

**Psychology/Neuroscience 201:
Statistics and Research Methods in Psychology**

**SPSS
Instructions**

Last updated: June 2022

Table of Contents

<u>Introduction to SPSS and entering data</u>	3
<u>Exploring your data (frequency distributions, graphs, descriptive statistics)</u>	11
<u>Annotating/printing output and ending your Citrix session</u> ...	15
<u>Basic data manipulations: Recoding variables and computing new variables</u>	17
<u>One-sample <i>t</i> test</u>	20
<u>Sample SPSS annotation</u>	22
<u>Independent-samples <i>t</i> test</u>	23
<u>One-way ANOVA</u>	25
<u>Paired-samples <i>t</i> test</u>	29
<u>Repeated-measures ANOVA</u>	31
<u>Correlation and regression</u>	36
<u>Chi square</u>	40
<u>2 X 2 Factorial ANOVA</u>	44
<u>2 X 3 Factorial ANOVA</u>	49

SPSS: An Introduction

Welcome to your first experience with SPSS (Statistics Package for the Social Sciences). I hope you find this packet useful as you begin to navigate your way through this statistics software package. You will refer to these instructions throughout the semester, but I highly recommend hanging on to the packet for use in future classes and (if you are a Psychology or Neuroscience concentrator) for your Senior Project.

Overview

This section of the packet will walk you through the following steps:

1. Logging on to the Citrix server to access SPSS.
2. Downloading a data file to your computer and saving it to your computer or uploading it to the SSS (student storage server).
3. Opening a data file in SPSS and saving it to your computer or to your SSS space.
4. Creating a data file in SPSS.

PART 1: Logging on to the Citrix server to access SPSS

SPSS for Windows is available via the Citrix server on any computer on campus, Macintosh or Windows. You are also able to use SPSS on your own computer via the Citrix Workspace App. The first time you use Citrix (and at the beginning of each academic year), you'll need to register (it's free). See <https://www.hamilton.edu/offices/lits/rc/registering-and-logging-into-citrix> if you need help.

1. I recommend using Firefox as your web browser; it works better with Citrix than Google Chrome does. Be sure that pop-ups are enabled. In the browser window, enter the following address: citrix.hamilton.edu. I recommend creating a bookmark called "Citrix" for easier navigation. Once you've registered (see above), you will be prompted to download and install the Citrix Workspace App. See <https://www.hamilton.edu/offices/lits/rc/installing-the-citrix-client-on-your-computer> for instructions. If you have any difficulty, please let me know ASAP.
2. Once the Citrix Workspace App is installed, the Citrix Metaframe window will open when you go to the above address, and you will be prompted for your username and password, which should be the same as your e-mail username and password (see Figure 1). After you type these, ensure the appropriate Domain is selected ("students.hamilton.edu") and click on "Log On."

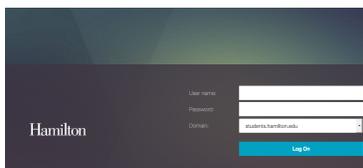


Figure 1

You should now see icons for the available software packages you can access through the Citrix server (see Figure 2). You will be using **IBM SPSS Statistics 28**. Find the correct icon and click on it.



Figure 2

- You may be prompted to open the Citrix Workspace Launcher. After doing so you will see a task progress window indicating that the application is starting. After a short lag (this could take up to 30 seconds or more), SPSS should be up and running and you can create a new data file or open an existing one. See instructions below in Part 3 for opening data files.

PART 2: Downloading a data file from Blackboard to the desktop and uploading it to your SSS space

For your homeworks, you will use an existing SPSS data set that can be found along with the homework assignments in the “Homework assignments and data sets” tab on Blackboard. SPSS data files are named with a **.sav** extension (e.g., ICPSR Monitoring the Future data 2016.sav, GSS2021.sav). **Note that you cannot simply double-click on an SPSS file to open it, because you are accessing SPSS via Citrix. You must be within the SPSS program in order to open files.** Therefore, when you click on the file, you will need to save it somewhere. You have a couple of options here:

- Save the file to a folder for this course that you create on your laptop. Use this option if you plan to exclusively use your own laptop for data analysis in this course.
- Save the file to your SSS. This option is the most flexible, because you can then access it no matter what computer you happen to be using. The easiest way to accomplish this is to temporarily store the file on your local computer’s desktop and then upload it to your SSS via the “Files” tab on your My Hamilton page. A folder called “Citrix” is in your SSS (it gets created the first time you open SPSS using Citrix) and there is a subfolder named “Documents” within that folder. Here is where you want to store all of your data files (see Figures 3 and 4 below). Once you’ve saved the file to your desktop, go to My Hamilton, choose the “Files” tab, click on “Citrix,” then “Documents,” and then choose “Upload File” (directly above “Name”) to place the data file in the documents folder within the Citrix folder on your SSS.

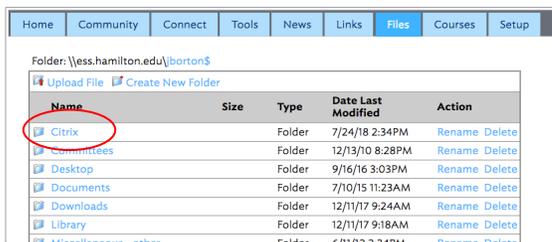


Figure 3

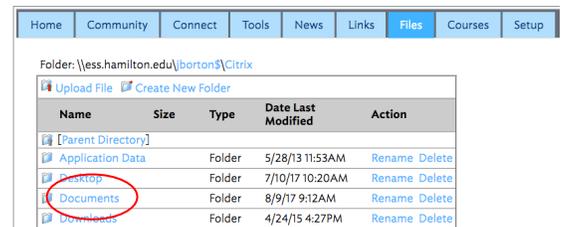


Figure 4

PART 3: Opening SPSS and saving your data file to your SSS space

When SPSS is first opened, it will prompt you as follows:

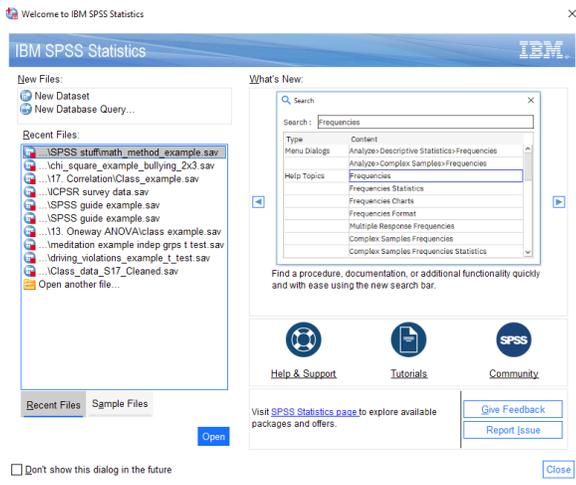


Figure 5

If you are using an existing data file, select **“Open another file...”** at the bottom of the list in the **“Recent Files:”** box and then click **“Open”** at the bottom of the window (or just double-click **“Open another file...”**). A box will pop up asking you how you want to access files from this application. Choose **“Read and Write Access”** and you can click the box so you aren’t asked the question again. A window will open to allow you to navigate to the pre-existing data file.

How to find your file:

1. If you saved it to a folder on your laptop (see Figure 6): Click the down arrow on the menu bar and navigate to Local Disk H. Note that Local Disk C is your hard drive and H is you, signed into your hard drive. It’s faster to just click H rather than having to click C, then find your username, then get to H. Once you’ve clicked on H, you can navigate to the folder where you stored your file (or to your desktop, if you just dumped it there). Click on the file and then click **“open”**. Your data file will open in SPSS.
2. If you saved it to your SSS (see Figure 7): Click the down arrow on the menu bar and navigate to your username followed by (\sss.hamilton.edu/users). (Note that for faculty it is ESS for “Employee Storage Space” rather than SSS.) If you click on that, you’ll then see the Citrix folder and the documents folder into which you saved your file earlier. Click on the file and then click **“open”**. Your data file will open in SPSS.

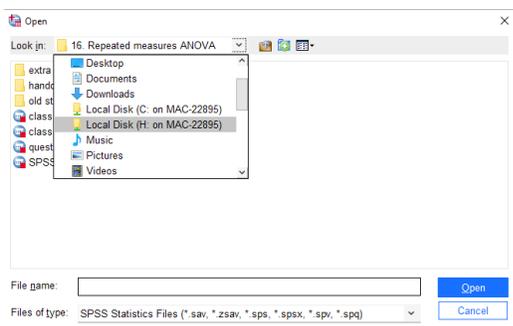


Figure 6

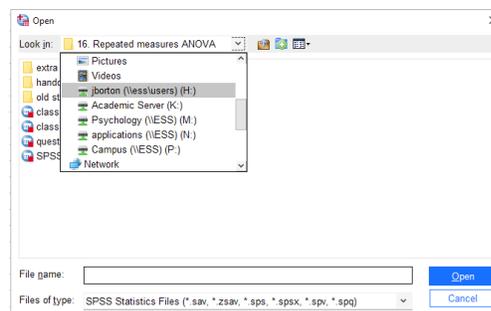


Figure 7

Saving files (SAVE, SAVE, SAVE!)

Be sure to save frequently so you don't lose your work due to unforeseen circumstances. If you make changes to the file, you can save an updated version of it by clicking on **File** in the SPSS menu bar, then **Save As**. A window similar to that shown in Figure 6 or 7 will appear. **Name your file with a meaningful, informative label, then click 'Save.'** A copy of your file will be saved in the folder you designate (either on your hard drive or on your SSS).

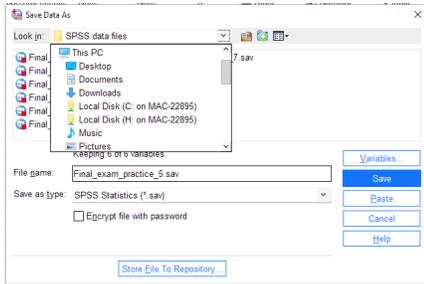


Figure 8

Remember: If you are saving the file somewhere on your computer, you will need to click on the down arrow (see Figure 8), scroll to and click on Local Disk H (if on a Mac), and then navigate to the folder you created for the class (or to your desktop, but I recommend keeping your files organized in a folder).

File types in SPSS

Note that different SPSS file types have different extensions:

.sav = data file

.spv = output file

.sps = syntax file (written code for SPSS to execute; we won't do much with syntax in this course, but you will become more familiar with it in subsequent courses. Note that any command you ask SPSS to run via the menus can be pasted into a syntax file and saved for later use. This is *very* handy when you're working on an actual research project.)

NOTE:

- If you click on the folder icon in a **data** window, SPSS will automatically try to open **data**.
- If you click on the folder icon in an **output** window, SPSS will automatically try to open **output**.
- If you click on the folder icon in a **syntax** window, SPSS will automatically try to open **syntax**.
- If you are in a data window and want to open either an output or syntax file, you will need to go to **File, Open**, and then choose data, output, or syntax.

PART 4: Creating a data file in SPSS

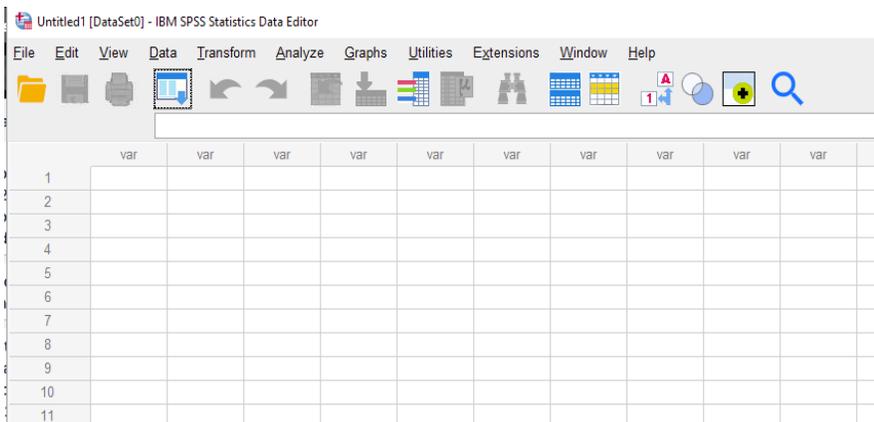


Figure 9

When you open SPSS, one of your choices in the “New Files:” box is “**New Dataset**” (see Figure 5, above). If you click that option, you will be presented with an untitled data file (see Figure 9). Note that this file looks like a standard spreadsheet.

Before you can analyze your data, you must first input them into this file. Notice that the rows are already numbered and the columns are labeled “var.” At this stage, the font in the columns is grey because they have not been activated with data or variable names. [Note that each column represents a variable and each row represents a participant’s data for each variable. So each row represents the scores from one particular participant.](#) To enter data, you will first need to create, name, and define the variables.

Data view vs. Variable view; Defining variables

You can examine your variables/data in two different screens or “views”: **data view** and **variable view**. In data view, you see the basic spreadsheet depicted in Figure 9. In variable view, you can easily name and define your variables (see Figure 10).

Helpful tips for switching back and forth between data and variable view:

- You can toggle back and forth between data view and variable view by clicking on the appropriate tab at the bottom left of the screen.
- Double-clicking on a “var” header in data view will automatically toggle you to variable view
- Double-clicking on a number in the left-hand column in variable view will return you to data view.

I recommend that your first variable always be participant ID (an arbitrary number you assign to each participant for record-keeping purposes). Below is an illustration of the variable view with the first variable added. Notice the variable label (Participant ID Number) in the “label” column. [It is important to get in the habit of labeling your variables. Labels help remind you what each variable is, and they also print out in the output so you know what you’re looking at.](#) When working with existing data sets, variable labels are very important in helping you understand what each variable represents.

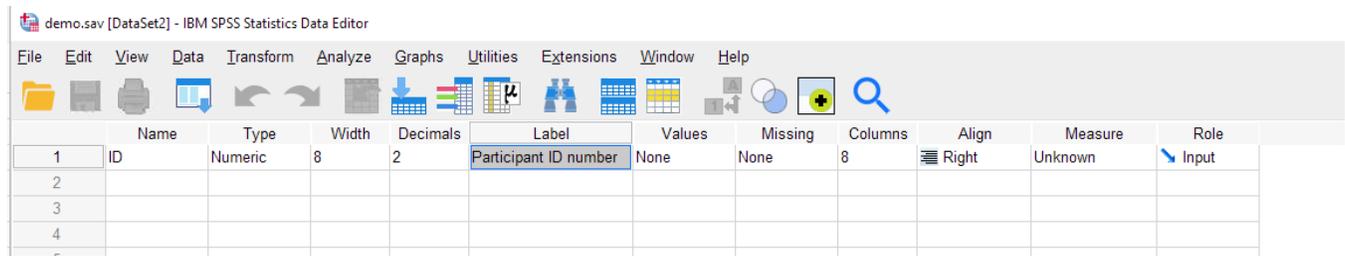


Figure 10

Let’s say your second variable is the respondent’s academic concentration. As with participant ID, you need to provide a **variable name** (a concise name, e.g., “Concentration”) and a **variable label** (a description of the variable to remind yourself of what the variable is; e.g., “participant’s academic concentration”). Keep in mind that SPSS won’t let you begin a variable name with a number or special character, such as a space.

For Concentration, you’ll need to provide **value labels** to indicate what different levels of your variable mean. For example, 1 = Economics, 2 = Psychology, 3 = Mathematics, etc. To add value labels, simply click in the appropriate cell in the “values” column (i.e., the cell that appears in the “concentration” row). A lightly shaded blue box appears within the cell, and if you click on it, a dialog box appears in the middle of the screen (see Figure 11). Simply type the value in one box, the value label in the box beneath it, and click “Add.” Once you’ve added all your values and value labels, click “OK.”

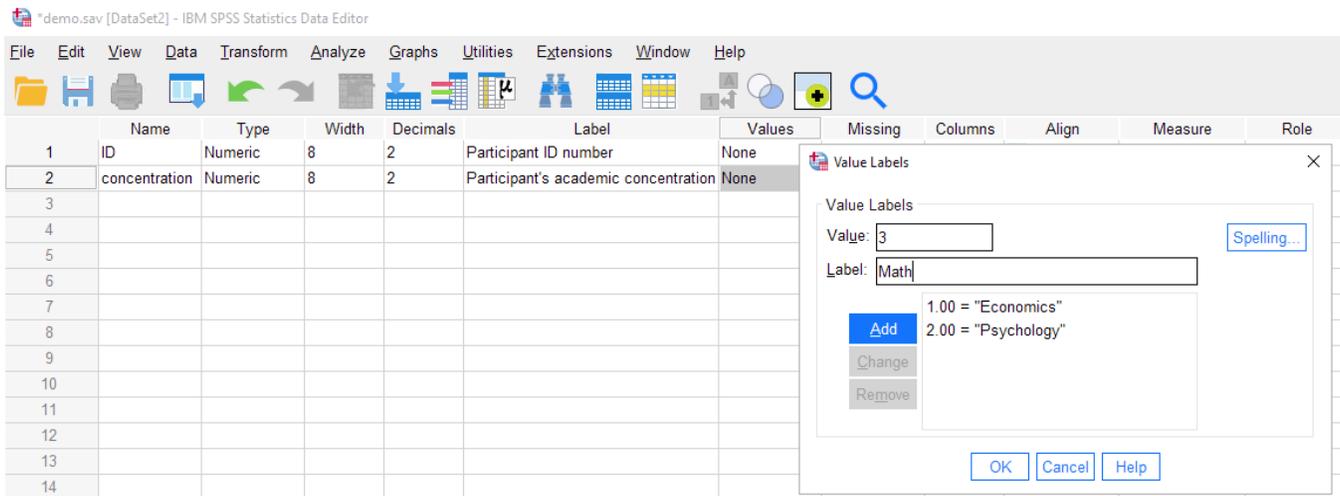


Figure 11

For some variables (e.g., age), you won't need value labels; you'll just enter in whatever number the participant reports.

Determining the number of decimal places shown in the data window

In addition to giving your variable a label and defining its values, you may find it convenient to choose the number of decimal places you want displayed for each variable in the data window. For instance, if your variable is "concentration," and the values are 1, 2, 3, 4, etc., it might annoy you to have SPSS display "1.00," "2.00," "3.00," etc., all the way down the column (the default is 2 decimal places). To change the number of decimal places displayed, simply click on the appropriate cell (e.g., the one in the "concentration" row and the "decimals" column). Up and down arrows appear in the right-hand part of the cell, and you can simply click on the down arrow until you have 0 decimal places (or you can type "0" directly).

Repeat this process of defining and labeling for all of your variables. **NOTE:** You're not entering any of the participants' data yet; you're only getting the data file set up by creating and labeling the variables.

