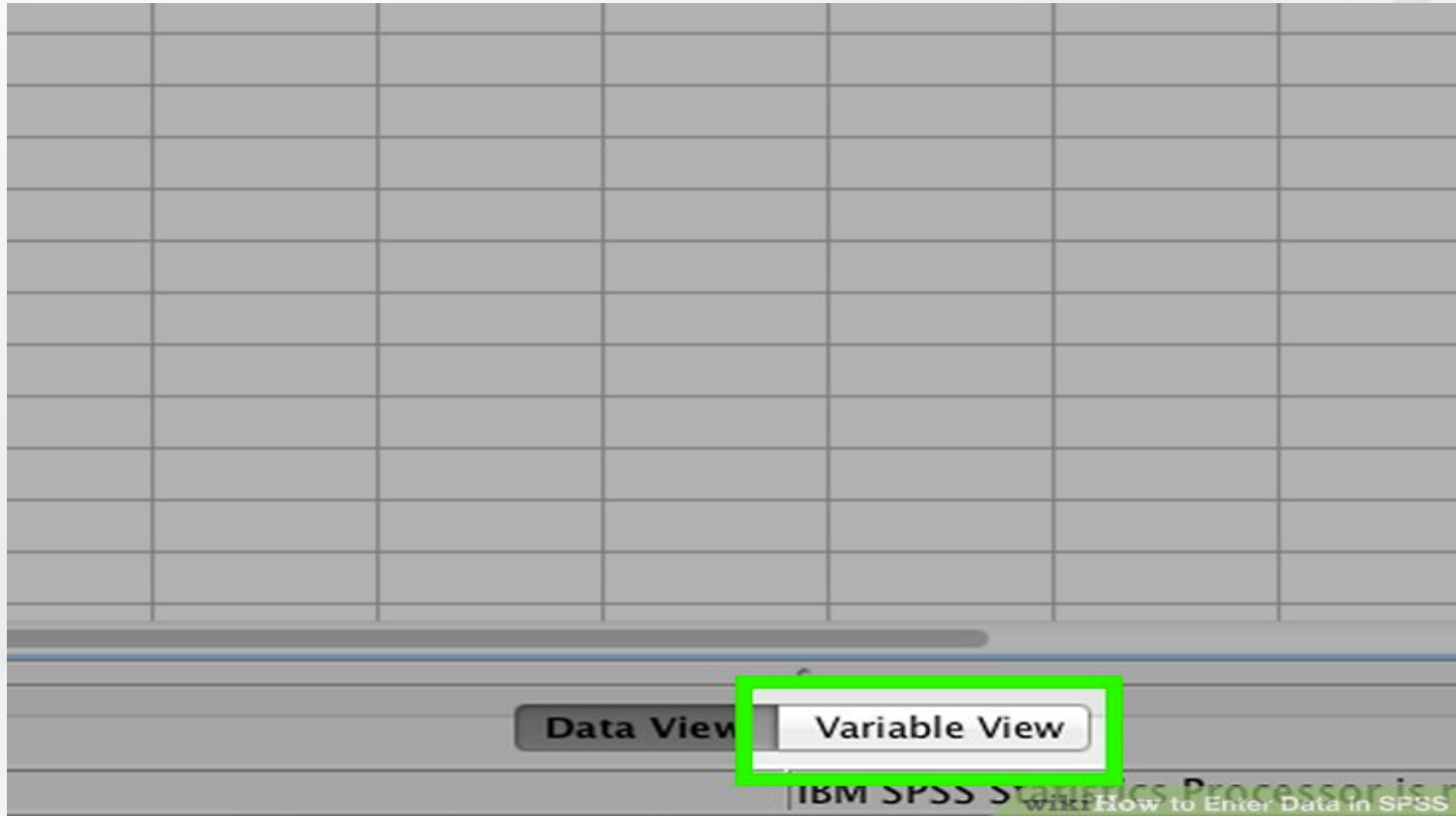
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How to label data in SPSS?

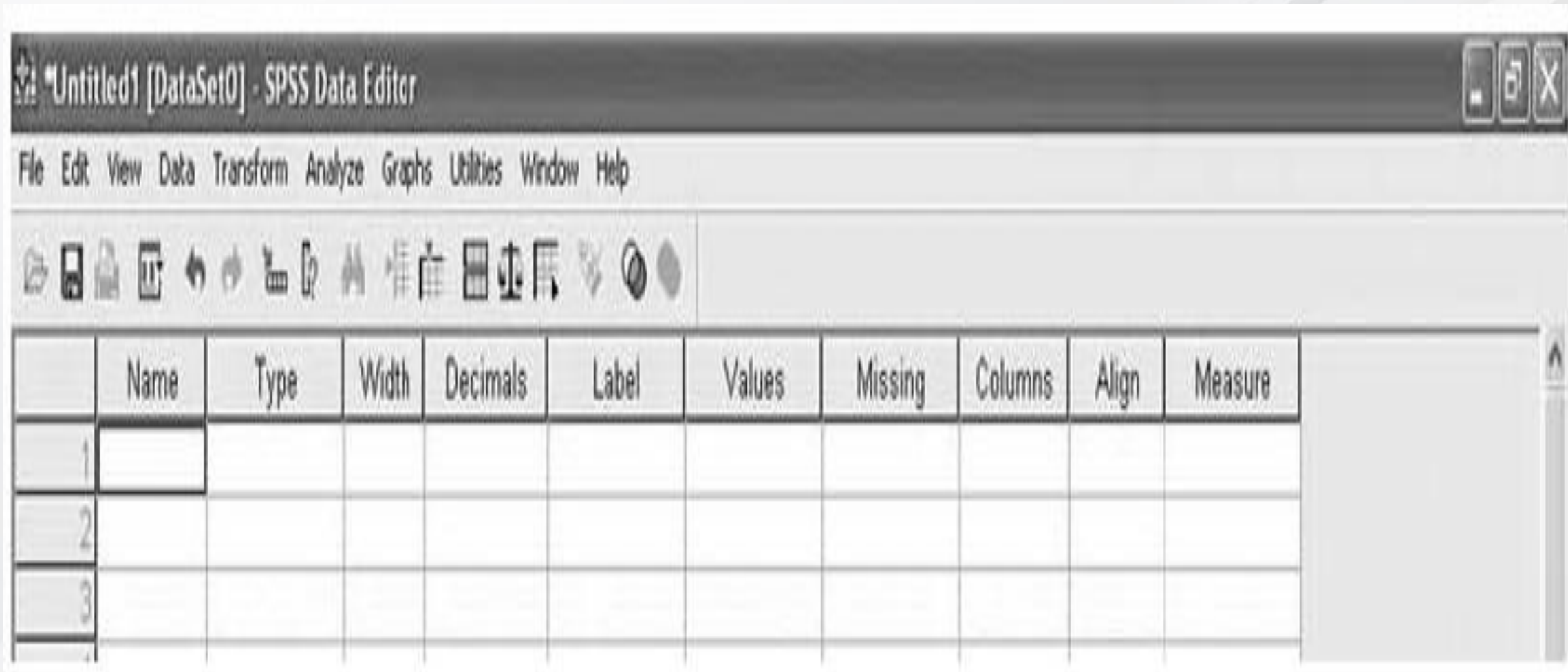
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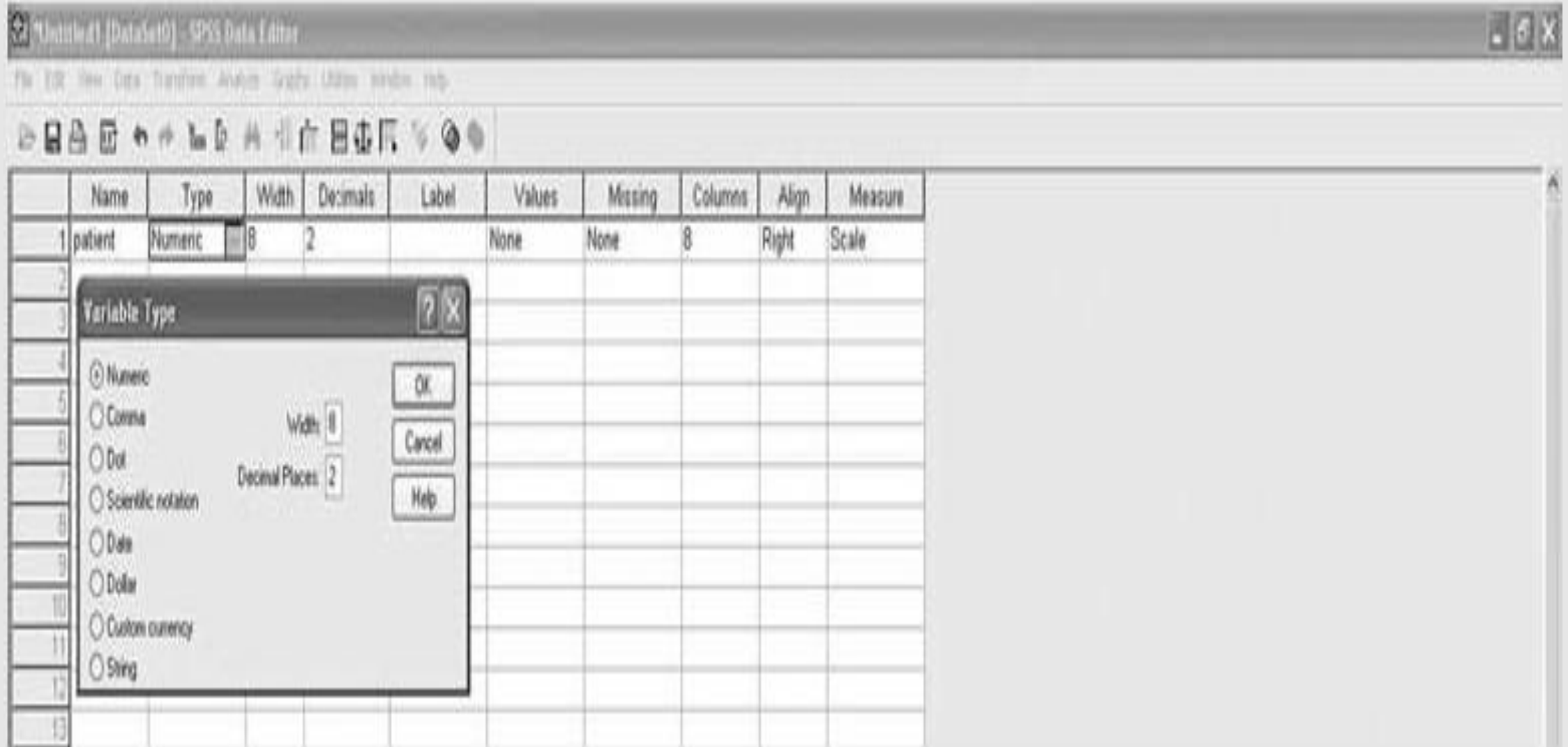