Setting missing values

In SPSS, if you leave a cell blank, you will simply get a period (".") in that cell, and it will not be included in any of the data analyses. In the large data set you'll use for some homework assignments (e.g., GSS data), a particular number is often used to represent missing data (e.g., 999, as long as 999 is not a valid value for that variable). In variable

	Name	Type	Width	Decimals	Label	Values	Missing
1	ID	Numeric	4	0	Respondent ID number	None	None
2	GENDER	Numeric	8	0	Respondent gender	{0, IAP}...	0, 8, 9
3	SEXORNT	Numeric	1	0	Sexual orientation	{0, IAP}...	0, 8, 9
4	AGE	Numeric	2	0	Age of respondent	{89, 89 OR OLDER}...	0, 98, 99
5	RACE	Numeric	3	0	Race of respondent	{0, IAP}...	0, 98, 99
6	MARITAL	Numeric	1	0	Marital status	{1, MARRIED}...	0, 9
7	DEGREE	Numeric	1	0	R's highest degree	{0, LT HIGH SCHOOL}...	7 - 9, -1
8	EDUC	Numeric	2	0	Highest year of school completed	{97, IAP}...	97 - 99, -1
9	CLASS	Numeric	1	0	Subjective class identification	{0, IAP}...	0, 8, 9
10	INCOME	Numeric	2	0	Total family income	{0, IAP}...	13 - 99, 0
11	PARSOL	Numeric	1	0	R's standard of living compared to parents	{0, IAP}...	0, 8, 9
12	WEIGHT	Numeric	8	0	R weighs how much	{0, IAP}...	0, 998, 999

Figure 12

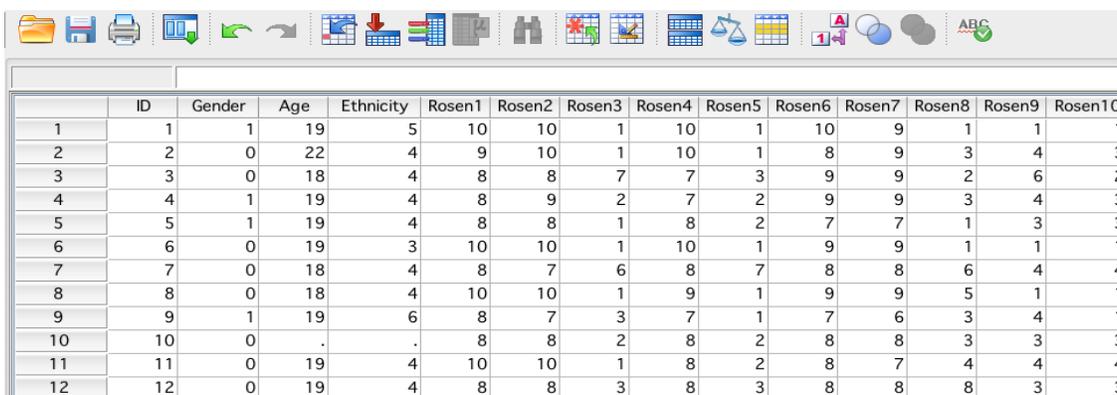
view, there is a column titled "Missing" that alerts you to all the missing values for each variable (see Figure 12). These values must be defined in the Missing column in order for SPSS not to use them when calculating statistics.

Entering data

Once you've defined all the variables you need, you're ready to enter the actual data. Generally, it's easiest to enter all the data from a single participant before moving on to the next participant. That is, work row by row. I find it easiest to use the numerical keypad on the right side of an external keyboard (laptops don't have these, which is why I hate entering data from a laptop!).

These days, with online surveys, it is very rare to have to enter data by hand, but you will need to do so for some of your homework problems. For those, given that you will have only a couple of variables, it will probably be easier for you to enter all of the data for one column (variable) and then enter all the data for the next column (variable).

Just for illustrative purposes, in Figure 13 you see the first portion of a sample questionnaire data file, showing 12 participants and their scores on the first several variables of a questionnaire. Note that participant 10 has missing data for age and ethnicity.



	ID	Gender	Age	Ethnicity	Rosen1	Rosen2	Rosen3	Rosen4	Rosen5	Rosen6	Rosen7	Rosen8	Rosen9	Rosen10
1	1	1	19	5	10	10	1	10	1	10	9	1	1	1
2	2	0	22	4	9	10	1	10	1	8	9	3	4	3
3	3	0	18	4	8	8	7	7	3	9	9	2	6	2
4	4	1	19	4	8	9	2	7	2	9	9	3	4	3
5	5	1	19	4	8	8	1	8	2	7	7	1	3	3
6	6	0	19	3	10	10	1	10	1	9	9	1	1	1
7	7	0	18	4	8	7	6	8	7	8	8	6	4	4
8	8	0	18	4	10	10	1	9	1	9	9	5	1	1
9	9	1	19	6	8	7	3	7	1	7	6	3	4	1
10	10	0	.	.	8	8	2	8	2	8	8	3	3	3
11	11	0	19	4	10	10	1	8	2	8	7	4	4	4
12	12	0	19	4	8	8	3	8	3	8	8	8	3	3

Figure 13

Checking for errors

This is one of the most important steps of entering and analyzing data. If you made any errors inputting the numbers, it could wreak havoc with your analyses and your interpretation of the data. If the errors are big or numerous, it could mean the difference between supporting and rejecting a hypothesis! Be VERY CAREFUL whenever you enter data, and always double-check everything.

If you've conducted an online survey in Qualtrics (which you might do in a future lab class or for your thesis) and have exported the data from it into SPSS, you still need to double-check it for errors. For instance, I have sometimes discovered that a scale that was supposed to range from 1 to 6 in Qualtrics actually exported as bizarre numbers instead: 23, 24, 25, 26, 27, 28 instead of 1, 2, 3, 4, 5, 6. This can happen if you make a lot of edits to a survey question by deleting options and then adding them. You can avoid this by recoding the values in Qualtrics before exporting the data, but if you don't notice until later, you will need to recode them in SPSS. The important point is that you need to NOTICE the error in order to correct it, so examining your data is vital.

Toggling back and forth between the data window and the output window

Whenever you ask SPSS to calculate something for you, you automatically get bumped into the output window (“SPSS viewer”) where the output from your commands (e.g., frequency tables, descriptive statistics, graphs) is displayed. To get back to the data window, simply go up to the “Window” menu, and scroll down until you see the name of the data file (see Figure 14, below). If you want to edit a graph, double-click on it in the output window and you will be bumped into the “Chart Editor.” Again, you can return to any other window by going up to the “Window” menu.

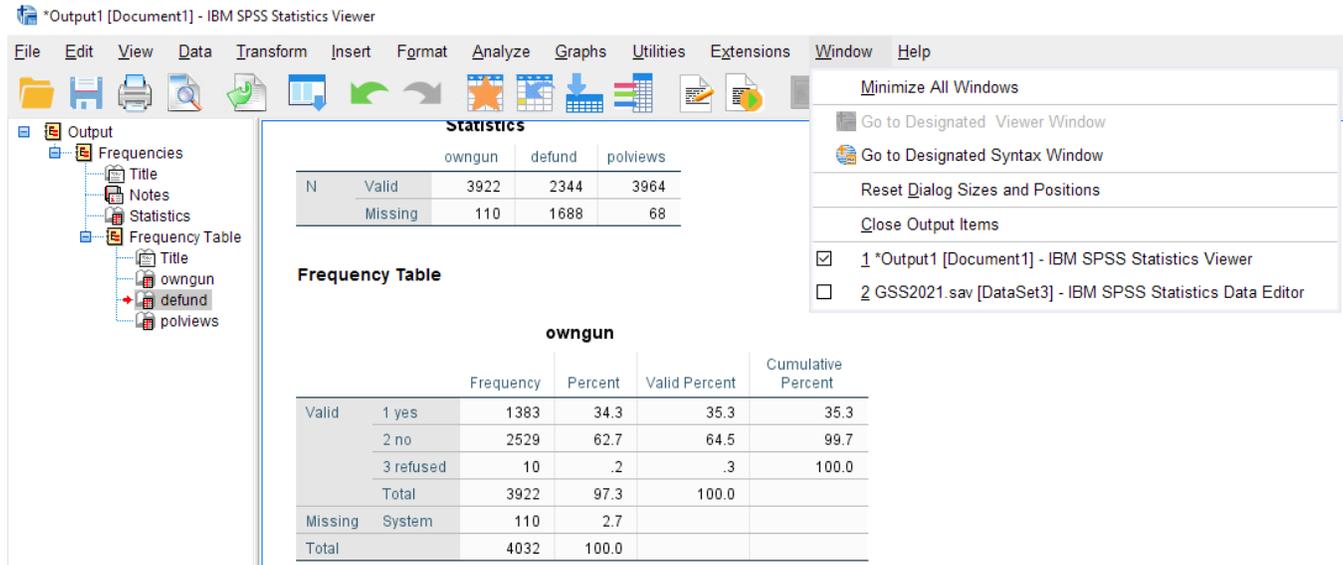


Figure 14

Helpful tip: Keyboard shortcuts for toggling between open windows

- Toggling between windows **within the same program**: On a Macintosh computer, selecting **Command + ~** (the tilde symbol, top left of your keyboard) will toggle back and forth between open windows within the same program. (Sorry, Windows computers don't have this functionality!)
- Toggling **between different programs**: This is useful for, say, going back and forth between SPSS and Microsoft Word if you're writing up your homework. Hold down **Command+tab** on a Mac or **Alt+tab** on a PC.

Exploring Your Data: Frequency Distributions, Graphs, Descriptive Statistics

Now you're ready to start taking a look at your data. Below are instructions for creating frequency distributions, grouped frequency distributions, histograms, and bar graphs, and for computing basic descriptive statistics (e.g., mode, median, mean, range, standard deviation).

Helpful tip: Changing display preferences

Display options for dialog boxes:

The SPSS default is to display the variable *labels* rather than the shorter variable *names* in the dialog boxes, which can make it difficult to find variables to select for analyses. To change the default, click on the **Edit** menu, then scroll to the bottom and select **Options**. Under the "General" tab, select "Display names" under Variable Lists at the top left. Note in Figure 1 below how the variable names, rather than long variable labels, appear in the column. **OR: When the list of variables appears when you're doing a frequencies or other command, you can just click on the variable while hitting the option key to switch from displaying variable labels to displaying variable names.**

Display options for the output window:

Under the "Output tab" in Options, you can specify that, in your output, you would like variables shown as names & labels, and variable values shown as values & labels. (Do so in both the "Outline Labeling" section and the "Pivot Table Labeling" section on the left of the dialog box.)

The "Frequencies" Command

If you want SPSS to print you a frequency distribution, go under the "Analyze" menu, scroll down to "Descriptive Statistics," and then choose "Frequencies." You'll get a window like the one in Figure 1.

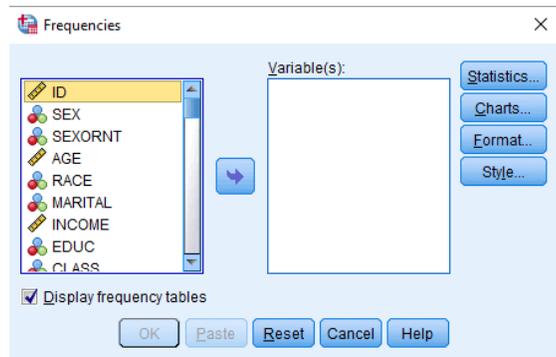


Figure 1

On the left side is a list of all the variables in your data file. If you have set your preferences as noted above, the variable names (not labels) will be listed. Simply click on the variable you want to examine, then either click the arrow to pop it into the "Variable(s)" box or just drag it there.

Helpful tip: Selecting multiple variables at a time

- Hold down the **Control** key while clicking on the variable names with the mouse to select more than one variable at a time.
- If the variables you need are listed in order in the data file, you may click on the first variable, hold down the **Shift** key and click on the last variable to select all of them.

Once you've selected the variables you'd like to examine, you need to decide what information you'd like. The default is just the frequency tables (notice the check mark in the box labeled "Display frequency tables"). If you don't want frequency tables, you can click on the box to remove the checkmark. If you click on the "Statistics" button, you can choose which measures of central tendency and variability you want to use. **REMEMBER:** You need to figure out what level of measurement a particular variable represents before willy-nilly choosing statistics. For example, calculating a mean gender doesn't make any sense, because gender is measured on a nominal scale. **SPSS WILL DO WHATEVER YOU TELL IT TO DO, EVEN IF YOU TELL IT TO DO SOMETHING WRONG!** So you have to make sure to choose your statistics wisely.

Grouped Frequency Tables

When you have a very large data set (and variables with many values), you can manually create grouped frequency tables. As an example, let's say that I want to create a grouped frequency table for the AGE variable in a very large dataset. First, I need to create a "binned" (grouped) variable based on the original variable, and then I need to use the frequency command on that new binned variable to produce the grouped frequency table.

To create the binned variable, go to the Transform menu and select "Visual Binning" (see Figure 2):

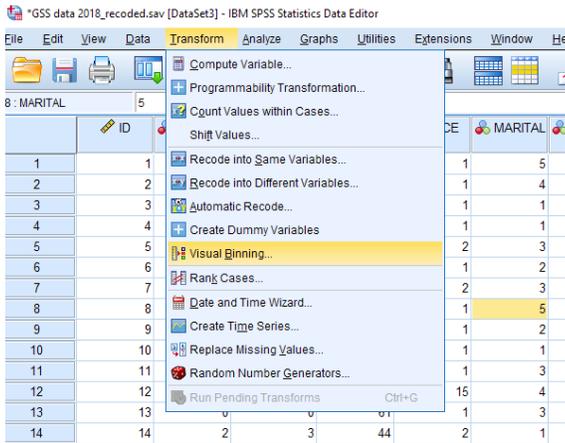


Figure 2

Note that only the subset of variables in the file appropriate for binning are displayed (see Figure 3). Select the variable you want to bin and click on the arrow to put it into the right-hand box. Then click "Continue."

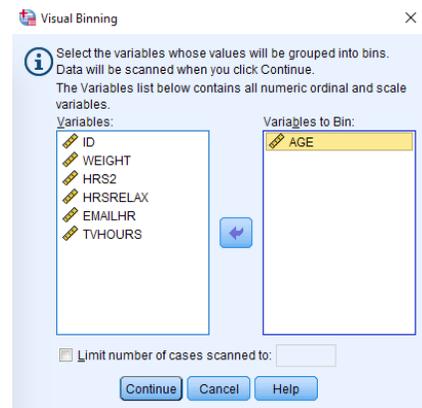


Figure 3

You'll get the dialog box shown below. Next, name the new binned variable (e.g., AGE_binned).

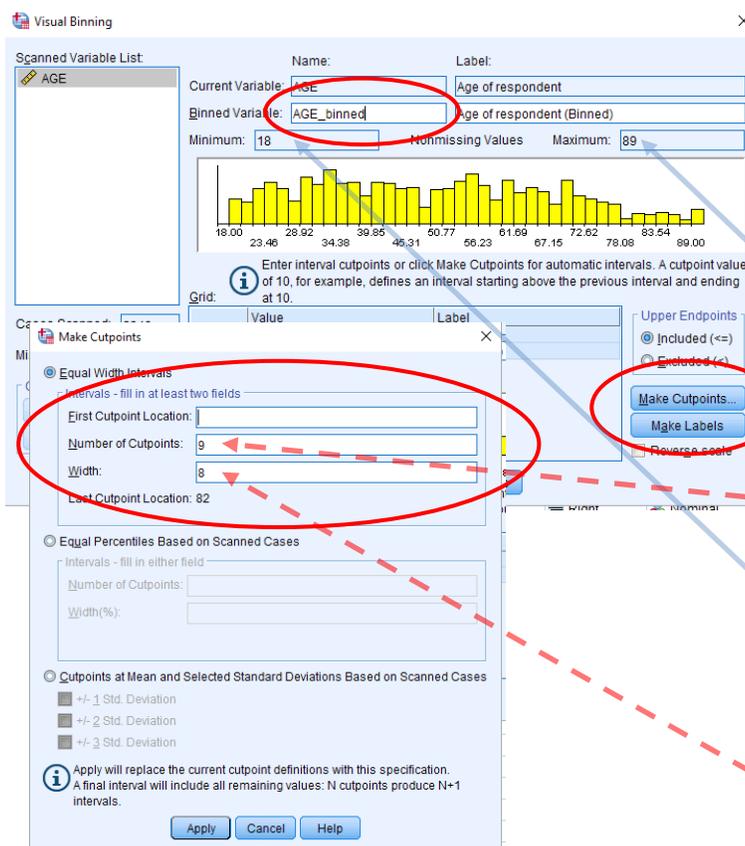


Figure 4

Next, choose "Make Cutpoints" (see Figure 4) to decide on the number of intervals and the width of each interval. Equal width intervals is the default selection. You must fill in 2 of the 3 fields (e.g., number of cutpoints and width of interval). Generally speaking, 10-15 intervals works well.

The number of cutpoints equals the number of intervals minus 1. (Think about it: if you wanted to cut a banana into 3 pieces, you'd have to make 2 cuts.) So if we wanted 10 intervals, we'd have 9 cutpoints.

For the width of each interval, (a) find the difference between the maximum and minimum values for the variable (shown in the dialog box), (b) divide this difference by the number of intervals (in this example, $[89 - 18]/10 = 7.1$), and (c) round up to the nearest whole number (8.0). Enter that number as interval width.

Click in the First Cutpoint Location box, which will then fill in automatically (see Figure 5). In this example, “18” automatically appears in that box. Click “Apply” to return to the main Visual Binning dialog box.

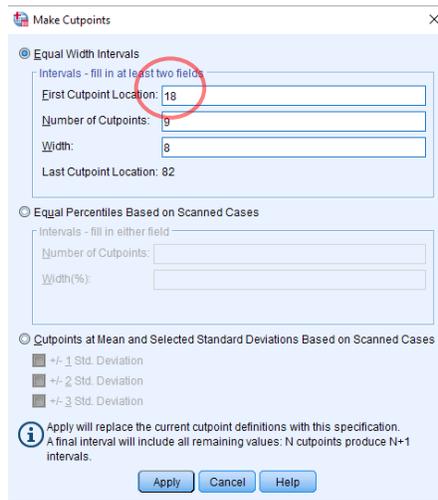


Figure 5

Click “Make Labels” to label each interval with the range of data it contains (see Figure 6). Note that for this example, the age ranges are a little strange. It’s more common to have age ranges of 10 years per interval. If you wanted to bin the data that way, you could have chosen to make 8 groups of 10 rather than 10 groups of 8 by selecting 10 as the interval width and 7 as the number of cutpoints. Once you have made your labels, click OK and then OK again to create the new binned variable, which you can see has been added as the last variable in your dataset.