Defining variables





*computer_parts.sav [

File	Edit	View	Data	Transform	Analyze	Direct Marketing	Graphs	Utilities	Add-ons	Window	Help
	Name	Type	Label	Values	Missing						
1	name	String	← STRING VARIABLE		None						
2	weight	Numeric			None						
3	date	Date	← NUMERIC VARIABLES		None						
4	time	Date			None						
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6	commission	(!)			None						
7	price	Dollar			None						
8											

Sample Data.sav [DataSet1] - IBM SPSS Statistics Data Editor

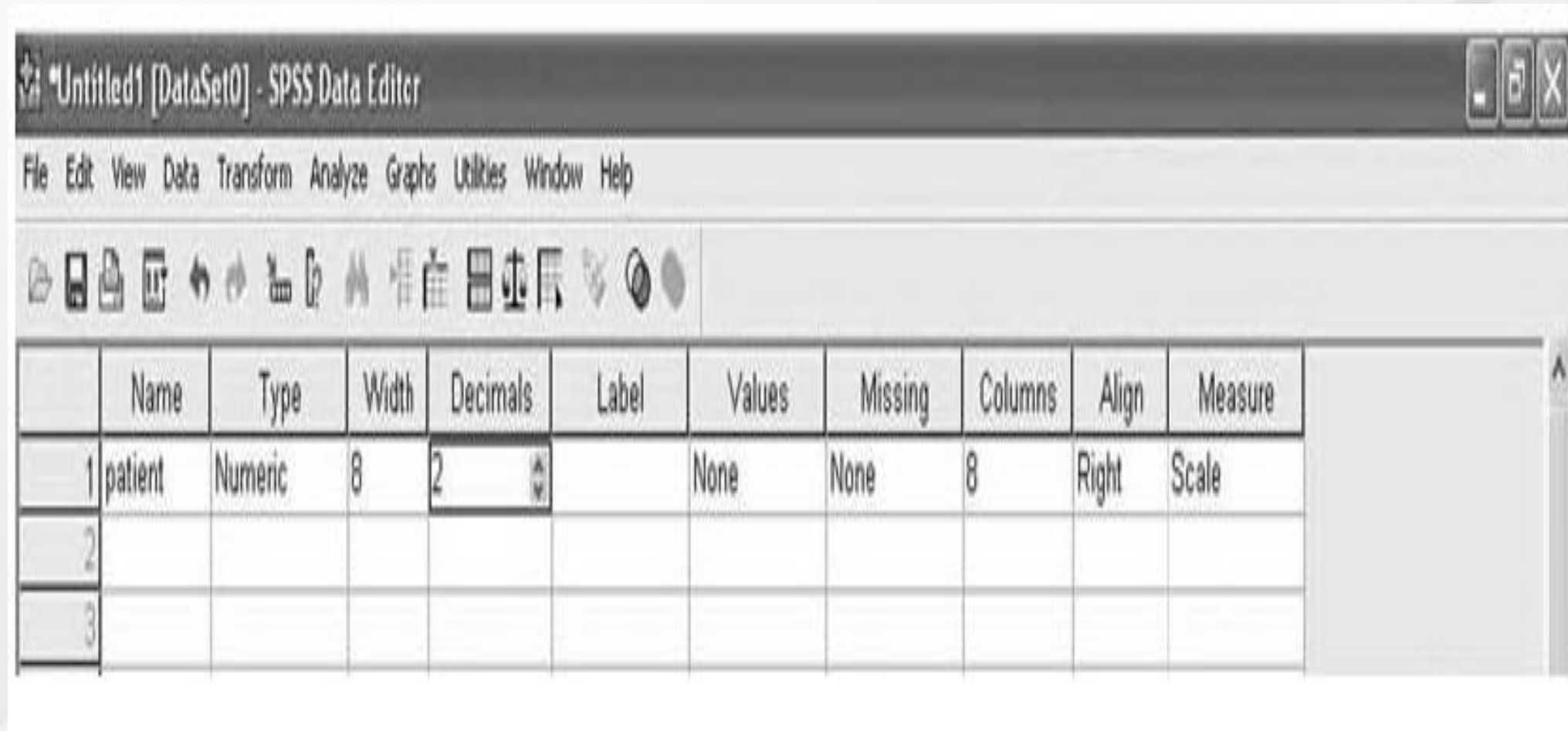
File Edit View Data Transform Analyze Direct Marketing Graphs Utilities Extensions Window Help

h Decimals Label Values Missing Columns Align Measure Role

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2	0		{1, Male}...	None	8	Right	Nominal	Input
3	0		{1, Caucasi...	None	8	Right	Nominal	Input
4	0		{1, Married}...	None	7	Right	Nominal	Input
5	0		{1, Some Hi...	None	8	Right	Ordinal	Input
6	0		{0, No}...	None	8	Right	Nominal	Input
7	0		None	None	8	Right	Scale	Input
8	0		{1, Rarely/N...	None	9	Right	Ordinal	Input
9							Scale	
10							Ordinal	
11							Nominal	
12								

Data View Variable View

IBM SPSS Statistics Processor is ready Unicode:ON



*Untitled2 [DataSet2] - IBM SPSS Statistics Data Editor

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

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2	Gender	Numeric	8	0	Gender	None	None	8	Right	Scale	Input
3	Travel_Time	Numeric	8	0	Time it takes to travel into Uni (min)	None	None	8	Right	Unknown	Input

Value Labels

Value Labels:

Value: 1

Label:

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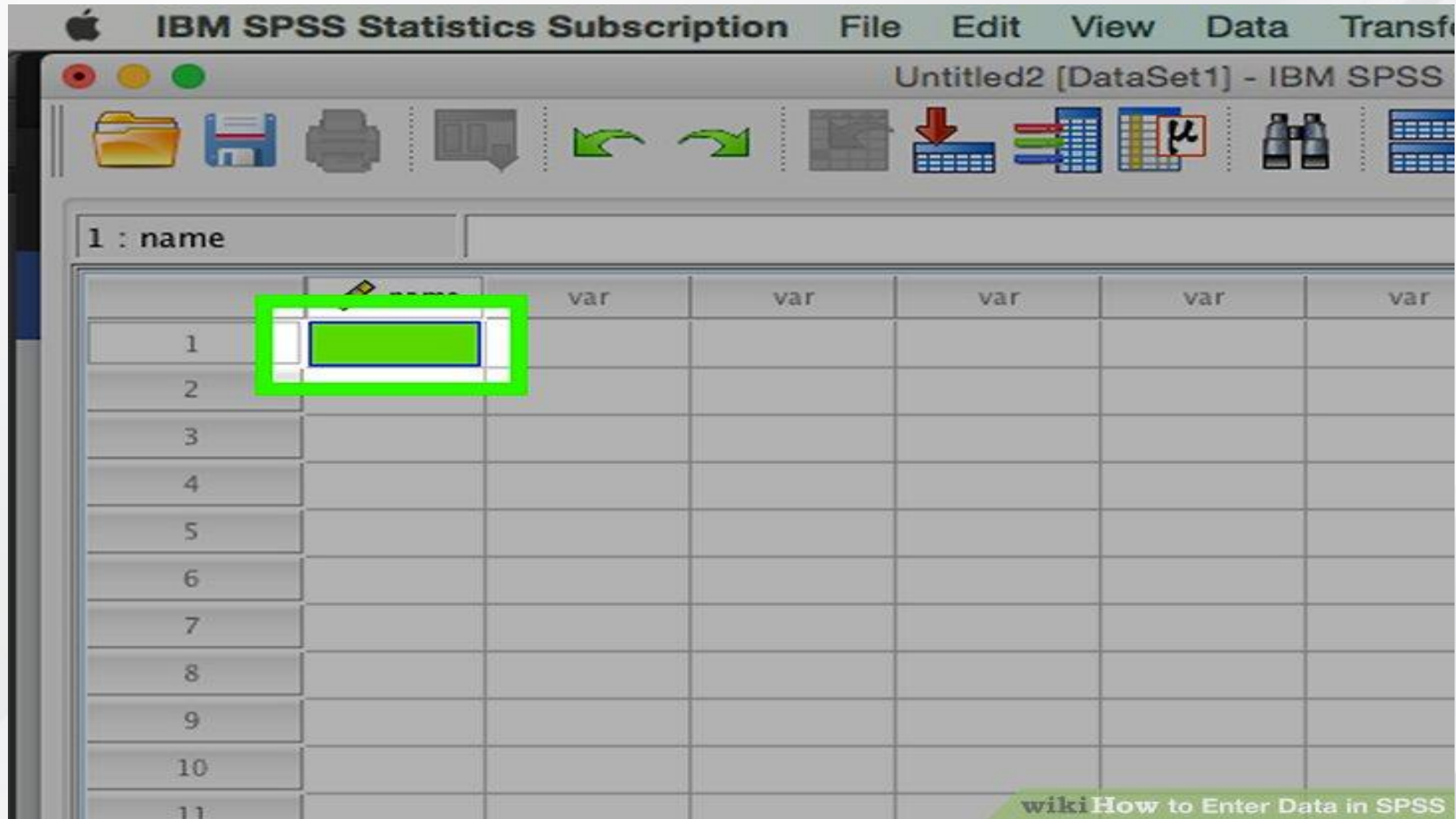
Add Change Remove

OK Cancel Help

ParticipantID	Gender	Travel
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2	0	15
3	1	42
4	0	65
5	1	27

Data View Variable View

IBM SPSS Statistics Processor is ready



*SPSS Original.sav [DataSet1] - IBM SPSS Statistics Data Editor

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How to compute a mean
variables?

4



SPSS Original.sav [DataSet1] - IBM SPSS Statistics Data Editor

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

Visible: 50 of 23

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1

Data View Variable View

IBM SPSS Statistics Processor is ready

SPSS Original.sav [DataSet1] - IBM SPSS Statistics Data Editor

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

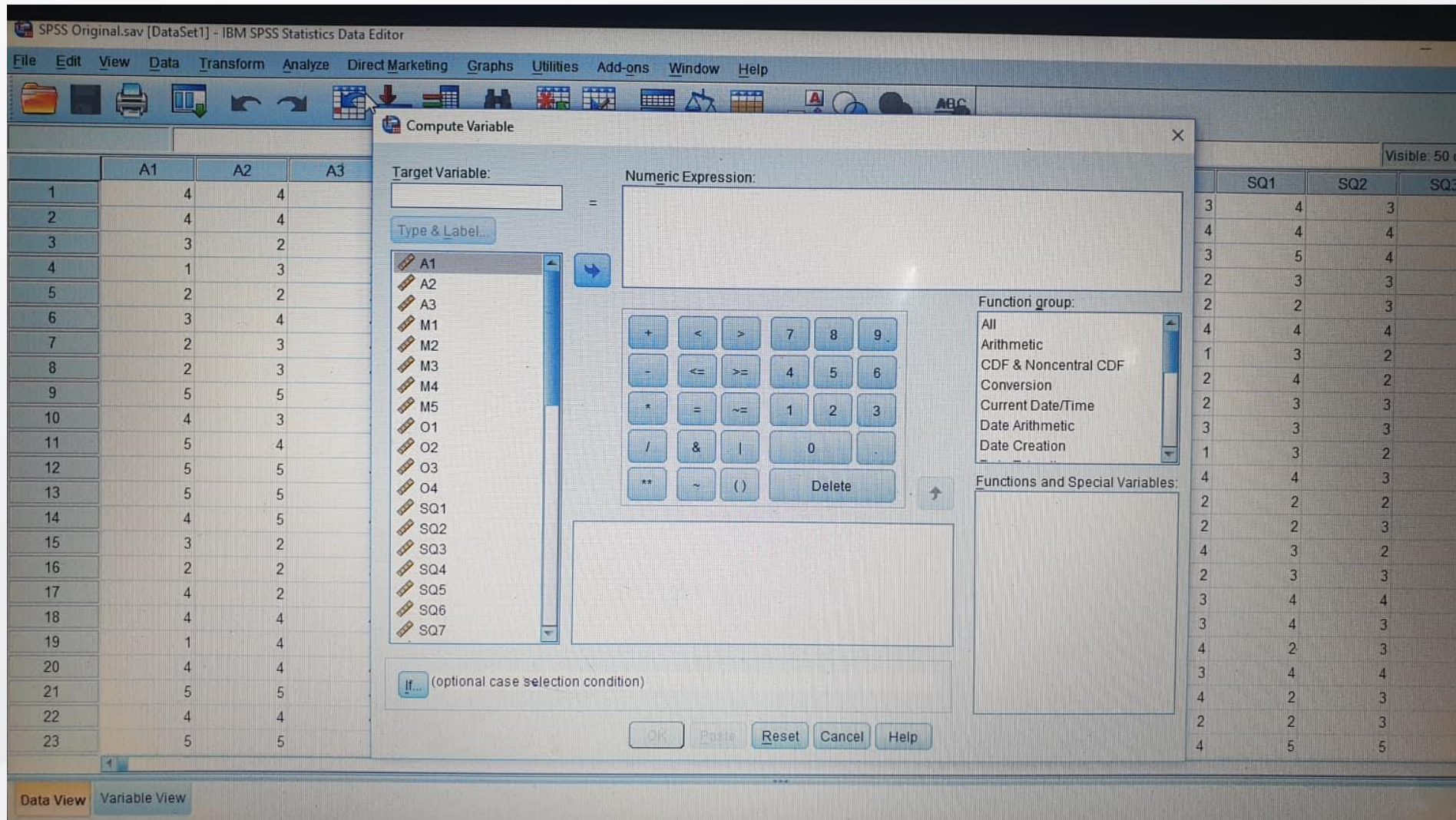
Compute Variable...
Count Values within Cases...
Shift Values...
Recode into Same Variables...
Recode into Different Variables...
Automatic Recode...
Visual Binning...
Optimal Binning...
Prepare Data for Modeling
Rank Cases...
Date and Time Wizard...
Create Time Series...
Replace Missing Values...
Random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

Visible: 50

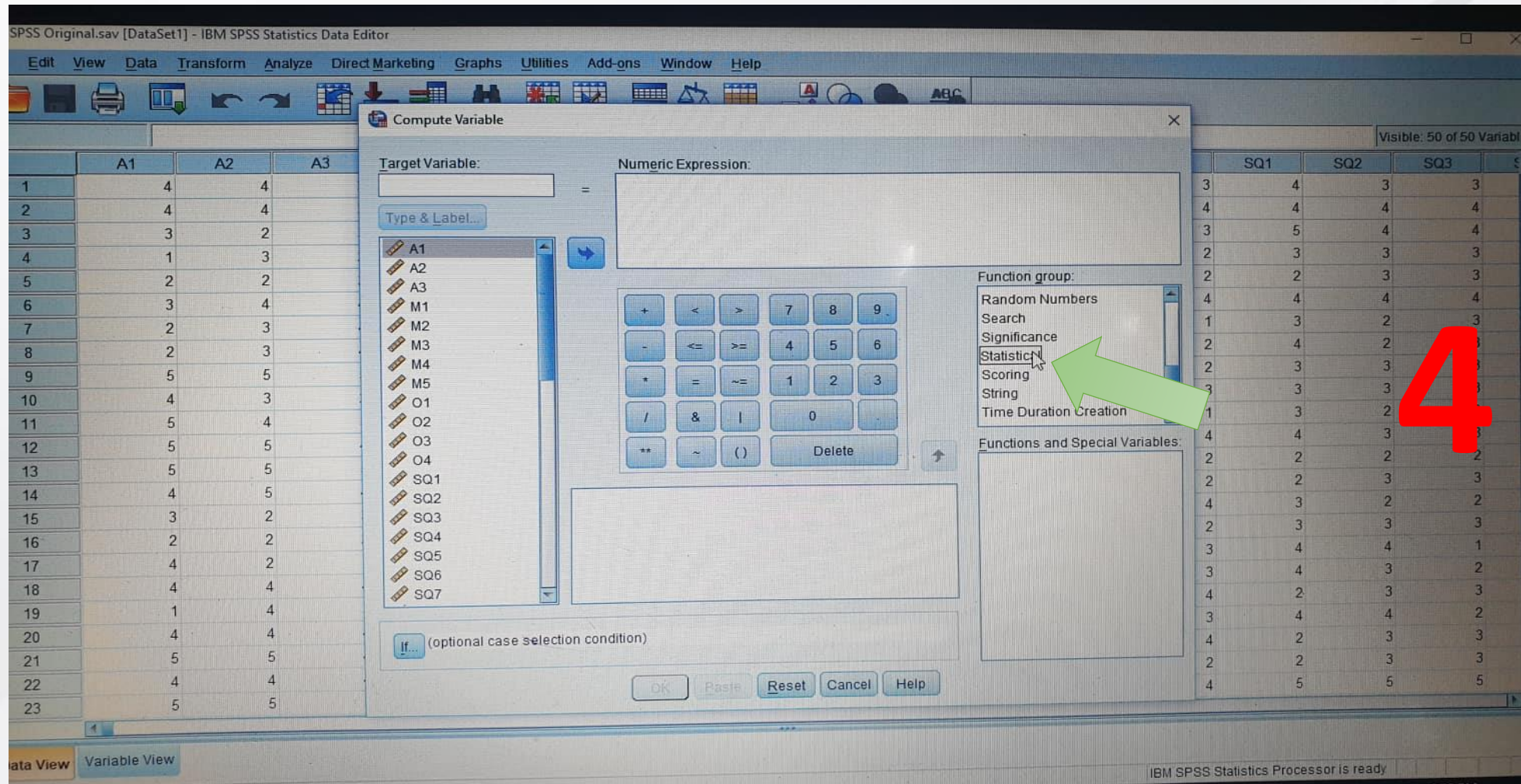
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Data View Variable View