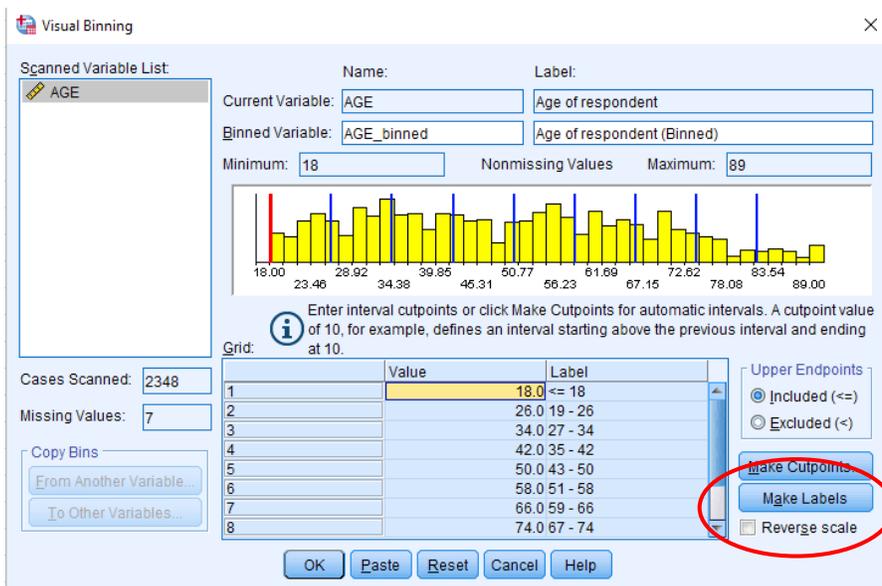


Figure 6

Now you can create the frequency distribution using the new binned variable by going to Analyze—Descriptive Statistics—Frequencies and selecting “AGE_binned” as the variable. You will get the output below:

Age of respondent (Binned)

	Frequency	Percent	Valid Percent	Cumulative Percent
Valid				
1 <= 18	22	.9	.9	.9
2 19 - 26	249	10.6	10.6	11.6
3 27 - 34	361	15.4	15.4	27.0
4 35 - 42	337	14.4	14.4	41.4
5 43 - 50	281	12.0	12.0	53.4
6 51 - 58	327	13.9	14.0	67.4
7 59 - 66	300	12.8	12.8	80.2
8 67 - 74	256	10.9	10.9	91.1
9 75 - 82	123	5.2	5.3	96.4
10 83+	85	3.6	3.6	100.0
Total	2341	99.7	100.0	
Missing	99 NA	.7	.3	
Total	2348	100.0		

Voila!

Histograms & Bar Graphs

If you want to look at your data graphically, you might choose to have SPSS draw you a histogram or a bar graph of a particular variable. Remember, histograms are used for variables that are continuous in nature (e.g., height), whereas bar graphs are used for discrete or categorical data (e.g., marital status). Simply click on the “Charts” button within the frequencies dialog box (see Figure 1) and choose which type of graph you want.

The “Descriptives” Command

Another way to get basic descriptive statistics is to go under “Analyze,” “Descriptive Statistics,” “Descriptives.” Here you’ll get many of the same options as with the “Frequencies” command, only you won’t get a frequency table (you also can’t get the median or mode). Use this command if you just want to get a quick mean and standard deviation (or standard error) for a bunch of variables at once.

Play around! Explore! Have fun!

SPSS is a fairly user-friendly program. If you get lost, simply scroll around in the menus until you find what you’re looking for. If you’re really lost, you can probably Google for help. Remember, though: SPSS will blindly do whatever you tell it to do, regardless of whether or not it’s a sensible command. So be smart about what you tell it to do. Now you’re ready to explore your data. Enjoy!

Annotating and Printing Output for Your Homework Assignments

Unfortunately, SPSS output is not printer-friendly. Printing output “as is” wastes a lot of trees. You can certainly save your output (.spv) files on your computer to look at on your screen, but note that in order to view those files, you’ll need to be in SPSS. Here’s what I recommend whenever you need to print output for assignments:

Take a [screen grab](#) of the relevant parts of the output (On a Mac: **Ctrl+Command+Shift+4**; for PCs, use the snipping tool) and paste them (**Command+v**) into a Microsoft Word or Google doc. You can then re-size the images to make them smaller to fit on your page (be sure to grab each one from the [corner](#) and drag so it adjusts height and width proportionally).

Many of the homework assignments require you to annotate (i.e., label and explain) your SPSS output. I recommend that you do so in one of three ways:

1. If you do your homework using Microsoft Word or Google docs: Print the relevant parts of the SPSS output that you’ve inserted into a Word or Google doc, write on the output in pen, take a clear photo of the annotated output with your phone, and insert the photo into the Microsoft Word or Google doc containing the rest of your homework. Save the Word doc as a pdf or download and save the Google doc as a pdf and upload to Gradescope.
2. If you do your homework by hand (pen and paper): Print the relevant parts of the SPSS output that you’ve inserted into a Word or Google doc, write on it in pen, and scan it with a phone scanning app (e.g., SwiftScan or Scanner Pro for iOS; Genius Scan or Mobile Doc Scanner for Android) as one of the pages of your homework; it will become part of the single pdf that you’ll upload to Gradescope. If you use this option, remember that all APA-style Results sections must be typed, so you’ll need to print that and scan it with the rest of your handwritten homework.
3. If you regularly use an iPad or other tablet to do your homework, you can use your favorite note-taking app to annotate output. Take screen grabs of the relevant portions of the output, insert them into your notes, and use the drawing tools to annotate them. If you do your homework by hand on the app (but type the APA-style Results section), save the whole thing as a pdf and upload to Gradescope.

If you can’t get the screen grab to work, you can export your output as “rich text format,” which will open in Microsoft Word, but this is fairly cumbersome and uses more trees than necessary. From within the output window, go to the “File” menu and choose “Export.” You will see the window shown in Figure 1. Choose “Word/RTF (*.doc)” as the type (it’s the default), click “browse” to decide where to save the file, give the file a descriptive name, and click OK in the Export window. You can now open the saved file in Microsoft Word, reformat the tables if you wish, and delete any unnecessary information.

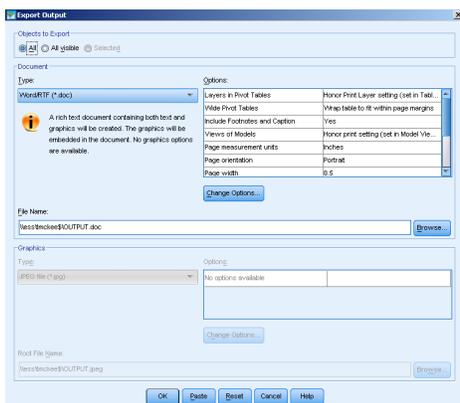


Figure 1

If you choose to export your output this way, you should print four pages to a sheet to save paper. To do so on a Macintosh, select “Print” from the “File menu.” Under the “Copies & Pages” pull-down menu, change the setting to “Layout,” and change “Pages per sheet” to 4 (see Figure 2):

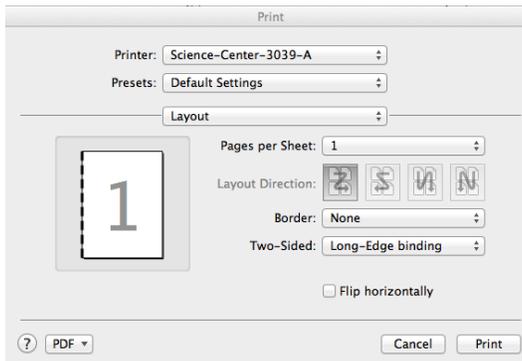


Figure 2

Ending your Citrix Session

When you are done working, remember to **save** your files. Then, from within SPSS, choose **File**, then **Exit**. This will automatically log you off of Citrix as well.

If you forget to do this and instead quit Citrix without first quitting SPSS, it is very important to select log off rather than disconnect so you don't have multiple Citrix sessions open.

Basic Data Manipulations: Recoding Variables and Computing New Variables

Recoding Variables

Sometimes it's useful to be able to combine existing categories of responses into broader categories. For example, in the 2018 General Social Survey, the income variable had very narrow categories (1 = under \$1,000; 2 = \$1,000-\$2,999; 3 = \$3,000-\$3,999; 4 = \$4,000 – 4,999, etc...through 26 = \$170,000 or over). Perhaps you don't need 26 different income categories, but would rather group them into more meaningful chunks. You could decide that you want the following categories instead:

1 = under \$20,000 (this would encompass values 1 – 12 in the old variable)

2 = between \$20,000 and \$40,000 (values 13 – 17 in the old variable)

3 = between \$40,000 and \$60,000 (values 18 – 19 in the old variable)

4 = between \$60,000 and \$90,000 (values 20 – 21 in the old variable; note that there's unfortunately not an even break at \$80,000 in the data set)

5 = between \$90,000 and \$130,000 (values 22 – 23 in the old variable)

6 = over \$130,000 (values 24 – 26 in the old variable)

To do this, you would need to recode the original values into new ones. The original values 1-12 would be recoded as a 1 (under \$20,000) in the new variable. The original 13-17 would become 2, and so on. To accomplish this in SPSS, you go to the **Transform** menu and scroll down to **Recode** (see Figure 1).

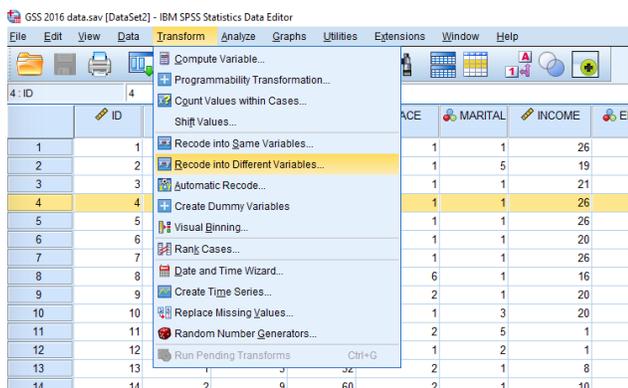


Figure 1

You get two options: “Recode into same variables” and “Recode into different variables.” The former changes the existing variable and the latter creates a new variable with the recoded values. I recommend always creating a new (different) variable and leaving the original intact. If you choose “Into different variables,” you will get the window you see in Figure 2, below.

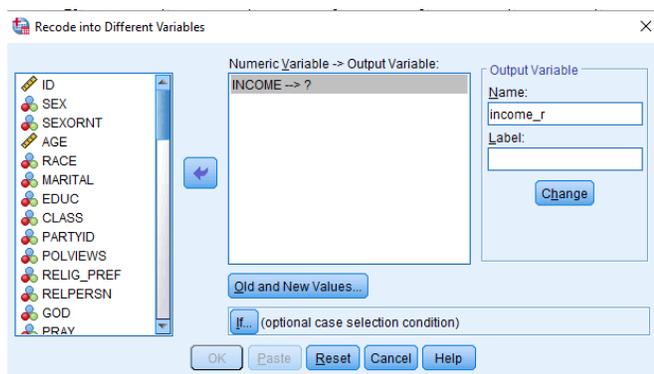


Figure 2

The names of all your variables will appear in the list on the left part of the window. Scroll down until you find the variable(s) you're looking for. In this case, I want to recode the INCOME variable. Simply click on the variable you want, then click on the arrow (which will be pointing the opposite of the way it's pointing in the figure). Now you need to tell SPSS what you want the new (recoded) variables to be called. To make life easier, I usually just add “r” to the original variable name, to remind myself that the variable has been recoded. In this case, income becomes income_r. Type this new name in the “output variable” box on the right of the window and click on the “Change” button.

Now you're ready to tell SPSS how to recode the variable. To do so, first click on the "Old and New Values" box. You'll get the screen you see below. In this case, we want the first 12 income categories of the old variable to become a "1" in the new, recoded variable. Notice that in the dialog box below, I've defined a range from 1-12 for "Old Value". On the right, I've entered a 1 under "New Value". You would then click on "Add," and keep going with the rest of the recodes (e.g., 13-17 becomes a 2, 18-19 becomes a 3, etc.). When you've added all the recodes to the Old→New box, click Continue.

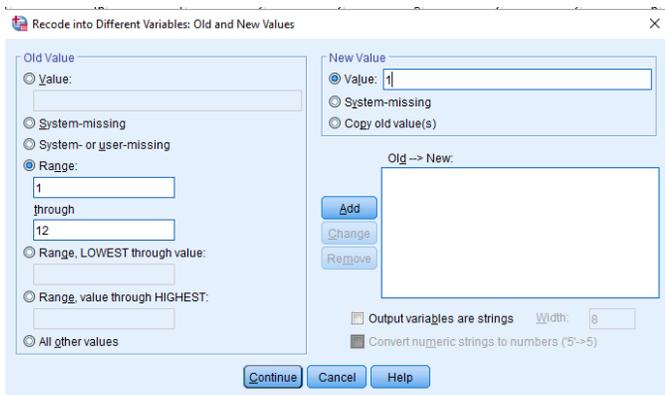


Figure 3

This will take you back to the window in Figure 2, and you can simply click "OK." If you now scroll to the end of your data file, you'll find a new column there called `income_r`. You can run a frequency on it (Analyze, Descriptive Statistics, Frequencies) to double-check that your categories look good.

Recoding is useful in other instances as well. For instance, questionnaires are often constructed such that approximately half of the questions are framed positively and the other half are framed negatively. For example, the 2016 General Social Survey included 6 items from the Life Orientation Test – Revised, a measure of optimism (see below). These items are scored on a 5-point Likert-type scale, from 1 (strongly disagree) to 5 (strongly agree). Note that items 2, 4, and 5 are reverse-worded, such that high numbers actually mean greater pessimism rather than greater optimism. Researchers generally want to combine items such as these into a single measure for analysis (i.e., a single optimism score that represents the mean of each respondent's rating for all six questions). To do so, we would first have to reverse-score the three reverse-worded items, so that higher numbers always mean higher optimism.

	Name	Type	Width	Decimals	Label	Values	Missing
24	LOTR1	Numeric	8	0	(Life Orientation Test - Revised; measure of Optimism). In uncertain times I usually expect the best.	{0, 1, 2, 3, 4, 5}	{0, 8, 9}
25	LOTR2	Numeric	8	0	If something can go wrong for me it will (R)	{0, 1, 2, 3, 4, 5}	{0, 8, 9}
26	LOTR3	Numeric	8	0	I'm always optimistic about my future	{0, 1, 2, 3, 4, 5}	{0, 8, 9}
27	LOTR4	Numeric	8	0	I hardly ever expect things to go my way (R)	{0, 1, 2, 3, 4, 5}	{0, 8, 9}
28	LOTR5	Numeric	8	0	I rarely count on good things happening to me	{0, 1, 2, 3, 4, 5}	{0, 8, 9}
29	LOTR6	Numeric	8	0	I expect more good things to happen to me than bad	{0, 1, 2, 3, 4, 5}	{0, 8, 9}

Figure 4

We could do this in a similar way to how we recoded the income variable, above. To reverse the response scale for items LOTR2, LOTR4, and LOTR5, we need to recode the values such that 1=5, 2=4, 3=3, 4=2, and 5=1. Since both variables are being recoded in the same way, we can put both of them in the box shown in Figure 2. When we click "Old and New Values," we'll get the following:

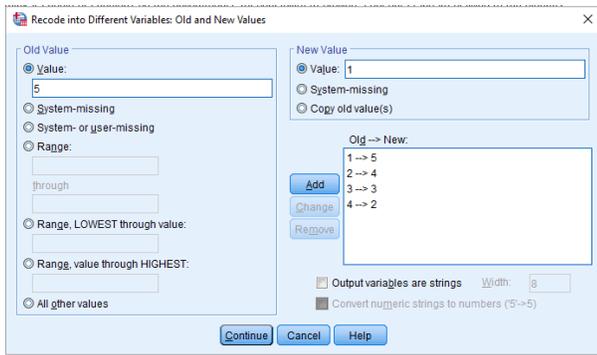


Figure 5

Note that this time we're recoding individual values rather than a range. Note how I've already recoded 1 into 5, 2 into 4, 3 into 3, and 4 into 2, and am in the process of changing 5 into 1.

Computing a new variable from existing ones

Once you have recoded any reverse-worded items, you can compute what is known as a "composite variable" for the questionnaire. That is, you will compute a variable that represents each participant's mean of all the questionnaire items. (Note: Technically you would only do this if you had ascertained that all of the variables were highly intercorrelated with one another, but that's a lesson for another course! Given that this is an established optimism scale, we'll go ahead and compute the mean.)

There are 6 items on the optimism scale, so if I wanted to compute each participant's mean optimism score based on those 6 items, I could use a compute statement. Don't forget that we need to use the recoded items instead of the originals for questions 2, 4, and 5. To create our compute statement, we would go up to the Transform menu again and scroll down to "Compute." You should then see a window that looks like the one below:

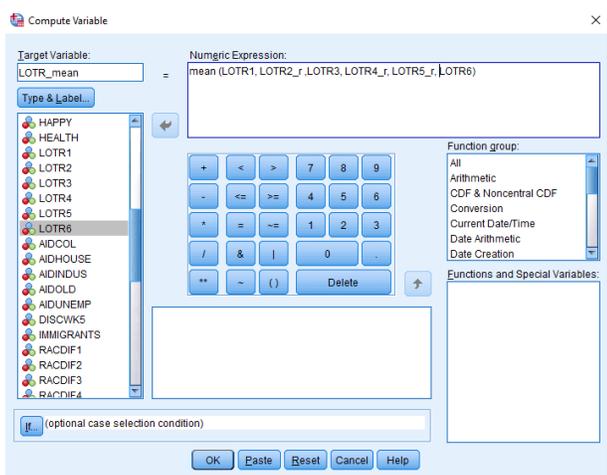


Figure 6

Note how I've typed "LOTR_mean" in the "Target Variable" box. That means I want SPSS to create a new column labeled "LOTR_mean" that will represent each participant's mean on the optimism scale. In the "Numeric Expression" box, I've indicated that I want this new variable to equal the mean of the items on the optimism scale, substituting the recoded items for the originals where appropriate. When you're all set, click "OK." If you scroll to the end of the data file, you'll see a new column labeled "LOTR_mean." This variable would represent each participant's average optimism score based on the 6-item questionnaire.

NOTE: You can use the compute command to perform any of a number of functions. I've chosen to calculate a mean.

Helpful tip: Pasting syntax

If you wanted to save this compute formula to use again later, you could click "Paste," and the formula would get pasted into the Syntax window, where you could run the command by highlighting it and clicking the green "go" button, and could also save it for later use.

SPSS Instructions for a One-Sample *t* Test

Let's use data from a previous semester of Psych Stats to illustrate how to conduct a one-sample *t* test. We will examine the number of hours of sleep per weekday that students get, and whether this number differs significantly from the recommended 8 hours. The first several cases of the file appear as follows:

*Class_data_S17_Cleaned.sav [DataSet3] - IBM SPSS Statistics Data Editor

1: sleep_wkday	books_required	cups_coffee	social_media	sleep_wkday	sleep_wkend	sleep_quality	tired
1	0	1	1	7	7	4	2
2	3	1	1	6	8	3	2
3	14	3	2	6	7	2	3
4	10	1	2	7	7	4	1
5	12	1	1	8	6	4	3
6	15	2	1	8	7	4	2
7	8	2	1	9	9	3	3
8	4	1	2	8	9	3	2
9	10	1	1	7	7	5	3
10	9	3	1	7	7	3	3
11	13	1	1	8	7	4	3

Figure 1

To conduct a one-sample *t* test in SPSS, go to the “Analyze” menu and click on “Compare means” and then “One-Sample T Test.” Click on the DV you want to analyze (in this case, “sleep_wkday”) and click on the arrow to put it in the “Test Variable(s)” box (see Figure 2).

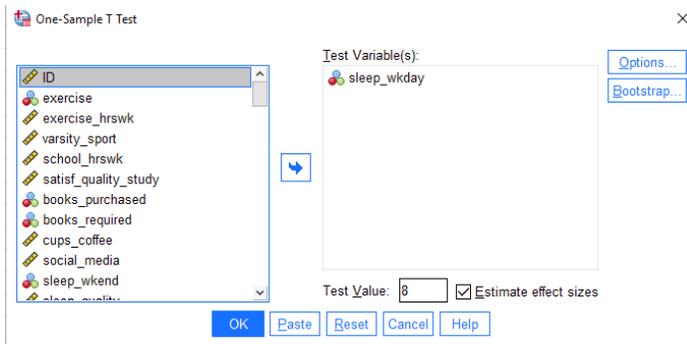


Figure 2

Next, you need to decide what your test value is going to be. This is the value to which you will compare the overall mean of the distribution. For our example, the test value is 8 hours, as we want to know whether the mean number of hours of sleep in our sample differs from 8. Type “8” in the “Test Value” box (see Figure 2). You will get the output shown below:

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
sleep_wkday How many hours of sleep do you get on the average weekday night?	121	7.35	1.022	.093

One-Sample Test

Test Value = 8

	t	df	Significance		Mean Difference	95% Confidence Interval of the Difference	
			One-Sided p	Two-Sided p		Lower	Upper
sleep_wkday How many hours of sleep do you get on the average weekday night?	-7.025	120	<.001	<.001	-.653	-.84	-.47

One-Sample Effect Sizes

	Standardizer ^a	Point Estimate	95% Confidence Interval	
			Lower	Upper
sleep_wkday How many hours of sleep do you get on the average weekday night?	Cohen's d	1.022	-.639	-.442
	Hedges' correction	1.029	-.635	-.439

a. The denominator used in estimating the effect sizes.
 Cohen's d uses the sample standard deviation.
 Hedges' correction uses the sample standard deviation, plus a correction factor.

The top box gives you the overall M and SD of the distribution. Here, we see that students in this sample get an average of 7.35 hours of sleep per weeknight. Is this number significantly different from the recommended 8 hours of sleep? To find out, look in the second box. You will find the t value (-7.02; notice that it is negative because it is *less* than the test value of 8. Round to make it an even number), the df ($N - 1$), and the significance value (use “Two-Sided p ” for a two-tailed test). The p value is less than .05 ($p < .001$), so students in this sample get significantly less than 8 hours or sleep per weeknight.

The 95% confidence interval of the difference is also shown; this interval represents the interval within which we are 95% certain the true difference between our observed mean of 7.35 and the population mean of 8 lies. This interval does *not* contain 0, so we are 95% confident that our observed mean does indeed differ from the test value of 8.

When doing CIs by hand for the one-sample t test, you typically build them around the observed mean, not the difference. To compute the 95% confidence interval around the observed mean based on the SPSS output, simply add μ (the test value or population mean specified under the null hypothesis; 8 in this case) to the lower and upper confidence limits. So we would be 95% certain that the true value of the population mean falls between 7.16 and 7.53, an interval that does NOT contain our test value of 8 hours.

SPSS provides Cohen's d by default; it's shown in the bottom box under “Point Estimate”.

Sample APA-Style Results Section:

A one-sample t test was conducted to determine whether Hamilton students get more or less than the recommended 8 hours of sleep per night during the week. The mean number of hours of sleep per weeknight reported by the sample ($M = 7.35$, $SD = 1.02$) was statistically significantly lower than 8 hours, $t(120) = -7.02$, $p < .001$, $d = -0.64$; 95% CI [7.16, 7.53].

Important details for writing a Results section involving a one-sample t test:

- Italicize M , SD , t , p , and d .
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$.
- When $p > .05$, report that the difference was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Round everything to 2 decimal places, except the p value, for which 3 decimal places should be reported.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1). Notice that I used a leading zero for Cohen's d (-0.64, not -.64).
- Be sure to state whether the observed mean was higher or lower than the test value for any significant test.
- Don't forget to report Cohen's d and the 95% confidence interval.

Sample SPSS Annotation

When you are asked to annotate your SPSS output for your homework assignments, you should do so in a manner similar to the example shown below.

T-Test

One-Sample Statistics			
	N	Mean	Std. Deviation
sleep_wkday	121	7.35	1.022

$S_{\bar{x}} = \frac{S}{\sqrt{N}} = \frac{1.022}{\sqrt{121}}$
 SD of the sampling distribution

One-Sample Test					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference
sleep_wkday	-7.025	120	.000	-.653	Lower: -.84, Upper: -.47

Test Value = 8
 Pop. mean (μ) to which you are comparing your sample mean. In this case, 8 hrs. of sleep.

Observed t value

$$t = \frac{\bar{X} - \mu}{S_{\bar{x}}} = \frac{7.35 - 8.00}{.093}$$

P value. Exact probability of obtaining the observed t value or higher assuming the null hyp. is true. Compare to $\alpha = .05$. If $p < \alpha$, reject H_0 .

This t is significant.

We are 95% confident that the true difference between \bar{X} and μ falls within this interval. Because the interval doesn't contain zero, reject H_0 .

		Standardize	Point Estimate	95% Confidence Interval	
sleep_wkday	Cohen's d	1.022	-.639	-.833	-.442
	Hedges' correction	1.029	-.635	-.828	-.439

a. The denominator used in estimating the effect sizes. Cohen's d uses the sample standard deviation. Hedges' correction uses the sample standard deviation, plus a correction factor.

Cohen's d (measure of effect size)
 medium effect

SPSS Instructions for Independent-Samples (a.k.a. “Independent-Groups”) *t* Test

Let’s use data from the 2018 General Social Survey to illustrate how to conduct an independent-samples *t* test. We will examine whether respondents who feel discriminated against on the basis of gender (variable = WKSEXISM, 1 = yes, feels discriminated against and 2 = no, does not) report being unhappy or depressed more often (variable = UNHAPPY, ranging from 1 = never to 5 = very often unhappy or depressed in past 4 weeks).

To conduct an independent-samples *t* test, open the data file, go to the “Analyze” menu, and click on “Compare means” and then “Independent-Samples T Test.” Click on the DV you want to analyze (in this case, “UNHAPPY”) and click on the arrow to put it in the “Test Variable(s)” box. Click on your IV (WKSEXISM) and put it in the “Grouping Variable” box (see Figure 1).

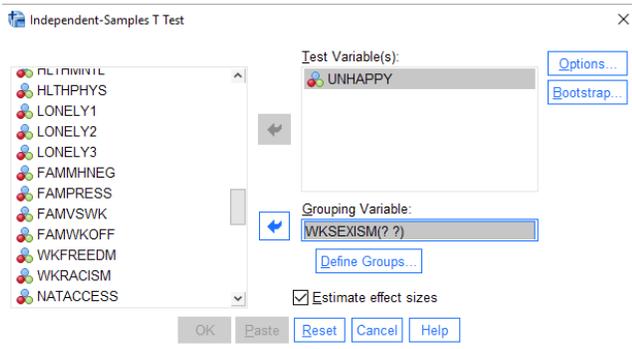


Figure 1

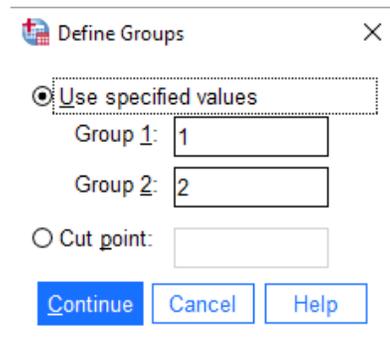


Figure 2

Notice the question marks next to WKSEXISM in the Grouping Variable box. Click on “Define Groups” and the box shown in Figure 2 will open where you can tell SPSS what numbers are used to represent each of the two groups (e.g., 1 = yes, 2 = no). Once you’ve done so, click “Continue” and then “OK.” SPSS will bump you to the Output window where you can examine the results of the *t* test.

T-Test

Group Statistics					
	WKSEXISM R feels discriminated because of gender	N	Mean	Std. Deviation	Std. Error Mean
	2 NO	651	1.96	.983	.039

Notice that SPSS computes the mean and SD of the DV (UNHAPPY) for each level of your IV (WKSEXISM).

Independent Samples Test											
		Levene's Test for Equality of Variances		t-test for Equality of Means							
		F	Sig.	t	df	Significance One-Sided p	Significance Two-Sided p	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
										Lower	Upper
UNHAPPY How often R was unhappy or depressed in past 4 weeks	Equal variances assumed	2.240	.135	3.734	695	<.001	<.001	.563	.151	.267	.859
	Equal variances not assumed			3.469	50.518	<.001	.001	.563	.162	.237	.889

Independent Samples Effect Sizes					
		Standardizer ^a	Point Estimate	95% Confidence Interval	
				Lower	Upper
UNHAPPY How often R was unhappy or depressed in past 4 weeks	Cohen's d	.989	.570	.269	.870
	Hedges' correction	.990	.569	.269	.869
	Glass's delta	.983	.573	.272	.873

a. The denominator used in estimating the effect sizes. Cohen's d uses the pooled standard deviation. Hedges' correction uses the pooled standard deviation, plus a correction factor. Glass's delta uses the sample standard deviation of the control group.

Use the point estimate for Cohen’s *d*. Here, Cohen’s $d = 0.57$.

To get the eta-squared, you will need to compute it by hand using the formula t^2 divided by $t^2 + df$. Be sure to use 3 decimal places for *t* in your computation.

Before you examine the results of the actual t test, you should check the results for **Levene's Test for Equality of Variances**, which assesses whether the variances of the two groups are significantly different from each other (i.e., whether the homogeneity of variance assumption has been violated). If the p value for the Levene's test (in the "Sig." column) is greater than .05, then the variances are *not* significantly different from one another (i.e., the homogeneity of variance assumption has been satisfied), and you may use the t value, degrees of freedom, and p value in the row marked "equal variances assumed." If the significance value for Levene's Test is less than .05, you will instead need to use the values reported in the row labeled "equal variances not assumed." Even if Levene's Test is significant, it is acceptable to use the df from the "equal variances assumed" row.

In the output shown here, the variances do not differ significantly ($p = .135$), so we can examine the t test results from the row labeled "equal variances assumed." We see that the observed t is 3.73. Note that SPSS provides both a one- and a two-tailed ("two-sided") p value. You will always report the two-sided p . Because $p < .05$, this test is statistically significant. We'll now look at the means to determine which group had the higher mean. It looks like respondents who reported feeling discriminated against on the basis of gender were unhappy more often ($M = 2.52$, $SD = 1.07$) than were respondents who did NOT feel discriminated against ($M = 1.96$, $SD = 0.98$). The 95% CI is built around the difference between the two means. The CI does not include zero (which would be the expected difference if the null hypothesis were true).

When writing up the results, be sure to include the t (rounded to two decimal places), df, p value, the M and SD for each group, the strength of the relationship (effect size measures), and the 95% CI.

Sample APA-Style Results Section for an Independent Samples t Test:

An independent-samples t test compared whether respondents who do and do not feel discriminated against on the basis of gender differed in how often they reported feeling unhappy over the previous four weeks. The test was statistically significant, $t(695) = 3.73$, $p < .001$, $d = 0.57$, $\eta^2 = .72$, indicating that respondents who reported feeling discriminated against on the basis of gender were unhappy more often ($M = 2.52$, $SD = 1.07$) than were respondents who did not ($M = 1.96$, $SD = 0.98$); 95% CI [0.27, 0.86].

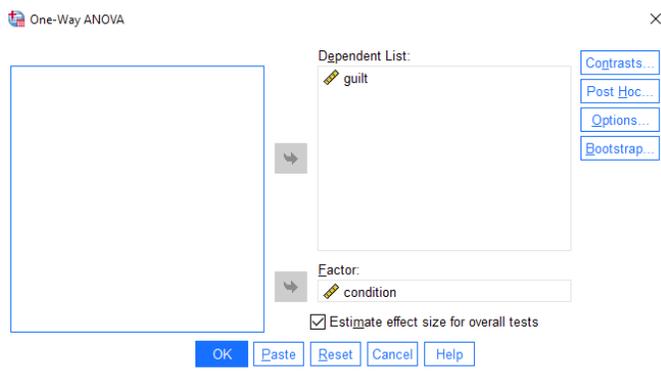
Important details for writing a Results section involving an independent-groups t test:

- Italicize M , SD , t , p , and d .
- Round M , SD , t , and d to 2 decimal places.
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$. Make sure you're reporting the two-sided p (non-directional test).
- When $p > .05$, report that the difference was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1). Notice that I used leading zeroes for one of the SDs, Cohen's d , and the CI values.
- Be sure to state the nature of any significant effect (which mean is higher).
- Don't forget to report estimated Cohen's d and η^2 (effect size) for any significant effect. To type the "eta" symbol, type the lower-case letter "h" and change it to Symbol font. Use 3 decimal places for t to compute η^2 .
- State the 95% confidence interval.

SPSS Instructions for a One-way ANOVA

Imagine we want to know whether providing a jury with information about a defendant's prior criminal record influences the extent to which they believe the defendant is guilty. Participants heard a recording of a case about a woman accused of writing bad checks, and were randomly assigned to one of three groups: Group 1 was told she had previously bounced checks (i.e., she had a criminal record); Group 2 was told that this was her first offense (i.e., she had a clean record); and Group 3 was given no information (control). The DV was a 1-10 rating of how guilty participants thought the defendant was. Because the DV is at least interval and the IV is between-subjects with more than 2 groups, a one-way ANOVA is appropriate.

To run a one-way ANOVA in SPSS, go under the "Analyze" menu to "Compare means" to "One-way ANOVA..." You will get the following window:



Click on the variable you want to use as your IV ("condition" in the above example) and move it to the "Factor" box by clicking on the appropriate arrow. Next, click on the variable you want to use as your DV ("guilt") and put it in the box labeled "Dependent List." If you wanted, you could put a whole bunch of DVs in the box at the same time, and SPSS would run a separate ANOVA for each DV.

Figure 1

Click the box labeled "Estimate effect size for overall tests" to get the eta-squared.

Now you need to tell SPSS which post-hoc multiple comparison procedure(s) you want to use (to compare pairs of means if the overall F is significant). Click on the box labeled "Post Hoc." SPSS will open the window in Figure 2 below. You are given the option to choose among various post-hoc tests. Tukey's HSD is the most widely-used procedure, so go ahead and click on the box next to "Tukey" (NOT "Tukey-b"). Click "Continue" to get back to the ANOVA window.

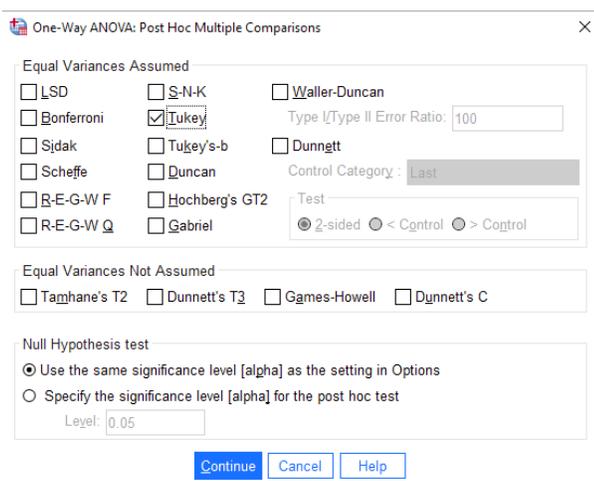


Figure 2

Next, you want to make sure that you get descriptive information printed out (means and standard deviations for each condition), as well as the labels of each condition. To do that, from the “One-way ANOVA” window, click on “Options.” When the window comes up, click in the box labeled “Descriptive” (See Figure 3, right) and then click “Continue.” When you get back to the main ANOVA window, click “OK”. Examine your output.

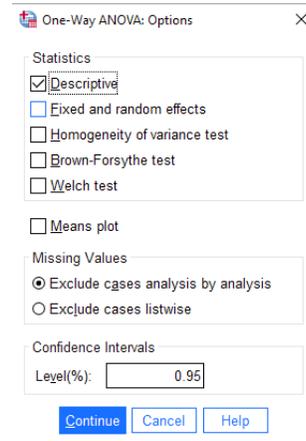


Figure 3

The first part of your output provides the *Ms* and *SDs* for each condition. Note also that you are given the standard errors for each condition, which are equal to the SD divided by the square root of *n* (in this case, 5). The confidence intervals here are around each mean, NOT around the difference between means (those are in a later piece of the output).

Descriptives

guilt

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1 criminal record	5	8.00	2.121	.949	5.37	10.63	5	10
2 clean record	5	4.00	2.236	1.000	1.22	6.78	1	7
3 no information	5	5.00	2.550	1.140	1.83	8.17	3	9
Total	15	5.67	2.769	.715	4.13	7.20	1	10

Next, you get your basic ANOVA source table, as shown below. You would write $F(2, 12) = 4.06, p = .045$.

ANOVA

rating of defendant's guilt

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	43.333	2	21.667	4.063	.045
Within Groups	64.000	12	5.333		
Total	107.333	14			

You are also given a table of effect sizes that contains the η^2 (see below; it's the value listed in the first row under “Point Estimate”: $\eta^2 = .40$). You would report η^2 if the *F* is significant, as it is here.

ANOVA Effect Sizes^{a,b}

	Point Estimate	95% Confidence Interval	
		Lower	Upper
guilt	Eta-squared	.404	.620
	Epsilon-squared	.304	.556
	Omega-squared Fixed-effect	.290	.539
	Omega-squared Random-effect	.170	.369

Given that the overall F is significant, you would go ahead and examine the post-hoc test output to determine which means are significantly different from one another. SPSS provides this information two different ways; the first appears below:

Post Hoc Tests

Multiple Comparisons

Dependent Variable: rating of defendant's guilt
Tukey HSD

(I) experimental condition	(J) experimental condition	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
criminal record	clean record	4.000*	1.461	.044	.10	7.90
	no information	3.000	1.461	.142	-.90	6.90
clean record	criminal record	-4.000*	1.461	.044	-7.90	-.10
	no information	-1.000	1.461	.777	-4.90	2.90
no information	criminal record	-3.000	1.461	.142	-6.90	.90
	clean record	1.000	1.461	.777	-2.90	4.90

*. The mean difference is significant at the 0.05 level.

In the above output, you can examine the size and significance of the three pairwise comparisons:

Criminal vs. clean ($p = .044$)

Criminal vs. no info ($p = .142$)

Clean vs. no info ($p = .777$)

Note that the same information is provided twice (e.g., criminal vs. clean, then clean vs. criminal), so you can ignore the duplicates. You can also use this table to find the 95% confidence interval around the difference between each pair of means (e.g., the 95% CI around the difference between criminal and clean is 0.10 – 7.90).

SPSS also provides another way of examining the differences between means:

Homogeneous Subsets

rating of defendant's guilt

Tukey HSD^a

experimental condition	N	Subset for alpha = 0.05	
		1	2
clean record	5	4.00	
no information	5	5.00	5.00
criminal record	5		8.00
Sig.		.777	.142

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 5.000.

Means in different subsets differ at $p < .05$, whereas means in the same subset do not. In the table above, clean record ($M = 4.00$) is in Subset 1 and criminal record ($M = 8.00$) is in Subset 2, so we know that they significantly differ. However, no information ($M = 5.00$) is in Subsets 1 AND 2, which means that it does not differ from either clean or criminal record. I find this way of interpreting the differences easier in terms of explaining the overall pattern of results in the simplest way.