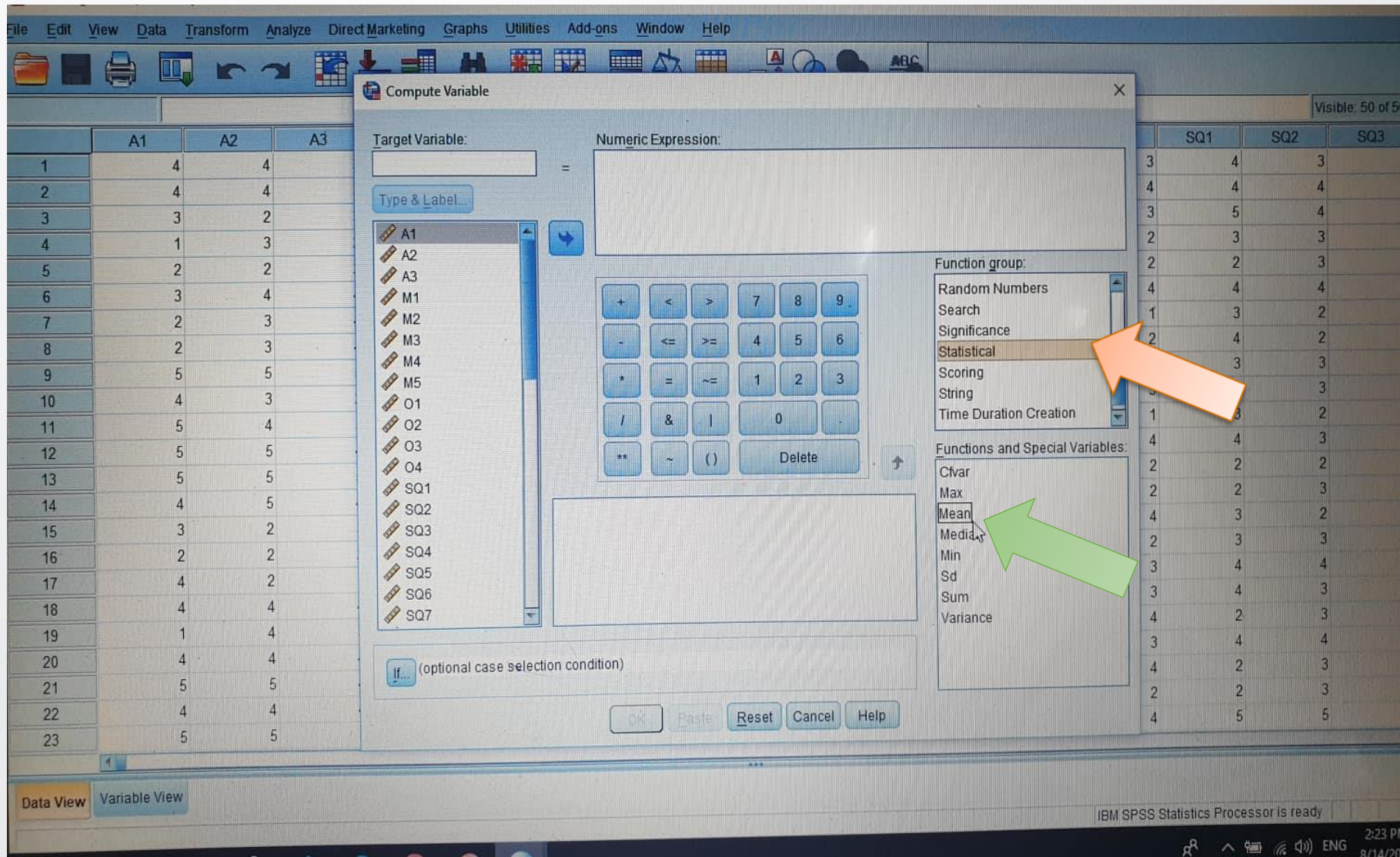
IBM SPSS Statistics Processor is ready

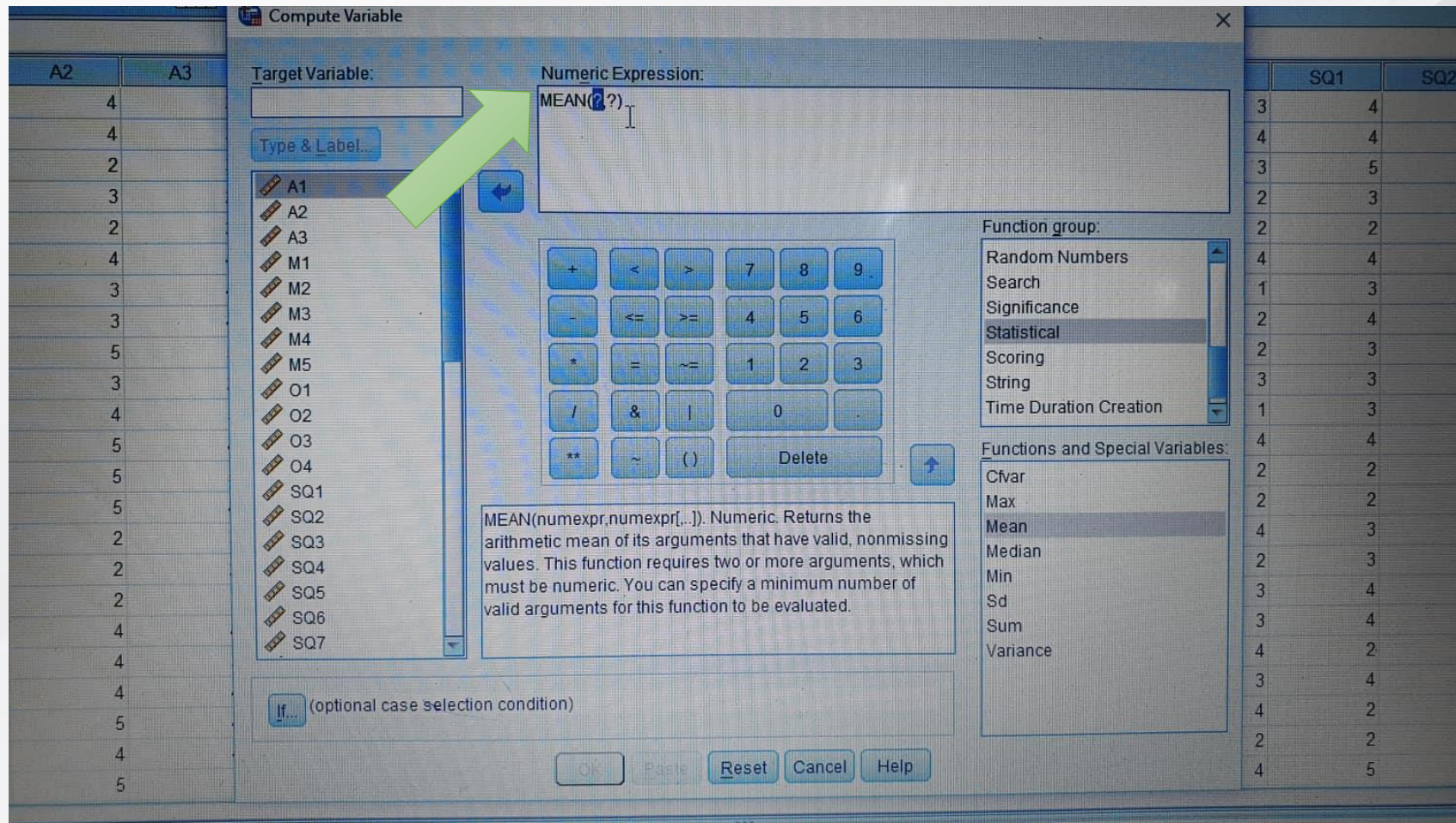


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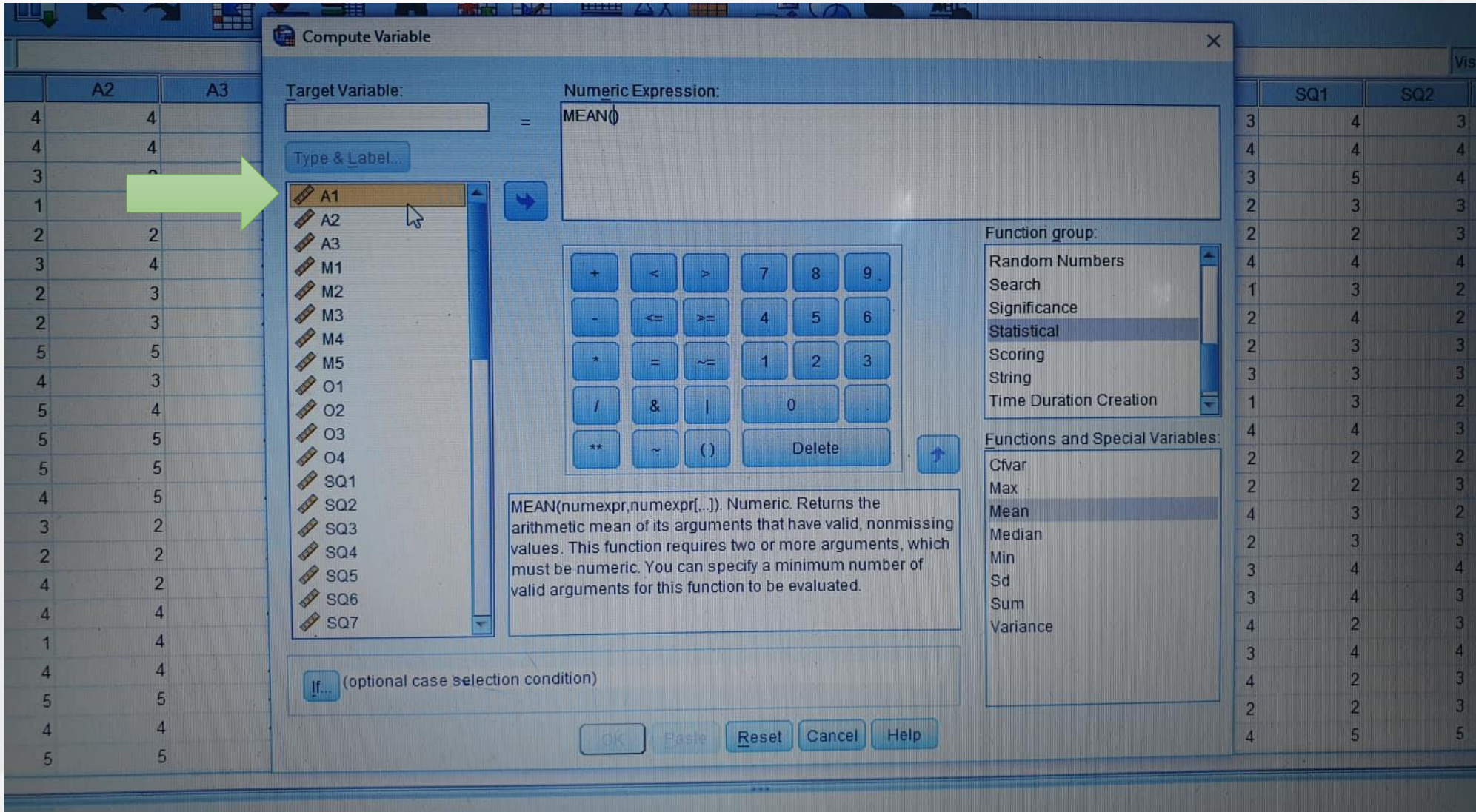


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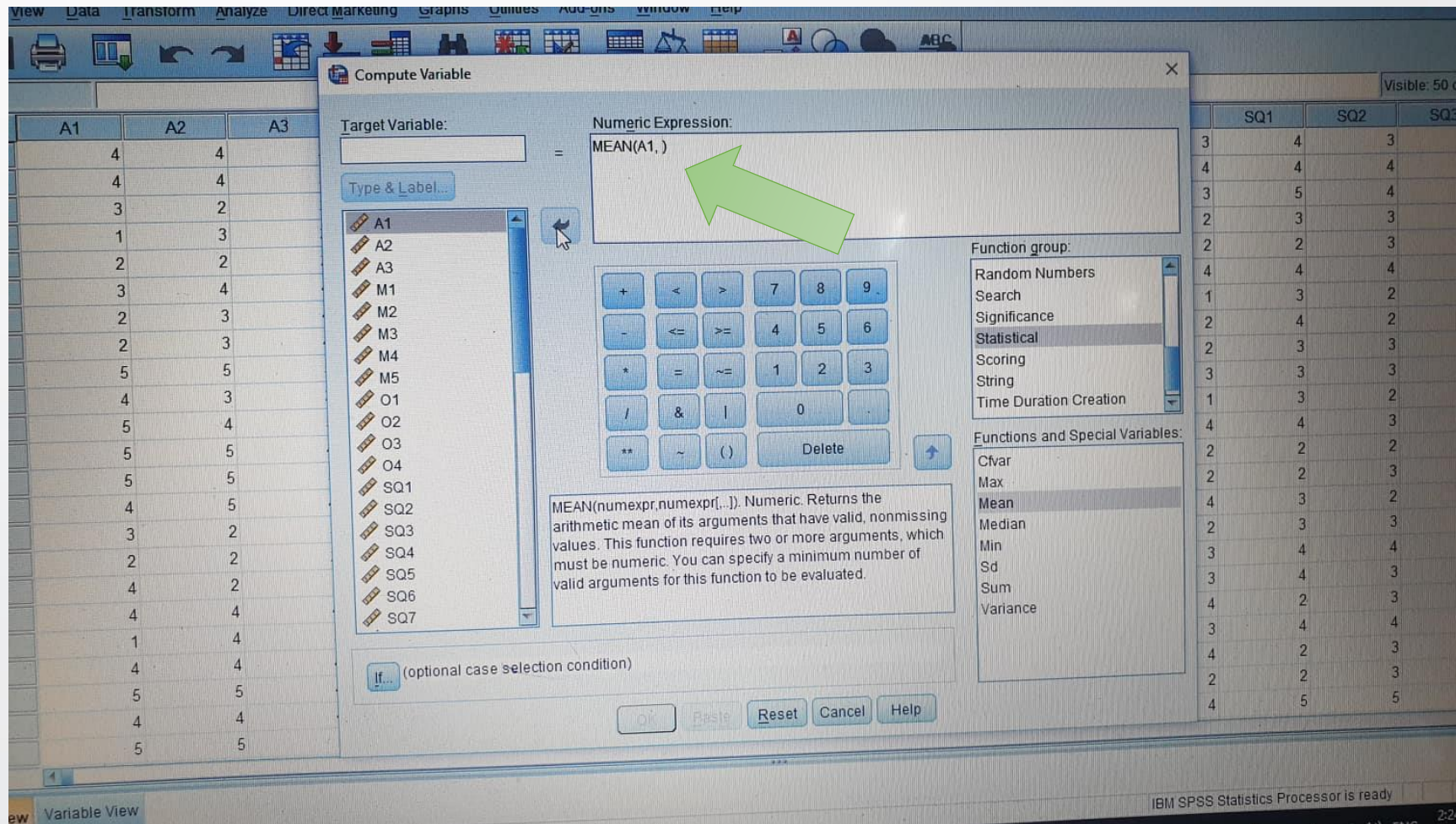




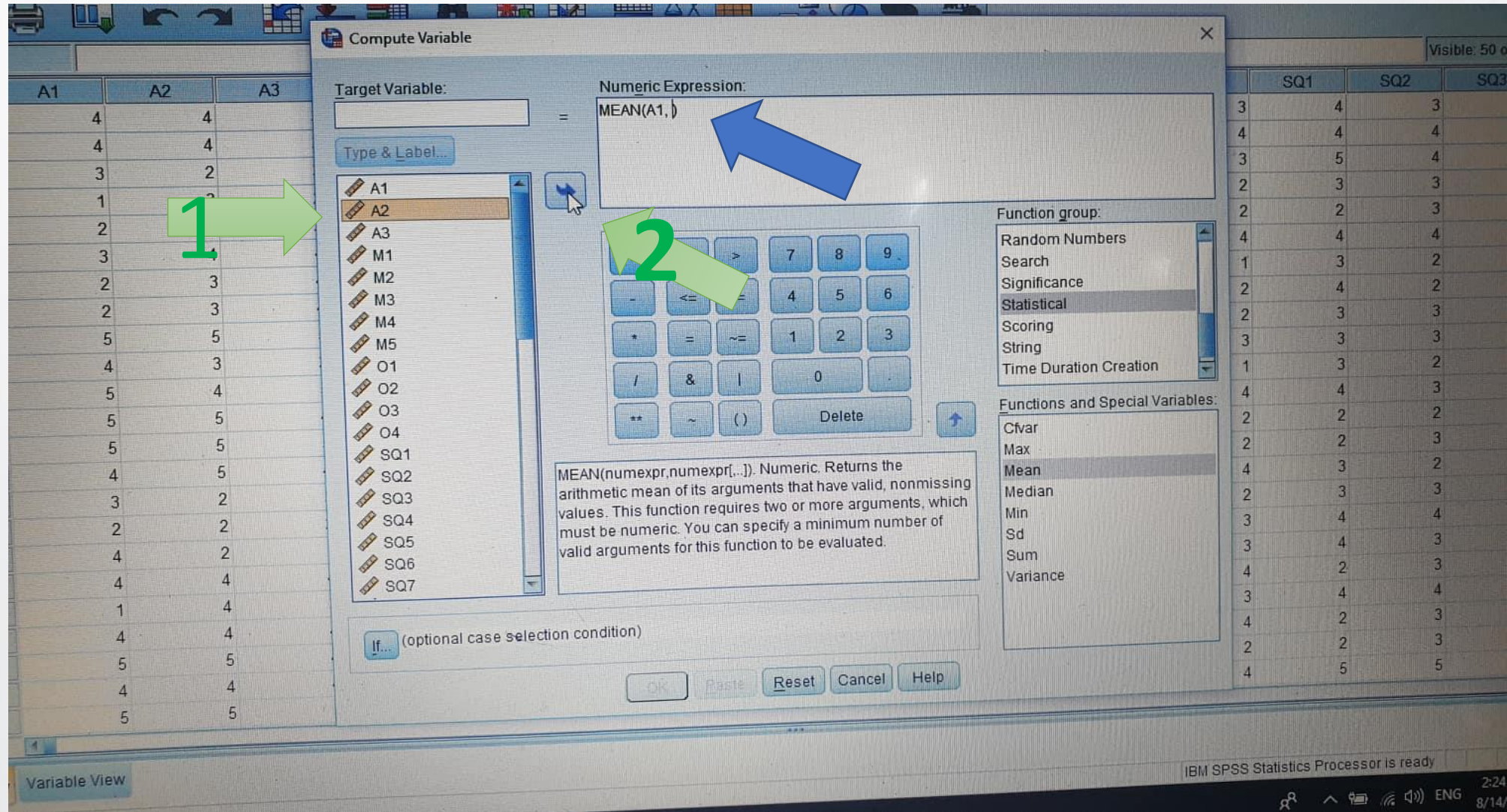
6



7



8



9

The screenshot shows the SPSS 'Compute Variable' dialog box. The 'Target Variable' is 'HPWSS'. The 'Numeric Expression' is 'MEAN(A1, A2)'. A list of variables is on the left, and a function keypad is in the center. A large red '10' is overlaid on the right side of the dialog.

A1	A2	A3	SQ1
4	4		3
4	4		4
3			3
1	3		2
2	2		2
3	4		4
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2	3		2
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3	2		2
2	2		4
4	2		2
4	4		3
1	4		3
4	4		4
5	5		2
4	4		4
5	5		4

Target Variable: HPWSS

Numeric Expression: MEAN(A1, A2)

Function group: Random Numbers, Search, Significance, **Statistical**, Scoring, String, Time Duration Creation

Functions and Special Variables: Cvar, Max, **Mean**, Median, Min, Sd, Sum, Variance

MEAN(numexpr,numexpr[...]). Numeric. Returns the arithmetic mean of its arguments that have valid, nonmissing values. This function requires two or more arguments, which must be numeric. You can specify a minimum number of valid arguments for this function to be evaluated.

If... (optional case selection condition)

OK Paste Reset Cancel Help

Target Variable: HPWSs

Numeric Expression: MEAN(A1, A2)

Type & Label...