Sample APA-Style Results Section:

A one-way ANOVA on guilt ratings as a function of prior information about a defendant was statistically significant, $F(2, 12) = 4.06, p = .045, \eta^2 = .40$. A Tukey HSD test indicated that mean guilt ratings were significantly higher for participants told a defendant had a prior criminal record ($M = 8.00, SD = 2.12$) than for those told she had a clean record ($M = 4.00, SD = 2.24$); 95% CI [0.10, 7.90]. Guilt ratings for those not given information about a prior criminal record ($M = 5.00, SD = 2.55$) did not differ from ratings in the criminal record and clean record conditions; 95% CIs [-0.90, 6.90] and [-4.90, 2.90], respectively.

Important details for writing a Results section involving a one-way ANOVA:

- Italicize $M, SD, F,$ and p .
- Don't forget to write the degrees of freedom, between and within, in parentheses.
- Round $M, SD,$ and F to 2 decimal places.
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$.
- When $p > .05$, report that the F value was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1). Notice that I used leading zeroes for some of the values in the CIs. Note that η^2 does NOT get a leading zero because its maximum value is 1.
- First, indicate whether the overall F was significant. If so, report the value of η^2 and discuss the results of the post hoc test (be sure to state which post hoc test you used). In describing the pattern of results, be sure to state the M s and SD s of each group in parentheses, and don't forget to report the 95% confidence intervals for the differences between group means.
- There is no need to provide the M and SD for the same group twice (i.e., if you are comparing that group to two different groups, you only need to provide the descriptive statistics the first time you mention that group).

SPSS Instructions for a Paired Samples (a.k.a. “Correlated Groups”) *t* Test

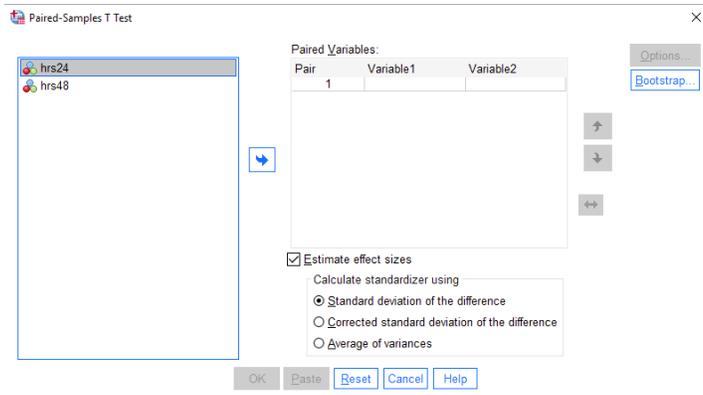
Imagine that a researcher was interested in the effect of sleep deprivation on motor skills performance. Twelve participants were tested on a motor-skills task after 24 hours of sleep deprivation and again after 48 hours. The DV is the number of errors made on the motor skills task. The data for this example appear below.

	hrs24	hrs48
1	0	1
2	2	3
3	1	2
4	1	4
5	1	2
6	1	3
7	2	4
8	3	1
9	3	3
10	1	5
11	2	2
12	0	1
13		

Note how these data are entered differently from the way data are entered for an independent-groups *t* test. In the repeated-measures case, each level of the IV is represented as a separate column.

Figure 1

To conduct a paired samples *t* tests in SPSS, go under the “Analyze” menu to “Compare Means” to “Paired-Samples T Test.” You will get the following window:



Choose which variables to compare by clicking on them and putting them in the “Paired Variables” box. If you shift+click on both, you can add them both at once. Then click “OK” and you will get bumped to the output window where you can examine your findings (see below).

Figure 2

Descriptive statistics for the two levels of your IV (# of errors as a function of condition):

Pair	Variable	Mean	N	Std. Deviation	Std. Error Mean
		hrs24	1.42	12	.996
hrs48	2.58	12	1.311	.379	

Ignore the next table. It represents the correlation (*r*) between the two variables.

Pair	Variables	N	Correlation	Significance	
				One-Sided p	Two-Sided p
Pair 1	hrs24 & hrs48	12	.145	.327	.653

This table provides you with the difference between the two means (-1.17), the observed t , df , p -value (use the “two-sided” p), and 95% CI.

		Paired Differences						Significance		
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	One-Sided p	Two-Sided p
					Lower	Upper				
Pair 1	hrs24 - hrs48	-1.167	1.528	.441	-2.137	-.196	-2.646	11	.011	.023

We see that the observed t , with 11 df , is -2.65, and the (two-sided) p value is .023, which is less than .05, so the difference between the two means is statistically significant. Looking at the means in the first table, we can see that people made significantly more errors on the motor skills test following 48 hours of sleep deprivation than following 24 hours.

Because the test was statistically significant, we should also report the strength (effect size). SPSS gives us Cohen’s d (see below; use the Point Estimate), but not η^2 , so you’ll need to conduct that one by hand with the formula t^2 divided by $t^2 + df$.

		Standardizer ^a	Point Estimate	95% Confidence Interval		
				Lower	Upper	
Pair 1	hrs24 - hrs48	Cohen's d	1.528	-.764	-1.398	-.103
		Hedges' correction	1.582	-.737	-1.350	-.099

a. The denominator used in estimating the effect sizes.
 Cohen's d uses the sample standard deviation of the mean difference.
 Hedges' correction uses the sample standard deviation of the mean difference, plus a correction factor.

Sample APA-Style Results Section:

A paired-samples t test comparing the average number of errors participants made on a motor skills task after 24 and 48 hours of sleep deprivation was significant, $t(11) = -2.65, p = .023, d = -0.76, \eta^2 = .79$. Participants made significantly more errors after 48 hours of sleep deprivation ($M = 2.58, SD = 1.31$) than after 24 hours ($M = 1.42, SD = 1.00$); 95% CI [-2.14, -0.20].

Important details for writing a Results section involving a paired-samples t test:

- Italicize M, SD, t, p , and d .
- Round M, SD, t , and d to 2 decimal places.
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$. Make sure you’re reporting the two-sided p (non-directional test).
- When $p > .05$, report that the difference was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Be sure to state the nature of any significant effect (which mean was higher).
- Be sure to report estimated Cohen’s d and η^2 (strength of the effect) for any significant effect.
- Don’t forget to report the 95% confidence interval for the mean difference.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1). Notice that I used leading zeroes for Cohen’s d , and one of the CI values.

SPSS Instructions for a Repeated-Measures ANOVA

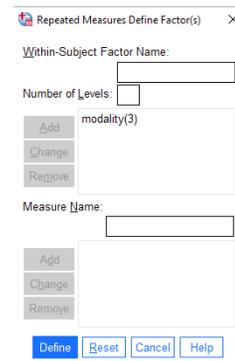
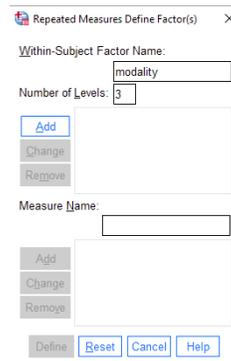
A researcher was interested in the effect of presentation modality on word recall. Words were presented to participants in all three of the following modalities: visual only, auditory only, both visual and auditory. The DV was the number of words recalled in each modality.

The data for this example appear below. Note how these data are entered differently from the way data are entered for a one-way between-subjects ANOVA. In the repeated-measures case, each level of the IV is represented as a separate column.

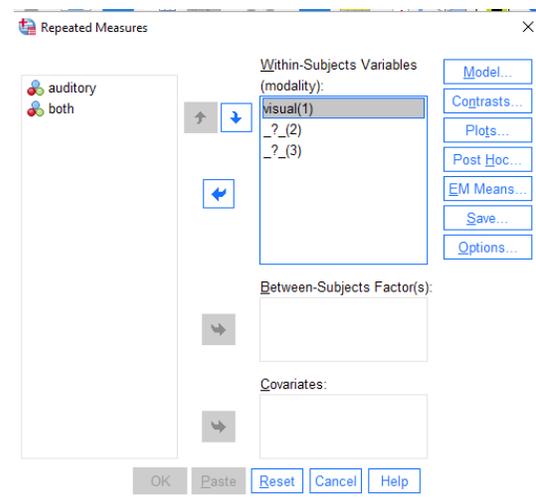
	visual	auditory	both	var
1	7	2	4	
2	8	3	7	
3	6	1	2	
4	5	1	3	
5	7	3	5	
6	9	2	6	
7	7	5	7	
8	5	3	4	
9	6	1	2	
10	8	2	5	
11	4	5	3	
12	2	6	7	
13	3	7	8	
14				

Run a one-way repeated-measures ANOVA in SPSS by going under the “Analyze” menu to “General Linear Model” then “Repeated Measures...” You will get the first window shown below, left.

Because your DV cannot be found in a single column, but rather is distributed across three columns, you need to specify a name for the within-subjects variable to tell SPSS where to find the data. In the middle window below, I have named this factor “modality” and noted that it has 3 levels. Next, I clicked on “Add” (see window below, right).

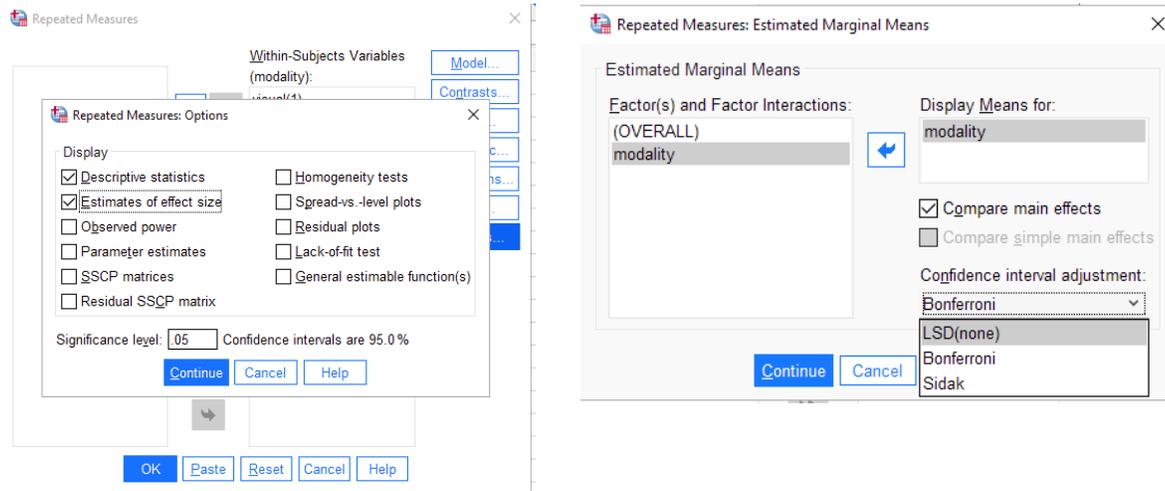


Next, select “Define” to define your within-subjects variable and you will see the window to the right. Simply click on the name of the level of the IV in the left column, then click on the arrow, and it will move into the right-hand box. Do this for all three levels of the IV (notice in the window that I have done it only for the first one so far). If you click on the first one, then shift+click on the last one, you can select all three at once.



Next, click on “Options,” then click on Descriptive statistics (to get means and *SDs* for each condition) and Estimates of effect size (to get partial η^2); see below left. Then click “Continue”.

When you’re back in the main dialog box, select “EM Means” to get the dialog box shown below, right. Here is where you will ask SPSS to conduct the post-hoc comparison of means. Select the factor (modality) and drag it to the “Display Means for” box (or click on the arrow to pop it in the box). Select “Compare main effects” and choose “Bonferroni” from the drop-down menu. Click “Continue”.



Now click on “OK” in the Repeated Measures box and you’ll get bumped to the output window, where you can examine your findings. SPSS produces a lot of output for the repeated-measures ANOVA, and you can ignore much of it. Note that you will be using the *F* value from the “Tests of Within-Subjects Effects” box (NOT the “Multivariate Tests” box).

As always, you get *Ms* and *SDs* for each condition. Note that, because this was a within-subjects design, the total sample size is 13 (i.e., the same 13 people were in each condition). Also note that the SD for the “both” condition would be rounded to 2.04 (it ends in exactly 5, so you would round to make it an even number).

Descriptive Statistics

	Mean	Std. Deviation	N
visual	5.92	2.060	13
auditory	3.15	1.994	13
both	4.85	2.035	13

You can ignore the following table:

Multivariate Tests^a

Effect		Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared
modality	Pillai's Trace	.567	7.207 ^b	2.000	11.000	.010	.567
	Wilks' Lambda	.433	7.207 ^b	2.000	11.000	.010	.567
	Hotelling's Trace	1.310	7.207 ^b	2.000	11.000	.010	.567
	Roy's Largest Root	1.310	7.207 ^b	2.000	11.000	.010	.567

Next, examine the results of the Mauchly test (see below), which tests for violations of the sphericity assumption. If Mauchly's test is significant (p -value in the Sig. column is less than .05), then the sphericity assumption has been violated. [In other words, the variance of difference scores isn't the same for all pairwise sets of difference scores; at least one variance significantly differs from another.]

Mauchly's Test of Sphericity^a

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon ^b		
					Greenhouse-Geisser	Huynh-Feldt	Lower-bound
modality	.404	9.983	2	.007	.626	.665	.500

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is proportional to an identity matrix.

a. Design: Intercept

Within Subjects Design: modality

b. May be used to adjust the degrees of freedom for the averaged tests of significance. Corrected tests are displayed in the Tests of Within-Subjects Effects table.

We can see here that Mauchly's test produced $p = .007$, which is significant (less than .05), indicating a violation of sphericity.

Unfortunately, the Mauchly test under-detects violations of sphericity in small samples (for example, on homework problems) and over-detects violations of sphericity in large samples (for example, in the GSS data set). **So researchers recommend always assuming sphericity has been violated and using a correction factor.** SPSS provides three:

- Greenhouse-Geisser epsilon (ϵ)
- Huynh-Feldt epsilon (ϵ)
- Lower-bound epsilon (ϵ) — we won't use this one (it is too conservative)

The Greenhouse-Geisser and Huynh-Feldt (pronounced HWIN FELT) estimates both range from the lower-bound estimate of sphericity (most severe departure from sphericity) to 1 (no departure from sphericity). The lower-bound for both the Greenhouse-Geisser and Huynh-Feldt epsilons is $1/(k - 1)$, where $k = \#$ of conditions. So, for 3 conditions, the Greenhouse-Geisser and Huynh-Feldt epsilons would range from .50 to 1. Notice that SPSS provides the lower-bound epsilon of .50. This correction is considered too conservative (i.e., results in more Type II errors) and so is not preferred. Also notice that, as k increases, the lower bound decreases, resulting in an increased potential for severe sphericity violations.

When the Greenhouse-Geisser ϵ is greater than 0.75, the correction is too conservative, but the Huynh-Feldt epsilon tends to overestimate sphericity. So use this rule of thumb:

- when the Greenhouse-Geisser $\epsilon \geq .75$, use the Huynh-Feldt correction
- when the Greenhouse-Geisser $\epsilon < .75$, use the Greenhouse-Geisser correction

In this case, Greenhouse-Geisser $\epsilon = .63$, so we will go ahead and use it. The correction is made by multiplying df_B and df_{error} by the appropriate epsilon to obtain new df. If sphericity hasn't been violated, the epsilons are close to 1 and won't affect the df that much. (This is why it's fine to always apply the correction.)

Recall that the shape of the F distribution is determined by df, so multiplying by the correction factor changes the shape of the F distribution and results in a new critical value to compare observed F to. Note that it doesn't change observed F , just critical F and the resulting p value. [In case you're curious, it doesn't affect observed F because ϵ shows up in both the numerator and denominator of the F ratio, and therefore cancels out.]

Next you'll see the ANOVA source table:

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
modality	Sphericity Assumed	50.667	2	25.333	6.247	.007	.342
	Greenhouse-Geisser	50.667	1.253	40.444	6.247	.019	.342
	Huynh-Feldt	50.667	1.329	38.117	6.247	.017	.342
	Lower-bound	50.667	1.000	50.667	6.247	.028	.342
Error(modality)	Sphericity Assumed	97.333	24	4.056			
	Greenhouse-Geisser	97.333	15.033	6.475			
	Huynh-Feldt	97.333	15.951	6.102			
	Lower-bound	97.333	12.000	8.111			

SPSS does not include the total SS or total df, so the table looks a little different than when you compute the ANOVA by hand.

You are given partial η^2 (.34), which is what you would get if you computed $SS_B/SS_B + SS_E$.

To determine whether your F is significant, examine the p value in the appropriate row of the source table depending on whether you applied the Greenhouse-Geisser or Huynh-Feldt correction. In this case, we used the Greenhouse-Geisser ϵ , so our p value would be .019 (significant). In your APA-style write-up, report the df associated with the “Sphericity Assumed” row even if you are using one of the correction factors (i.e., don't report fractional df). But be sure to report the appropriate p value that corresponds to the correction factor you chose.

Our F was significant, so next we must examine the post-hoc comparison of means (see below):

Pairwise Comparisons

Measure: MEASURE_1

(I) modality	(J) modality	Mean Difference (I-J)	Std. Error	Sig. ^b	95% Confidence Interval for Difference ^b	
					Lower Bound	Upper Bound
1	2	2.769	1.007	.053	-.031	5.569
	3	1.077	.820	.641	-1.203	3.356
2	1	-2.769	1.007	.053	-5.569	.031
	3	-1.692*	.429	.006	-2.886	-.499
3	1	-1.077	.820	.641	-3.356	1.203
	2	1.692*	.429	.006	.499	2.886

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Recall that we selected Bonferroni comparisons. The Bonferroni approach allows us to run multiple comparisons while still controlling the Type I error rate. Because there were three possible pairwise comparisons, the original p values were multiplied by 3. (If there had been 4 pairwise comparisons, the original p values would have been multiplied by 4.) If these new (higher) p values in the table above are less than .05, the comparison is significant.

The “1,” “2,” and “3” for modality are determined by the order in which you entered them into the repeated-measures dialog box in SPSS: 1 = visual only, 2 = auditory only, and 3 = visual+auditory. Here we see that the only significant difference was between auditory and visual+auditory.

To understand the nature (direction) of the difference, you must examine the means in the descriptive statistics box that appeared earlier in the output. From there, we can see that recall was significantly poorer for the auditory-only condition than for either the visual or visual+auditory conditions, which didn't differ from each other.

Note that the 95% confidence interval has also been Bonferroni-adjusted.

Sample APA-Style Results Section:

A one-way repeated measures ANOVA was conducted on word recall as a function of modality of presentation (visual only, auditory only, or both visual and auditory). Mauchly's test indicated that the assumption of sphericity was violated, $\chi^2(2) = 9.98, p = .007$, so the degrees of freedom were corrected using the Greenhouse-Geisser estimate of sphericity ($\epsilon = .63$). There was a significant effect of modality, $F(2, 24) = 6.25, p = .019$, partial $\eta^2 = .34$. Post-hoc pairwise comparisons using the Bonferroni correction indicated that average recall was significantly better when words were presented in both modalities ($M = 4.85, SD = 2.04$) than when they were presented only auditorily ($M = 3.15, SD = 1.99$), $p = .006$; 95% CI [0.50, 2.89]. Recall did not differ between words presented visually ($M = 5.92, SD = 2.06$) and those presented either auditorily, $p = .053$; 95% CI [-0.03, 5.57], or in both modalities combined, $p = .641$, 95% CI [-1.20, -3.36].