Function group: Statistical

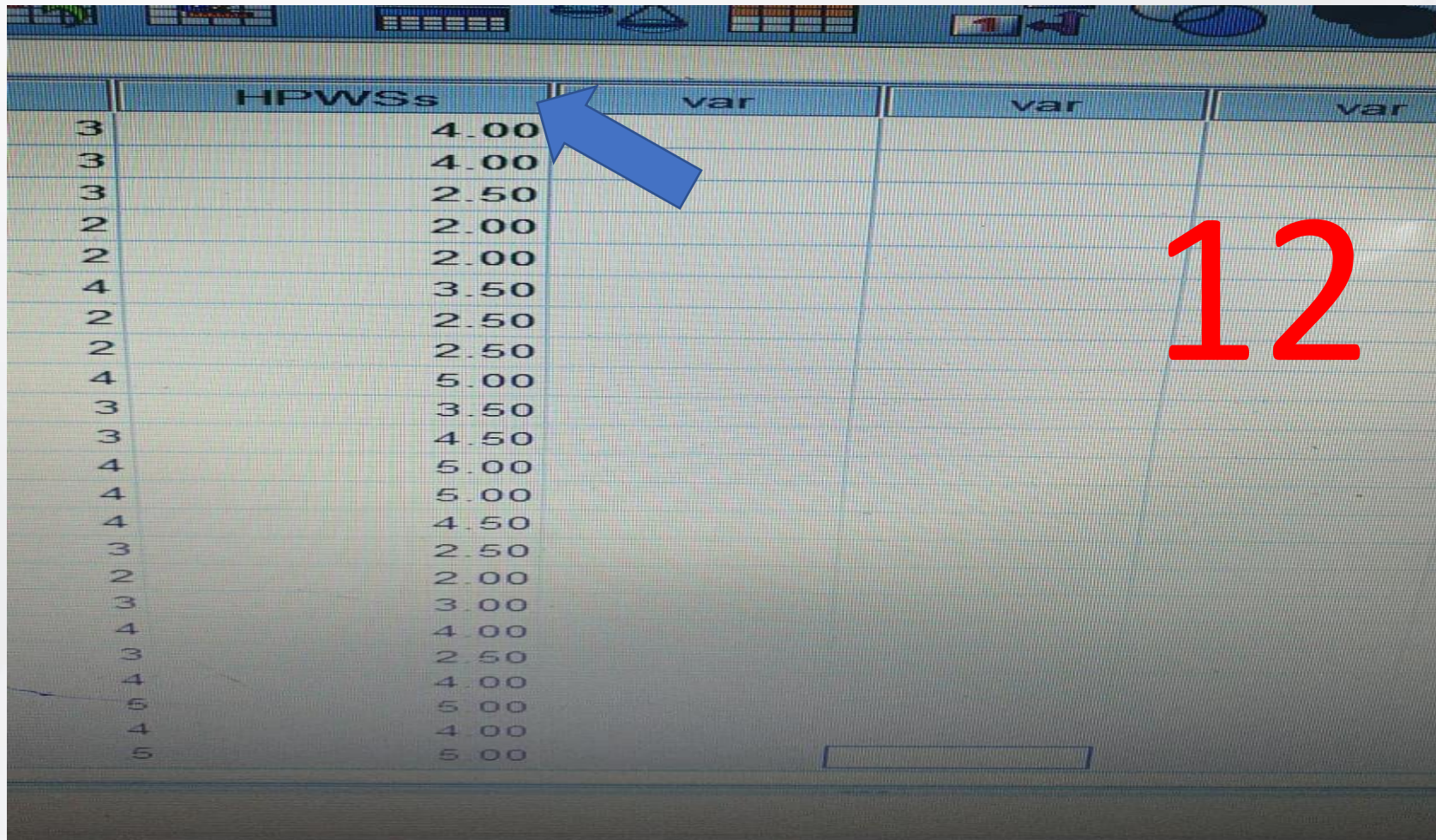
Functions and Special Variables: Mean

MEAN(numexpr,numexpr[...]). Numeric. Returns the arithmetic mean of its arguments that have valid, nonmissing values. This function requires two or more arguments, which must be numeric. You can specify a minimum number of valid arguments for this function to be evaluated.

If... (optional case selection condition)

OK Paste Reset Cancel Help

11



	HPWSs	var	var	var
3	4.00			
3	4.00			
3	2.50			
2	2.00			
2	2.00			
4	3.50			
2	2.50			
2	2.50			
4	5.00			
3	3.50			
3	4.50			
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3	2.50			
2	2.00			
3	3.00			
4	4.00			
3	2.50			
4	4.00			
5	5.00			
4	4.00			
5	5.00			

اختبار Construct Validity

الصدق للمقياس

(الصدق التقاربي Convergent validity)

التحليل العائلي Factor Analysis

5



□ What is factor analysis?

- Factor analysis is a very useful and popular method of multivariate research technique, mostly used in social and behavioral 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.

□ What is factor analysis? 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.

□ Some concepts used in factor analysis. Cont.

- **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 analyzed.
- **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.

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

التحليل العاملي الإستكشافي



CaregivingJourneyRev1_Added Scales (1).sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

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

Factor...

Correspondence Analysis...

Optimal Scaling...

Income AgeChild Dx SxSeventy DxDate Admissions

00 2.00 6.00 14.00 3.00 1.00 0.00

00 3.00 10.00 14.00 1.00 1.00 1.00

00 2.00 2.00 14.00 1.00 2.00 3.00

00 2.00 10.00 1.00 4.00 3.00

00 0.00 3.00 1.00 2.00

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00 3.00 9.00 4.00 2.00 2.00 1.00

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00 11.00 2.00 1.00 4.00

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00 0.00 5.00 6.00 2.00 2.00 1.00

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00 3.00 7.50 5.00 2.00 2.00 2.00

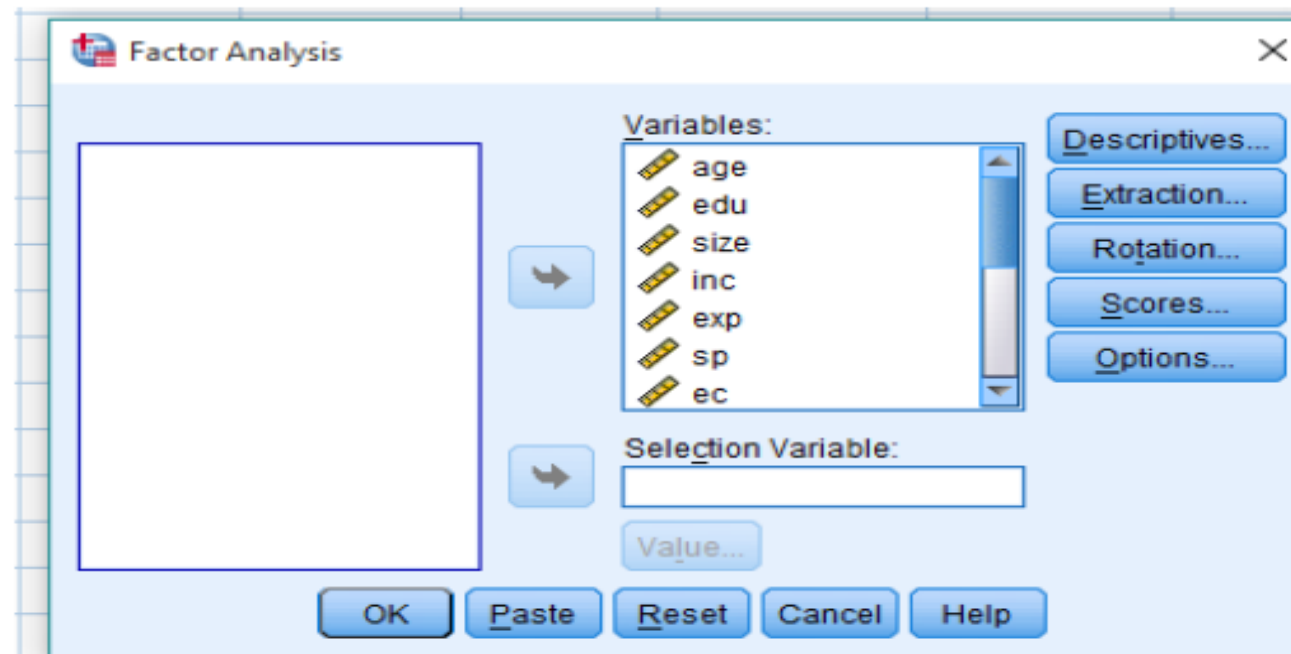
00 0.00 2.00 1.00 1.00

00 1.00 7.00 2.00 4.00

Visible: 103 of 103 Variables

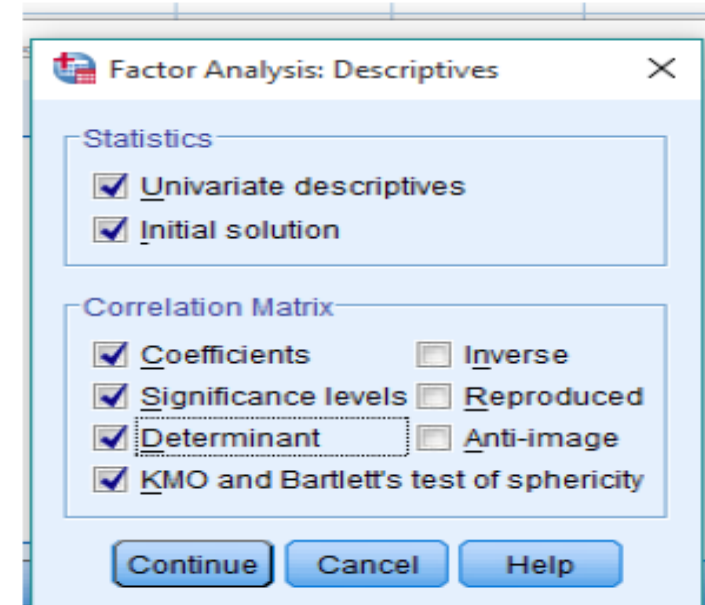
HOW TO CARRY OUT FACTOR ANALYSIS IN SPSS?

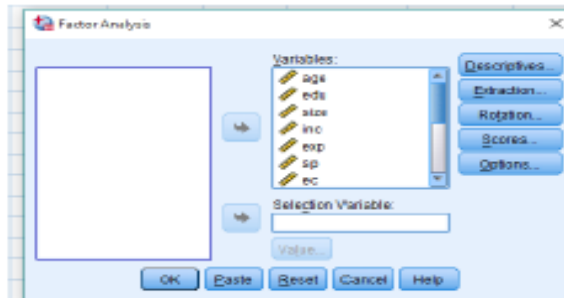
- Access the main dialog box by using the Analyze⇒Data Reduction⇒Factor menu path. Simply select the variables you want to include in the analysis and transfer them to the box labelled Variables by clicking on the button.





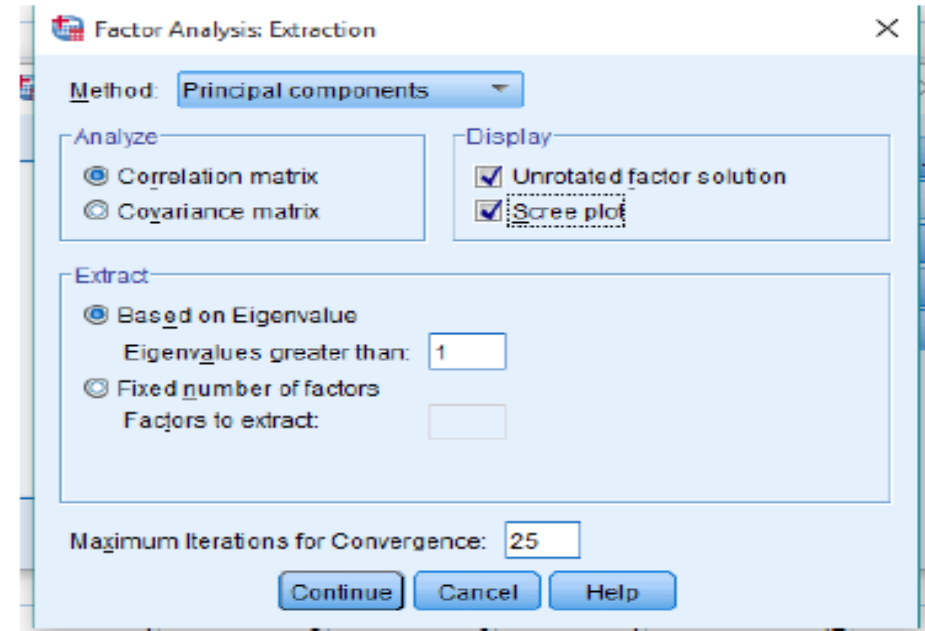
- The *Coefficients* option produces the R-matrix, and the *Significance levels* option will produce a matrix indicating the significance value of each correlation in the R-matrix. You can also ask for the *Determinant* of this matrix and this option is vital for testing for multicollinearity or singularity. *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.



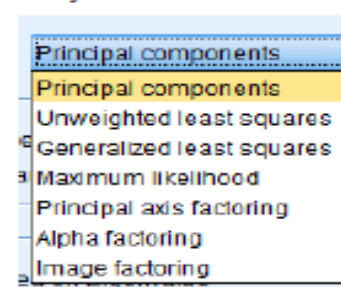


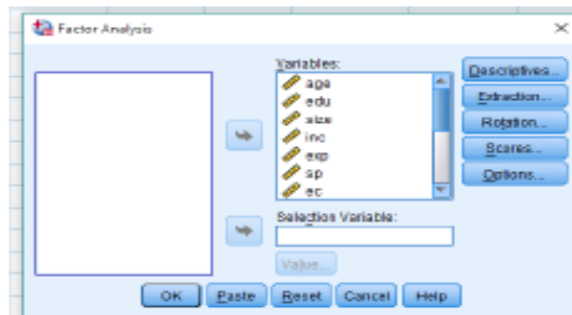
EXTRACTION

- 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.



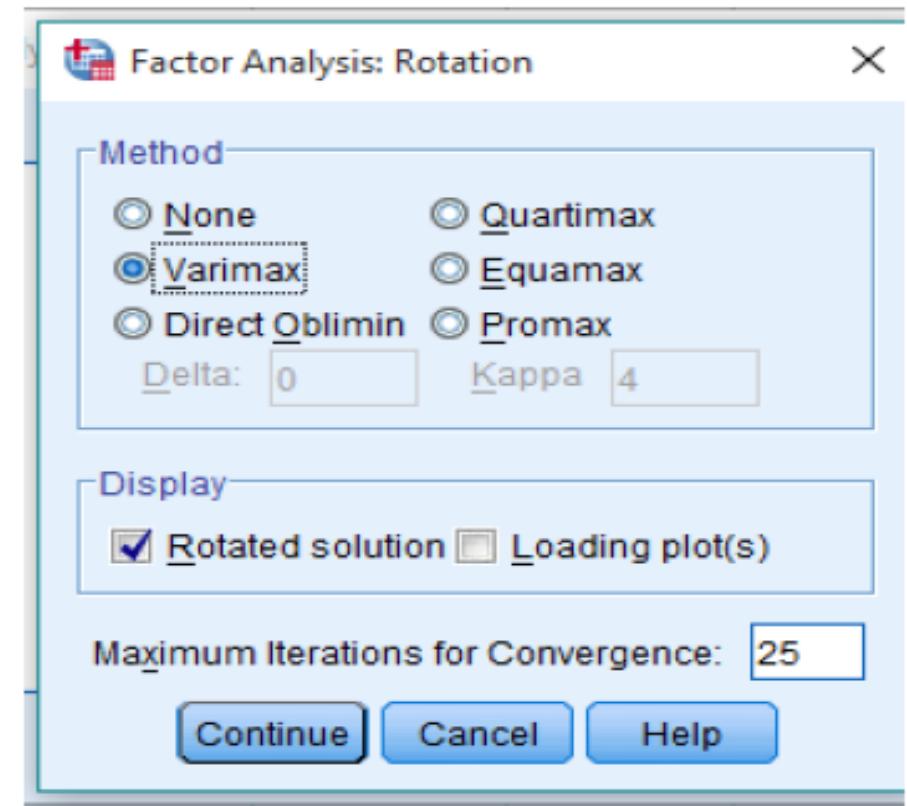
Analysis: Extraction

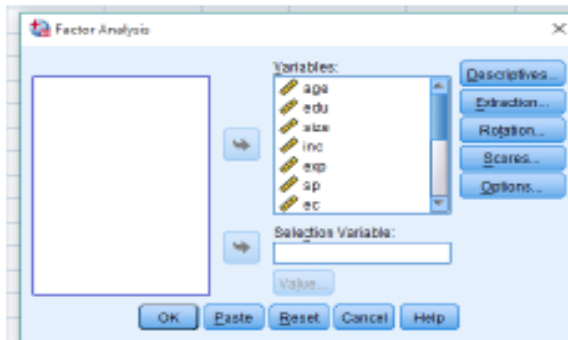




ROTATION

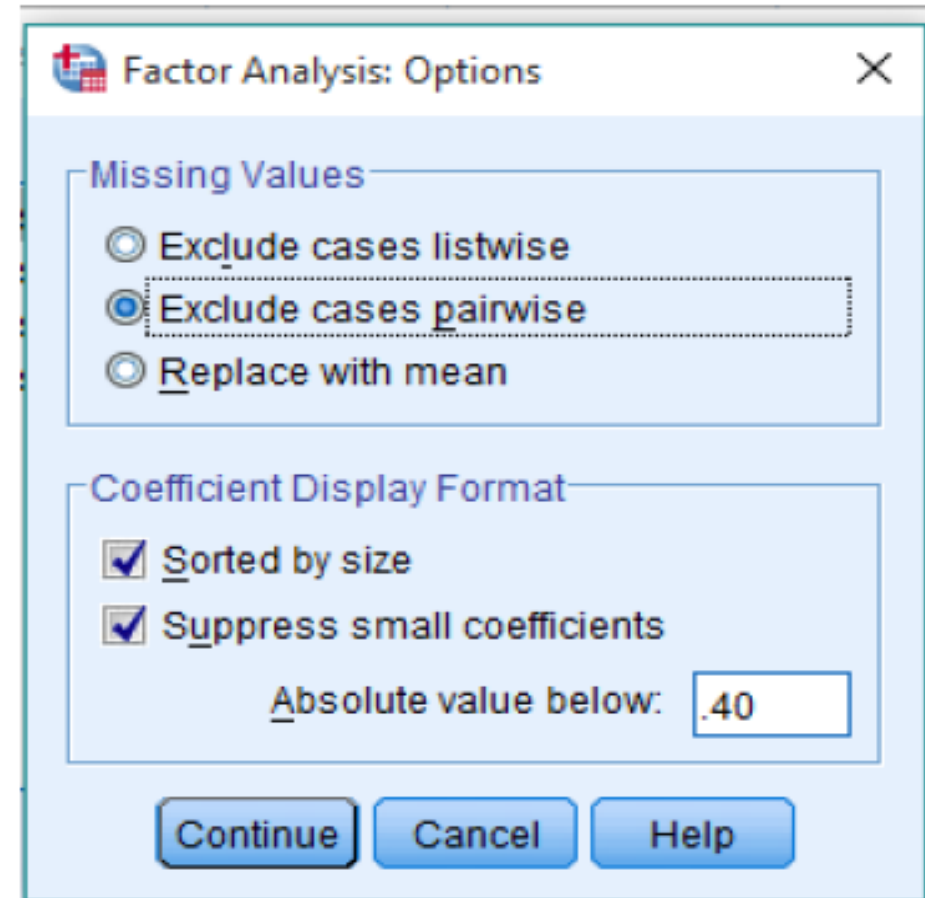
- The interpretability of factors can be improved through rotation. Rotation maximizes the loading of each variable on one of the extracted factors whilst minimizing the loading on all other factors.
- Varimax, quartimax and equamax are orthogonal rotations whereas direct oblimin and promax are oblique 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	lsb	rta	cosmp	mmp	envi
Correlation	age	edu	size	inc	exp	sp	ec	so	mo	em	lsb	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	.2
	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	-.068	-.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	-.068	.533	.618	.499	1.000	.551	.525	.457	.620	.5
	em	-.251	.188	.100	.159	-.154	.346	.339	.554	.551	1.000	.328	.418	.219	.380
	lsb	-.353	.221	.193	.241	-.301	.300	.414	.379	.543	.328	1.000	.316	.448	.420
	rta	-.201	.142	.103	.009	-.132	.363	.333	.278	.625	.418	.316	1.000	.290	.395
	cosmp	-.186	.158	.555	.427	-.072	.584	.539	.339	.457	.219	.448	.290	1.000	.565
	mmp	-.243	.273	.273	.129	-.029	.595	.606	.329	.620	.380	.420	.395	.565	1.000
	envi	-.359	.294	.238	.263	-.281	.443	.463	.368	.554	.263	.557	.324	.495	.682
Sig. (1-tailed)	age		.000	.000	.000	.000	.005	.000	.045	.003	.000	.014	.021	.004	.0
	edu			.153	.273	.142	.005	.014	.035	.008	.020	.008	.061	.043	.001
	size				.010	.000	.000	.059	.016	.018	.140	.017	.131	.000	.001
	inc					.000	.023	.114	.000	.186	.042	.004	.462	.000	.080
	exp						.048	.193	.002	.229	.047	.000	.075	.219	.376
	sp							.000	.005	.000	.000	.000	.000	.000	.0
	ec								.000	.000	.000	.000	.000	.000	.0
	so								.000	.000	.000	.001	.000	.000	.0
	mo								.000	.000	.000	.000	.000	.000	.0
	em								.000	.000	.000	.000	.000	.000	.0
	lsb								.000	.000	.000	.000	.000	.000	.0
	rta								.000	.000	.000	.000	.000	.000	.0