Note: If Mauchly's test is not significant, it's still recommended to apply the correction factor. In that case, you'd write something like the following: Mauchly's test indicated that the assumption of sphericity was not violated, $\chi^2(2) = 1.13, p = .439$, but because the test is highly sensitive to sample size, the degrees of freedom were still corrected using the Greenhouse-Geisser estimate of sphericity ($\epsilon = .63$).

Important details for writing a Results section involving a repeated-measures ANOVA:

- Italicize M , SD , F , and p .
- Don't forget to write the degrees of freedom, between and within, in parentheses.
- Round M , SD , and F to 2 decimal places.
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$.
- When $p > .05$, report that the F value was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1). Notice that I used leading zeroes for some of the values in the CIs. Note that epsilon and partial η^2 do NOT get a leading zero because their maximum value is 1.
- Report the results of the Mauchly test as shown above and note which correction factor you used.
- Indicate whether the overall F was significant. If so, report the value of partial η^2 and discuss the results of the Bonferroni-corrected pairwise comparisons. In describing the pattern of results, be sure to state the *direction* of the differences. Report the M s and SD s of each group in parentheses and include the 95% confidence intervals for the differences between group means. Be sure your wording makes it clear that it was a within-subjects design (i.e., do not talk about different groups).
- There is no need to provide the M and SD for the same group twice (i.e., if you are comparing that group to two different groups, you only need to provide the descriptive statistics the first time you mention that group).

SPSS Instructions for Correlation and Regression

For our correlation and regression example, we'll use data from the "Monitoring the Future" national survey of twelfth graders conducted by the Inter-university Consortium for Political and Social Research (ICPSR). Let's imagine we were interested in the extent to which students' self-reported intelligence and school ability predict their liking for school. So there are two predictor variables (intelligence, school ability) and one criterion variable (liking for school).

Correlation

Before we conduct a regression to determine whether our predictor variables predict our criterion, it's a good idea to examine the bivariate correlations between each pair of variables. Before you do *that*, however, it's important to examine a scatterplot of your variables to get an idea about whether they are linearly related to one another.

To demonstrate, we'll look at the scatterplot for the relation between perceived school ability and liking for school. [Note that one should look at the scatterplots for all possible pairs of variables before running bivariate correlations]. To produce a scatterplot in SPSS, go under the "Graphs" menu to "Legacy Dialogs" and choose "Scatter/Dot..." You will see the window in Figure 1. Choose "Simple Scatter" (it should already be selected) and click on "Define." You will now see a window like the one in Figure 2.

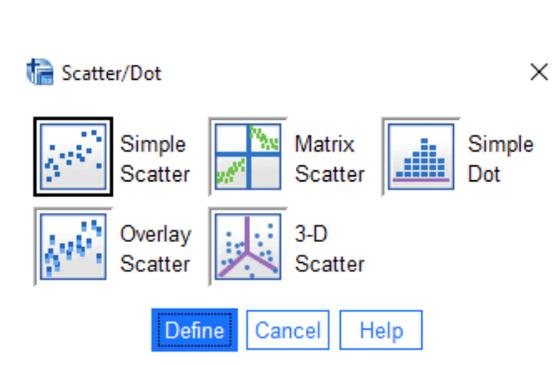


Figure 1

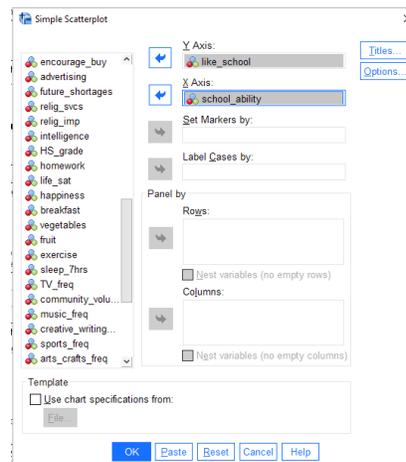


Figure 2

Scroll down the list of variables on the left until you find the variable you want on the Y axis (the criterion variable; in this case, "like_school"). Click on this variable, then click the top arrow. The variable name should now appear in the box labeled "Y Axis." Now find the variable you want on the X axis (the predictor variable; in this case, "school_ability"). Click on this variable, then click on the arrow next to the "X axis" box. Click OK. SPSS will bump you into the output window, where you'll see your scatterplot. Take a look at it. Are there any outliers? Does the relationship appear linear? (If it's curvilinear, a Pearson's r is inappropriate to use.) Double-click on the graph, and when SPSS bumps you into the chart editor, go under the "Elements" menu and choose "Fit line at total." [You can close the "Properties" box if it pops up.] SPSS will draw in the least-squares line, which will better help you see whether the data are linearly related, and whether the relationship is positive or negative. [Note that if you are correlating variables measured on rating scales with only a few levels, say a 1-5 scale, the scatterplot may look a little wonky because the options for where points might fall are limited.]

If your scatterplots look OK, you're ready to calculate correlations. To do so, go to the "Analyze" menu, scroll down to "Correlate" and choose "Bivariate." You will see a window like the one in Figure 3.

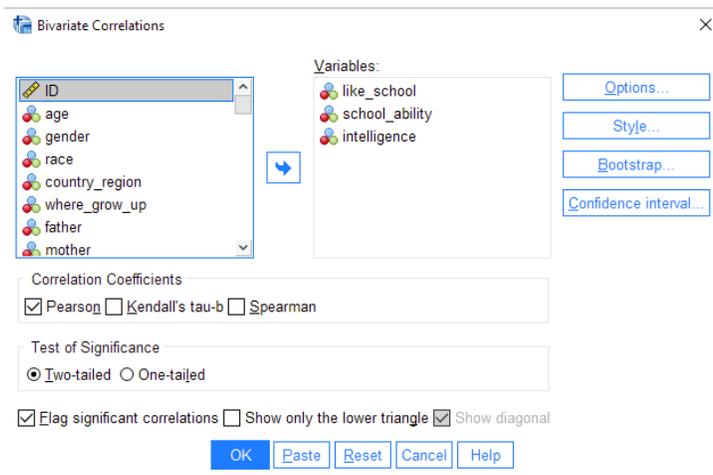


Figure 3

Click on “Confidence interval” and you will get the dialog box shown at right in Figure 4. Check the first box as shown and the “Apply the bias adjustment” box to get bias-adjusted confidence intervals for the correlation.

Click “OK” and SPSS will bump you into the output window (see below).

Find the variables you want from the list on the left and click the arrow to place them in the box labeled “Variables.” Here I’ve entered all three variables of interest. Note that you can put as many variables into a correlation matrix as you like.

Under “Correlation Coefficients,” make sure that “Pearson” is selected (this is the default).

Click on “Options” and check the box that will give you means and SDs for the two variables.

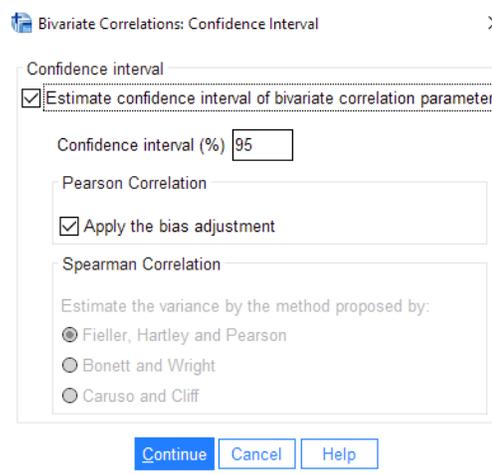


Figure 4

Descriptive Statistics

	Mean	Std. Deviation	N
like_school	2.99	1.125	1828
school_ability	4.91	1.226	1949
intelligence	5.01	1.243	1953

Correlations

		like_school	school_ability	intelligence
like_school	Pearson Correlation	1	.210**	.165**
	Sig. (2-tailed)		<.001	<.001
	N	1828	1791	1794
school_ability	Pearson Correlation	.210**	1	.720**
	Sig. (2-tailed)	<.001		.000
	N	1791	1949	1941
intelligence	Pearson Correlation	.165**	.720**	1
	Sig. (2-tailed)	<.001	.000	
	N	1794	1941	1953

** . Correlation is significant at the 0.01 level (2-tailed).

Here you are provided with the following correlations:

- liking for school & school ability ($r = .21$)
- liking for school & intelligence ($r = .16$)
- school ability & intelligence ($r = .72$)

The diagonal of 1s just shows each variable correlated with itself.

You'll note that this matrix produces redundant information, with the same correlations provided both above and below the diagonal. For each group of three numbers (e.g., like_school correlated with school_ability) the top value is Pearson's r (the correlation). Below that, the "Sig (2-tailed)" value is the p value, or the probability of getting a correlation that big or bigger if there really was no relationship between the two variables in the population. Finally, the bottom number is N (the sample size). Note that even though two of these correlations are quite small, they are highly significant because of the very large sample size.

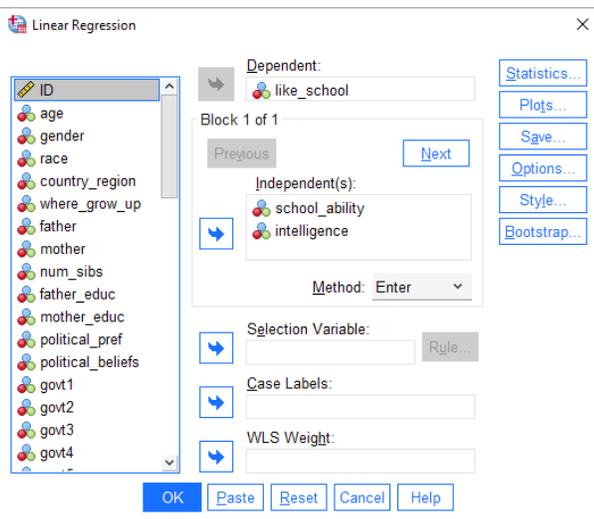
	Confidence Intervals			
	Pearson Correlation	Sig. (2-tailed)	95% Confidence Intervals (2-tailed) ^a	
			Lower	Upper
like_school - school_ability	.210	<.001	.165	.254
like_school - intelligence	.165	<.001	.120	.210
school_ability - intelligence	.720	.000	.698	.741

a. Estimation is based on Fisher's r-to-z transformation with bias adjustment.

The next part of the output provides the bias-corrected confidence intervals for all three correlations. As you can see, because all three of these correlations are significant, none of the confidence intervals include zero.

Regression (one predictor) and Multiple Regression (two or more predictors)

If two variables are significantly correlated, then scores on one variable can be used to predict scores on the other. To conduct a linear regression in SPSS, go under "Analyze," "Regression," "Linear" and you'll see a window like the one in Figure 5.



Put the criterion (Y) variable in the box labeled "Dependent" and all the predictor (X) variables in the box labeled "Independent(s)." Click OK and you'll be bumped to the output window.

Figure 5

In the "Model Summary" table (see below), note that R is provided, which represents the correlation between observed and predicted Y values; it can range from 0 to 1. (Note the difference between lower case r and capital R.) The R Square is the coefficient of determination and ranges from 0 to 1. R Square represents the total variability in Y explained by all of the predictor(s). (Adjusted R square adjusts for the number of predictors in the model; when there are a large number of predictors and a small N , the difference between R square and adjusted R square is larger; we won't worry about it here.)

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.210 ^a	.044	.043	1.099

a. Predictors: (Constant), intelligence, school_ability

The Standard Error of the Estimate estimates the amount of error we have when using the predictors to predict Y. It is the square root of the Mean Square residual in the ANOVA table below.

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	98.965	2	49.482	40.951	<.001 ^b
	Residual	2152.021	1781	1.208		
	Total	2250.986	1783			

a. Dependent Variable: like_school

b. Predictors: (Constant), intelligence, school_ability

The ANOVA table indicates whether the overall model is significant. It can be interpreted just like a regular ANOVA table, with the “regression” row representing the predictors (analogous to the “between-subjects” row) and the “residual” row representing the error. Here, $p < .001$, so the two predictors together significantly predict liking for school.

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.004	.117		17.077	<.001
	school_ability	.173	.031	.186	5.549	<.001
	intelligence	.029	.030	.032	.943	.346

a. Dependent Variable: like_school

In the “Coefficients” table you’ll see numbers listed under the “B” column for your predictor variables and for (Constant). For your predictor variables, these numbers represent the *unstandardized* slopes—they are the slopes expressed in the original units of each variable and can be plugged into the regression equation to predict \hat{Y} . The number under B next to (Constant) is the Y intercept of the regression line. The *standardized* Beta coefficients are a standardized version of a slope (like a Z score) – they refer to how many standard deviations a dependent variable will change, per standard deviation increase in the predictor variable; because they are independent of the original units, they can be easily compared. The larger the β , the stronger the relationship. With only one variable in the equation, $\beta = r$. You can write the regression equation based on this output, using the Bs for the slopes: $\hat{Y} = 2.00 + 0.03x_1 + 0.17x_2$. (If the Bs had been negative, you would have used the minus sign instead of the plus sign.)

Notice that, although each of the predictors independently predicts liking for school (i.e., the bivariate correlations were significant), because there was such a high correlation between the two predictors perceived school ability and perceived intelligence ($r = .72$ from the correlation table), when we put both predictors in the equation to predict liking for school, intelligence is no longer significant ($p = .346$), whereas school ability remains significant ($p < .001$).

Sample APA-Style Results Section for Correlation/Regression:

Self-reported school ability ($M = 4.91$, $SD = 1.23$) and intelligence ($M = 5.01$, $SD = 1.24$) were both significantly positively correlated with liking for school ($M = 2.99$, $SD = 1.12$), $r(1789) = .21$, $p < .001$, bias-corrected 95% CI [.16, .25] for school ability and $r(1792) = .16$, $p < .001$, bias-corrected 95% CI [.12, .21] for intelligence. The overall regression model predicting liking for school from both school ability and intelligence was significant, $F(2, 1781) = 40.95$, $p < .001$, $R^2 = .04$ (standard error of estimate = 1.10). With both variables in the equation, self-reported school ability significantly predicted liking for school ($b = 0.17$, $p < .001$), but perceived intelligence did not ($b = 0.03$, $p = .346$).

Note: There is no need to report r^2 values for the bivariate correlations, as these are easily computed by the reader if desired. More important is to present the R^2 value from the regression if there are two or more predictors.

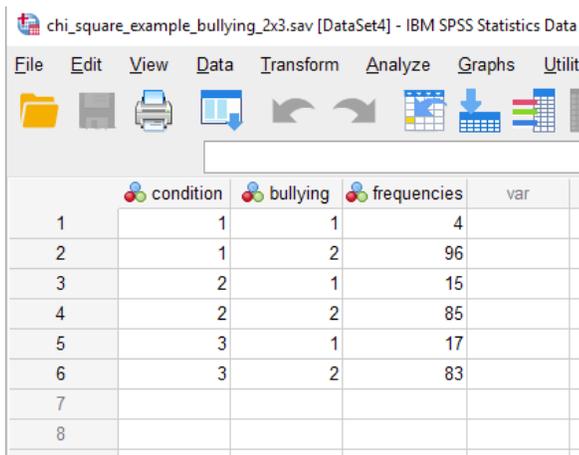
Once you get beyond just a couple of predictor variables, the text starts to become so cluttered with numbers that it's better to present them in a table. For example, you could present one table with the means, SDs, bivariate correlations, and bias-adjusted 95% confidence intervals (see handout for how to do that), and a second table with the b and p values for each predictor in the multiple regression. Be sure to refer to the table in the text (e.g., "As shown in Table 1...") and then do not include those values in the results section.

Important details for writing a Results section involving correlation/regression:

- Italicize M , SD , r , p , F , and b .
- Note that for a correlation, $df = N-2$
- Be sure to include the r , df , p value, the M and SD for each variable, and the value of R^2 for a multiple regression with two or more predictors.
- Round M , SD , r , F , R^2 , and b to 2 decimal places.
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$.
- When $p > .05$, report that the finding was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1). Notice that I used leading zeroes for the unstandardized slopes.
- Typically, we do not write out the regression equation, but might include the important values in a table if there are a lot of predictor variables.

SPSS Instructions for a Chi-Square

The MacArthur “Genius” award winner Elizabeth (Betsy) Levy Paluck’s research on bullying has demonstrated that an effective way to reduce bullying in middle schools is to identify students with a great deal of social influence among their peers and provide them with an intervention encouraging them to take a stance against bad behavior in their school. Imagine that one school received this social influence intervention, one received a traditional anti-bullying education intervention, and one received nothing (control). The behavior of 100 students at each of the three schools was monitored for 8 months afterwards to see if any bullying occurred. [Note: because one of the variables has marginal frequencies that are fixed—100 people in each of the three conditions—the test would be a chi-square test of homogeneity.] The data would be entered as shown in Figure 1, with one column for the IV, one column for the DV, and a column of frequencies specifying the number of participants in each IV/DV combination.



	condition	bullying	frequencies	var
1	1	1	4	
2	1	2	96	
3	2	1	15	
4	2	2	85	
5	3	1	17	
6	3	2	83	
7				
8				

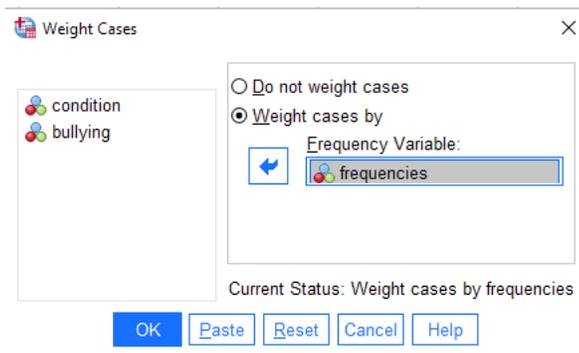
Condition 1 = social influence intervention
 Condition 2 = traditional intervention
 Condition 3 = no-intervention control

Bullying: 1 = did bully; 2 = did not bully

Here you can see that only 4 students in the social influence intervention condition engaged in bullying, compared with 15 in the traditional intervention and 17 in the control condition.

Figure 1

Note that, instead of entering the data this way, you could have entered 300 rows of data, one for each participant (or you could be working with an existing data set that has one row for each participant). For this example there would be four rows in which condition = 1, bullying = 1 to represent the four participants in the social influence intervention condition who bullied. Then there would be 96 rows of condition = 1, bullying = 2, and so on. That’s a bit cumbersome when entering data just for a chi-square test, so instead we simply delineated the six combinations and listed the frequencies with which each occurred. Because of that, however, we now need to tell SPSS to weight the cases (i.e., rows) by their frequencies. To do so, go to the Data menu, then all the way down to the bottom to “Weight Cases”. You’ll get the box shown in Figure 2:



Select “Weight cases by” and move “frequencies” into the “Frequency Variable:” box, then click OK.

Figure 2

Once the data are entered (and cases are weighted, if necessary), go to the “Analyze” menu, scroll down to “Descriptive Statistics,” and then select “Crosstabs.” You will see a window like the one in Figure 3 below. Select bullying as the row variable and condition as the column variable (it doesn’t matter which is which).

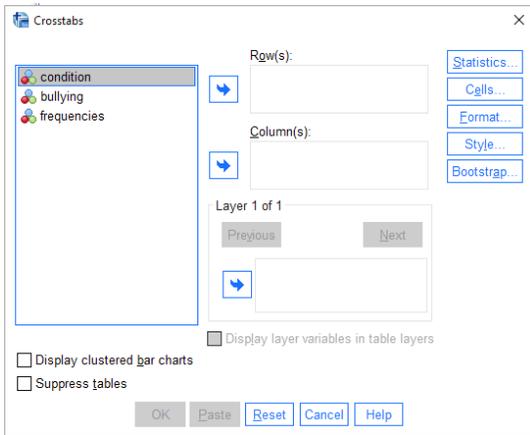


Figure 3

Click on the “Statistics” button and you will see a box like the one in Figure 4 below. Select “Chi-Square” as well as “Phi and Cramer’s V” under “Nominal” and then click “Continue.” Then click on the “Cells” button and you will see a window like the one in Figure 5 below. “Observed” is already selected under “Counts,” but you also need to select “Adjusted standardized” under “Residuals” and then click “Continue.”

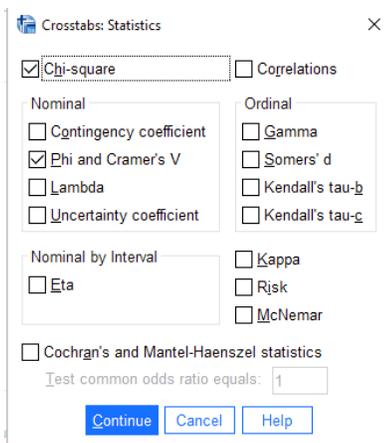


Figure 4

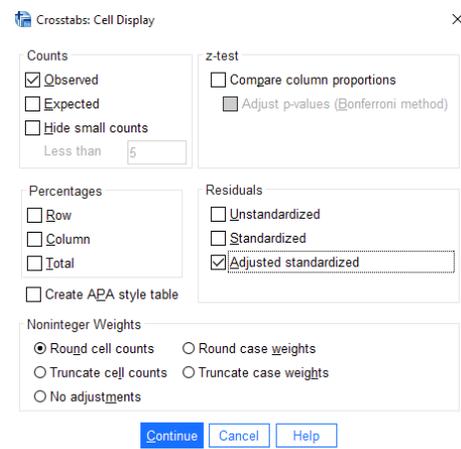


Figure 5

Click the “OK” button and you will get bumped to the output window where your output will look like the following:

bullying * condition Crosstabulation

			condition			Total
			1 social network	2 traditional	3 control	
bullying	1 bullied	Count	4	15	17	36
		Adjusted Residual	-3.0	1.1	1.9	
	2 did not bully	Count	96	85	83	264
		Adjusted Residual	3.0	-1.1	-1.9	
Total		Count	100	100	100	300

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	9.280 ^a	2	.010
Likelihood Ratio	10.847	2	.004
Linear-by-Linear Association	7.975	1	.005
N of Valid Cases	300		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 12.00.

The first table provides the observed counts for your cells as well as the adjusted standardized residuals, which you use to determine the nature of the relationship if the chi-square is significant. More on that in a moment.

The second table provides the chi-square statistic, df, and *p*-value in the first row and the total *N* in the last row. The other two rows can be ignored. In this case, it appears that the chi-square statistic is significant, as *p* = .010. Now we can go back to the first table and determine the nature of the effect by interpreting the adjusted standardized residuals.

If the value for the adjusted standardized residual for a cell is greater than the absolute value of 1.96 (i.e., the z-score that cuts off 5% of the distribution), then the observed frequency significantly differs from the expected frequency for that cell—i.e., the cell is contributing to the nature of the effect.

In this case, it appears that the number of people who bullied (vs. didn't) in the social network condition is different from what would be expected by chance (adjusted standardized residual = -3.0/+3.0). However, the residuals indicate that the counts for the traditional intervention and control conditions don't differ from chance (adjusted standardized residuals were less than |1.96|). You could interpret this pattern as demonstrating that there was significantly less bullying than expected following the social influence intervention than following either the traditional intervention or no intervention.

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.176	.010
	Cramer's V	.176	.010
N of Valid Cases		300	

The final table provides Phi (Φ) and Cramer's V statistics, which you use to interpret the strength of a significant relationship (use Φ for 2 x 2 tables and Cramer's V for tables larger than 2 x 2). Both vary between 0 and 1.

The table below (from p. 601 of the Privitera text) lists norms that can be used to interpret Φ /Cramer's V ; df_{smaller} is the df of the variable with the fewer levels.

TABLE 17.14

Effect Size Conventions for Cramer's V as Proposed by J. Cohen (1988)

df_{smaller}	Effect Size		
	Small	Medium	Large
1	.10	.30	.50
2	.07	.21	.35
3	.06	.17	.29

Sample APA-Style Results section:

A chi-square test of the relationship between intervention condition and bullying behavior was statistically significant, $\chi^2(2, N = 300) = 9.28, p = .010$, Cramer's $V = .18$. Students were less likely to bully and more likely not to bully than expected in the social influence intervention condition, but not in the traditional intervention or control conditions.

Important details for writing a Results section involving correlation/regression:

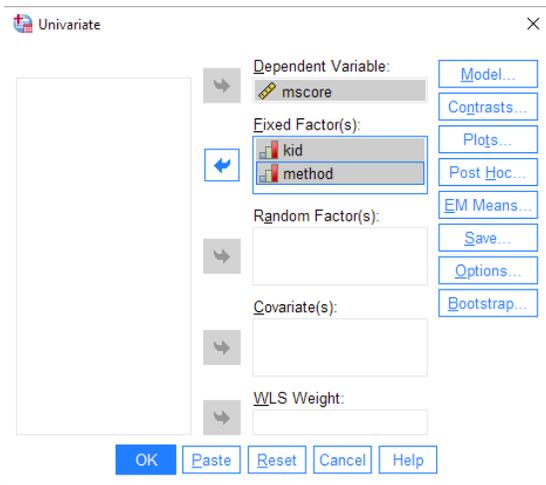
- Italicize N , p , and V .
- Round χ^2 and V to 2 decimal places.
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$.
- When $p > .05$, report that the finding was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1).
- Be sure to describe all cells that contribute to the nature of a significant effect (e.g., less likely to * and more likely not to *)

SPSS Instructions for a 2 x 2 Factorial ANOVA

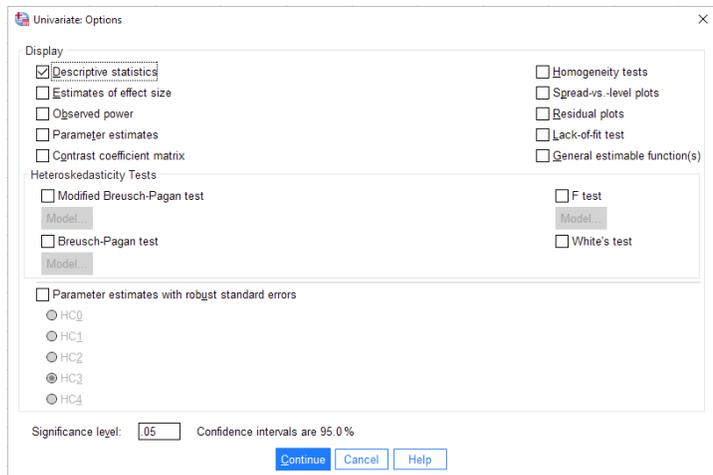
Imagine that an educational psychologist was interested in assessing the effects of two different ways of teaching math (Method A and Method B). She assumed that Method B would be better than Method A, but only for kids who were struggling in math. For kids who typically do well in math, both methods should be equally effective. Her data appear below (numbers indicate scores on the last math test):

	Method A		Method B	
Kids who struggle	75	65	85	86
	70	55	82	90
	80	82	79	86
	68	73	77	80
	64	53	70	91
Kids who do well	88	85	92	96
	84	90	84	82
	88	96	97	80
	94	91	79	95
	85	81	87	89

The first thing you need to do is to figure out how to get these data into SPSS. You have 2 IVs and one DV, so you'll need 3 columns of data: kid type (1 = struggle, 2 = does well), method (1 = A, 2 = B), and math score. Next, you need to do the overall factorial ANOVA. Go up to the Analyze menu to General Linear Model. Choose Univariate (for one dependent variable). When the window (pictured below) comes up, put the dependent variable (which I've called "mscore") into the appropriate box. Next, enter each factor (IV) into the "Fixed Factor(s)" box.



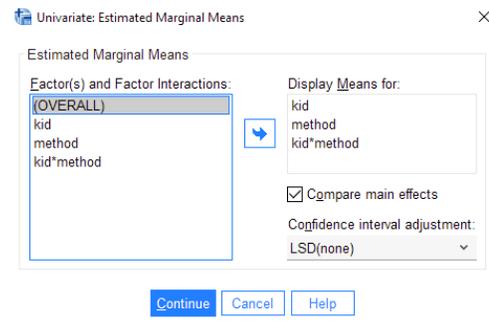
Next, click on the "Options" box to instruct SPSS to give you descriptive statistics (means and standard deviations) for each condition. You will get the window you see below:



Click on the "Descriptive statistics" box and then click "Continue." **Note: Do NOT select "Estimates of effect size". It will produce *partial* η^2 values for each predictor ($SS_B/SS_B + SS_{error}$) rather than just η^2 values (SS_B/SS_{total}). You will need to compute η^2 by hand.**

Note: If any of your IVs had three or more levels, you would next need to choose “Post Hoc” from the initial ANOVA window in order to get SPSS to run a Tukey HSD test to follow up on any significant main effects for that IV. Our two IVs have only two levels each, so we can skip this step, because we can determine the nature of a significant main effect by simply examining the means.

Click on the “EM Means” button to get the dialog box, below. Enter the two main effects and interaction into the “Display Means for” box. Click “compare main effects” and leave the confidence interval adjustment at “LSD(none)”. Click “continue”. This will produce a table of means that includes the standard errors (useful if you are producing a graph), and will also give you the 95% confidence intervals.



Click OK in the initial ANOVA window and you will get the output pictured below:

Univariate Analysis of Variance

Descriptive Statistics

Dependent Variable: mscore

kid	method	Mean	Std. Deviation	N
1 kids who struggle	1 Method A	68.50	9.629	10
	2 Method B	82.60	6.363	10
	Total	75.55	10.743	20
2 kids who do well	1 Method A	88.20	4.662	10
	2 Method B	88.10	6.740	10
	Total	88.15	5.641	20
Total	1 Method A	78.35	12.504	20
	2 Method B	85.35	6.976	20
	Total	81.85	10.604	40

Tests of Between-Subjects Effects

Dependent Variable: mscore

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2581.700 ^a	3	860.567	17.179	<.001
Intercept	267976.900	1	267976.900	5349.434	<.001
kid	1587.600	1	1587.600	31.692	<.001
method	490.000	1	490.000	9.782	.003
kid * method	504.100	1	504.100	10.063	.003
Error	1803.400	36	50.094		
Total	272362.000	40			
Corrected Total	4385.100	39			

a. R Squared = .589 (Adjusted R Squared = .554)

Looking first at the source table, disregard the first two rows, and focus only on the rows for kid, method, kid * method, error, and corrected total. It appears that there’s a significant main effect for kid, a significant main effect for method, and a significant interaction between the two. Note that the interaction may qualify the main effects, so we need to determine that when we look at the nature of the interaction.

Understanding the Nature of the Main Effects

Note that because each of factor has just two levels, you can understand the nature of each significant main effect simply by examining the means. You can find them in the “Descriptive Statistics” box (see above).

First, looking at the main effect for kid, it appears that the mean for kids who typically do well (88.15) is higher than the mean for kids who typically struggle (75.55). This finding isn’t too surprising.

Next, looking at the main effect for method, you can see that Method B ($M = 85.35$) results in higher math scores than Method A ($M = 78.35$).

Use the pairwise comparisons boxes (see below) to get the 95% confidence interval for each main effect (it’s given twice; just pick one).

Pairwise Comparisons

Dependent Variable: mscore

(I) kid	(J) kid	Mean Difference (I-J)	Std. Error	Sig. ^b	95% Confidence Interval for Difference ^b	
					Lower Bound	Upper Bound
1 kids who struggle	2 kids who do well	-12.600 [*]	2.238	<.001	-17.139	-8.061
2 kids who do well	1 kids who struggle	12.600 [*]	2.238	<.001	8.061	17.139

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

So, the 95% CI for the “kid type” variable is [-17.14, -8.06].

Pairwise Comparisons

Dependent Variable: mscore

(I) method	(J) method	Mean Difference (I-J)	Std. Error	Sig. ^b	95% Confidence Interval for Difference ^b	
					Lower Bound	Upper Bound
1 Method A	2 Method B	-7.000 [*]	2.238	.003	-11.539	-2.461
2 Method B	1 Method A	7.000 [*]	2.238	.003	2.461	11.539

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

The 95% CI for the Method variable is [-11.54, -2.46].

Understanding the Nature of the Interaction (examining the “simple effects”)

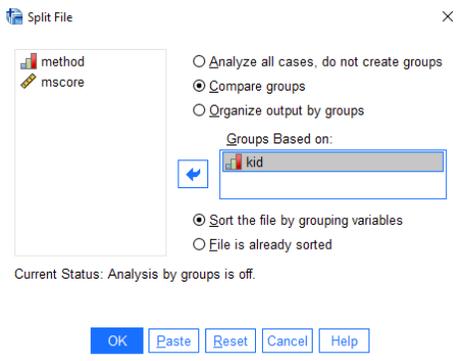
Just eyeballing at the means, it looks like there’s a big difference in math scores by method for the kids who struggle, but not much of a difference for kids who typically do well. Of course, you know that we can’t just *assume* this pattern; we need to actually check it out by testing the significance of the simple effects. We could do this in one of two ways:

1. Examine the differences in the two methods within kid type (Method A vs. Method B for kids who do well; Method A vs. Method B for kids who struggle) or
2. Examine the differences in “kid type” within method (kids who do well vs. kids who struggle for Method A; kids who do well vs. kids who struggle for Method B).

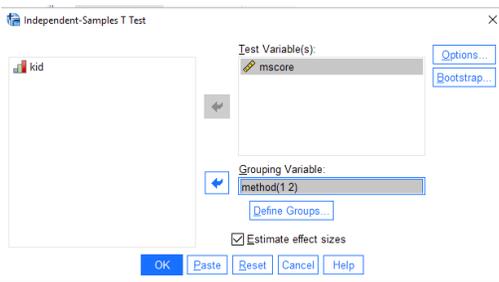
Either comparison is OK, but you shouldn’t do both. Let’s look at method within kid type.

To do so, we will need to ask SPSS to split the file on “kid type” and conduct two *t* tests comparing Method A to Method B: one for kids who do well and one for kids who struggle.

Go to the “Data” menu and choose “Split file”. You will see the window below:



Click on “compare groups” and select “kid,” then the right arrow to put it into the box labeled “Groups Based on:”. Then click OK. SPSS will now conduct all analyses on kids who do well and kids who struggle separately.



Next, you’ll need to conduct an independent-groups *t* test examining the effect of method on score. Go to “Analyze,” “Compare Means,” “Independent Samples T Test” and put in mscore as the Test Variable (DV) and method as the grouping variable (IV). You’ll need to indicate that method is coded as 1 or 2.

You’ll get the output shown below.

T-Test

Group Statistics

kid	method	N	Mean	Std. Deviation	Std. Error Mean
1 kids who struggle	1 Method A	10	68.50	9.629	3.045
	2 Method B	10	82.60	6.363	2.012
2 kids who do well	1 Method A	10	88.20	4.662	1.474
	2 Method B	10	88.10	6.740	2.132

Independent Samples Test

kid	mscore	Levene's Test for Equality of Variances		t-test for Equality of Means								
		F	Sig.	t	df	Significance		Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference		
						One-Sided p	Two-Sided p			Lower	Upper	
1 kids who struggle	mscore	Equal variances assumed	1.456	.243	-3.863	18	<.001	.001	-14.100	3.650	-21.768	-6.432
		Equal variances not assumed			-3.863	15.601	<.001	.001	-14.100	3.650	-21.853	-6.347
2 kids who do well	mscore	Equal variances assumed	2.596	.125	.039	18	.485	.970	.100	2.592	-5.345	5.545
		Equal variances not assumed			.039	16.007	.485	.970	.100	2.592	-5.394	5.594

As you can see, the *t* value is significant for kids who struggle, but not for kids who do well. (Remember to use the two-sided *p* value.) By looking at the means, we see that Method B is superior to Method A for kids who struggle, and the methods are equally helpful for kids who do well. This interaction qualifies the main effect for method: That is, although it appeared that, overall, Method B was more effective than Method A, we know from examining the interaction that Method B is better only for kids who struggle. Thus, we wouldn’t want to make any general statement about Method B being better for everyone. (This is what it means for an interaction to *qualify* a main effect.) It’s probably still safe to interpret the main effect that kids who typically do well do better than kids who typically struggle, regardless of teaching method.

Notice that in the sample results section below, you do not need to explicitly state that you split the file. Just make it clear which comparisons you examined.

Sample APA-Style Results Section:

A 2 (teaching method: Method A vs. Method B) x 2 (student skill level: struggling vs. doing well) between-subjects factorial ANOVA was conducted on math exam scores. There was a significant main effect of teaching method, $F(1,36) = 9.78, p = .003, \eta^2 = .11$, such that students who were instructed with Method B ($M = 85.35, SD = 6.98$) performed better on the math test than did students who were instructed with Method A ($M = 78.35, SD = 12.50$); 95% CI [-11.54, -2.46]. As predicted, the main effect for type of student was also significant, $F(1,36) = 31.69, p < .001, \eta^2 = .36$, such that students who struggle with math ($M = 75.55, SD = 10.74$) performed worse on the math exam than did students who do well with math ($M = 88.15, SD = 5.64$); 95% CI [-17.14, -8.06].