- 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

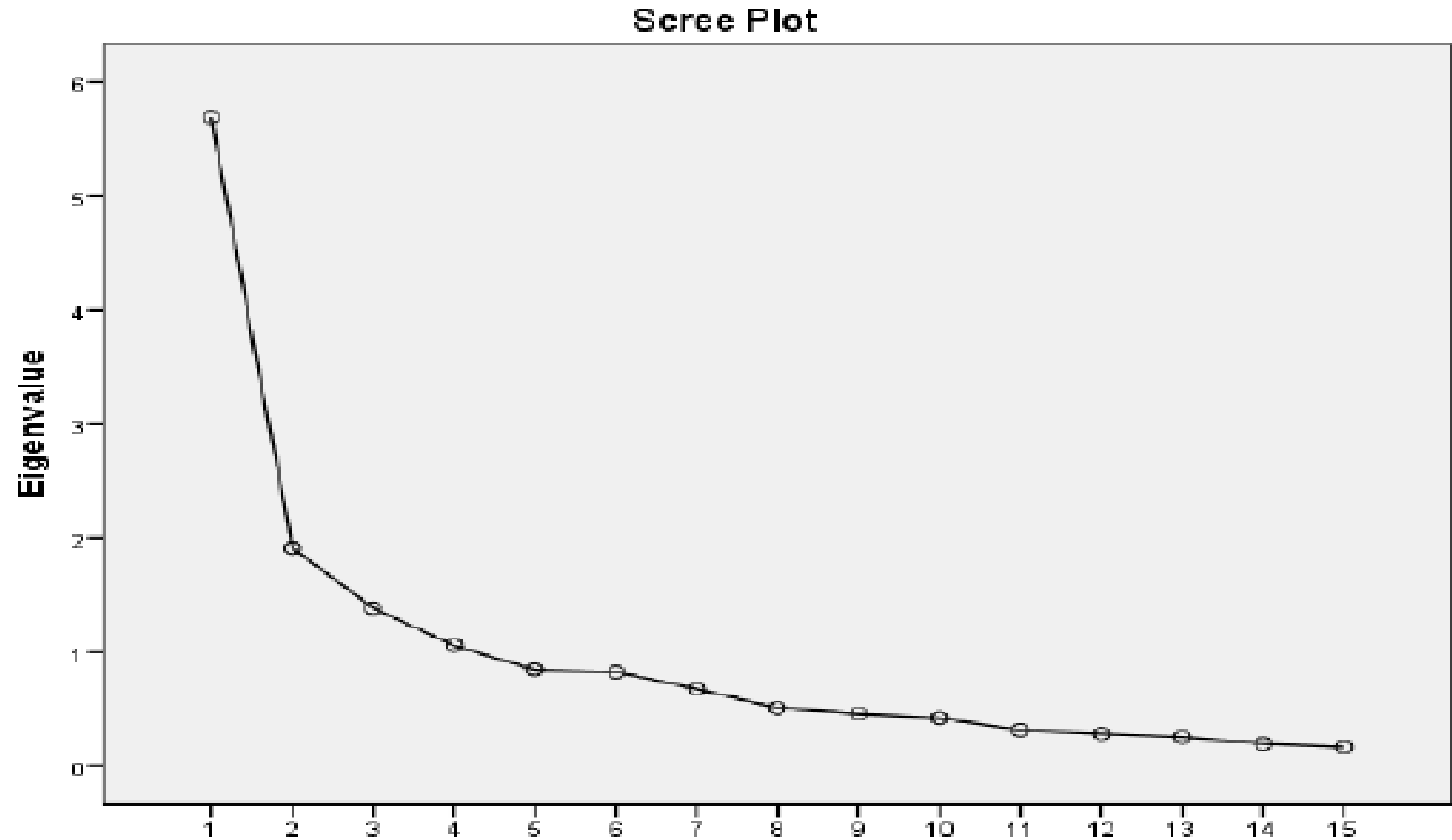
Component Matrix^a

	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.

Reliability (Cronbach`s alpha)

6



❖ Reliability

- 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

- 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.

❖ Cronbach's alpha

- 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	Qu5	Qu6	Qu7	Qu8
1	3		4	4	4	4
2	6		2	3	3	3
3	5		3	3	2	3
4	4		5	6	5	6
5	4		5	6	5	6
6	6		3	3	2	3
7	6		2	3	4	4
8	5		3	4	4	5
9	6		3	2	3	2
10	6		3	3	2	3
11	5		2	3	4	4
12	6		3	4	4	5
13	6		4	5	4	4
14	6		3	3	2	3
15	5		4	5	4	4
16	4		3	3	2	3
17	6	6	3	3	2	3
18	6	3	2	3	4	4

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...

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

☐ Tukey's test of additivity

☐ Intraclass correlation coefficient

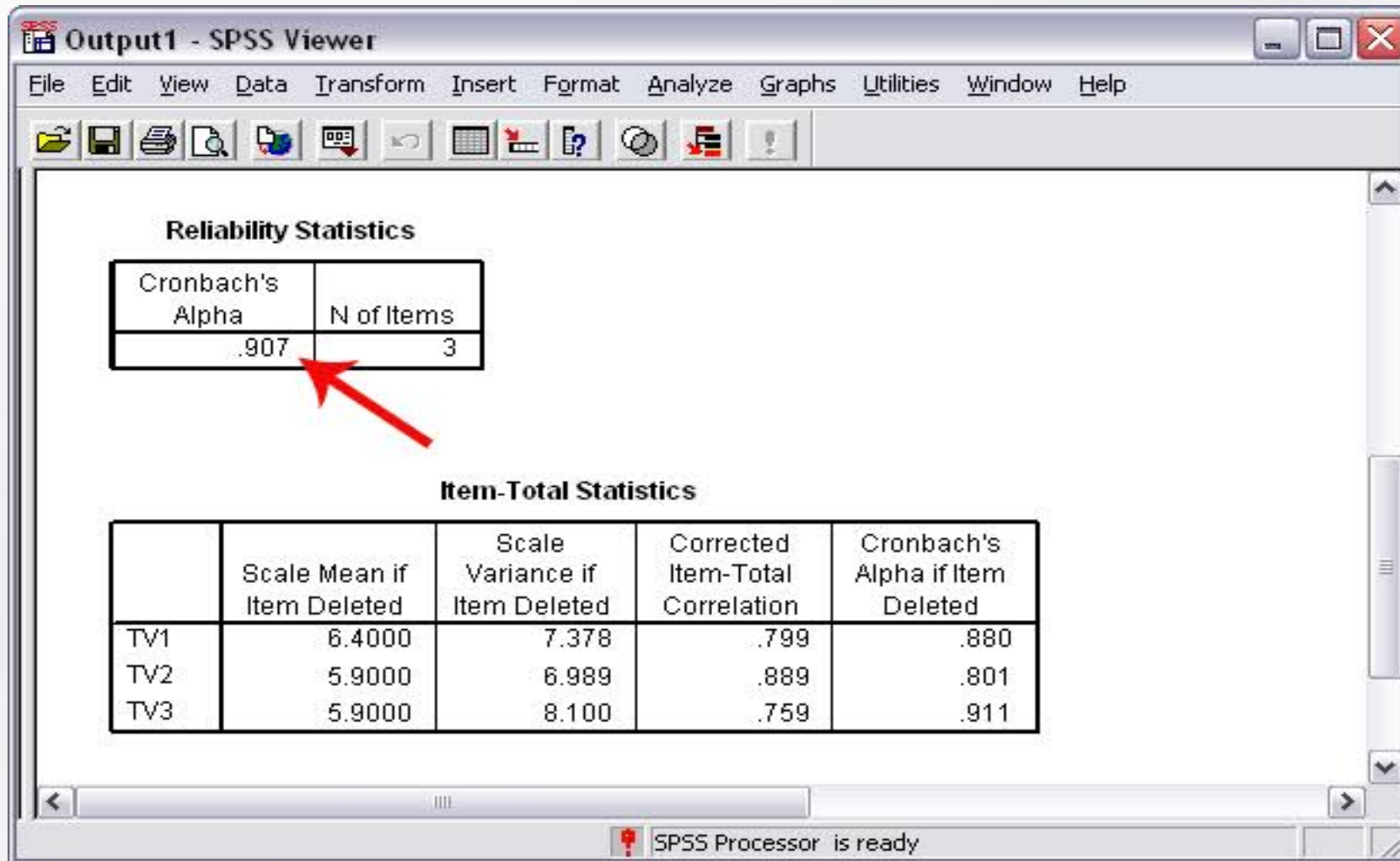
Model: Two-Way Mixed

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

❖ Cronbach's alpha

- 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.

❖ Cronbach's alpha

- 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



Thank You