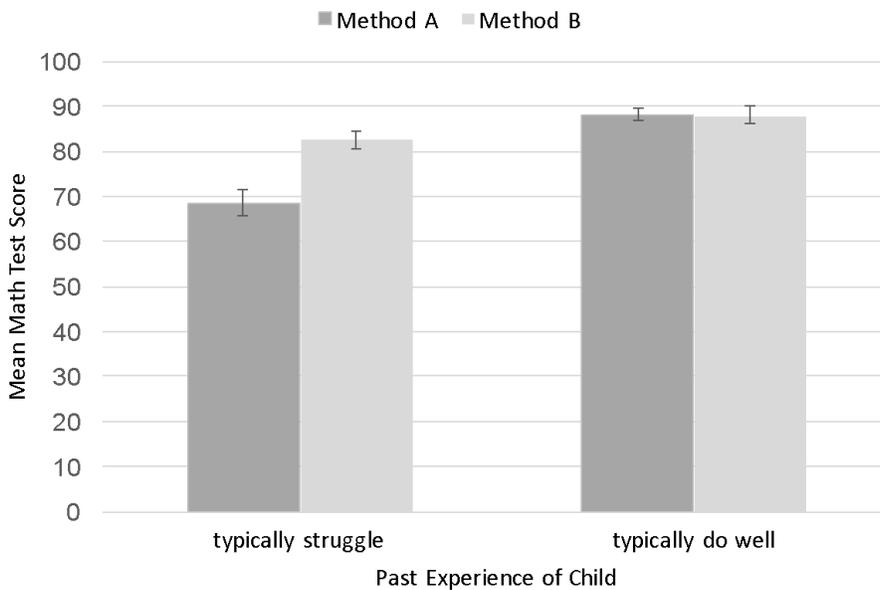
The main effect of teaching method was qualified by a significant interaction between teaching method and type of student, $F(1,36) = 10.06, p = .003, \eta^2 = .11$. To understand the nature of the interaction, two independent-groups t tests, comparing Method A to Method B, were conducted: one for students who do well in math and one for students who struggle. As seen in Figure 1, and consistent with the hypothesis, for students who do well, there was no significant difference in math exam scores for those instructed with Method A ($M = 88.20, SD = 4.66$) and those instructed with Method B ($M = 88.10, SD = 6.74$), $t(18) = .04, p = .970$; 95% CI [-5.35, 5.55]. However, students who struggle in math performed significantly better on the math exam when instructed with Method B ($M = 82.60, SD = 6.36$) than with Method A ($M = 68.50, SD = 9.63$), $t(18) = -3.86, p = .001$; 95% CI [-21.77, -6.43].

The figure you create (see below) should be consistent with the way in which you split the file. Because we compared the two methods within the two levels of “kid type,” the figure below is organized so that the reader can compare the method bars (which should touch each other) for each type of child. If you had split the file the other way, you would need to have the two method types on the x-axis and the two “kid types” as the differently-shaded bars.

Excel Tip: You can easily swap which variable is on the x-axis and which in the legend by clicking on the graph, going to the “Chart Design” toolbar, and selecting “Switch Row/Column.” See separate handout for how to create the figure in Excel.

Figure 1

Mean Math Test Score as a Function of Teaching Method and Past Experience



Note. Error bars represent one standard error above and below the mean.

SPSS Instructions for a 2 X 3 Factorial ANOVA

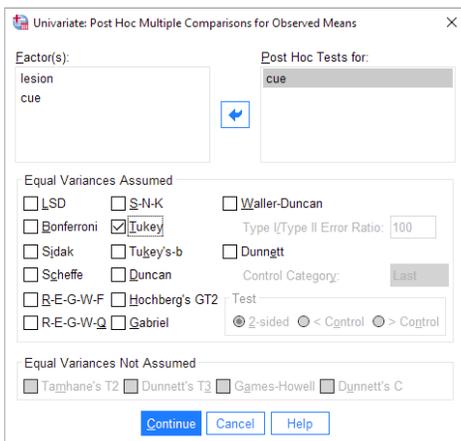
When people are given a display of objects (e.g., an apple) to memorize and later recall, they typically recall more when given a recall cue, whether spatial (location of the object; e.g., top left) or semantic (word related to the object; e.g., pie). Because the medial temporal lobes are involved in memory, one would expect that people with damage to the medial temporal lobes would perform poorly on a free recall task. In addition, because the temporal lobes are also involved in spatial processing, a spatial cue should not help people with medial temporal lobe lesions. A neuroscientist gave 15 control participants and 15 participants with a medial temporal lobe lesion 36 objects to memorize. Participants in each group were randomly assigned to receive a spatial cue, a semantic cue, or no cue upon recall. Number of objects recalled was recorded for each participant. What do the data suggest?

	Free recall	Spatial cue	Semantic cue
Control participants	15	18	18
	17	34	19
	11	25	23
	15	30	17
	18	17	32
Participants with temporal lobe lesion	9	9	22
	5	6	21
	6	4	30
	3	1	34
	2	3	21

Use the same procedure you used for the 2 x 2 ANOVA for getting the data into SPSS, keeping in mind that your “cue” variable will need three levels (1 = free recall, 2 = spatial cue, 3 = semantic cue).

Conduct the factorial ANOVA as you did before, with recall as your dependent variable and lesion and cue as your fixed factors. Be sure to select “Descriptive statistics” from the Options menu to get your means and standard deviations.

Because the cue variable has more than two levels, you should click on “Post Hoc” and click on the “Tukey” box (see below). If the cue main effect is significant, you will be able to see how the three means differ from one another.



Click “Continue” and then “OK” to get bumped into the output window (see next page).

Descriptive Statistics

Dependent Variable: recall

lesion	cue	Mean	Std. Deviation	N
1 control	1 free recall	15.20	2.683	5
	2 auditory cue	24.80	7.396	5
	3 visual cue	21.80	6.140	5
	Total	20.60	6.759	15
2 temporal lobe lesion	1 free recall	5.00	2.739	5
	2 auditory cue	4.60	3.050	5
	3 visual cue	25.60	6.025	5
	Total	11.73	10.872	15
Total	1 free recall	10.10	5.953	10
	2 auditory cue	14.70	11.908	10
	3 visual cue	23.70	6.075	10
	Total	16.17	9.973	30

Tests of Between-Subjects Effects

Dependent Variable: recall recall score (# of items recalled)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2273.367 ^a	5	454.673	17.865	<.001
Intercept	7840.833	1	7840.833	308.088	<.001
lesion	589.633	1	589.633	23.168	<.001
cue	957.067	2	478.533	18.803	<.001
lesion * cue	726.667	2	363.333	14.276	<.001
Error	610.800	24	25.450		
Total	10725.000	30			
Corrected Total	2884.167	29			

a. R Squared = .788 (Adjusted R Squared = .744)

So, there's a significant main effect for lesion, a significant main effect for cue, and a significant lesion x cue interaction.

Understanding the Nature of the Main Effects

Lesion main effect: Looking at the means in the descriptive statistics box (above), we can see that those with a temporal lobe lesion recalled significantly fewer objects than did controls. As with the 2 x 2 ANOVA, the 95% CI can be found in the pairwise comparisons box that you get when you click on EM Means (see below).

Pairwise Comparisons

Dependent Variable: recall

(I) lesion condition	(J) lesion condition	Mean Difference (I-J)	Std. Error	Sig. ^b	95% Confidence Interval for Difference ^b	
					Lower Bound	Upper Bound
1 control	2 temporal lobe lesion	8.867 [*]	1.842	<.001	5.065	12.669
2 temporal lobe lesion	1 control	-8.867 [*]	1.842	<.001	-12.669	-5.065

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

Cue main effect: Because the cue variable has three levels, you need to examine the output from the Tukey test to understand it.

Post Hoc Tests (Tukey test for recall cue condition main effect)

Post Hoc Tests

recall cue condition

Multiple Comparisons

Dependent Variable: recall recall score (# of items recalled)
Tukey HSD

(I) recall cue condition	(J) recall cue condition	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
1 free recall	2 spatial cue	-4.60	2.256	.125	-10.23	1.03
	3 semantic cue	-13.60*	2.256	<.001	-19.23	-7.97
2 spatial cue	1 free recall	4.60	2.256	.125	-1.03	10.23
	3 semantic cue	-9.00*	2.256	.002	-14.63	-3.37
3 semantic cue	1 free recall	13.60*	2.256	<.001	7.97	19.23
	2 spatial cue	9.00*	2.256	.002	3.37	14.63

Based on observed means.
The error term is Mean Square(Error) = 25.450.

*. The mean difference is significant at the .05 level.

Homogeneous Subsets

recall recall score (# of items recalled)

Tukey HSD^{a,b}

recall cue condition	N	Subset	
		1	2
1 free recall	10	10.10	
2 spatial cue	10	14.70	
3 semantic cue	10		23.70
Sig.		.125	1.000

Means for groups in homogeneous subsets are displayed.

Based on observed means.
The error term is Mean Square(Error) = 25.450.

a. Uses Harmonic Mean Sample Size = 10.000.

b. Alpha = .05.

The nature of the main effect for cue is such that participants provided with a semantic cue performed significantly better than did those provided with either a spatial cue or no cue (i.e., free recall), who did not differ from each other.

Understanding the Nature of the Interaction (examining the “simple effects”)

Next we need to interpret the nature of the significant interaction. As you did for the 2 x 2 ANOVA, you’ll need to split the file on one of the two IVs and examine the effect of the other IV on the DV. In this case, I thought it made sense to compare the effect of cue type on recall for those with and without a temporal lobe lesion. So we’ll need to split the file on the lesion variable and conduct a one-way ANOVA on recall as a function of cue type.

Again, go to “Data,” “Split file,” “Compare groups”. Select the lesion variable to group the data.

Once you’ve created these groups, go to “Analyze,” “Compare means,” “One-way ANOVA”. Remember to use the *other* IV (not the one you grouped on!). So DV = recall, IV = cue type.

Remember to select the Tukey post-hoc test so you can see which levels of the cue variable differ within each level of the lesion variable.

Because you split the file, you’ll get two one-way ANOVAs: one for the lesion participants and one for the control participants (see below).

Oneway

Descriptives

recall recall score (# of items recalled)

lesion lesion condition		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
1 control	1 free recall	5	15.20	2.683	1.200	11.87	18.53	11	18
	2 spatial cue	5	24.80	7.396	3.308	15.62	33.98	17	34
	3 semantic cue	5	21.80	6.140	2.746	14.18	29.42	17	32
	Total	15	20.60	6.759	1.745	16.86	24.34	11	34
2 medial temporal lobe lesion	1 free recall	5	5.00	2.739	1.225	1.60	8.40	2	9
	2 spatial cue	5	4.60	3.050	1.364	.81	8.39	1	9
	3 semantic cue	5	25.60	6.025	2.694	18.12	33.08	21	34
	Total	15	11.73	10.872	2.807	5.71	17.75	1	34

ANOVA

recall recall score (# of items recalled)

lesion lesion condition		Sum of Squares	df	Mean Square	F	Sig.
	Within Groups	398.400	12	33.200		
	Total	639.600	14			
2 medial temporal lobe lesion	Between Groups	1442.533	2	721.267	40.750	<.001
	Within Groups	212.400	12	17.700		
	Total	1654.933	14			

For the control participants, there was no significant effect of cue type on recall. For the participants with a lesion, there was a significant effect of cue type on recall. We need to examine the Tukey test to interpret the nature of the effect of cue type on recall for the participants with a lesion.

Post Hoc Tests

Multiple Comparisons

Dependent Variable: recall recall score (# of items recalled)

Tukey HSD

lesion lesion condition	(I) cue recall cue condition	(J) cue recall cue condition	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
1 control	1 free recall	2 spatial cue	-9.600	3.644	.053	-19.32	.12
		3 semantic cue	-6.600	3.644	.208	-16.32	3.12
	2 spatial cue	1 free recall	9.600	3.644	.053	-.12	19.32
		3 semantic cue	3.000	3.644	.696	-6.72	12.72
	3 semantic cue	1 free recall	6.600	3.644	.208	-3.12	16.32
		2 spatial cue	-3.000	3.644	.696	-12.72	6.72
2 medial temporal lobe lesion	1 free recall	2 spatial cue	.400	2.661	.988	-6.70	7.50
		3 semantic cue	-20.600*	2.661	<.001	-27.70	-13.50
	2 spatial cue	1 free recall	-.400	2.661	.988	-7.50	6.70
		3 semantic cue	-21.000*	2.661	<.001	-28.10	-13.90
	3 semantic cue	1 free recall	20.600*	2.661	<.001	13.50	27.70
		2 spatial cue	21.000*	2.661	<.001	13.90	28.10

*. The mean difference is significant at the 0.05 level.

Homogeneous Subsets

recall

lesion lesion condition=1 control

Tukey HSD^a

cue recall cue condition	N	Subset for alpha = 0.05	
		1	2
1 free recall	5	15.20	
3 semantic cue	5	21.80	
2 spatial cue	5	24.80	
Sig.		.053	

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 5.000.

lesion lesion condition=2 medial temporal lobe lesion

Tukey HSD^a

cue recall cue condition	N	Subset for alpha = 0.05	
		1	2
2 spatial cue	5	4.60	
1 free recall	5	5.00	
3 semantic cue	5		25.60
Sig.		.988	1.000

Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 5.000.

The ANOVA was not significant for the control participants, so that post-hoc test does not need to be interpreted (notice that SPSS prints it out anyway; you have to know better not to look at it!)

For the participants with a lesion, providing semantic cues resulted in significantly better recall than providing either spatial cues or no cues, which did not differ from each other. Thus, the main effect of type of cue was qualified by the significant interaction. The pattern holds only for the participants with a temporal lobe lesion.

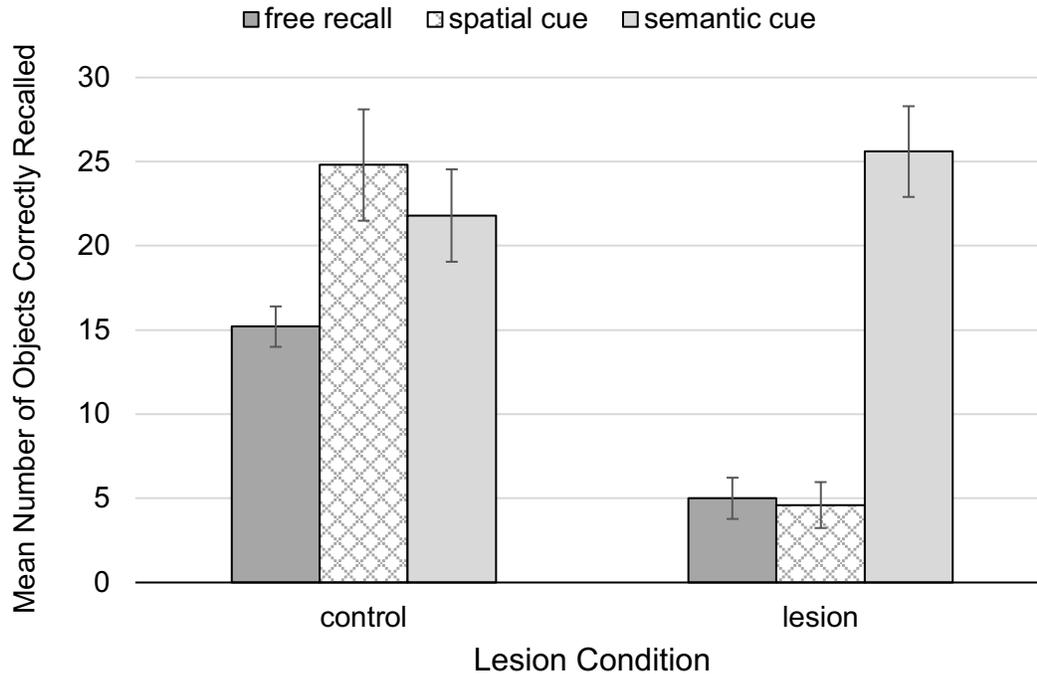
Sample APA-Style Results Section:

A 2 (condition: control vs. participants with a temporal lobe lesion) x 3 (type of recall cue: spatial, semantic, none) between-subjects factorial ANOVA was conducted on number of objects recalled from an array. As predicted, there was a significant main effect of condition, $F(1,24) = 23.17, p < .001, \eta^2 = .20$, such that participants with a temporal lobe lesion recalled significantly fewer words ($M = 11.73, SD = 10.87$) than did participants in the control condition ($M = 20.60, SD = 6.76$); 95% CI [5.06, 12.67]. The main effect of cue type was also significant, $F(2,24) = 18.80, p < .001, \eta^2 = .33$. A Tukey HSD test indicated that participants provided with a semantic cue ($M = 23.70, SD = 6.08$) performed significantly better than did those provided with either a spatial cue ($M = 14.70, SD = 11.91$); 95% CI [3.37, 14.63] or no cue ($M = 10.10, SD = 5.95$); 95% CI [7.97, 19.23], who did not differ from each other; 95% CI [-1.03, 10.23].

These two main effects were qualified by a significant interaction between condition and cue type, $F(2,24) = 14.28, p < .001, \eta^2 = .25$. To understand the nature of the interaction, two one-way between-subjects ANOVAs comparing cue type were conducted: one for control participants and one for participants with a temporal lobe lesion. As shown in Figure 1, for control participants, the one-way ANOVA was not significant, $F(2,12) = 3.63, p = .058$. There was no significant difference in number of objects recalled between those provided with no cue ($M = 15.20, SD = 2.68$) and those provided with either a spatial cue ($M = 24.80, SD = 7.40$); 95% CI [-19.32, 0.12] or a semantic cue ($M = 21.80, SD = 6.14$); 95% CI [-16.32, 3.12], nor was there a difference in recall between those provided with a semantic versus a spatial cue; 95% CI [-6.72, 12.72]. In contrast, the one-way ANOVA for participants with a temporal lobe lesion was significant, $F(2,12) = 40.75, p < .001$. A Tukey HSD test indicated that, as hypothesized, participants with a temporal lobe lesion performed significantly better on the recall task when provided with a semantic cue ($M = 25.60, SD = 6.03$) than those provided with either a spatial cue ($M = 4.60, SD = 3.05$; 95% CI [13.90, 28.10]) or no cue ($M = 5.00, SD = 2.74$; 95% CI [13.50, 27.70]), who did not differ from each other; 95% CI [-7.50, 6.70].

Figure 1

Mean Recall as a Function of Lesion Condition and Cue Condition



Note. Error bars represent one standard error above and below the mean.

Important details for writing a Results section involving a factorial ANOVA:

- Italicize M , SD , F , t (if using t-tests to understand the nature of an interaction) and p .
- Don't forget to write the degrees of freedom, between and within (error), in parentheses.
- Round M , SD , F , t , η^2 , and CI to 2 decimal places.
- Report p to 3 decimal places. Always provide the exact p value (e.g., $p = .004$) unless $p < .001$, in which case you simply write $p < .001$.
- When $p > .05$, report that the finding was NONsignificant, not INsignificant. Report the exact p value even if the test is not significant.
- Use a leading zero for numbers less than one that can take on values less than or greater than 1 (or -1). Note that η^2 does NOT get a leading zero because its maximum value is 1.
- First indicate whether or not any of the main effects were significant. If so, report the value of η^2 and describe the nature of the significant effect(s), including the results of any post hoc Tukey HSD test(s). In describing the pattern of results, be sure to state the M s and SD s of each group in parentheses; however, there is no need to provide the M and SD for the same group twice (i.e., if you are comparing that group to two different groups, you only need to provide the descriptive statistics the first time you mention that group).
- Next indicate whether or not the interaction was significant. If so, report the value of η^2 and indicate if the interaction qualified the main effect(s) (if not, simply state that the interaction was significant). For a significant interaction, next describe the analyses you conducted to determine the nature of the interaction. Be sure to refer to a Figure when describing the pattern of results. Report M s, SD s, 95% CIs, and F or t statements, but do not report strength for any significant F or t tests conducted solely to determine the nature of a significant interaction because you already reported η^2 for the interaction itself.
- Don't forget to include confidence intervals, where appropriate.

